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A Spatial Analysis of Regional Consumption Network Effects in Japan[1]

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1. Introduction

The effectiveness of fiscal policies is of primary interest for policymakers and economists. Many studies have tackled the effects of fiscal policy; however, as Cogan et al. (2010) point out, "Macroeconomists remain quite uncertain about the quantitative effects of fiscal policy. This uncertainty derives not only from the usual errors in empirical estimation but also from different views on the proper theoretical framework and econometric methodology."

The purpose of the present paper is to contribute to the literature on the quantitative effects of fiscal policies in both theoretical and methodological aspects. First, we adopt the interdependent preference in consumption as a theoretical framework: in the modeling of the effects of fiscal policy, one agent's consumption decision influences another agent's consumption decision in the absence of market transactions. Second, because our interest is the social influence of the consumption behavior among *regions*, we adopt the spatial approach as an econometric methodology.

Starting from Veblen (1899) and Duesenberry (1949), a vast literature on the interdependent preference in consumption has emphasized the importance of incorporating the social aspects of the consumption behavior in economic models (Leibenstein, 1950; Pollak, 1969; Gali, 1994; Binder and Peseran, 2001; Bell, 2002). Empirical studies have also been conducted (Kapteyn et al., 1994; Maurer and Meier, 2008; Alvarez-Cuadrado et al., 2015; De Giorgi et al., 2016). One implication of incorporating externalities in the modeling of consumer behavior is, as stated in De Giorgi et al. (2016), their potential aggregate effects. If geographically and psychologically closed groups share a similar code of consumption behavior, the effects of group-targeted fiscal policy (such as an income transfer to households) on consumption spread beyond the target group.

In general, the magnitude of the effects of the fiscal policy depends on the size, timing, and target

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group (individuals, households, and regions). A fiscal policy targeting a group that has a close consumption network with another group produces more aggregate consumption in comparison with a less connected group. In this respect, De Giorgi et al. (2016) report some interesting policy simulations based on the empirical estimates of consumption network effects. They examine the effects of transferring the equivalent of 1% of the aggregate consumption to (a) households in the top 10% of the consumption distribution (presumably, wealthier households), (b) a 10% random sample of households, and (c) households in the bottom 10% of the consumption distribution (presumably, poorer households). Their experiment shows that aggregate consumption is the highest for the households in the bottom 10% of the consumption distribution because their consumption behavior is characterized by larger and denser direct networks involving similar households.

The spirit of our paper is in line with De Giorgi et al. (2016). We apply the theoretical framework of consumption network effects to the "spatial" consumption network in Japan, and we try to identify the regions that should be targeted by the country's fiscal policy to maximize aggregate consumption. With the exception of Case (1991), the consumption network effects in the spatial perspective have been hardly addressed in the literature, even though, in recent years, econometric modeling targeting spatial interaction and heterogeneity has been an area of growing interest in applied econometrics. With respect to Japan, Kakamu and Wago (2005) and Kakamu et al. (2010) estimated the spatial interaction of economic activities in the business cycle. On the other hand, Brückner and Tuladhar (2013) studied spatial heterogeneity in the impact of government spending in Japan. In particular, they estimate the local government spending multipliers using prefecture panel data and find that the local government spending multiplier varies across prefectures, in Japan. They also find that the cross-prefecture heterogeneities in local government spending multipliers are determined by commercial land prices, which affect local firms' financial constraints in shaping the size of the multiplier.

The remainder of this paper is organized as follows. In Section 2, we present a spatial panel data model of regional consumption, which incorporates the network effects among regions. Section 3 shows the empirical results of regional consumption network effects and simulates the effects of an income transfer policy to the regions. Section 4 discusses the significance of our findings in the context of regional economic policy and potential applications of our model.

