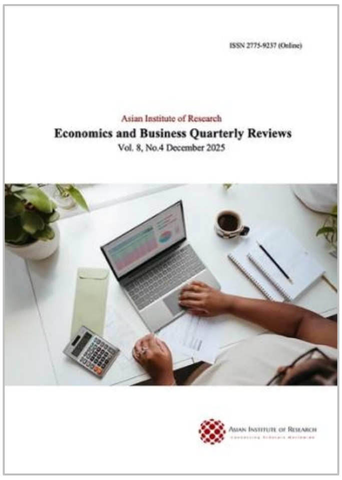

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Estimating Demographic Effects on Inflation in Japan using the Phillips Curve

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Abstract
The population distribution in Japan has shifted towards advanced ages with lower fertility rates following the so-called baby boom and increased life expectancy over the last few decades. The relation between the change in population composition and the accompanying downturn in economic growth has attracted public interest. Taking these factors into consideration, this study aims to explore the demographic effects on price level in Japan by panel data analysis at the prefectural level. Concretely, our empirical study tries to examine the impact of a change in the relative ratio of younger and older generations on inflation through the estimation with the special type of regional Phillips curve by using the two-way fixed effects model and the Arellano-Bond type GMM method. Our dynamic panel data analysis following the Arellano-Bond type GMM specification finds that a change in the young-age dependency ratio puts inflationary pressures and a change in the old-age dependency ratio applies deflationary pressures on price level.

Keywords: Aging Population, Demography, Old-Age Dependency Ratio, Philipps Curve, Young-Age Dependency Ratio
JEL Classification Code: C33, E31, E52, J11

1. Introduction

In reality, the distribution of population in Japan has shifted to advanced ages with longer life expectancy and lower fertility rates over the last several decades. The total population peaked in 2010, and the working age population has been rapidly decreased since the early 1990s. In addition, old-age dependency ratio has more than doubled since 1990s. Given these facts, there appears to be an increasing concern about the impact of aging and decreasing population on economy.

Anderson *et al.* (2014) and Yoon *et al.* (2014) insist that an aging or an increasing share of old population has significant deflationary effects on economy. Juselius and Takats (2015) and Aksoy *et al.* (2019) find that the full age pattern of population has a huge influence on inflation. McMillan and Baesel (1990) and Lindh and Malmberg (2000) find that the age structure can be a predictor of future trend inflation through their elderly research. On the other hand, Barbiellini *et al.* (2019) insist that aging is likely to dampen inflation by the analysis using regional data of Italy.

Considering the findings of these previous studies, we know that investigation into the relation between demographics and inflation should be conducted. Thus, this paper aims to empirically examine the impact of

Japan's aging population on inflation through the panel data analysis. Concretely, the estimations based on the two-way fixed effects model and the Arellano-Bond type dynamic panel analysis are conducted.

The remainder of this paper is organized as follows. Section 2 explains the data set for our empirical analysis. Section 3 illustrates the structures of the two-way fixed effects model and the dynamic panel data analysis. The result of empirical analysis is described in Section 4. Finally, Section 5 presents the concluding remarks.

2. The Data

This section describes the data set used in our empirical analysis. In our panel data set, each variable includes 5 years (the years 2020 to 2024), and 47 cross-sections (prefectures in Japan) – Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa, Niigata, Toyama, Ishikawa, Fukui, Yamanashi, Nagano, Gifu, Shizuoka, Aichi, Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama, Tottori, Shimane, Okayama, Hiroshima, Yamaguchi, Tokushima, Kagawa, Ehime, Kochi, Fukuoka, Saga, Nagasaki, Kumamoto, Oita. Miyazaki, Kagoshima, Okinawa – are included. The elements described above make the balanced panel. Our dataset is composed of the following variables.[1]

INF: Changes from the previous year of consumer price index (CPI), annual, all items, excluding fresh food, Base year: 2020, annual estimates, unit: %, issued by the Ministry of Internal Affairs and Communications.

