Dynamic Relationship between Population Aging and Transition of Industrial Structure Based on VAR Model: Empirical Evidence from Post-World War II Japan

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Table of Contents

List of Figures

List of Tables

Certification

I, Shanshan XIA (Student ID 51217601) hereby declare that the contents of this Master's Research Report are original and true and have not been submitted at any other university or educational institution for the award of degree or diploma.

All the information derived from other published or unpublished sources has been cited and acknowledged appropriately.

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Abstract

This paper empirically analyzes the dynamic relationship between population aging and transition of industrial structure using three main-sector data of post-war Japan over the period from 1955 to 2016. Two concepts are introduced to measure transition of industrial structure from two dimensions, namely rationalization of industrial structure and upgrading of industrial structure. A trivariate vector autoregression (VAR) model of the lag order 4 is employed to conduct empirical analysis. Based on results of Granger causality test, impulse response function and variance decomposition, it is found that: (1) The empirical evidence confirms a long-run mutual relationship between population aging and changes in the industrial structure. (2) Changes in the aging of the population can lead to changes in the industrial structure via the channel of changes of productivity level or employment structure among different industries, which is consistent with the results of relevant economic theories and other related studies. (3) The industrial structure has a certain role in promoting the aging of the population in the service-oriented process, which is a novel conclusion drawn from the empirical analysis of this study. (4) the degree of influence of aging population on the rationalization of the industrial structure continuously strengthen over time， while the degree of effect of industrial upgrading （or economic servitization） on the population aging is fluctuating, which means it gradually increases and then declines after peaking.

Key words: population aging, industrial structure, post-war Japan, VAR model

Chapter 1: Introduction

After the second World War, economy development of Japan experienced four phrases alongside transition of industrial structure, namely the postwar recovery stage (1946-1954), the high growth stage (1955-1973), the stable growth stage (1974-1991) and economic transformation period (since 1992) (Yabe, 2016). Simultaneously, Japan's population also witnessed significant changes with characteristics of low fertility rate and high life expectancy, which gradually led Japan to step into an aged society. Japan's population aging, as an underlying factor, directly or indirectly affects Japan's economy and its transition of industrial structure (Matsutani, 2006). From the perspective of the labor force, the Japanese economy began to grow at a high speed in 1955, when Japan's aging rate was only 5.3% according to figure of statistics bureau of Japan. In the 1960s, the sufficient number of labor was an important guarantee of economic boom and the leading industries were labor-intensive sectors, such as light industry like food, beverages and textiles and heavy chemical industries like steel, shipbuilding, chemistry, etc. (Itagaki, 2016). Since the 1970s, especially after the 1980s, the problem of labor shortage caused by the aging of the population is becoming more and more severe (Hamada & Kato, 2007). The industrial structure also simultaneously underwent a significant change. Service industry, financial industry and information industry developed rapidly, whose proportion in the industrial structure were in a steady expansion (Yabe, 2016).

The objective of this study is not to analyze population aging per se or the transition of industrial structure, but to dissect dynamic correlation between the population aging and transition of industrial structure in the long run based on empirical evidence. In other words, this study focuses on exploring the relationship between the population aging and the transition of industrial structure through the relationships that data reflects, rather than empirically verifying their relationship through an economic theory.

So far, researches on this topic have generally undergone the following evolutionary process. Early studies mainly focused on the impact of the total population on economic development. Subsequently, some scholars turned their attention to the detailed study on the influence of demographic structure on economic growth and economic (industrial) structure. Later, with the widespread appearance of population aging, researchers shifted their direction to the impact of population aging on economic growth and industrial structure.

Based on literature review, the study found that there were three characteristics in the existing research: First, most studies focused on the impact of population structure on economic growth or the impact of population aging on economic growth, while the number of studies on the impact of population aging on industrial structure were relatively inadequate. Second, the majority of researches focused on unidirectional relationship, that is, regarding the demographic structure or population aging as an independent variable, and less researches focused on the mutual relationship between them. Third, among those empirical researches, the majority focused on conventional structural equations, which was usually based on the corresponding economic theoretical framework.

Moreover, according to literature conclusion, it can be known that there exist some linkages between population aging and industrial structure, different researches and different perspectives lead to different results. Many studies have shown that the aging of the population have a one-way effect on the industrial structure. In addition, are there any two-way relationship between them? What is the mechanism of this mutual influence? What is the degree of the mutual effect?