2. Model

Although the theory of consumer demand has been refined since the 18^{th} century, Hotelling (1932), Court (1941), and Roy (1947) extended the theory of consumer demand introducing the concepts of duality and functional structure. Hotelling (1932) derived the indirect utility as a function of prices and income. Roy (1947) showed that the indirect utility function leads to an explicit expression for the demand functions by expressing them as ratios of the partial derivatives of the indirect utility function with respect to prices and income. The econometric model proposed in this paper is based on the classical theory of consumer demand and aims at describing regional consumption in the perspective of network effects in Japan. First, we assume that consumption in each region is not affected by the consumption patterns of surrounding regions We define the logarithmic linear consumption function as follows:

$$\ln C_{it} = \alpha_i + \beta \ln I_{it} + \gamma \ln P_{it} + \theta Z_{it} + \epsilon_{it}, \quad \text{for } i = 1, \ldots, N, t = 1, \ldots T, \tag{1}$$

where C_{it} is the consumption of the *i*-th region at *t*, I_{it} is the income of the *i*-th region at *t*, P_{it} is the price in the *i*-th region at *t*, and Z_{it} are the demographic variables representing the attributes of the *i*-th region at *t*. If we assume that the law of one price is valid in Japan, the price of each region will be equal in all regions, as follows:

$$\ln C_{it} = \alpha_i + \beta \ln I_{it} + \gamma \ln P_t + \theta Z_{it} + \epsilon_{it}. \tag{2}$$

In this model, the price term only depends on the time parameter and can be regarded as a macro shock. Equation 2 describes a panel model with time effect. Next, we add network effects to this model to capture the effect of interactions with the surrounding regions, as follows:

$$\ln C_{it} = \alpha_i + \beta \ln I_{it} + \gamma \ln P_t + \ln S_{it} + \theta Z_{it} + \epsilon_{it}, \tag{3}$$

where $\ln S_{it}$ represents the network effect of the *i*-th region and is not directly observable. In the previous study, the value of the adjacent region has been used for estimating the network effect $\ln S_{it}$. In this study, we estimate the network effect by using the following proxy variables, as suggested by Kakamu and Wago (2005):

$$\ln S_{it} = \sum_{j=1}^{N} \delta_{ij} \ln C_{jt}, \tag{4}$$

where, if the *i*-th and *j*-th regions are equal, $\delta_{ii} = 0$, and if the *i*-th and *j*-th regions are not adjacent, $\delta_{ij} = 0$. Substituting Equation (4) into Equation (3) yields the following formulation:

$$\ln C_{it} = \alpha_i + \beta \ln I_{it} + \gamma \ln P_t + \sum_{j=1}^{N} \delta_{ij} \ln C_{jt} + \theta Z_{it} + \epsilon_{it}, \tag{5}$$

where $\ln C_{jt}$ represents consumption in adjacent region *j* for each region *i*. Since $\ln C_{jt}$ is an endogenous variable, which appears on both sides of Equation (5), this model represents a simultaneous equation system. To eliminate the time and price effects, we calculate the model using the average of Equation (5) between cross-sectional dimensions at each point in time, as follows:

$$\overline{\ln C_t} = \bar{\alpha} + \beta \overline{\ln I_t} + \gamma \ln P_t + \frac{1}{N} \sum_{j=1}^{N} \delta_j \ln C_{jt} + \theta \bar{Z}_t + \bar{\epsilon}_t, \tag{6}$$

where the upper bars indicate the average in cross-section i, and $\delta_j = \frac{1}{N}\sum_{m=1}^{N}\delta_{mj}$. Finally, by subtracting Equation (5) from Equation (6), we obtain the following model:

$$\ln C_{it}^{*} = \alpha_i^{*} + \beta \ln I_{it}{}^{*} + \sum_{j=1}^{N}\{(\delta_{ij} - \delta_j)\ln C_{jt}^{*}\} + \theta Z_{it}^{*} + \epsilon_t^{*}, \tag{7}$$

where $\alpha_i^{*} = \alpha_i - \bar{\alpha}$, $\ln I_{it}^{*} = \ln I_{it} - \overline{\ln I_t}$, $\ln C_{it}^{*} = \ln C_{it} - \overline{\ln C_t}$, $Z_{it}^{*} = Z_{it} - \bar{Z}_t$, and $\epsilon_t^{*} = \epsilon_{it} - \bar{\epsilon}_t$. This model considers the consumption of the adjacent regions as the determinants of consumption in each region. It can be also regarded as a panel model that takes both the time effect and the individual effect into account. Since the consumption variable, $\ln C_{jt}^{*}$, appears on both sides of Equation (7) and is an endogenous variable, the OLS estimator is not consistent. Several estimation techniques allow dealing with endogenous variables, such as the maximum likelihood method. In this study, we estimate Equation (7) by Hansen (1982)'s generalized method of moments (GMM), and we use the lagged log income of the adjacent region as instrumental variables.