YDR: Young-age dependency ratio (Child dependency ratio): Population composition ratio (by age) by Sex, Age (3 groups) and All nationality or Japanese, annual estimates, unit: %, issued by the Ministry of Internal Affairs and Communications.

$$\mathrm{YDR} = 100 \cdot \frac{\text{number of people aged 0 to 14}}{\text{number of people aged 15 to 64}}$$

ODR: Old-age dependency ratio (Elderly dependency ratio, Aged dependency ratio): Population composition ratio (by age) by Sex, Age (4 groups) and All nationality or Japanese, annual estimates, unit: %, issued by the Ministry of Internal Affairs and Communications.

$$\mathrm{ODR} = 100 \cdot \frac{\text{number of people aged 65 and over}}{\text{number of people aged 15 to 64}}$$

UER: Unemployment rate: Unemployment rate by age group, in Reference table, prefectural, by the estimation model, both sexes, Total, percent, quarterly estimates, unit: %, issued by Statistics Bureau, Ministry of Internal Affairs and Communications.

In this study, we should pay careful attention to the city-level annual data on consumer price index (CPI) and its changes from the previous year (as inflation rate). To be specific, statistics of the annual regional consumer price index and the CPI-based inflation rate are observed on the cities that exist in the prefectural capitals and the special wards, or on the cities with large economy. In other words, we cannot obtain their prefectural-level data. Therefore, we have no choice but to utilize the city-level data observed in prefectural capitals as the proxy variables for the prefectural-level data. Quarterly estimates of unemployment rate are converted into annual series by taking the average values of four quarters in each year.

3. Panel Data Analysis

3.1 Two-Way Fixed Effects Model for Panel Data Analysis

The standard linear regression model for panel data analysis can be expressed as

$$y_{it} = \alpha + x_{it}'\beta + u_{it}, \qquad (1)$$

where x_{it} is K-dimensional vector of independent variables, i represents the individuals $(i = 1, \dots, N)$ and t is for time period $(t = 1, \dots, T)$. The constant (or intercept) α term is a scaler, and the slope coefficient β is a $K \times 1$ matrix. The α and β are identical for all individuals and for time periods. The disturbance terms are described as

$$u_{it} = \mu_i + v_{it}. \qquad (2)$$

[1] The data for our estimation can be retrieved from the website of the "e-stat" (https://www.e-stat.go.jp).

The stochastic variable μ_i denotes the individual-specific unobservable effect, and $E(\mu_i) = 0$. It is time-invariant and explains any individual-specific effect that is not included in the regression. The v_{it} represents the reminder disturbance varying with individuals and with time. For v_{it}, we have the following assumptions:
$E(v_{it}) = 0, Var(v_{it}) = E(v_{it}^2) = \sigma_v^2$, for all i, t. (3)
$E(v_{it}v_{js}) = Cov(v_{it}, v_{js}) = 0$, for $i \neq j$ or $s \neq t$. (4)
We assume that x_{it} is not correlated with v_{is} for all i, s and t. Or, this assumption should be explained in terms of the strong exogeneity:
$E(v_{it}|\mu_i, x_{i1}, x_{i2}, \dots x_{iT}) = 0$. (5)
The so-called "random effects model" in the context of panel data analysis is described with the condition that μ_i and x_{it} are not correlated:
$E(\mu_i x_{it}) = cov(\mu_i, x_{it}) = 0$, (6)
where μ_i represents "random effects." By contrast, the so-called "fixed effects model" in the context of panel data analysis is described with the condition that μ_i and x_{it} are correlated:
$E(\mu_i x_{it}) = cov(\mu_i, x_{it}) \neq 0$, (7)
where μ_i explains "fixed effects." In this case, this model can be expressed as
$y_{it} = \alpha_i + x_{it}'\beta + v_{it}$, (8)
where α_i are fixed unknown constants or fixed (individual) effects, v_{it} is usually assumed to be *i.i.d.* over individuals and time. The overall constant term α in equation (1) is omitted since it is subsumed by α_i in equation (8), which grasp all (un)observable time-invariant differences across individuals. In this specification, consistent estimation does not impose the condition that α_i and x_{it} are uncorrelated.

