Otemon Gakuin University

Faculty of Economics

Working Paper No.2021-3

Forecasting consumption expenditure using a dynamic panel model with cross-section dependence: The case of Japan

Manami Ogura

2021 年 11 月

氏名：小椋　真奈美
E-mail：maogura@otemon.ac.jp

Forecasting consumption expenditure using a dynamic panel model with cross-section dependence: The case of Japan

Manami Ogura

Department of Economics, Otemon Gakuin University

Abstract

In this study, we predict the future trends of consumption expenditure in disaggregated age groups in both the within-sample and out-of-sample periods. In addition, we incorporate the estimation of a dynamic panel model with cross-section dependence into our forecasting methodology. As a whole, our dynamic panel model generates accurate forecasts for within-sample. In particular, the accuracy is better in the 40–49 age group, while it is the most inaccurate for the over-70 age group. The out-of-sample period forecast results show that the dynamic panel model generates more accurate than the AR model in almost all age groups. Further, the impact of the COVID-19 shock in 2020 will be retained in many age groups for some time, leading to a decline in consumption. However, after a while, this impact will gradually disappear, and consumption will increase for most age groups. On the other hand, the out-of-sample period forecast results show that the older age group drags out the COVID-19 shock longer than the younger age group and will take longer to recover its consumption levels. In addition, aging of the heads of Japanese households will make it difficult for these households to maintain their current consumption levels unless some measures are taken to deal with the older age group.

JEL: C33, D12

Keywords: Forecasting; Cross-section dependence; Panel unit root test; Dynamic panel model; Disaggregate age group

1. Introduction

Japanese households are facing a change in demographic factors, such as a decline in the number of people aged under 18 years due to the declining birthrate, increase in the age of household heads due to population aging, and increase in the number of people aged over 65 years. In fact, the aging rate has risen from 17.4% in 2000 to 28.9% in 2020 (Annual Report on the Aging Society 2020).[1] Further, the rate of people under the age of 18 to the total population has declined from 19.3% in 2000 to 16.4% in 2020.[2] Changes in age and family structure within households affect current and future consumption trends. In addition to these factors, exogenous macro shocks such as the Lehman shock in 2008 and the coronavirus disease of 2019 (COVID-19) shock in 2020 have caused an additional

[1] The aging rate is the ratio of people aged 65 years and over to the total population. The rate is expected to rise to 32.8% in 2035. These data are based on the results of the Population Census conducted by the Statistics Bureau of Japan until 2015, and on the midpoint of births and deaths in the National Institute of Population and Social Security Research's "Future Population Projections for Japan" since 2020.

[2] The rate is expected to decline to 14.1% in 2035. The data sources are the same as in Footnote 1.

problem of long-term stagnation in consumption expenditure, which underpins domestic demand in the Japanese economy. On the other hand, susceptibility to these exogenous shocks differs by age group. For instance, older groups of those aged over 70 years are the most susceptible to the effects of changes in household income due to exogenous shocks, because their average propensity to consume (APC) is higher than that of the other age groups.[3] In addition, the weight of households with heads aged over 70 years among the total households is the highest in all age groups, and the influence of the over-70 age group on consumption trends is high (Fujimura and Sato 2017).[4] On the other hand, the 30–39 age group had the lowest APC among all age groups, although their consumption was the same as that of the over-70 age group. In addition, because the 30–39 age group accounts for a smaller weight among total households, their impact on overall consumption is relatively low. In other words, it is more effective to approach targeted age groups than to have a unified policy for all age groups to recover consumption in the future.

This study aims to predict future consumption in disaggregated age groups by using a dynamic panel model. Based on the results of the projections, we discuss which policies need to be introduced in which age group to increase consumption in the future. Furthermore, we incorporate the cross-section dependence methods into our forecast analysis. As a theoretical contribution, we aim to use a model that considers the cross-sectional correlation between age groups to obtain a consistent estimator of the parameters. Therefore, we use a dynamic panel model that introduces correlations between cross-sections in a factor model (Sarafidis et al. 2009). We also incorporate the method of performing the panel unit root test on a series after removing the factors, because ignoring the correlations between the cross-sections would lead to size distortions (Pesaran 2007). The dynamic panel model can be estimated by the generalized method of moments (GMM) using instrumental variables that take the deviation from the cross-section average; this is because the bias becomes smaller than the GMM estimator without considering the correlation between cross-sections.

A variety of studies have been published on the theoretical aspects of panel analysis of forecasts. For example, Baltagi (2008) proposed the basis of forecasting methods in static and dynamic panel analysis, and later introduced the method applied to the case of spatial correlation in Baltagi et al. (2012). In the literature focusing on cross-section dependence, Phillips and Sul (2003, 2007) discussed the issues of homogeneity restrictions and small sample bias in dynamic panel estimation under cross-section dependence. Moreover, although there are many studies on the empirical aspects of panel analysis of forecasts, such as Ince (2014) and Kim et al. (2016), few have incorporated cross-section dependence methods into their analysis. This is one of the main contributions of this study.