3. Estimation and Empirical Results

The data used in this study range from January 2000 to December 2010 and refer to 47 regions in Japan, with a total of 6204 observations (= 132×47). Our dataset includes information regarding the aggregate consumption expenditure, available income, and household's demographic variables, such as the number of people in the household and the age of the household head, and is obtained from the *Family Income and Expenditure Survey* ("Kakei Chosa" in Japanese) carried on by the Japanese Statistics Bureau. In addition, we use the average temperature data obtained from the Meteorological Agency as an indicator of the characteristics of each region. Monthly household survey data for 47 regions are available from January 2000 for working households with two or more people in the household. In particular, the *Family Income and Expenditure Survey* has begun including households whose members engage in agriculture, forestry, and fisheries since 2000 to expand the scope of the survey.

Table 1 shows the average log consumption and log income over the period between January 2000 and December 2010 for the 47 regions. The national average of log consumption is 12.694, and that of log income is 12.967. Log consumption is the highest in Toyama, followed by Kanazawa. This is proportional to the high income level of these two areas. Also, Toyama and Kanazawa are adjacent regions. On the other hand, Naha has the lowest income and consumption. Tokyo, the capital of Japan, has higher consumption than the national average and shows a small standard deviation, far smaller than other regions. This suggests that the disparity in consumption in Tokyo is small and concentrates around the mean. In addition, Yokohama and Saitama, adjacent to Tokyo, also have a high level of consumption compared with other regions. Considering Tokyo as the center of Japan, consumption tends to be high in the regions around Tokyo and declines as the distance to the center increases. Even in Nagoya and Osaka, the two largest cities in Japan together with Tokyo, the average log consumption is lower than in the regions around Tokyo. For instance, in many regions located in the Kinki district (including Otsu, Kyoto, Osaka, Kobe, Nara, and Wakayama), to which Osaka belongs, log consumption is lower than the national average and tends to be inferior to that in the Kanto district, to which Tokyo belongs. The same holds for log income; the log income of most regions in the Kinki district is lower than the national average. Similar trends can also be found in other districts; log consumption is similar in all districts that belong to these regions, in particular between adjacent regions. In other words, national consumption is parted into a number of regional blocks, and the degree of resemblance differs across blocks.

First, Equation (7) was estimated using panel data for 47 regions in Japan observed between January 2000 and December 2010. We used aggregate consumption expenditure and individual commodities as consumption variables. Since our data refer to 10 commodities, we estimate the model 10 times for each individual commodity. The demographic variables, Z_{it}, include the number of household members, the age of the head of the household, and the average temperature in the region. As expected, the household consumption increases with the number of household members. It is also possible that the household consumption pattern differs depending on the cohort to which the head of the household belongs. From the geographical point of view, the average temperature affects consumption expenditure, for instance through heating expenses. When the coefficient on a certain variable is not significant, the variable is excluded from the model, which is, then, estimated again. Table 2 shows the estimated results of the full model. Income has a significant positive effect on all commodities. An increase in income by 1% will increase the consumption of each commodity except fuel, light, and water charges by 0.2-0.3%. The coefficient on fuel, light, and water charges is lower than that on the other items and only increases by 0.085%.

Next, we test the presence of spatial peer effects between adjacent regions. If all the coefficients on the spatial terms are not significant, there are no spatial peer effects. On the other hand, if at least one parameter is significant, the spatial peer effect exists. The null hypothesis and the alternative hypothesis are as follows:

$$\mathrm{H_0}: \delta_{ij} = 0 \ \ for \ \ all \ \ j;$$
$$\mathrm{H_A}: \ otherwise.$$

We test this hypothesis using a Chi-square test. The test statistic has a Chi-square distribution with 180 degrees of freedom, as there are 180 adjacent regions. The *Family Income and Expenditure Survey* reports information on 10 commodities as well as data on the aggregate consumption. Since the peer effect might be different according to the type of commodity, we tested it separately for each commodity. The result of the test is shown in Table 3.

