Prediction of the Prefectural Economy in Japan Using a Stochastic Model

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Working Paper Series Vol. 2013-02
March 2013

The International Centre for the Study of East Asian Development, Kitakyushu

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Abstract

This study develops a simple forecasting model using Japanese prefectural data. The Markov chain, known as a stochastic model, corresponds to a first-order vector auto-regressive (VAR) model. If the transition probability matrix can be appropriately estimated, a forecasting model using the Markov chain can be constructed. This study introduces a methodology for estimating the transition probability matrix of the Markov chain using least-squares optimization. The model is used first to analyze economy-wide changes encompassing all Japanese prefectures up to 2020. Second, a shock emanating from one prefecture is inserted into the transition probability matrix to investigate its influence on the other prefectures. Finally, a Monte Carlo experiment is conducted to refine the model's predicted outcomes. Although this study's model is simple, we provide more sophisticated forecasting information for prefectural economies in Japan.

JEL classification: C15, C53, C61, O53, R12
Keywords: Prefectural economy, Japan, Stochastic model, Markov chain

[♦] For their useful comments, the author thanks the participants of the Applied Regional Science Conference 2011 meeting (Toyama University, Japan) and the 52nd European Regional Science Association conference (Bratislava, Slovakia, 2012), where this paper was presented. The author would like to thank Enago (www.enago.jp) for the English language review. The author is responsible for all errors.

1. Introduction

Since 1990, the Japanese economy has experienced neither extreme growth nor downturns. Factors such as Japan's low birthrate, rising longevity, and decline in population have been noted since 2000, and the concentration of power and population in Tokyo that began before the bubble has persisted. On the other hand, economic growth has been reported in prefectures outside the capital region. A tool to quantitatively analyze such information is needed, although it is essential to understand how economic resources, including people, material, capital, and information, are distributed. That is the starting point of this study.

It is preferable to create an economic model that captures the distribution of economic resources between regions.[1] Nonetheless, a model based on changes in the macro index of GDP for all prefectures merits consideration. To explain nationwide economic changes, this study employs a stochastic model created using a Markov chain. It is a simple forecasting model that derives the next term in a numerical sequence from information in its predecessor term. Moreover, it is a form of vector auto-regressive (VAR) model advocated by Sims (1980).[2]

Forecasting models using a Markov chain have existed for many years, and researchers have advocated its use to measure economic convergence between countries or regions.[3] Sakamoto (2010b) predicts demographic shifts among Chinese prefectures using a Markov chain. Although predictions are more easily derived from stochastic models than from econometric models, predicted outcomes of the former models are not always reliable. To strengthen reliability of predictions, the Monte Carlo experiment is used.[4]

2. Model

The Markov chain is a well-known tool for deriving probabilistic chains (Romanovski, 1948). For each Markov transition matrix $M = (p_{ij})$ with transitional probabilities, $0 \le p_{ij} \le 1$, $\sum_{i=1} p_{ij} = 1$, a linear probabilistic chain can be derived as $p_{t+1} = M\, p_t$, $t = 0, 1, 2, \ldots$ (Sonis and Dendrinos, 2009). The Markov transition matrix also can be used to model the dynamics of economic growth. Let F_t be the vector comprising the GDP of all prefectures in period t and F_{t+1} denote the same for period $t + 1$. Suppose M_t is the matrix that maps F_t onto F_{t+1}. Therefore, we have

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1 Sakamoto (2011) considers research from this viewpoint.

2 However, both the character and estimation of a parameter (transition probability matrix) is quite different.

3 See Quah (1993, 1996a and b) and Sakamoto and Islam (2008).

4 The Monte Carlo experiment is featured in research by Sakamoto (2010a).

$$F_{t+1} = F_t \cdot M_t . \quad (1)$$

Assuming transition matrix M_t is time specific, the share vector after period s, F_{t+s}, will be given by

$$F_{t+s} = F_t \cdot M_t \cdot M_{t+1} \cdots\cdots M_{t+s-1} = F_t \cdot \prod_{i=0}^{s-1} M_{t+i} . \quad (2)$$

Therefore, current GDP is indeed modeled by the Markov chain.

Second, we introduce how to estimate the transition matrix M_t using actual data. In research that measures the convergence of income distributions, such as Quah (1993, 1996a and b), data from each country or each region are collected, a suitable grid line is assumed for the whole sample, a sample is classified for every state of income based on the grid line, and the method of estimating a matrix by totaling the temporal response of each country or region is adopted. In this case, a range of income from low to high is summarized for several states (around five). However, this procedure cannot express individual or intra-regional changes. To investigate prefecture-level changes, this study employs the following processes in its estimation method.