The remainder of this paper proceeds as follows. Section 2 explains the data used in this study, and Section 3 presents the dynamic panel model with cross-section dependence between age groups. Section 4 shows the estimation results by the GMM, and Section 5 presents the forecasting results for

---

[3] The average APC from January 2000 to November 2020 is highest in the over-70 age group at 0.82 and lowest in the 30–39 age group at 0.67. The higher the APC, the higher the ratio of consumption expenditure to disposable income.

[4] As Japan's population ages, the number of households heads aged 60 years or older are increasing. In Japan's household survey, more than 50% of the surveyed household heads are 60 years old or older. In addition, there is a growing body of research focusing on the consumption trends of senior households.

the within-sample and out-of-sample. Finally, Section 6 presents the conclusions of this study.

2. Data

The household survey data employed in this study comprise monthly data for six age groups. We sourced data on consumption expenditures, disposable income, and household demographics from the Family Income and Expenditure Survey (*Kakei Chosa* in Japanese) conducted between January 2000 and November 2020 by the Japanese Statistics Bureau. The demographic data indicate the number of household members, age of the household heads, number of people under 18, and number of people aged over 65 years. We also obtain price data from the consumer price index (CPI) for 2015 as the standard. The CPI used was identical across the six age groups because of data limitations.

The age group in this study was divided into six groups: under 29, 30–39, 40–49, 50–59, 60–69, and over 70 years. Figure 1 shows the annual average of logarithm consumption expenditure by age group. Overall, there has been a gradual decline in consumption expenditure for most age groups since 2000. In Japan, the consumption of the under-29 age group is the lowest, and that of the 50–59 and 60–69 age groups are the highest. In particular, the 60–69 age group consumed the most since 2012, surpassing the 50–59 age group. In other words, consumption in Japan is supported by the 50–59 and 60–69 age groups. On the other hand, consumption of the under-29 and over-70 age groups has time-series fluctuations, and the decline due to the Lehman shock in 2008 is particularly noticeable compared with other age groups. This is because both age groups were immediately affected by the shock through a decrease in their disposable incomes. In all groups, a decrease in consumption was observed due to the impact of the COVID-19 shock in 2020. Further, data movements in consumption for the groups aged 30–60 years were similar. These age groups must have different lifestyles and family structures, but their time-series consumption trends appear to be similar. Therefore, we expect that there is a correlation between age groups in consumption trends.

On the other hand, as shown in Figure 2, the logarithm disposable income has been on a gradual upward trend, except for the over-70 age group. In particular, since the latter half of the 2010s, consumption has not been on an upward trend, even though disposable incomes have increased. This is due to an increase in the savings rate among Japanese households. By experiencing macro shocks, such as the Lehman shock in 2008, Japanese households may be preparing for future shocks by increasing their savings.[5] However, this trend does not hold for the over-70 age group.

Table 1 shows the group-averaged statistics used in this study. There is a large difference in the values of consumption expenditure and disposable income between age groups, and this tendency is particularly noticeable for disposable income. The minimum value of disposable income is smaller than that of consumption expenditure, and the difference in disposable income between age groups is remarkable. In other words, it is clear that the low-income age group cannot expect higher consumption expenditure than the high-income age groups. In Japan, age of the household heads is increasing, and the antilogarithm of the average value is 44.3 years old. On the contrary, the number of household members is decreasing, and the antilogarithm of the average value is 3.28 per household.

[5] From January 2000 to November 2020, the average savings rate for the 30–39 age group was the highest at 22.4%, while that for the over-70 age group was the lowest at -1.9%. In other words, we find that the 30–39 age group is reducing consumption and increasing savings.

In addition, due to the declining birthrate, the number of people aged under 18 years is 0.55 per household. On the contrary, due to population aging, the number of people aged over 65 years is increasing by 0.14 per household.

In this study, to produce out-of-sample forecasts, we split the forecasts into two components: within-sample and out-of-sample. For the first step, using data from January 2000 to December 2017, we estimate the dynamic panel model and calculate the within-sample forecast. For the second step, the out-of-sample forecast can be calculated from January 2018 to November 2020 based on the GMM estimates. For the final step, we calculate the out-of-sample forecast for 10 years.

[Figs 1 and 2 would be inserted here.]

Table 1. Descriptive statistics

variable	average	S.D.	max	min
$\ln C_{it}$	12.618	0.204	13.148	12.098
$\ln Y_{it}$	12.880	0.361	13.881	11.530
$\ln P_t$	4.583	0.014	4.617	4.561
ln *Age*[a]	3.792	0.337	4.309	3.207
ln *Num*[b]	1.188	0.155	1.411	0.747
ln *Under 18*[c]	-0.598	1.477	0.563	-6.908
ln *Over 65*[d]	-1.989	1.712	0.693	-6.908

Notes: [a]Age denotes the age of head of households, [b]Num denotes the number of households, [c]Under 18 denotes the number of under 18, and [d]Over 65 denotes the number of over 65.