The results suggest that the spatial peer effects have a significant impact on the aggregate consumption expenditure. However, when examining the spatial peer effects separately for individual commodities, the results are mixed: spatial peer effects are significant for fuel, light and water charges, clothing and footwear, medical care, and culture and recreation; on the other hand, no significant effects are observed in food, housing, transportation and communication, education, and other consumption expenditures.

When the spatial peer effects are "conspicuous," the differences in the statistical significance of the effects can be interpreted as an indicator of the "visibility" of commodities, namely, more "visible" expenditures in some regions can be seen signals that stimulate the neighbors' consumption behavior. With respect to the visibility of commodities, Heffetz (2011) introduces visibility indices and rankings. If the conspicuous consumption hypothesis can be applied to our setting, the commodities for which the spatial peer effects are significant should be highly ranked in the indices proposed by Heffetz (2011). As shown in Table 3, clothing and recreation rank high among the various consumption items (3rd and 6th, respectively) in the index. This is consistent with our results, which indicates that spatial peer effects are significant in fuel, clothing and footwear, and culture and recreation. However, gasoline and health care rank lower (21st and 22nd, respectively), and this seems to contradict our results, which indicate that spatial peer effects are significant in fuel, light and water charges, and medical care.

The conspicuous consumption hypothesis can only partly explain our results. Another possible explanation for is the presence of region-specific effects. With respect to the significant spatial peer effects in fuel, light, and water charges, it is likely that locally monopolized public utility charges for gas, electricity, and water cause a local correlation with public expenditures. On the other hand, medical care expenditure, as a result of the frequency of the medical treatment, causes correlations among local areas because doctors and medical institutions are unequally distributed across regions.

Among the commodities for which the spatial peer effects are not significant, education ranks high (ranked as 13th). It seems conceivable that income constraints in some households restrain the spatial peer effects of education expenditures, even if education is "conspicuous."

Next, to estimate the effect of aggregate consumption on adjacent regions, we estimate Equation (7) including log consumption in the adjacent regions, $\ln C_{jt}^{*}$, for each region that appears on the right-hand side of the equation. There are a total of 180 adjacent regions for the 47 regions considered in this study. However, estimating network effects without any constraints may lead to very unstable results. Therefore, before estimating Equation (7), we attempted to identify the variables that best describe log consumption in adjacent regions, since the non-negativity for the network effects should be satisfied in all equations, as follows:

$$\delta_{ij} > 0,$$

where $j = 1, \ldots, 47$. Theoretically, network effects could be negative if the "snob" effect is present in the consumption behavior across regions. However, a negative influence has not been found in the previous empirical literature on the social influences on consumption. As Bell (2002) points out, negative network effects could be induced by negative feedback mechanisms through price changes.[2] However, heterogeneity in regional price levels is not allowed in our model; hence, this possibility is excluded. Therefore, we need to identify log consumption in adjacent regions, $\ln C_{jt}^{*}$, along with the elimination of the non-negativity for network effects; hence, we discard some variables according to the following procedure:

1. We first estimate Equation (7) including all log consumptions in adjacent regions, $\ln C_{jt}^{*}$, and other variables, using the generalized method of moments (GMM).
2. Based on the estimation results, we exclude from the consumption function the log consumption variables in adjacent regions with the largest *p*-value.
3. Step 2 is iterated until the estimation of $\hat{\delta}_{ij}$ becomes positive.

In the estimation of Step 1, since log consumption in adjacent regions on the right-hand side of the equation is correlated with the error term, we estimate the parameters of Equation (7) using the GMM technique and instrumental variables. We used the lagged available income of adjacent regions against consumption in the region as instruments in the GMM estimations. In Step 2, we delete the log consumptions in adjacent regions whose *p*-value is higher than 0.2 in an upper one-sided test. As a result, the number of variables is reduced to 65 from an initial total of 180 variables. Table 4 details this result.