Since M_t cannot be obtained from actual data, an estimation procedure is necessary. The procedure implemented in this study runs along the following lines:

If F_t is (3 x 1), the transition matrix M_t for time t will be (3 x 3) and will appear as

$$M_t = \begin{pmatrix} a_{t,11} & a_{t,12} & a_{t,13} \\ a_{t,21} & a_{t,22} & a_{t,23} \\ a_{t,31} & a_{t,32} & a_{t,33} \end{pmatrix} . \quad (3)$$

Suppose $F_t' = (b_{t,1}\ b_{t,2}\ b_{t,3})$ and $F_{t+1}' = (b_{t+1,1}\ b_{t+1,2}\ b_{t+1,3})$. Per equation (1), we have

$$b_{t+1,1} = b_{t,1}*a_{t,11} + b_{t,2}*a_{t,12} + b_{t,3}*a_{t,13} \text{ (4-1)},$$
$$b_{t+1,2} = b_{t,1}*a_{t,21} + b_{t,2}*a_{t,22} + b_{t,3}*a_{t,23} \text{ (4-2)},$$
$$b_{t+1,3} = b_{t,1}*a_{t,31} + b_{t,2}*a_{t,32} + b_{t,3}*a_{t,33} \text{ (4-3)}.$$

However, in this formula the property of the Markov chain may not hold when the sum of the columns of probability matrix M_t equals 1.

$$\sum_{k=1}^{3} a_{t,jk} = 1 \quad \forall j . \quad (5)$$

Therefore, since we assume the adjustment parameter will hold its properties, we adopt the total growth rate of GDP, g_t , as an adjustment parameter. g_t is defined by

$$g_t = \sum_{j=1}^{3} b_{t+1,j} \Big/ \sum_{j=1}^{3} b_{t,j} \ . \quad (6)$$

Then we modify the equations to

$$b_{t+1,1} = g_t\,(b_{t,1}*a_{t,11} + b_{t,2}*a_{t,12} + b_{t,3}*a_{t,13}) \text{ (4'-1)},$$
$$b_{t+1,2} = g_t\,(b_{t,1}*a_{t,21} + b_{t,2}*a_{t,22} + b_{t,3}*a_{t,23}) \text{ (4'-2)},$$
$$b_{t+1,3} = g_t\,(b_{t,1}*a_{t,31} + b_{t,2}*a_{t,32} + b_{t,3}*a_{t,33}) \text{ (4'-3)}.$$

However, these three restrictions are insufficient for a unique solution to the nine elements of matrix M_t; more restrictions are needed. An identity matrix offers a trivial solution of M_t. Although not the desired solution, it sources the necessary restrictions. Assuming the distribution does not vary greatly by period, the elements of M_t are such that the matrix will mimic the identity matrix. Using this idea and generalizing M_t to n x n, we estimate the elements of M_t based on the following minimization procedure:

$$\text{Minimize} \quad \sum_{j=1}^{n}\sum_{k=1}^{n}\left(a_{t,jk} - i_{jk}\right)^2$$

$$\text{Subject to} \quad b_{t+1,j} = g_t \cdot \sum_{k=1}^{n} b_{t,k} \cdot a_{t,jk} \ , \quad \forall j \ ,$$

$$\text{and} \quad \sum_{k=1}^{n} a_{t,jk} = 1, \quad \forall j \ , \quad (7)$$

where i_{jk} is an element of identity matrix I and g_t is the total growth rate of GDP ($g_t = \sum_{j=1}^{n} b_{t+1,j} \Big/ \sum_{j=1}^{n} b_{t,j}$). This minimization problem can be solved by non-linear programming to produce a unique solution for the elements $a_{t,jk}$.

Third, we construct the transition matrix $\overline{M}$ for forecasting. Since the estimated transition matrix M_t is time specific, we first consider the average of the elements:

$$\overline{M} = \sum_{t=1}^{s} M_t \Big/ s \ . \quad (8)$$

In this study, prediction, simulations, and the Monte Carlo experiment are conducted based on this averaged transition matrix:

$$F_{t+1} = F_t \cdot \overline{M} \ . \quad (9)$$

3. Data

Data are "gross expenditure of prefectures" from the Annual Report of Prefectural Accounts (*Kenmin Keizai Keisan*) for all 47 prefectures. A GDP deflator is based on a chained price index in 2000. Since real GDP by the chain price in 2000 was released from 1996, data of 1995 or before are estimated using the growth rate of real GDP by the chain price in 1995. The period 1990–2007 is used. Official data are fiscal year data. To convert to a calendar year, each year's official GDP data was divided by four, and one quarter of the current year's GDP was added to the previous fiscal year.