In order to answer the above questions, this paper employed a multi-variate vector autoregression (VAR) model to evaluate the dynamic relationship between population aging and transition of industrial structure by using three main-industry data of post-war Japan over the period from 1955 to 2016. The classification of industry in this paper followed three broad category, that is primary industry, secondary industry, and tertiary industry. The primary industry contained agriculture, fishing, and forestry. The secondary industry included mining, manufacturing and construction. The tertiary industry mainly referred to service industry. In order to clarify the transition of industrial structure and serve for the modeling, this paper introduced two definitions to measure industrial structure from two dimensions, namely rationalization of industrial structure and upgrading of industrial structure. The rationalization of industrial structure essentially referred to the degree of coordination between input and output which not only reflected whether the industrial structure was coordinated but also reflected whether the use of resources was rational (Gan,Zheng &Yu,2011). The upgrading of industrial structure referred to the service-oriented process (Gan et al., 2011). In other words, the upgrading of industrial structure reflected whether the industrial structure was moving in the direction of servitization. In terms of population aging, this paper measured it by the aged population ratio.

The rest of this paper is organized as follows. Chapter 2 briefly reviews the related literature on this subject. Chapter 3 describes the main methods used in this study. Chapter 4 describes data and indicators used in the following chapter for modeling process. Chapter 5 is about the modeling process empirical results. Chapter 6 discuss the findings based on empirical results and concludes.

Chapter 2: Literature Review

Since the developed countries experienced the process of population transition earlier, the initial research focused mainly on the impact of the total population on economic development. Based on Bucci (2008), there are three representative views to analyze the impact of population on economic development: pessimistic view, optimistic view and so-called population neutralism view. Pessimistic theory argues that an increase in the population hinders economic growth and has an inhibitory effect on economic development. On the contrary, optimism regards population growth as the driving force for the development of economies of scale and the promotion of technological and institutional innovation. Moderation theory suggests that there is no significant evidence that population growth may slow down or encourage economic growth.

Subsequently, some scholars turned their attention to the detailed study on the age structure of the population from the total population, mainly involving both the economic growth and the economic (industrial) structure.

2.1 Demographic Structure and Economic Growth

Based on the Romer's model of endogenous technical change, human capital theory and the life cycle theory of savings, Malmberg (1994) argued that the change in the population age structure is an important factor affecting the economic growth rate and the economic growth rate depends on the age structure of the population. He analyzed the empirical data of Sweden's economic growth from 1950 to 1989, demonstrating the existence of population age structure effects.

Based on data from 1965-1990 in East Asia region, Bloom and Williamson (1998) found that East Asian countries experienced increases in their per-capita productive capacity, as the growth rate of the working-age population was much higher than the dependency ratio during this period, which played a huge role in promoting the realization of the economic miracle in East Asia region and therefore found the connection between changes in population structure and economic growth.

By using panel data from the 1950-1990 OECD countries, Lindh and Malmberg(1999) argued that the growth mode of GDP per capita in OECD countries could largely be explained by changes in the age structure of the population. People in the 50-64 age group played a positive role in economic growth, while people over 65 years old had a negative effect. However, the impact of young population groups was less clear.

By developing a flexible framework including a "productivity" model and a "translation" model, Kelley and Schmidt (2005) verified that influence of demographic change could explain approximately one-fifth of per capita output growth impacts based on a cross-country panel data spanning from 1960 to 1995.

2.2 Population Aging and Economic Growth

Based on extended overlapping-generation (OLG) models, Fougère and Mérette (1999) argued that when models are characterized by endogenous growth, population aging may significantly reduce the negative impact of aging on per capita output by providing more opportunities for future generations to invest in human capital, which in turn stimulates economic growth.

Combining various channels such as adjustments in the savings rate, labor supply, factor prices and capital deepening, Gonzalez-Eiras and Niepelt (2012) established a rich, traceable framework to analyze the impact of population aging on economic growth. The decline in fertility and the extension of life expectancy increased the share of social security transfers in GDP, which in turn had a negative impact on economic growth, which meant the transfer of social security squeezed the ratio of productive public investment to GDP.

Serban (2012) argued that population aging not only affected the number and scale of working-age people, changed the social occupational structure, but also increased the pressure on the social security system and affected labor productivity. Because the elderly tent to have the rigidity of skills learning, it was difficult to adapt to the changes brought about by globalization by retraining new skills and new jobs.

Based on endogenous and semi-endogenous growth models, Prettner(2013) found that increase in longevity had a positive influence on per capita output growth while decreases in fertility had a negative impact on per capita output growth.

By assessing the impact of the rate of population aging on per capita national output across U.S. states over the period of 1980-2010, Bloom, Canning and Sevilla (2016) found that when the proportion of people over the age of 60 increased by 10%, the growth rate of per capita GDP dropped by 5.5%. Two-thirds of the decline was due to the slowdown in workers' labor productivity, while one-third of the decrease was due to the slowdown in labor force growth.