Further, we perform the economic simulation for the surrounding regions based on the adjacent coefficient matrix built on the estimation results of Equation (7). The coefficient on the network effect shows how much consumption in the adjacent region will increase when the consumption in the considered region rises. We proceed as follows.

First, we calculate the increment in consumption in the relevant region and surrounding regions when income increases by 10,000 Yen per person in the household by estimating the following equations. First, we express Equation (7) in matrix notation:

$$\mathbf{C_t} = \mathbf{BI_t} + \mathbf{DC_t} + \boldsymbol{\theta}\mathbf{Z_t}, \tag{8}$$

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[2] Nagayasu (2015) finds that increases in the consumption of non-tradable goods in neighboring regions raise inflation pressures in the analyzed region.

where $\mathbf{C_t} = (\ln C_{1t}^*, \ln C_{2t}^*, \dots, \ln C_{Nt}^*)'$, and $\mathbf{D}$ is an $N \times N$ adjacent effect matrix with zero diagonal elements, as follows:

$$\mathbf{D} = \begin{bmatrix} 0 & \cdots & (\delta_{1N} - \delta_N) \\ \vdots & \ddots & \vdots \\ (\delta_{N1} - \delta_1) & \cdots & 0 \end{bmatrix}.$$

We summarize this formula as:

$$\mathbf{C_t} = (\mathbf{I} - \mathbf{D})^{-1}\mathbf{B}\mathbf{I_t} + (\mathbf{I} - \mathbf{D})^{-1}\boldsymbol{\theta}\mathbf{Z_t}, \quad (9)$$

where I is an $N \times N$ identity matrix with diagonal elements equal to 1. Further, we express this as the increment in consumption, as follows:

$$\mathbf{\Delta C_t} = (\mathbf{I} - \mathbf{D})^{-1}\mathbf{B}\mathbf{\Delta I_t}. \quad (10)$$

Second, we substitute this value with its amount since the increment in consumption is a logarithmic value. In addition, we also calculate the total amount of the increase in consumption induced by each region in other regions.

Table 5 shows the increase in consumption for other regions when the income of a certain region increases by 10,000 Yen per person in the households. This value was obtained by deducting the increase in consumption in a particular region from the total consumption increase. In other words, these results measure how much consumption in other regions increases as income in a certain region increases. The advantage of this simulation is that we can predict the impact of a policy that delivers 10,000 Yen per person to each household in some region on the *aggregate* consumption of the whole country through network effects.

In the Tohoku district, an income increase of 10,000 Yen per person in the households in Aomori increases the consumption of other regions in the same district (Sapporo, Morioka, Sendai, and Akita) by 2557 Yen in total. Similarly, the same income increase in Morioka, Sendai, and Akita has considerable effects on adjacent regions' consumption. In addition, Niigata and Nagoya, in the Chubu district, and Osaka, Kobe, Nara, and Wakayama, in the Kinki district, and Fukuoka, Saga, Kumamoto, and Oita, in the Kyushu district, also have considerable consumption network effects on adjacent regions' consumption. In Chugoku and Shikoku districts, regional consumption network effects are hardly observed. Surprisingly, the impact of Tokyo, the capital city, in the Kanto district, on the adjacent region's consumption is limited to Yokohama and has relatively small effects, equal to 507 Yen per person. Other neighboring regions, such as Yokohama, Saitama, and Chiba, also have a small influence on the adjacent region's consumption. On the other hand, Kofu, and Nagano, in the Chubu district, affect vast regions, such as Saitama, Tokyo, and Yokohama, although the observed impact is not large. As a whole, the influence of vast regions on the consumption pattern in other regions is not necessarily large. The response to the increase in consumption due to income increases varies across districts rather than regions.

In the context of macroeconomic policies aimed at increasing the aggregate consumption, our results suggest that macroeconomic policies targeted at metropolitan areas such as Kanto, Chubu, and Kinki districts have a limited aggregate effect. On the other hand, income transfers/redistributive policies targeting Tohoku and Kyushu districts would have a large impact on aggregate consumption.