Further, the u_{it} in equation (1) and (2) can be described as
$u_{it} = \mu_i + c_t + v_{it}$, (9)
where μ_i is the unobservable individual-specific effect. It is individual-invariant and accounts for any time-specific effect that the regression cannot include. The c_t denotes the unobservable time-specific effect that is identical for all individuals, and v_{it} represents reminder stochastic disturbance. In this case, if μ_i and c_t are correlated with x_{it}, we have a special type of fixed effects model, the so called "two-way fixed effects model." On the other hand, if μ_i and c_t are not correlated with x_{it}, we get a special specification, the so called "two-way random effects model."

3.2 Dynamic Panel Data Analysis

Unlike the static models mentioned in previous section, y_{it} depends on its past realizations and y_{it-1} depends on α_i irrespective of the method of the treatment for α_i in a dynamic panel data analysis. The linear dynamic model with exogenous variables and a lagged dependent variable can be described as
$y_{it} = \gamma y_{it-1} + x_{it}'\beta + \alpha_i + v_{it}$, (10)
where x_{it} is uncorrelated with v_{it} for all i and t variables (in short, uncorrelated across individuals and time), or it should be strictly exogenous. The α_i represents fixed individual effects and v_{it} is assumed $\mathrm{IID}(0, \sigma_u^2)$. Since y_{it-1} is correlated with α_i (because of the fact that y_{it-1} is a function of α_i), OLS (ordinary lease squares) and GLS (generalized least squares) estimators are inconsistent and biased. In addition, WG (within group) estimators are biased and inconsistent. The reason of the biasedness and inconsistency in this case is that the independent variable will be endogenous (or $\bar{y}_i$ is correlated with $\bar{v}_i$) when we use variable deviations from mean in the transformed model. The so-called first-difference transformation is one of the processes to remove α_i. Concretely, we have the specification:
$\Delta y_{it} = \gamma \Delta y_{it-1} + \Delta x_{it}'\beta + \Delta v_{it}$. (11)
WG and GLS estimators cannot be appropriate. Since Δy_{it-1} has a correlation with Δv_{it}, this specification cannot avoid endogeneity problem.

To control this endogeneity, Arellano and Bond (1991) recommend the procedure that utilizes all possible instrumental variables with GMM (Generalized Method of Moments) estimation. Their study suggest that the list of instruments can be extended by considering additional moment conditions and letting their number vary with t. State differently, their method obtains estimators utilizing the moment conditions given by lagged levels of the dependent variable ($y_{it-2}, y_{it-3}, \dots$.) and Δv_{it}. Arellano and Bond (1991) evaluate the validity of estimators given by GMM, OLS, and WG, and come to their conclusion that GMM estimator has the smallest bias and variance. On the other hand, Anderson and Hsiao (1982) proposed the method by applying Δy_{it-2} or y_{it-2} as the instrumental variables for Δy_{it-1}. Indeed, we obtain more instruments than unknown parameters if the panel for our analysis includes three or more time periods.

4. Empirical Results

With the characteristics of the two-way fixed effects model and the dynamic panel data analysis described in the previous sections, our study proceeds to the empirical analysis that examines demographic effects on inflation through the estimation with the data on Japan's 47 prefectures for period from 2020 to 2024. Concretely, our empirical study tries to examine the impact of change in relative ratio of younger and older generations on inflation through the estimations with the special type of regional Phillips curve by using the two-way fixed effects model and the Arellano-Bond type GMM method. The following two types of specification are applied in our empirical study:

<Model 1> (for fixed effects panel data analysis)

$$INF_{it} = \alpha_i + \beta_1 CYDR_{it} + \beta_2 CODR_{it} + \beta_3 UER_{it} + \varepsilon_{it}, \quad (12)$$

<Model 2> (for dynamic panel data analysis)

$$INF_{it} = \alpha_i + \gamma INF_{it-1} + \beta_1 CYDR_{it} + \beta_2 CODR_{it} + \beta_3 UER_{it} + \varepsilon_{it}, \quad (13)$$