3. The model

We first define the dynamic panel model of consumption expenditure as follows.

$$\ln C_{it} = \alpha \ln C_{i,t-1} + \beta \ln Y_{it} + \gamma \ln P_t + \boldsymbol{\delta} \ln \mathbf{D}_{it} + \varepsilon_{it} \tag{1}$$

$$i = 1, \dots, N, t = 1, \dots, T$$

where $\ln C_{it}$ is the logarithm of consumption expenditure in the ith age group of period t, $\ln Y_{it}$ is the logarithm of real disposable income in the ith age group of period t, $\ln P_t$ is the logarithm of the CPI in period t, and $\ln \mathbf{D}_{it} = (\ln Age_{it}, \ln Num_{it}, \ln Under18_{it}, \ln Over65_{it})'$ denotes the logarithm of the demographic variables of the age of the household head, number of households, number of people aged under 18 years, and number of people aged over 65 years. $\ln P_t$ is common throughout cross-section i owing to data limitations. The stationarity assumption requires $|\alpha| < 1$. Further, we assume homogeneous coefficients, where $\alpha_i = \alpha$, $\beta_i = \beta$, $\gamma_i = \gamma$, and $\boldsymbol{\delta}_i = \boldsymbol{\delta}$ for all i.

As discussed in Sections 1 and 2, the error term in (1) can be correlated between the cross-sections. Therefore, we assume that the unobserved common factor error structure is

$$\varepsilon_{it} = \mu_i + \boldsymbol{\lambda}_i' \mathbf{f}_t + v_{it}, \tag{2}$$

where μ_i is an individual effect that is assumed to be $iid(0, \sigma_\mu^2)$, and v_{it} is the remainder effect that is assumed to be $iid(0, \sigma_v^2)$. $\boldsymbol{\lambda}_i = (\lambda_{i1}, \lambda_{i2}, \dots, \lambda_{im})'$ is an $m \times 1$ vector of factor loadings and a non-random variable, and $\mathbf{f}_t = (f_{1t}, f_{2t}, \dots, f_{mt})'$ is an m-dimensional vector of unobservable common factors and a random variable with $E(\mathbf{f}_t) = 0$ and $V(\mathbf{f}_t) = \mathbf{\Sigma}_f$. In addition, because $E(\boldsymbol{\lambda}_i'\mathbf{f}_t\mathbf{f}_t'\boldsymbol{\lambda}_j) = \boldsymbol{\lambda}_i'\mathbf{\Sigma}_f\boldsymbol{\lambda}_j \neq 0$ for a different cross-sectional unit $i \neq j$, the dependent variable $\ln C_{it}$ is correlated between cross-sections. In this case, the GMM estimators of (1) are not consistent, but the bias can be reduced by including the time effect in the model (Sarafidis et al. 2009). That is, we calculated the deviation from the cross-sectional average.

Second, we apply the time effect to (1) as follows:

$$\overline{\ln C}_{it} = \alpha \overline{\ln C}_{i,t-1} + \beta \overline{\ln Y}_{it} + \boldsymbol{\delta}\overline{\ln \mathbf{D}}_{it} + \bar{\mu}_i + \bar{\boldsymbol{\lambda}}_i'\mathbf{f}_t + \bar{v}_{it}, \tag{3}$$

where

$$\overline{\ln C}_{it} = \ln C_{it} - \frac{1}{N}\sum_{j=1}^{N} \ln C_{jt},$$

$$\overline{\ln C}_{i,t-1} = \ln C_{i,t-1} - \frac{1}{N}\sum_{j=1}^{N} \ln C_{j,t-1},$$

$$\overline{\ln Y}_{it} = \ln Y_{it} - \frac{1}{N}\sum_{j=1}^{N} \ln Y_{jt},$$

$$\overline{\ln \mathbf{D}}_{it} = \ln \mathbf{D}_{it} - \frac{1}{N}\sum_{j=1}^{N} \ln \mathbf{D}_{jt},$$

$$\bar{\mu}_i = \mu_i - \frac{1}{N}\sum_{j=1}^{N} \mu_j,$$

$$\bar{\boldsymbol{\lambda}}_i = \boldsymbol{\lambda}_i - \frac{1}{N}\sum_{j=1}^{N} \boldsymbol{\lambda}_j,$$

$$\bar{v}_{it} = v_{it} - \frac{1}{N}\sum_{j=1}^{N} v_{jt}.$$

Because the deviation from the cross-sectional average of $\ln P_t$ is zero, it disappears from (3). Furthermore, the first difference of (3) is given by

$$\Delta\overline{\ln C}_{it} = \zeta\Delta\overline{\ln C}_{i,t-1} + \eta\Delta\overline{\ln Y}_{it} + \boldsymbol{\vartheta}\Delta\overline{\ln \mathbf{D}}_{it} + \bar{\boldsymbol{\lambda}}_i'\Delta\mathbf{f}_t + \Delta\bar{v}_{it}, \tag{4}$$

$$i = 1, \dots, N, t = 2, \dots, T.$$

We eliminate the individual effect μ_i in (3), which is correlated with the lagged dependent variable. The first difference GMM estimator of (4) uses the instrumental variable $\overline{\ln C}_{is}$ $(s = 0, \dots, t-2)$, which takes the deviation from the cross-section average because the bias becomes smaller than the GMM estimator without considering the correlation between the cross-section (Sarafidis et al. 2009).