4. Conclusions

This paper uses the spatial approach to explore the regional consumption network effects in Japan. We build a spatial model that, using macro data, extends the classic consumption function approach and estimates the regional-level consumption functions incorporating the effects of adjacent regions' consumption patterns. Further, based on the parameters that describe the spatial correlations of the consumption functions, we simulate the effects of income increases to stimulate the aggregate consumption through spatial consumption network effects. Our findings are summarized as follows:

(1) Consumption network effects among regions are present in Japan, but such effects are different across the items of consumption: the effects are significant in fuel, light and water charges, clothing and footwear, medical care, and culture and recreation. On the other hand, significant effects are not observed in food, housing, transportation and communication, education, and other consumption expenditures.

(2) The intensities of the network effects are different across districts (Hokkaido and Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, Kyushu). We simulated the effects of an increase in income by 10,000 Yen per person in the households of a certain region on aggregate consumption and found that aggregate consumption is larger in local districts, such as Tohoku and Kyushu, than in metropolitan districts, such as Kanto, Chubu, and Kinki.

Since our estimation model ignores the impact on consumer behavior of different price mechanisms and due to the limited availability of control variables, our results can be considered as an approximation of the reality. However, the second result has important implications for local economic policies. Namely, a locally targeted economic policy is desirable not only to address the economic disparities between the metropolitan area and local districts but also to increase the economic "scale" of the whole nation by stimulating local consumer behaviors. Our results suggest the need to pay attention to "regional economic network effects" in the country's economic policies.

Our empirical model can be applied to a broad range of social behaviors of economic agents and is not limited to the analysis of interdependent consumption behaviors among regions. Various potential extensions beyond our study exist, such as spatial patterns of unemployment due to the social networks of job search (Conley and Topa, 2002) and the spatial crime patterns (Anselin et al., 2000). Currently, we are exploring these and other potential extensions of our model.

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Table 1. Summary statistics of log consumption and log income

Regions	Log consumption				Log income			
	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max
National Ave.	12.694	0.147	12.175	13.411	12.967	0.292	12.285	14.538
Sapporo	12.652	0.124	12.441	13.017	12.906	0.267	12.524	13.663
Aomori	12.599	0.122	12.333	12.903	12.869	0.278	12.459	13.803
Morioka	12.682	0.130	12.428	13.168	12.921	0.283	12.557	13.846
Sendai	12.666	0.113	12.425	12.965	12.828	0.258	12.428	13.629
Akita	12.702	0.132	12.439	13.059	13.030	0.314	12.523	14.241
Yamagata	12.729	0.139	12.378	13.203	13.017	0.272	12.639	13.937
Fukushima	12.761	0.147	12.449	13.195	13.105	0.309	12.658	13.963
Mito	12.723	0.117	12.475	13.057	13.011	0.294	12.605	13.852
Utsunomiya	12.765	0.131	12.532	13.142	13.030	0.317	12.628	13.916
Maebashi	12.658	0.147	12.317	13.411	12.801	0.258	12.347	13.534
Saitama	12.782	0.120	12.546	13.191	13.077	0.255	12.756	13.860
Chiba	12.720	0.142	12.427	13.254	12.958	0.254	12.586	13.746
Tokyo	12.781	0.081	12.595	13.050	13.045	0.226	12.798	13.737
Yokohama	12.771	0.105	12.568	13.119	13.058	0.257	12.663	14.022
Niigata	12.722	0.122	12.444	13.184	13.018	0.295	12.645	13.938
Toyama	12.884	0.145	12.495	13.229	13.233	0.294	12.820	14.327