Next, population differences among prefectures pose a problem in the analysis. Since this study examines changes in GDP for each prefecture, per capita GDP was converted into prefectural GDP using 2007 population as the base year. This changes to and analyzes the GDP at the time of converting with the population as of 2007, although each year's GDP is calculated using each year's population. Therefore, if the population during a particular year was smaller (larger) than that in 2007, estimated GDP for that year will also be larger (smaller) and the influence of changes in population during a measurement period will be eliminated.

4. Simulation

The simulation is conducted in three parts. First, we form a prediction for the period 2008–2020 using a Markov chain based on equation (9). Next we analyze changes in predicted outcomes after inserting an economic shock into the Markov chain transition matrix. The simulated shock was a natural disaster equivalent to Japan's March 2011 earthquake. Finally, we introduce uncertainty into each element of the transition matrix before and after the shock and conduct a Monte Carlo experiment to establish the robustness and predictive accuracy of the estimation result. Hereafter, we divide the Monte Carlo experiment into pre- and post-shock periods when presenting analytic details and results.

4-1. Analysis of the deterministic path before Monte Carlo experiment

Table 1 shows partial results from the transition matrix based on equation (9). The transition matrix was estimated based on the optimization problem of equation (7) for 1990-2007, and the arithmetic average is taken. The table shows the transition matrix of Hokkaido to Hokkaido as 0.991877 and that of Hokkaido to Aomori Prefecture as 0.000117. Predictions up to 2020 were performed using this transition matrix. Because it is impossible to depict growth of the entire Japanese economy merely by multiplying a transition matrix, an exogenous growth rate of 1% is inserted and carried up to probability change.

Next, the economic shock accompanying a big earthquake is considered. The 2011 East Japan earthquake directly and indirectly damaged many prefectures. Three northeastern prefectures─Iwate, Miyagi, and Fukushima─were seriously damaged, and recovery will take considerable time. One way to reflect a disaster shock in a transition matrix is to change the elements of the matrix. Many factors essential to GDP, such as capital stock, are destroyed in a natural disaster, adversely affecting GDP. We multiply each element of the transition matrix by a factor less than 1 to make smaller GDP than before shock. Following the prefectures and their rates of shock are assumed: Aomori 0.95, Iwate 0.90, Miyagi 0.90, Fukushima 0.90, Ibaraki 0.95, Chiba 0.97, and Tokyo 0.97. These rates of the shock apply to all the prefectures.

For example, since the transition matrix of Iwate to Hokkaido is 0.000071, Iwate to Aomori is 0.000050, and Iwate to Iwate is 0.997486 in Table 1, we calculate the probabilities by multiplying a number by 0.90 at the time of a shock. In addition, the shock is inserted only into the transition matrix for 2010–2011 because we consider the case of the Great East Japan earthquake, which occurred in 2011.

Figures 1 and 2 assess the deterministic path before the Monte Carlo experiment by comparing cases with and without a disaster shock. The figures represent both the prefecture in which the shock originated and the entire country. Growth rates differ in each prefecture, and it is expected that regional disparity changes. On the other hand, when a disaster shock is inserted, economic growth falls in the year of the shock but recovers thereafter. However, the recovery does not overcome the decline in growth experienced at the time of the shock. It is considered that the element of a transition matrix changes only once in a year and original matrix is carried forward to the next year.

Next, we analyze how predictions for the entire economy change as a result of the simulation. Table 2 shows the total rate of change (not annual averages) in GDP for each prefecture from 2007 to 2020. Since exogenous growth of 1% per year is a given, the change during a period exceeds 13%. Prefectures exhibiting below-average growth of 10% or less are Hokkaido, Chiba, Kanagawa, Osaka, and Hyogo. Many economically significant prefectures, except Aichi Prefecture, are below average. Therefore, the economic changes indicated by this model suggest that regional disparity is reducible.

On the other hand, in terms of post-shock change, although the prefectures where the shock originated have declined economic growth rates on the rate of the shock suitability, since they remain in the growth rate fall below the rate of the shock, some rally effect is seen about these prefectures. Growth declined in all other prefectures, which were also affected by the disaster shock, but the difference was negligible.

4-2. Analysis of the indefinite path after the Monte Carlo experiment

Next, we consider the case wherein these paths are not deterministic. The Monte Carlo experiment requires data based on information acquired in estimating the transition matrix of equation (9). The experiment is conducted on the assumption that uncertainty is an element of the transition matrix. That is, after giving width to the number of Table 1, it predicts using the transition matrix obtained on the basis of the experiment. It assumes that the numbers in Table 1 have width according to a normal distribution with an average and standard deviation. The average is the numbers in Table 1. Standard deviation is obtained from the result of the transition matrix for each year from 1990 to 2007. The results are shown in Table 3. That is, it experiments by generating a random number according to the average (Table 1) and the standard deviation (Table 3). Since this experiment involves a simulated economic shock, pre-shock and post-shock periods are compared. It is assumed that 300 random numbers are generated when conducting a Monte Carlo experiment. A greater number of repetitions produces not only more precise results but also more complicated calculations; therefore, in this study, repetitions were halted within a range that is easily treated.