4. Empirical results

4.1 Pre-test results for cross-section dependence

We expect there to be a correlation between the cross-sections because consumption trends are similar when the age groups are close. First, we investigate the presence of error cross-section dependence. It is well-known that ignoring the panel cross-section dependence in estimation can have serious consequences, with unaccounted for residual dependence resulting in estimator efficiency loss and invalid test statistics. We assume that ρ_{ij} is the correlation between the error terms in different cross-sectional units i, j. The null hypothesis is commonly represented as $H_0\colon \rho_{ij} = 0$ for all t and $i \neq j$. In other words, there is no cross-section dependence in terms of the correlations between the error terms in different cross-sectional units. Table 2 shows that the null hypothesis of no cross-section dependence is rejected at the 5% level. That is, we find that there is a cross-sectional correlation between i and j. As described above, when the error term is correlated between cross-sections, the GMM estimators of (1) are not consistent. Therefore, we use (3) or (4), including the common factor error structure, to obtain consistent estimators.

Second, we carry out the following panel unit root tests with cross-section dependence: the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) and truncated CIPS tests by Pesaran (2007), which extended the Im, Pesaran, and Shin (2003) test to the correlation between cross-sections. Table 3 shows that the null hypothesis of the panel unit root is rejected at the 5% level for both cases. In other words, the CIPS and truncated CIPS test results show that all variables are stationary, $I(0)$. Therefore, we use the stationary panel dynamic model in (4) in the next subsection.

Table 2. The panel cross-sectional dependence tests

Test	Test statistics	P-value
Breusch-Pagan LM[a]	362.445	0.000
Pesaran scaled LM[b]	63.434	0.000
Pesaran CD[c]	9.386	0.000

Notes: [a]Breusch-Pagan LM denotes the most well-known the Breusch-Pagan (1980) Lagrange Multiplier (LM) test, [b]Pesaran scaled LM denotes the correction test for large *N* of the Breusch-Pagan (1980) LM test, and [c]Pesaran CD is the test to address the size distortion of Breusch-Pagan LM and Pesaran scaled LM tests.

Table 3. The panel unit root tests with cross-sectional dependence

	CIPS		Truncated CIPS	
	constant	constant+trend	constant	constant+trend
$\ln C_{it}$	-7.564	-7.616	-5.367	-5.449
$\ln Y_{it}$	-4.762	-5.133	-4.698	-5.098
$\ln Age_{it}$	-4.708	-4.806	-4.708	-4.806
$\ln Num_{it}$	-3.647	-5.724	-3.647	-5.486
$\ln Under18_{it}$	-3.622	-5.408	-3.622	-5.408
$\ln Over65_{it}$	-3.358	-5.569	-3.242	-5.400

Notes: $\ln P_t$ cannot test the nonstationary because of having the common data between cross-sections. The critical value at the 5% level in the CIPS and truncated CIPS tests is -2.32 for constant and -2.83 for constant and trend.

4.2 Estimation results

As a result, we perform a stationary dynamic panel estimation of (4). We select lag order 6 as the autoregressive (AR) model for (1) according to the Akaike information criterion. In the GMM estimation of (4), the instruments $\overline{\ln C_{is}}$ $(s = 0, \ldots, 6)$ are used to reduce the bias rather than the GMM estimator without considering the cross-sectional correlation. Table 4 shows that the estimated coefficients are all significant at the 5% level. The increase in the lagged first-difference term of consumption $\Delta\overline{\ln C}_{i,t-s}$ decreases the first difference in consumption expenditure, but the negative effect gradually decreases as the lag increases. Further, the increase in the first-difference terms of real disposable income, age of the household heads, and number of households increases the first difference in consumption expenditure. In particular, we find that the first difference in household heads' age rather than real disposable income increases the first difference in consumption expenditure. On the other hand, the increase in first-difference terms of the number of those aged under 18 and over 65 years decreases the first difference in consumption expenditure.

Table 4. The first difference GMM estimates of dynamic panel model

variable	coefficient	Std.error	p-value
$\Delta\overline{\ln C}_{i,t-1}$	-0.5542	0.028	0.000
$\Delta\overline{\ln C}_{i,t-2}$	-0.5403	0.032	0.000
$\Delta\overline{\ln C}_{i,t-3}$	-0.4092	0.033	0.000
$\Delta\overline{\ln C}_{i,t-4}$	-0.3770	0.033	0.000
$\Delta\overline{\ln C}_{i,t-5}$	-0.1920	0.032	0.000
$\Delta\overline{\ln C}_{i,t-6}$	-0.1453	0.028	0.000
$\Delta\ln Y_{it}$	0.0341	0.007	0.000
$\Delta\ln Age_{it}$	1.7027	0.657	0.009
$\Delta\ln Num_{it}$	0.3790	0.119	0.002
$\Delta\ln Under18_{it}$	-0.0152	0.005	0.004
$\Delta\ln Over65_{it}$	-0.0109	0.005	0.022