Kanazawa	12.818	0.132	12.497	13.232	13.127	0.305	12.733	14.538
Fukui	12.684	0.144	12.379	13.113	13.069	0.260	12.730	13.872
Kofu	12.713	0.144	12.362	13.052	12.962	0.279	12.555	13.942
Nagano	12.716	0.114	12.458	13.026	12.965	0.284	12.522	13.818
Gifu	12.733	0.137	12.405	13.081	13.018	0.271	12.609	13.884
Shizuoka	12.708	0.116	12.501	13.121	13.013	0.287	12.630	13.965
Nagoya	12.678	0.116	12.414	13.102	12.967	0.250	12.633	13.847
Tsu	12.695	0.132	12.403	13.007	12.965	0.295	12.517	13.858
Otsu	12.716	0.128	12.366	13.017	12.914	0.282	12.457	13.885
Kyoto	12.687	0.143	12.443	13.266	12.955	0.266	12.379	13.777
Osaka	12.590	0.110	12.335	12.848	12.856	0.218	12.540	13.615
Kobe	12.635	0.132	12.339	13.016	12.883	0.254	12.468	13.858
Nara	12.753	0.137	12.435	13.161	13.006	0.272	12.660	13.894
Wakayama	12.579	0.144	12.175	12.944	12.932	0.272	12.536	13.768
Tottori	12.566	0.122	12.226	12.898	12.844	0.261	12.378	13.617
Matsue	12.675	0.127	12.399	13.011	13.012	0.300	12.604	13.932
Okayama	12.691	0.136	12.442	13.198	12.899	0.257	12.503	13.749
Hiroshima	12.739	0.133	12.470	13.085	13.017	0.265	12.691	13.940
Yamaguchi	12.745	0.130	12.459	13.190	13.019	0.303	12.632	13.928
Tokushima	12.750	0.145	12.387	13.230	13.028	0.289	12.557	13.959
Takamatsu	12.737	0.124	12.412	13.004	13.058	0.308	12.610	13.981
Matsuyama	12.615	0.117	12.360	12.940	12.916	0.272	12.601	13.774
Kochi	12.721	0.126	12.466	13.174	13.005	0.297	12.658	13.855
Fukuoka	12.701	0.120	12.496	13.213	12.856	0.260	12.424	13.813
Saga	12.699	0.123	12.430	13.162	12.938	0.294	12.497	13.814
Nagasaki	12.595	0.133	12.353	12.980	12.803	0.277	12.285	13.633
Kumamoto	12.652	0.125	12.411	13.109	12.909	0.274	12.540	13.933
Oita	12.666	0.116	12.417	13.013	13.009	0.299	12.612	13.929
Miyazaki	12.613	0.127	12.290	12.995	12.889	0.307	12.462	13.889
Kagoshima	12.693	0.108	12.473	12.971	12.973	0.292	12.551	13.818
Naha	12.437	0.116	12.198	12.781	12.736	0.227	12.423	13.505

Table 2. Estimated results of full-model

	Aggregate consumption	Food	Housing	Fuel, light & water charges
constant	0.004	-0.077	-0.001	-0.113 ***
	(0.019)	(0.065)	(0.016)	(0.015)
income	0.279 ***	0.318 ***	0.265 ***	0.085 ***
	(0.016)	(0.032)	(0.042)	(0.014)
number of household	0.140 ***	0.289 ***	0.268 ***	0.501 ***
	(0.039)	(0.087)	(0.100)	(0.036)
age of household head	0.401 ***	0.291 ***	0.389 ***	0.559 ***
	(0.049)	(0.110)	(0.145)	(0.048)
temperature	0.001	-0.009 **	-0.009	-0.012 ***
	(0.002)	(0.004)	(0.006)	(0.005)
precipitation	0.000	-0.002	-0.001	-0.003
	(0.002)	(0.005)	(0.006)	(0.003)
spatial peer effects	yes	yes	yes	yes
	Furniture & household utensils	Clothing & footwear	Medical care	Transportation & communication
constant	-0.007	-0.001	0.006	0.053
	(0.023)	(0.019)	(0.026)	(0.034)
income	0.245 ***	0.270 ***	0.233 ***	0.208 ***
	(0.050)	(0.034)	(0.051)	(0.062)
number of household	0.125	0.268 ***	0.251 *	0.102
	(0.127)	(0.086)	(0.136)	(0.146)
age of household head	0.767 ***	0.363 ***	0.273	0.130
	(0.165)	(0.108)	(0.168)	(0.195)
temperature	0.006	-0.010 *	0.001	0.000
	(0.008)	(0.005)	(0.007)	(0.009)
precipitation	0.015 *	-0.005	-0.001	0.006
	(0.008)	(0.005)	(0.008)	(0.010)
spatial peer effects	yes	yes	yes	yes