Tables 4 and 5 show the pre-shock averages and coefficients of variation in GDP for each prefecture after the Monte Carlo experiment. The coefficient of variation (the standard deviation divided by the average) increases as it is set to 2020. To generate the random number to the transition matrix of each year, the more this tends toward the future, the more it means that uncertainty increases. However, this number itself is about 2%. Since the number in Table 3 is also quite small, uncertainty also is apparently small. However, growth of the Japanese economy is less than 1% of the present condition, and it is not clear if there is uncertainty of 2% using standard deviation. Moreover, the prefecture's feature about the difference in the coefficient of variation is not observed, it is said to be changing on a random basis (Table 3).

Tables 6 and 7 show the post-shock average and coefficients of variation in GDP for each prefecture after the Monte Carlo experiment. Since the shock occurred between 2010 and 2011, the 2010 result is omitted because it is the same as that in Tables 4 and 5. The right half of the table shows comparisons before the shock. Since the difference in the average for the prefecture where the shock originated declines from 2015 to 2020, growth gradually recovers after the shock. Although the coefficient of variation rises for the prefecture where the shock originated, it falls slightly in each of the other prefectures. Perhaps uncertainty in the prospect of future recovery was elevated by the disaster shock, as the increased coefficient of variation suggests.

Finally, we investigate the degree of duplication (similarity) in the Monte Carlo sample that overlapped the pre- and post-shock periods. A frequency table was created using the Monte Carlo experiment to calculate an average on the basis of all prefectures before the shock in 2015 and 2020 with logarithms and the width of 0.005. Then, the frequency of duplications before and after the shock is calculated. Table 8 shows that the distribution is the same before and after the shock if it is close to 100 (%). Although the number near 100%, in general, emerges for prefectures from which the shock did not originate, since it may fully not be 100%, given that it may suffer slight repercussions of the disaster. On the other hand, Miyagi and Fukushima Prefectures have no overlapping sample, and their economies languish after the shock even if uncertainly is assumed. Prefectures such as Tokyo that suffer only slight effects from the shock show a suitable degree of duplication around 30%. Even if this prefecture experiences the shock, its negative effect may be offset by uncertainty.

5. Conclusion

This study showed changes in GDP for all prefectures of Japan using a stochastic model and explored for predictions. In addition, it adopted the probability element of the stochastic model and analyzed predictions after the occurrence of a shock such as the East Japan earthquake. It also considered a recovery tendency as possible means to explore predictions of disaster shocks that may occur in the future. After inserting the element of uncertainty into the Monte Carlo experiment, the stochastic model was applied and a possibility was shown that a negative effect such as a disaster shock can be negated.

However, the stochastic model needs improvement. For example, the mutual effect among all prefectures is small. Although that may actually be the case, they may have an increasing influence on the people, material, capital, and the present condition with prosperous traffic of information. However, the model presents thought-provoking issues about the future Japanese economy.

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Table 1 Transition matrix (average)

	Hokkaido	Aomori	Iwate	Miyagi	Akita	…	Okinawa
Hokkaido	0.991877	0.000117	0.000055	0.000080	0.000144		0.000001
Aomori	0.000003	0.996611	0.000052	0.000033	0.000027		0.000027
Iwate	0.000071	0.000050	0.997486	0.000001	0.000048		0.000051
Miyagi	0.000034	0.000041	0.000037	0.996496	0.000049		0.000010
Akita	0.000032	0.000008	0.000027	0.000043	0.997642		0.000007
…						…	
Okinawa	0.000097	0.000106	0.000129	0.000106	0.000119		0.993580

Source: All table and figure is author's calculation

Figure 1 Prediction before the Monte Carlo experiment (1) (Billion yen)