5. Forecasting the consumption expenditure in disaggregate age groups

5.1 Within-sample forecasting performance

We first predict the within-sample based on the GMM estimates in Table 4, from August 2000 to December 2017. For example, for the one-step ahead forecast at time *T*, we consider the following equation:

$$\Delta\overline{\ln C}_{it+1} = a\Delta\overline{\ln C}_{i,t} + b\Delta\overline{\ln Y}_{it+1} + \boldsymbol{c}\Delta\overline{\ln\mathbf{D}}_{it+1} + \bar{\boldsymbol{\lambda}}_i'\Delta\mathbf{f}_{t+1} + \Delta\bar{v}_{it+1}, \tag{5}$$

where $\Delta\overline{\ln C}_{it+1}$ is the first difference in $\overline{\ln C}_{it+1}$. From $\Delta\overline{\ln C}_{it+1}$ at the $T = t + 1$ period, we recalculate levels $\ln\hat{C}_{i,t+1|T}$ of the $t + 1$ period ahead by returning the difference and the deviation from the cross-section average. Further, by repeating this step, we calculate $\ln\hat{C}_{i,t+S|T}$ of the S-period ahead.

We present the accuracy of the sample forecasts using two forecast evaluation criteria. First, the S-period-ahead root mean squared prediction error (RMSPE) is defined as

$$RMSPE_S = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\ln\hat{C}_{i,t+S|T} - \ln C_{i,t+S})^2}, \tag{6}$$

where $\ln\hat{C}_{i,t+S|T}$ is the S-period-ahead forecast of $\ln C_{i,t+S}$ using the observations available at time t.

For within-sample forecasting, $S = 0$ and the sample forecast are conducted within the available observations. Second, we calculated an alternative forecast evaluation using the mean absolute prediction error (MAPE):

$$MAPE_S = \frac{1}{T}\sum_{t=1}^{T}\left|\ln\hat{C}_{i,t+S|T} - \ln C_{i,t+S}\right|. \tag{7}$$

Table 5 shows the simulation result for within-sample periods based on the GMM estimates from August 2000 to December 2017. The RMSE and MAPE of each age group are calculated using (6) and (7). The average of the simulations is similar to the observed average, but the 95% confidence interval differs from the observed values as the age increases. In particular, the difference of the 95% confidence interval in the over-70 age group is remarkable. Further, both the RMSE and MAPE calculated the increase in the accuracy of prediction between the under-29 and over-70 age groups. In particular, the prediction is inaccurate for the over-70 age group. On the contrary, the accuracy is better in the 40–49 age group, which represents the average age of the household head. As a whole, we find that our dynamic panel model generates accurate forecasts for within-sample.

Table 5. Within-sample forecasting

Age group	Observed		Simulation			
	Average	S.D.	Average	S.D.	RMSE	MAPE
Under 29	12.321	0.109	12.321	0.095	0.086	0.069
	[12.258, 12.336]		[12.308, 12.334]			
30-39	12.517	0.070	12.518	0.075	0.049	0.038
	[12.507, 12.526]		[12.508, 12.528]			
40-49	12.724	0.085	12.724	0.076	0.040	0.032
	[12.712, 12.735]		[12.714, 12.734]			
50-59	12.809	0.095	12.809	0.075	0.051	0.041
	[12.796, 12.822]		[12.799, 12.819]			
60-69	12.796	0.087	12.795	0.072	0.052	0.041
	[12.784, 12.808]		[12.786, 12.805]			
Over 70	12.529	0.153	12.527	0.101	0.125	0.094
	[12.508, 12.549]		[12.513, 12.541]			
Average[a]	12.664	0.108	12.663	0.083	0.073	0.057
	[12.649, 12.678]		[12.652, 12.675]			

Note: The values in square bracket indicate the 95% confidence interval. [a]Average is weighted by the number of households.

5.2 Out-of-sample forecasting performance

We first introduce the forecasting performance of the dynamic panel model for the out-of-sample period, compared with the AR model. Both models are estimated based on Table 4 using the data up to December 2017, and the out-of-sample observations from January 2018 to November 2020 are used to measure the one-to-three-years-ahead forecasting accuracy. Table 6 shows the comparison of the out-of-sample forecasting performance between the dynamic panel model and AR model. The upper half of the table refers to the forecasts of the dynamic panel model. In the RMSPE and MAPE, the one-to-three-years-ahead forecasting accuracy improves as the years pass in many age groups. However, in 60–69 age group, the forecasting accuracy worsens as the years pass. In both forecast evaluations, the dynamic panel model generates relatively accurate out-of-sample forecasts. The lower half of the table refers to the forecasts of the AR model. In both the RMSPE and MAPE, the one-to-three-years-ahead forecasting accuracy worsens as the years pass in almost all age groups. In other words, when the AR model measures long-run forecasts, the accuracy of the forecasting worsens. The forecast results suggest that the dynamic panel model generates more accurate forecasts than the AR model. In particular, the difference in accuracy between the dynamic panel model and AR model is remarkable in the under-29, 50–59, and 60–69 age groups.