These specifications can be interpreted as the special types of regional Phillips curve where the intercept term captures time (or period) fixed effects and regional demographic variation. Especially, the Model 2 is a kind of regional Phillips curve with backward-looking expectation. In these specifications, the INF_{it} denotes annual inflation for prefecture i at time t. The α_i is the time-invariant fixed effect. The $CYDR_{it}$ is the rate of change of the YDR (young-age dependency ratio). The $CODR_{it}$ is the rate of change of the ODR (old-age dependency ratio). The UER_{it} is the unemployment rate, and this term is included in order to grasp the regional excess demand dynamics. The INF_{it-1} is the lagged inflation rate. It works as the proxy variable for INF_{it}^{e} based on the assumption of adaptive inflation expectations. The ε_{it} represents the error term. It varies over individuals and time, and captures unobservable all elements that affect INF_{it}.

First, we consider which is better for us to choose the fixed effects model or the random effects model with regard to the model 1. The random effects model can be consistently estimated by both the fixed effects and the random effects estimators. The random effects estimator would be preferred if we are sure that the individual specific effect is certainly an unrelated effect, in short, it is random and uncorrelated with the explanatory variables for all past, current, and future periods of the same agent. The Wu-Hausman test[2] is constructed to find a violation of the assumption for the random effects model insisting that the independent variables are orthogonal to the unit (individual) effects. If no correlation between the independent variables and the unit effects is found, then $\hat{\beta}_{FE}$, estimates of β in the fixed effects model, would be close to $\hat{\beta}_{RE}$, estimates of β in the random effects model. Therefore, the test statistic H is described as

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{FE}), \quad (14)$$

with the condition under the null hypothesis:

$$Var(\hat{\beta}_{FE} - \hat{\beta}_{RE}) = Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE}). \quad (15)$$

The H follows chi-square distribution with degrees of freedom that equal to the number of regressors under the null hypothesis of orthogonality. Rejection of null hypothesis[3] implies that the two models are different enough, and we do not prefer the random effects model.

The results of the Wu-Hausman tests for our model 1 is indicated in Table 1. The test statistic shows the rejection of null hypotheses at 1% level of significance. Considering this result, we prefer the fixed effects model for our model 1. However, the Wu-Hausman test has some weak points. For example, it is only valid under *i.i.d.* of error term, and it cannot be applied to the specification that includes time (or period) fixed effects. Considering the latter

[2] The explanation of the Wu-Hausman test in this section is mainly based on Greene (2017) and Verbeek (2017).

[3] Precisely speaking, rejection of null hypothesis should not directly be the evidence for the comparative advantage of the fixed effects model. As to the lower power with respect to the severe pretest bias of the Wu-Hausman test, see Guggenberger (2010).

Table 1: Wu-Hausman Test

Chi-Sq. Statistic	Chi-Sq. d.f.	p-value
190.905424	3	0.0000

Table 2: Redundant Fixed Effects Tests (cross-section and period fixed effects)

F / χ^2	Statistic	d.f.	p-value
Cross-section F	2.826573	(46,135)	0.0000
Cross-section χ^2	126.813419	46	0.0000
Period F	353.043436	(3,135)	0.0000
Period χ^2	409.820945	3	0.0000
Cross-Section / Period F	57.573368	(49,135)	0.0000
Cross-Section / Period χ^2	580.233734	49	0.0000

Table 3: Panel Data Analysis by the Two-Way Fixed Effects Model

Variable	Coefficient	Std. Error	t-Statistic	p-value
const.	2.133102	0.407880	5.229732	0.0000
CYDR	-0.055659	0.034764	-1.601041	0.1117
CODR	-0.115047	0.062378	-1.844339	0.0673
UER	-0.077877	0.173157	-0.449750	0.6536
Effects Specification: Two-way fixed effects model (Cross-section fixed (dummy variables) and Period fixed (dummy variables))				
R-squared	0.971091	Log likelihood	10.40377	
Adjusted R-squared	0.959956	F-statistic	87.20914	
S.E. of regression	0.270173	Prob (F-statistic)	0.000000	
Sum squared resid	9.854089			

Notes: Dependent Variable: INF. Sample Period: 2021 – 2024. Effective Sample Period: 2021 – 2024 (because of the first difference variables). Cross-sections included: 47. Total panel (balanced) observations: 188.

problem, we implement the redundant fixed effects test in order to detect the existence of both cross-section and period fixed effects.