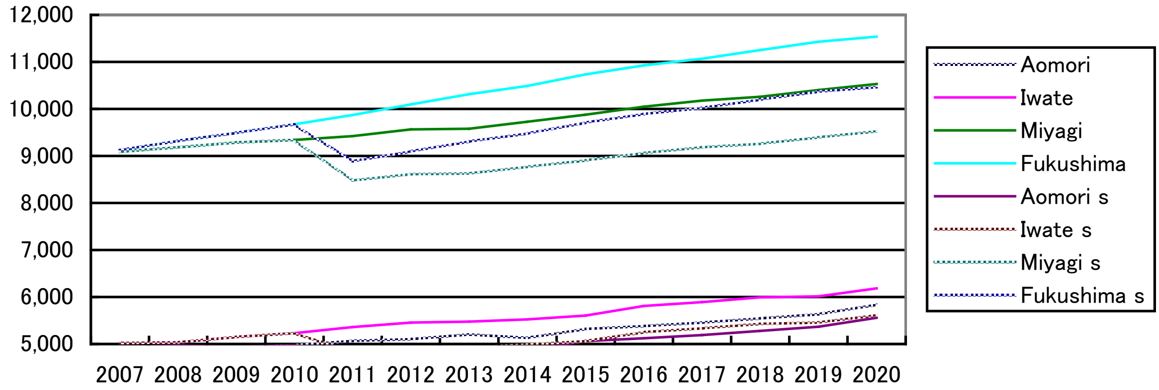
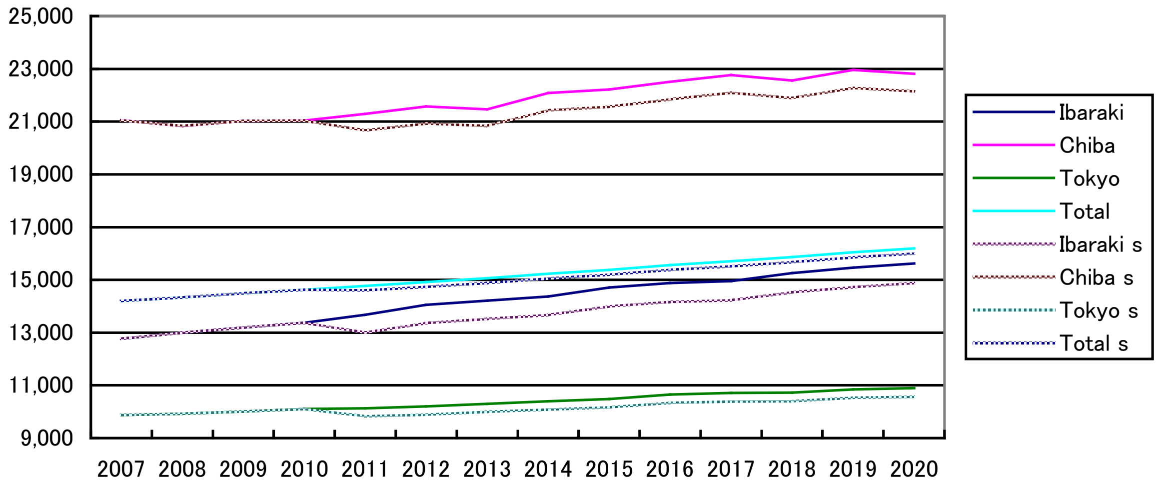


Figure 2 Prediction before the Monte Carlo experiment (2) (Billion yen)



Note: Tokyo is in a scale of 1/10 and the entire country (Total) is in a scale of 1/40.

Table 2 Change of GDP of each prefecture (rate of change from 2007 to 2020 in %)

	Pre shock	Post shock	Change		Pre shock	Post shock	Change
Hokkaido	7.85	7.78	−0.07	Shiga	12.05	12.01	−0.04
Aomori	18.18	12.63	−5.55	Kyoto	14.89	14.85	−0.04
Iwate	23.11	11.79	−11.31	Osaka	3.58	3.56	−0.02
Miyagi	15.92	4.78	−11.14	Hyogo	6.63	6.55	−0.08
Akita	24.58	24.52	−0.06	Nara	12.09	12.03	−0.06
Yamagata	26.74	26.64	−0.10	Wakayama	12.63	12.60	−0.02
Fukushima	26.51	14.75	−11.76	Tottori	18.28	18.21	−0.07
Ibaraki	22.41	16.61	−5.80	Shimane	21.12	21.05	−0.07
Tochigi	14.86	14.81	−0.05	Okayama	12.09	12.03	−0.06
Gunma	15.18	15.15	−0.03	Hiroshima	14.93	14.90	−0.02
Saitama	11.18	11.15	−0.03	Yamaguchi	19.29	19.20	−0.09
Chiba	8.36	5.17	−3.19	Tokushima	23.72	23.66	−0.07
Tokyo	10.31	7.05	−3.27	Kagawa	18.23	18.18	−0.04
Kanagawa	−0.68	−0.68	0.00	Ehime	24.68	24.64	−0.04
Niigata	23.36	23.25	−0.12	Kochi	23.57	23.55	−0.02
Toyama	18.59	18.53	−0.06	Fukuoka	14.37	14.31	−0.06
Ishikawa	19.16	19.11	−0.05	Saga	30.45	30.38	−0.07
Fukui	22.57	22.51	−0.06	Nagasaki	15.65	15.64	−0.01
Yamanashi	16.38	16.33	−0.05	Kumamoto	16.04	16.00	−0.03
Nagano	20.76	20.70	−0.06	Oita	31.39	31.31	−0.08
Gifu	13.43	13.39	−0.04	Miyazaki	17.55	17.54	−0.02
Shizuoka	25.14	25.03	−0.11	Kagoshima	26.66	26.60	−0.06
Aichi	20.94	20.72	−0.21	Okinawa	13.98	13.95	−0.03
Mie	31.89	31.69	−0.20	Total	14.02	12.64	−1.38