Next, we calculate the long-run forecast for the out-of-sample using the simulation model based on (5). It is assumed that no exogenous macro shocks occur during the forecast period. In (5), $\Delta\overline{\ln Y}_{it+1}$ denotes the first difference of $\overline{\ln Y}_{it+1}$, and $\Delta\overline{\ln \mathbf{D}}_{it+1}$ denotes the first difference of $\overline{\ln \mathbf{D}}_{it+1}$. For the one-step ahead forecast, the series of $\overline{\ln Y}_{it+1}$ and $\overline{\ln \mathbf{D}}_{it+1}$ are calculated using the AR(p) model. For example, to calculate the first-difference $\Delta\overline{\ln Y}_{it+1}$, the level variable $\overline{\ln \hat{Y}}_{it+1|T}$ can be estimated using the AR(6) model as follows:

$$\overline{\ln Y}_{it} = \theta_1 \overline{\ln Y}_{it-1} + \theta_2 \overline{\ln Y}_{it-2} + \cdots + \theta_6 \overline{\ln Y}_{it-6} + e_{it}, \tag{8}$$

Moreover, the one-step ahead forecast at time T is

$$\overline{\ln \hat{Y}}_{it+1|T} = \hat{\theta}_1 \overline{\ln Y}_{it} + \hat{\theta}_2 \overline{\ln Y}_{it-1} + \cdots + \hat{\theta}_6 \overline{\ln Y}_{it-5}, \tag{9}$$

where $\overline{\ln \hat{Y}}_{it+1|T}$ denotes the estimated value of $\overline{\ln Y}_{it+1}$ based on results of $\overline{\ln Y}_{it}$ at time T.

For the two-step ahead forecast at time T, we obtain

$$\overline{\ln \hat{Y}}_{it+2|T} = \hat{\theta}_1 \overline{\ln \hat{Y}}_{it+1|T} + \hat{\theta}_2 \overline{\ln Y}_{it} + \cdots + \hat{\theta}_6 \overline{\ln Y}_{it-4}. \tag{10}$$

Further, to obtain $\Delta\overline{\ln \hat{Y}}_{it+S}$, we extend (10) to the S-step ahead and repeat the calculations (8) through (10). By applying the same method, we can also obtain $\Delta\overline{\ln \mathbf{D}}_{it+S}$ for the S-step ahead.

The left half of Table 7 shows the observed and simulated results from December 2018 to November 2020. For younger age groups below 50 years, the simulated results have lower average values than the observed results. For age groups over 50 years, the simulated results have higher average values. In Japan, which has a large number of households with heads aged over 60 years, the results of the older age groups are highly weighted. Therefore, the final average values are skewed toward the middle-aged and older age groups. As in the case of the within-sample in Table 5, the accuracy of forecasting for the under-29 and over-70 age groups is relatively poor. The right half of Table 7 shows the out-of-sample forecasting based on the dynamic panel model for two periods: December 2020 to December 2025 and January 2026 to December 2030. From December 2020 to December 2025, logarithm consumption is expected to increase among younger and early middle-aged groups, that is, the under-29, 30–39, and 40–49 age groups. On the other hand, consumption expenditure will decrease in age groups of over 50 years. In particular, consumption in the over-70 age group will decline significantly. As a result, consumption of the over-70 age group will be lower than that of the under-29 age group. From January 2026 to December 2030, consumption is expected to increase not only among the younger age groups of under 29 and 30–39 years, but also the middle-aged groups of those 40–49, 50–59, and 60–69 years old. Only the over-70 age group is on the decline. On average, among the age groups, consumption is expected to increase in the near future after decreasing once. In addition, the 50–59 age group will remain the most consumptive in the future, similar to the observed and simulated results until November 2020.

From December 2020 to December 2025, the impact of the COVID-19 shock in 2020 will be retained in many age groups, leading to a decline in consumption. The impact will be felt especially in middle-aged and older age groups of over 50 years. However, from January 2026 to December 2030, this impact will gradually disappear, and consumption will increase for most age groups. However, for younger age groups of under 29 and 30–39 years, the impact of the COVID-19 shock is not retained, and consumption increases immediately. On the other hand, in the over-70 age group, once consumption begins to decline, there is no sign of recovery, and the effects of the COVID-19 shock remain with them. As can be observed in Figure 1, this age group experienced large fluctuations in consumption and was the most affected by the COVID-19 shock. The main difference between this and the younger age groups is that they have higher APCs and lower savings rates, which means that the effects of macro shocks are longer lasting. A generous policy for this older generation is necessary to encourage consumption.

As a whole, consumption by the middle-aged and older age groups of 50 years and over, which has underpinned Japan's consumption to date, has declined. However, the consumption of young people of the under-29, 30–39, and 40–49 age groups is predicted to increase in the future. However, Japanese households, whose heads are generally aged 60 years and over, account for a high weight of the total, and their average consumption is likely to decline compared with the past. Furthermore, if we assume that the population will continue to age, a further decline in consumption is inevitable. In other words, policies to promote consumption among households whose heads are aged 60 years and above are necessary.