Table 2 depicts the result of the redundant fixed effects (cross-section and period fixed effects) test. The test statistics reveal that the null hypotheses for the individual fixed effects and the period fixed effects are rejected. In addition, the joint null hypotheses are also rejected. The test result implies that there exist the individual effects[4] and the time (or period) effects in the context of the fixed effects model. In this respect, we have to choose the so-called "two-way fixed effects model," explained in Section 3.1, rather than the usual one-way fixed effects model for our estimation.

The result of estimation for the model 1 based on the two-way fixed effects model with our balanced panel data set is displayed in Table 3. Considering the result, no variable (except constant term) is significantly estimated at the conventional level. If I had to say, the rate of change of the old-age dependency ratio is barely significant at 10% with a negative sign. It may imply that population ageing is a deflationary element of inflation. Unfortunately, change of the young-age dependency ratio is not significant even at 10% level of significance. In addition. its estimated sign is negative, but positive one is normally be expected. To put it another way, it is usually assumed that the young-age dependency ratio is an inflationary element of inflation. Thus, the signs of the old-age dependency ratio and the young-age dependency ratio are controversial in this context. On the other hand, the unemployment rate does not work as the factor to affect inflation because of its insignificance. Taken as a whole, the estimation result based on our model 1 does not have any valuable implications.

[4] Because of the existence of individual fixed effects, pooled estimation is inappropriate for us.

Table 4: Arellano-Bond Serial Correlation Test

Test order	m-Statistic	ρ	Std. Error (ρ)	p-value
AR(1)	-3.398583	-109.713931	32.282256	0.0007
AR(2)	2.437673	37.401699	15.343199	0.0148

Notes: Sample: 2020 – 2024. Included observations: 141

Table 5: Panel Data Analysis by the Arellano-Bond-type Dynamic Panel Data Analysis

Variable	Coefficient	Std. Error	t-Statistic	p-value
INF(-1)	0.159618	0.024667	6.470998	0.0000
CYDR	0.139056	0.043467	3.199134	0.0025
CODR	-2.063497	0.088328	-23.36165	0.0000
UER	-2.496321	0.218383	-11.43095	0.0000
Effects Specification: Cross-section fixed (first differences)				
Mean dependent var	0.968085	S.D. dependent var	1.273876	
S.E. of regression	1.279599	Sum squared resid	224.3203	
J-statistic	34.3643	Instrument rank	30	
Prob(J-statistic)	0.126096			

Notes: Dependent Variable: INF. Constant added to instrument list. Method: Panel Generalized Method of Moments. Transformation: First Differences Sample (adjusted): 2022-2024. Periods included: 3. Cross-sections included: 47. Total panel (balanced) observations: 141. White period (period correlation) instrument weighting matrix. White period (cross-section cluster) standard errors and covariance (d.f. corrected). Convergence achieved after 40 weight iterations. Standard error and t-statistic probabilities adjusted for clustering.

In order to get out of this ambiguous situation, we should take a different approach by using the model 2 for estimation. At this stage, one difficulty arises. Under the existent circumstances for data availability, we practically cannot obtain the estimated value of expected inflation rate (π_{it}^{e}) at the prefectural level. Consequently, we have no choice but to use the proxy variable in light of the adaptive expectations hypothesis. Namely, we set the proxy variable as $\pi_{it}^{e} = \pi_{it-1}$. It incidentally captures the degree of inflation persistence in our estimation.

This treatment brings us to a new phase in that the lagged term of dependent variable is included as a regressor in the specification. In other words, a dynamic panel data analysis explained in section 3.2 should be applied. In this study, the Arellano-Bond (1991) type GMM (generalized method of moments) method[5] is utilized to conduct the estimation of dynamic panel specification. No period dummy variable is included in our estimation although it is often used to control period fixed effect, and the first difference transformation is applied[6] to each variable in order to remove cross-section fixed effects. As the Arellano-Bond type dynamic panel instrumental variables with lags – INF_{t-1}, $CDYR_{t-1}$, $CODR_{t-1}$, UER_{t-1}– are adopted in addition to the usual instruments for GMM (with transformation by taking differences) – *CYDR*, *CODR*, *UER* –. The White period GMM weighting matrix and robust (White) standard errors are applied. Further, the procedure of n-step iterations to convergence is utilized.