Table 3 Standard deviation of a transition matrix

	Hokkaido	Aomori	Iwate	Miyagi	Akita	…	Okinawa
Hokkaido	0.009272	0.000330	0.000139	0.000217	0.000366		0.000000
Aomori	0.000005	0.005170	0.000138	0.000127	0.000104		0.000086
Iwate	0.000274	0.000170	0.005833	0.000000	0.000174		0.000198
Miyagi	0.000071	0.000116	0.000099	0.004646	0.000164		0.000035
Akita	0.000100	0.000019	0.000075	0.000112	0.003158		0.000018
…						…	
Okinawa	0.000211	0.000187	0.000208	0.000207	0.000188		0.006972

Table 4 Pre-shock average and coefficient of variation of GDP for each prefecture after the Monte Carlo experiment (1)

	2010		2015		2020	
	Average	CV	Average	CV	Average	CV
Hokkaido	20,102.67	0.016995	20,616.20	0.027946	21,149.83	0.035109
Aomori	5,162.40	0.015976	5,554.39	0.024648	5,972.96	0.029269
Iwate	5,262.26	0.011921	5,683.56	0.021108	6,130.25	0.025444
Miyagi	9,347.59	0.008341	9,812.48	0.013795	10,311.74	0.017530
Akita	4,309.61	0.010410	4,662.53	0.016434	5,039.93	0.019850
Yamagata	5,193.04	0.010709	5,700.16	0.016941	6,237.31	0.020651
Fukushima	9,648.00	0.009602	10,582.54	0.013522	11,561.13	0.016920
Ibaraki	13,264.11	0.011575	14,153.98	0.017416	15,118.57	0.022093
Tochigi	9,739.26	0.009999	10,386.34	0.015685	11,063.41	0.018918
Gunma	8,690.66	0.012525	9,109.75	0.020279	9,541.39	0.025551
Saitama	23,601.54	0.010762	24,540.60	0.018035	25,555.31	0.023007
Chiba	21,511.46	0.015375	22,202.99	0.023933	22,932.97	0.030810
Tokyo	101,085.10	0.009190	105,220.60	0.014007	109,407.76	0.017464
Kanagawa	34,619.17	0.010367	34,876.32	0.017364	35,157.53	0.022615
Niigata	10,460.88	0.009526	11,215.69	0.015782	12,019.55	0.019572
Toyama	5,299.22	0.009969	5,622.46	0.017205	5,965.89	0.022520
Ishikawa	5,405.25	0.009106	5,737.48	0.014332	6,092.96	0.017526
Fukui	4,023.59	0.009050	4,356.11	0.015033	4,704.45	0.018658
Yamanashi	3,937.22	0.014793	4,228.66	0.022723	4,534.47	0.030119
Nagano	10,211.98	0.011136	11,128.13	0.016536	12,076.97	0.019782
Gifu	8,438.48	0.007904	8,890.68	0.013344	9,383.27	0.017124
Shizuoka	19,946.56	0.008956	21,466.43	0.014431	23,074.61	0.018017
Aichi	42,367.07	0.011383	45,291.32	0.017465	48,386.63	0.021943
Mie	10,211.41	0.014147	11,378.67	0.020190	12,610.94	0.024033

Note: Average is billion yen.

Table 5 Pre-shock average and coefficient of variation of GDP for each prefecture after the Monte Carlo experiment (2)