Table 6. Comparison of forecasting accuracy from December 2018 to November 2020

	Measure	U29	30-39	40-49	50-59	60-69	Over 70	Average
(i) dynamic panel model								
1year	RMSPE	0.099	0.081	0.038	0.036	0.050	0.085	0.061
	MAPE	0.086	0.065	0.030	0.026	0.020	0.009	0.024
2years	RMSPE	0.101	0.069	0.022	0.045	0.056	0.080	0.057
	MAPE	0.085	0.057	0.018	0.036	0.043	0.067	0.047
3years	RMSPE	0.097	0.061	0.028	0.034	0.057	0.077	0.055
	MAPE	0.073	0.053	0.023	0.027	0.050	0.066	0.047
(ii) AR model								
1year	RMSPE	0.245	0.075	0.084	0.137	0.140	0.094	0.109
	MAPE	0.223	0.065	0.078	0.132	0.132	0.074	0.098
2years	RMSPE	0.246	0.079	0.080	0.138	0.147	0.109	0.115
	MAPE	0.228	0.063	0.077	0.130	0.137	0.099	0.106
3years	RMSPE	0.235	0.089	0.093	0.144	0.142	0.108	0.118
	MAPE	0.222	0.077	0.089	0.140	0.132	0.095	0.109

Table 7. Out-of-sample forecasting performance

Age group	Observed		Simulation						
	2018/12-2020/11		2018/12-2020/11			2020/12-2025/12		2026/1-2030/12	
	Average	S.D.	Average	S.D.	RMSE	Average	S.D.	Average	S.D.
Under 29	12.274	0.122	12.271	0.080	0.099	12.563	0.063	12.578	0.058
	[12.258, 12.290]		[12.260, 12.285]			[12.547, 12.579]		[12.563, 12.593]	
30-39	12.506	0.090	12.501	0.077	0.071	12.616	0.062	12.623	0.058
	[12.494, 12.518]		[12.491, 12.512]			[12.600, 12.632]		[12.609, 12.638]	
40-49	12.688	0.052	12.685	0.057	0.030	12.714	0.061	12.719	0.058
	[12.681, 12.696]		[12.678, 12.693]			[12.699, 12.730]		[12.704, 12.734]	
50-59	12.763	0.071	12.764	0.059	0.039	12.726	0.062	12.730	0.058
	[12.754, 12.773]		[12.756, 12.772]			[12.710, 12.741]		[12.715, 12.744]	
60-69	12.763	0.078	12.763	0.059	0.054	12.711	0.064	12.714	0.057
	[12.753, 12.774]		[12.755, 12.771]			[12.696, 12.727]		[12.699, 12.729]	
Over 70	12.473	0.101	12.484	0.080	0.081	12.293	0.067	12.292	0.059
	[12.459, 12.487]		[12.473, 12.495]			[12.276, 12.310]		[12.277, 12.306]	
Average[a]	12.623	0.081	12.626	0.068	0.058	12.567	0.064	12.570	0.058
	[12.612, 12.634]		[12.616, 12.635]			[12.559, 12.576]		[12.562, 12.578]	

Note: The values in square bracket indicate the 95% confidence interval. [a]Average is weighted by the number of households.

6. Conclusion

In Japan, consumption expenditure gradually decreased among most age groups. In addition, the recent COVID-19 shock caused another temporary decline. In this study, therefore, by forecasting the trends of future consumption expenditure in disaggregated age groups, we aimed to determine what policies are necessary for which age groups to increase consumption in the future. We account for correlations between age groups by incorporating the estimates of a dynamic panel model with cross-section dependence into our forecasting methodology. We obtained the following results from our forecasts. First, from December 2020 to December 2025, the impact of the COVID-19 shock in 2020 will be retained in many age groups, which will experience a decline in consumption. The impact will be especially felt in middle-aged and older age groups of over 50 years. However, from January 2026 to December 2030, this impact will gradually disappear, and consumption will increase for most age groups. On the other hand, in the over-70 age group, once consumption begins to decline, there will be no sign of recovery, and the effects of the COVID-19 shock will remain with them for a long time. Second, Japanese households with a high weight of total household heads aged 60 years or older are likely to experience a decline in average consumption due to this effect. Furthermore, as the population continues to age, a further decline in consumption is inevitable if no measures are taken to deal with older age groups. In other words, factors in two directions—temporary macro shocks and demographic factors—cause consumption fluctuations in forecasts.

Based on these results, we suggest that it is necessary to maintain disposable income by extending the retirement age system for the age groups of 60 years and over. Maintaining disposable income has the effect not decreasing consumption. In addition, when macro shocks occur, the effects tend to drag on for a long time for the age groups of 60 years and above. Therefore, providing income compensation for a certain period, such as lump-sum benefits, would be effective. In addition, this study does not assume that further macro shocks will occur during the forecast period. Our forecasting model will require improvements if we must account for such future macro shocks. On the other hand, in such an event, a further decline in consumption by older age groups will be inevitable.

In future research, we aim to use cohort data to predict changes in each current age group 10 or 20 years from now. In other words, it will be possible to confirm whether the results of this forecasting of consumption are a trend specific to a certain age group or whether they are due to an age effect.