Table 4 shows the result of Arellano-Bond Serial Correlation Test for serial correlation in the error terms. The null hypothesis is that there is no serial correlation of a given order. The test statistic is computed as proposed by Arellano and Bond (1991) and Arellano (2003). The test result of AR(1) with respect to the first difference of the error term shows that the null hypothesis cannot be rejected, while the result of AR(2) displays that the null hypothesis is rejected at 5% level of significance. These results do not contradict our assumption.

Table 5 describes the estimation result of dynamic panel data analysis based on the Arellano-Bond type specification. As mentioned before, the procedure of n-step iterations to convergence is adopted. The convergence of our estimation was achieved after 40 weight iterations. First, we should check the result of the Hansen test (of overidentifying restrictions validity) in order to examine the suitability of the instrumental variables. In this case, the null hypothesis is that the instrumental variables are not over-identified. The probability for J-statistic in the bottom row of Table 5 shows that the null hypothesis is not rejected at the conventional level. Thus, we need not

[5] For the Arellano-Bond type GMM estimation, see Arellano and Bond (1991), Pesaran (2015), Verbeek (2017), and Baltagi (2021) for details.
[6] If the innovations of the variables are *i.i.d..,* the transformed innovations follow an integrated MA(1) process.

re-consider or replace the instrumental variables. Regarding the estimated four coefficients, INF_{t-1}, the proxy variable for expected inflation rate, is significantly estimated at 1% level of significance. Change of the young-age dependency ratio is significant with a positive sign, while the rate of change of the old-age dependency ratio is also significant with a negative sign. This combination is consistent with the usual assumption – the young-age dependency ratio is an inflationary element and the old-age dependency ratio is a deflationary element –. The estimated coefficient of unemployment rate is significant with a negative sign. It is consistent with the expected condition.

Considering the results of estimations comprehensively, it can be concluded that our dynamic panel data analysis by utilizing the Arellano-Bond type specification suggests comparatively clear implication compared with the two-way fixed effects model. Namely, we find that a change in the young-age dependency ratio puts inflationary pressures and a change in the old-age dependency ratio applies deflationary pressures on price level.

5. Concluding Remarks

Considering the findings of the previous studies, we know that investigation into the relation between demographics and inflation should be conducted. Therefore, this study aims to empirically examine the impact of Japan's aging population on inflation by utilizing the panel data analysis. The estimations by using the two-way fixed effects model and the Arellano-Bond type dynamic panel specification based on a kind of backward-looking regional Phillips curve are conducted with Japan's data on 47 prefectures for the period from 2020 to 2024. Concretely, our empirical study tries to examine whether an increase in the relative ratio of older generation has deflationary pressures and increase in the younger generation's relative ratio has inflationary pressures on price level.

The result of the estimation for the model 1 by following the two-way fixed effects model shows no valuable information. If I had to say, the rate of change of the old-age dependency ratio is barely significant at 10% level of significance with a negative sign. It may imply that population ageing is a deflationary element of inflation. Unfortunately, change of the young-age dependency ratio is not significant even at 10% level with unexpected sign. In addition, the unemployment rate does not work as the factor to affect inflation.

On the other hand, our dynamic panel data analysis following the Arellano-Bond type GMM specification based on the model 2 suggests comparatively clear implication about the impacts of the young-age dependency ratio and the old-age dependency ratio on inflation. Concretely, we find that a change in the young-age dependency ratio puts inflationary pressures and a change in the old-age dependency ratio applies deflationary pressures on price level. The estimated coefficient of unemployment rate is significant with a negative sign. It is consistent with the expected condition.

The findings of our empirical study could be applied to some regional economic policies at the micro- and macro-levels. However, a natural extension and further investigation of our research topic are required since the empirical analysis in this paper has some uncertain factors.

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