	2010		2015		2020	
	Average	CV	Average	CV	Average	CV
Shiga	7,253.40	0.017691	7,748.94	0.029712	8,283.94	0.034432
Kyoto	11,307.93	0.010584	11,885.97	0.017107	12,513.07	0.020585
Osaka	41,868.23	0.010208	42,788.31	0.017852	43,735.95	0.022156
Hyogo	21,364.67	0.020009	21,648.06	0.032491	21,991.39	0.038387
Nara	4,261.61	0.013099	4,478.86	0.021409	4,702.97	0.026200
Wakayama	3,615.14	0.010032	3,794.14	0.017336	3,985.55	0.021982
Tottori	2,408.97	0.010327	2,567.31	0.015867	2,735.41	0.020235
Shimane	2,921.05	0.010227	3,184.20	0.017355	3,464.79	0.021101
Okayama	8,417.42	0.016099	8,845.91	0.026216	9,295.51	0.033781
Hiroshima	13,178.64	0.011002	13,761.46	0.019088	14,363.01	0.022861
Yamaguchi	6,503.31	0.009017	7,005.37	0.014122	7,525.86	0.017138
Tokushima	3,071.20	0.014610	3,303.91	0.023450	3,550.39	0.028203
Kagawa	4,054.65	0.015487	4,270.07	0.023386	4,487.23	0.029808
Ehime	5,687.90	0.012421	6,096.04	0.019056	6,516.00	0.022752
Kochi	2,589.73	0.016447	2,754.53	0.028454	2,926.80	0.035202
Fukuoka	20,257.22	0.007947	21,307.12	0.011927	22,401.28	0.015058
Saga	3,498.44	0.009849	3,820.41	0.016822	4,168.38	0.020541
Nagasaki	4,876.74	0.008758	5,220.48	0.013794	5,583.50	0.017835
Kumamoto	6,549.65	0.007707	6,966.47	0.011425	7,394.57	0.014735
Oita	5,390.17	0.008714	5,911.70	0.013523	6,463.30	0.015951
Miyazaki	4,024.63	0.010624	4,287.43	0.017217	4,563.30	0.020886
Kagoshima	6,337.23	0.009998	6,876.77	0.015005	7,454.04	0.018592
Okinawa	3,974.99	0.012712	4,130.88	0.020988	4,290.66	0.026985
Total	585,251.44	0.002407	615,072.41	0.003910	646,426.68	0.005075

Note: Average is billion yen.

Table 6 Post-shock average and coefficient of variation of GDP for each prefecture after the Monte Carlo experiment (1)

	Result				Change of pre shock (%)			
	2015		2020		2015		2020	
	Average	CV	Average	CV	Average	CV	Average	CV
Hokkaido	20,613.38	0.027929	21,143.41	0.035081	-0.01	-0.06	-0.03	-0.08
Aomori	5,283.75	0.025062	5,690.75	0.029739	-4.87	1.68	-4.72	1.60
Iwate	5,132.27	0.021771	5,557.15	0.026208	-9.70	3.14	-9.35	3.00
Miyagi	8,843.79	0.014089	9,309.63	0.017811	-9.87	2.14	-9.72	1.60
Akita	4,661.56	0.016391	5,037.67	0.019783	-0.02	-0.26	-0.04	-0.33
Yamagata	5,698.12	0.016853	6,232.39	0.020490	-0.04	-0.52	-0.08	-0.78
Fukushima	9,560.61	0.014172	10,488.73	0.017857	-9.66	4.80	-9.28	5.54
Ibaraki	13,460.57	0.017608	14,396.59	0.022306	-4.90	1.10	-4.78	0.96
Tochigi	10,383.91	0.015674	11,057.90	0.018903	-0.02	-0.07	-0.05	-0.08
Gunma	9,108.30	0.020260	9,538.09	0.025535	-0.02	-0.09	-0.03	-0.06
Saitama	24,537.36	0.018026	25,547.86	0.022993	-0.01	-0.05	-0.03	-0.06
Chiba	21,541.01	0.024002	22,254.36	0.030864	-2.98	0.29	-2.96	0.17
Tokyo	102,100.05	0.014092	106,205.54	0.017547	-2.97	0.61	-2.93	0.47
Kanagawa	34,875.89	0.017364	35,156.47	0.022615	0.00	0.00	0.00	0.00
Niigata	11,212.80	0.015711	12,012.48	0.019462	-0.03	-0.45	-0.06	-0.56
Toyama	5,621.49	0.017189	5,963.56	0.022475	-0.02	-0.09	-0.04	-0.20
Ishikawa	5,736.78	0.014321	6,091.27	0.017506	-0.01	-0.08	-0.03	-0.11
Fukui	4,355.14	0.015013	4,702.27	0.018632	-0.02	-0.13	-0.05	-0.14
Yamanashi	4,227.19	0.022689	4,531.06	0.030086	-0.03	-0.15	-0.08	-0.11
Nagano	11,124.11	0.016483	12,067.83	0.019708	-0.04	-0.32	-0.08	-0.38
Gifu	8,889.58	0.013335	9,380.58	0.017109	-0.01	-0.06	-0.03	-0.08
Shizuoka	21,458.73	0.014323	23,056.80	0.017831	-0.04	-0.75	-0.08	-1.03
Aichi	45,268.99	0.017380	48,334.39	0.021810	-0.05	-0.49	-0.11	-0.61
Mie	11,370.64	0.020019	12,592.62	0.023747	-0.07	-0.85	-0.15	-1.19

Note: Average is billion yen.