	Education		Culture & recreation		Other	
constant	-0.004		-0.129	***	0.027	
	(0.012)		(0.017)		(0.018)	
income	0.312	***	0.334	***	0.311	***
	(0.036)		(0.029)		(0.030)	
number of household	0.232	***	0.243	***	0.283	***
	(0.087)		(0.069)		(0.079)	
age of household head	0.272	**	0.400	***	0.353	***
	(0.123)		(0.093)		(0.099)	
temperature	-0.007		-0.004		-0.006	
	(0.006)		(0.004)		(0.004)	
precipitation	-0.007		-0.006		-0.008	*
	(0.006)		(0.004)		(0.005)	
spatial peer effects	yes		yes		yes	

Notes: Standard errors are in parentheses.

*** Significant at the 1 percent level; ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 3 Test for adjacent effect

Item	Value	df	*p*-value
Aggregate consumption expenditures	253.988	180	0.000
Food	189.179	180	0.305
Housing	154.385	180	0.917
Fuel, light & water charges	483.685	180	0.000
Furniture & household utensils	189.206	180	0.304
Clothing & footwear	256.971	180	0.000
Medical care	213.149	180	0.046
Transportation & communication	146.890	180	0.966
Education	140.419	180	0.987
Culture & recreation	243.633	180	0.001
Other consumption expenditures	203.094	180	0.114

Table 4. Estimated result for the aggregate consumption

variable	Coefficient	
Constant	-0.022	***
	(0.005)	
Income	0.292	***
	(0.012)	
number of household	0.172	***
	(0.030)	
age of household head	0.409	***
	(0.038)	
network peer effects	Yes	—

Notes: Standard errors are in parentheses.

*** Significant at the 1 percent level; ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 5 The increase in consumption in each region (Yen per person)

District	Region	Increase in consumption	Regions where consumption increased
Hokkaido	Sapporo	604	Aomori, Morioka, Sendai, Akita
Tohoku	Aomori	2,557	Sapporo, Morioka, Sendai, Akita
	Morioka	1,402	Sendai, Yamagata, Fukushima, Maebashi
	Sendai	1,640	Yamagata, Fukushima, Maebashi
	Akita	1,001	Sapporo, Aomori, Morioka, Sendai, Yamagata, Fukushima
	Yamagata	0	—
	Fukushima	554	Maebashi
Kanto	Mito	778	Chiba
	Utsunomiya	422	Saitama
	Maebashi	0	—
	Saitama	0	—
	Chiba	431	Mito
	Tokyo	507	Yokohama
	Yokohama	355	Tokyo
Chubu	Niigata	1,812	Fukushima, Maebashi, Toyama, Kanazawa, Gifu
	Toyama	300	Kanazawa
	Kanazawa	398	Gifu, Otsu
	Fukui	725	Kyoto
	Kofu	876	Saitama, Tokyo, Yokohama
	Nagano	798	Saitama, Tokyo, Yokohama, Kofu
	Gifu	378	Otsu
	Shizuoka	697	Nagoya, Tsu
	Nagoya	1,399	Shizuoka, Tsu
Kinki	Tsu	0	—
	Otsu	0	—
	Kyoto	0	—
	Osaka	1,433	Kobe, Tottori
	Kobe	963	Tottori
	Nara	1,272	Osaka, Kobe, Wakayama, Tottori
	Wakayama	2,168	Osaka, Kobe, Nara, Tottori
Chugoku	Tottori	0	—

	Matsue	0	—
	Okayama	0	—
	Hiroshima	0	—
	Yamaguchi	640	Matsue
Shikoku	Tokushima	634	Kochi
	Takamatsu	724	Okayama
	Matsuyama	0	—
	Kochi	0	—
Kyushu	Fukuoka	2,384	Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima
	Saga	1,049	Nagasaki
	Nagasaki	343	Saga
	Kumamoto	802	Miyazaki, Kagoshima
	Oita	1,460	Fukuoka, Saga, Nagasaki, Kumamoto, Kagoshima
	Miyazaki	0	—
	Kagoshima	813	Miyazaki
Okinawa	Naha	0	—