Fig1. The annual average of log consumption expenditure

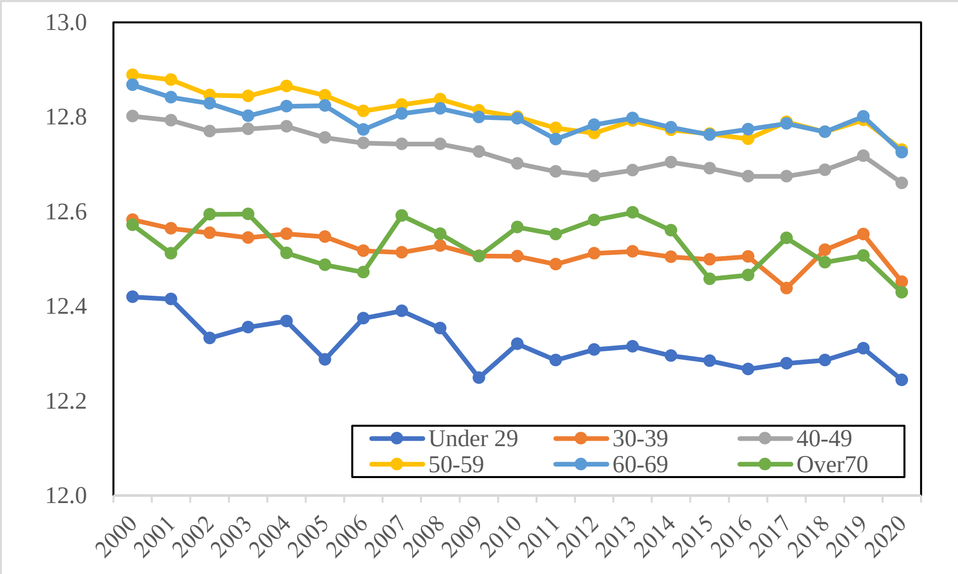
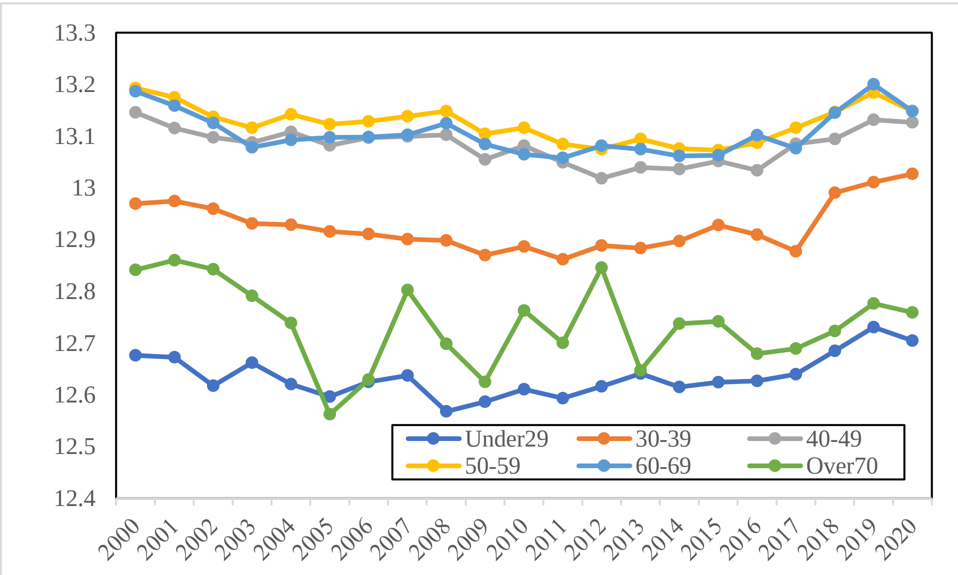


Fig2. The annual average of log disposal income



Reference

Annual Report on the Aging Society (2020) Cabinet Office Web. https://www8. cao.go.jp/kourei/english/annualreport/2020/pdf/2020.pdf

Baltagi BH (2008) Forecasting with panel data. Journal of Forecasting 27: 153-173.

Baltagi BH, Bresson G, Pirotte A (2012) Forecasting with spatial panel data. Computational Statistics and Data Analysis 56: 3381-3397.

Fujimura T, Sato M (2017) Shinia setai no shohi to shotoku no genjo (in Japanese). Ministry of Finance Web. https://www.mof.go.jp/public_relations/finance/201712/201712l.pdf

Im KS, Pesaran HM, Shin Y (2003) Testing for unit roots in heterogeneous panels. Journal of Econometrics 115, issue 1: 53-74.

Ince O (2014) Forecasting exchange rates out-of-sample with panel methods and real-time data. Journal of International Money and Finance 43: 1-18.

Kim K, GJD Hewings, Kratena K (2016) Household disaggregation and forecasting in a regional econometric input-output model. Letters in Spatial and Resource Sciences 9: 73-91.

Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics 22: 265–312

Phillips PCB, Sul D (2003) Dynamic panel estimation and homogeneity testing under cross section dependence. Econometrics Journal 6: 217–259.

Phillips PCB, Sul D (2007) Bias in dynamic panel estimation with fixed effects, incidental trends and cross section dependence. Journal of Econometrics 137: 162-188.

Sarafidis V, Yamagata T, Robertson D (2009) A test of cross section dependence for a linear dynamic panel model with regressors. Journal of Econometrics 148, issue 2: 149-161.