Table 7 Post-shock average and coefficient of variation of GDP of each prefecture after the Monte Carlo experiment (2)

	Result				Change of pre shock (%)			
	2015		2020		2015		2020	
	Average	CV	Average	CV	Average	CV	Average	CV
Shiga	7,746.28	0.029664	8,277.58	0.034395	−0.03	−0.16	−0.08	−0.11
Kyoto	11,883.53	0.017074	12,507.26	0.020541	−0.02	−0.19	−0.05	−0.21
Osaka	42,784.28	0.017802	43,727.12	0.022065	−0.01	−0.28	−0.02	−0.41
Hyogo	21,642.32	0.032464	21,979.01	0.038322	−0.03	−0.08	−0.06	−0.17
Nara	4,477.98	0.021391	4,701.04	0.026169	−0.02	−0.09	−0.04	−0.12
Wakayama	3,793.70	0.017328	3,984.50	0.021978	−0.01	−0.04	−0.03	−0.02
Tottori	2,566.87	0.015865	2,734.37	0.020225	−0.02	−0.01	−0.04	−0.05
Shimane	3,183.52	0.017328	3,463.23	0.021080	−0.02	−0.16	−0.04	−0.10
Okayama	8,843.48	0.026146	9,290.08	0.033655	−0.03	−0.27	−0.06	−0.37
Hiroshima	13,758.88	0.019019	14,356.98	0.022735	−0.02	−0.36	−0.04	−0.55
Yamaguchi	7,003.39	0.014043	7,521.13	0.017011	−0.03	−0.56	−0.06	−0.74
Tokushima	3,303.00	0.023435	3,548.21	0.028180	−0.03	−0.06	−0.06	−0.08
Kagawa	4,269.34	0.023378	4,485.50	0.029801	−0.02	−0.04	−0.04	−0.02
Ehime	6,094.82	0.019042	6,513.26	0.022714	−0.02	−0.08	−0.04	−0.17
Kochi	2,754.20	0.028455	2,926.02	0.035205	−0.01	0.00	−0.03	0.01
Fukuoka	21,303.86	0.011892	22,393.75	0.015006	−0.02	−0.29	−0.03	−0.35
Saga	3,819.44	0.016779	4,166.11	0.020495	−0.03	−0.25	−0.05	−0.22
Nagasaki	5,219.79	0.013784	5,581.88	0.017815	−0.01	−0.07	−0.03	−0.12
Kumamoto	6,965.57	0.011415	7,392.42	0.014712	−0.01	−0.09	−0.03	−0.16
Oita	5,910.23	0.013494	6,459.91	0.015912	−0.02	−0.22	−0.05	−0.25
Miyazaki	4,286.71	0.017212	4,561.59	0.020876	−0.02	−0.03	−0.04	−0.05
Kagoshima	6,875.79	0.014995	7,451.74	0.018581	−0.01	−0.06	−0.03	−0.06
Okinawa	4,130.53	0.020992	4,289.80	0.026985	−0.01	0.02	−0.02	0.00
Total	607,683.54	0.003907	638,661.93	0.005068	−1.20	−0.07	−1.20	−0.14

Note: Average is billion yen.

Table 8 Multiplicity of distribution pre and post shock (%)

	2015	2020		2015	2020
Hokkaido	97.67	97.00	Shiga	96.33	94.67
Aomori	30.00	36.33	Kyoto	98.00	95.67
Iwate	1.67	5.67	Osaka	99.00	97.00
Miyagi	0.00	0.33	Hyogo	97.33	94.33
Akita	96.00	96.33	Nara	98.00	95.00
Yamagata	96.00	95.33	Wakayama	97.33	96.33
Fukushima	0.00	0.67	Tottori	98.00	96.33
Ibaraki	15.67	25.67	Shimane	99.00	95.33
Tochigi	98.67	97.33	Okayama	97.00	96.00
Gunma	98.00	96.67	Hiroshima	97.00	94.33
Saitama	98.67	97.33	Yamaguchi	97.67	93.67
Chiba	50.33	63.33	Tokushima	96.00	93.33
Tokyo	30.00	38.67	Kagawa	97.00	96.67
Kanagawa	100.00	99.00	Ehime	95.67	96.33
Niigata	97.33	94.67	Kochi	97.67	96.00
Toyama	98.33	95.67	Fukuoka	98.33	98.33
Ishikawa	97.67	97.67	Saga	97.33	95.33
Fukui	97.67	98.33	Nagasaki	98.33	96.33
Yamanashi	97.00	93.67	Kumamoto	97.67	97.00
Nagano	96.00	95.67	Oita	97.33	97.00
Gifu	98.33	97.00	Miyazaki	98.00	97.33
Shizuoka	97.33	94.33	Kagoshima	98.00	96.67
Aichi	97.67	91.33	Okinawa	99.33	98.00
Mie	96.00	92.67			

Appendix figure Prefectures in Japan