2.3 Population Aging and Industrial Structure

Generally, the population aging does not play a direct and obvious role in the aspect of the adjustment of industrial structure. More often, it indirectly influences the adjustment of industrial structure through certain intermediary factors. Therefore, the study on the impact of population aging on the industrial structure is later than the study on the impact on economic growth.

With the proposal of Lewis binary economic model, the research perspective shifted from the impact of changes in the age structure of the population on economic growth to the impact on the industrial structure.

Börsch-Supan(2013) conducted a study based on the German sample and argued that expenditures needed to compensate for the impact of the aging population on economic growth by increasing labor productivity so as to adapt to the industrial restructuring brought about by changes in demand structure.

Using a computable overlapping-generations model, Annabi et al. (2009) concluded that the supply of labor due to population aging would not accelerate economic decline and would not expand the scale of those low-labor value-added industries as well based on empirical analysis in Canada.

Siliverstovs et al. (2011) discussed the possible path of the impact of population aging on industrial structure from six aspects of labor supply, consumption pattern, capital supply, total factor productivity, financial market and government debt. And they selected statistical data of 51 industries including developed countries and developing countries spanned from 1970 to 2004 for empirical research. After controlling variables such as per capita income, share of trade, share of government spending, population size and so on, they argued that population aging had significantly different effects on employment shares in different sectors. For agriculture, manufacturing, construction and extractive industries, population aging had a significant negative effect, while it had a significant positive effect on service industries, especially the financial industry.

Using panel data of 54 selected developing and developed economies, Thieben (2007) used sectoral employment shares as the dependent variable to analyzed the effect of aging on the employment structure. With increasing per capita income, the agricultural employment share would continuously decline. Relative employment in sectors of manufacturing, construction, wholesale and retail trade, restaurants and hotels and transport, storage, and communication first rose and then dropped. And the employment shares of the other two large services sectors of financial and related services and community, social, and personal services would continuously increase with increasing per capita income. The conclusion was similar to that of Siliverstovs.

2.4 Summary of Literature Review

Through reviewing and summarizing the existing literatures, some conclusions can be drawn as follow:

Firstly, based on both qualitative theoretical mechanism analysis or quantitative empirical experience verification, it is proved that there is a significant correlation between population structure change and economic growth.

Secondly, population aging has some effects on economic growth through different channels such as labor supply, consumption pattern, saving, investment etc. The results of studies are controversial, some results are positive, some are negative.

Thirdly, population aging mainly acts on the industrial structure through labor supply and consumer demand, which in turn has some impact on the adjustment of the industrial structure.

On the other hand, through reviewing and summarizing the existing literature, following gaps are found:

First, while a large number of studies on the relationship between population and economic performance have focused on the relationship between population structure and economic growth, both qualitatively and qualitatively, studies on the effect of structure changes of population age on industrial structure are relatively limited.

Second, the review of the existing literature on the impact of population aging on industrial structure shows that mainly qualitative analysis are used to explore the impact of population aging on industrial structure. And the empirical research on the topic is very limited.

Thirdly, the limited number of studies with quantitative analysis on the topic show that most of the econometric models constructed by scholars in the empirical analysis of econometrics are mainly structural models based on the corresponding economic theory. And there has been little consideration for adding lags of industrial structure into the independent variables during the process of model construction.

Since the purpose of this research is the dynamic change between population aging and industrial structure rather than the structural relationship between them, the paper will examine the dynamic relationship between variables reflected by the data. In addition, the economic activities often have the characteristics of inertia, and the industrial structure tends to be affected by the previous period in the process of its evolution. Therefore, responding to the limitation of existing literature in research perspectives and research methods, this paper considers the inclusion of lagged items of industrial structure into independent variables when constructing econometric models and intends to adopt unstructured vector autoregressive model, expecting that the analysis can further enrich the research in this field to some extent.

Chapter 3: Methodology

Conventional structural models are usually based on corresponding economic theories and try to use models to describe the structural relationships among variables. Unfortunately, economic theory is not sufficiently capable to explain all the variables in real world. Furthermore, when we study a lot of practical problems, we actually do not pay attention to the structure among variables, but only focus on determining the dynamic relationship between them, that is, to detect the dynamic changes between variables based on data. To prevent such a problem in this study, a non-structural method is proposed to establish the relationship between variables. The vector autoregressive model is a theory-free, unstructural dynamic model with lagged variables.

In this paper, the main empirical methodology is based on vector autoregression (VAR) framework.

3.1. Vector Autoregression (VAR) Process

The VAR model, first proposed by Sims (1980), who promoted the wide application of dynamic analysis of economic systems, is one of the mainstream models in the world today. It has received widespread attention in the field of macroeconomic analysis and is widely used. The VAR model is mainly used to forecast and analyze the dynamic shock of a random disturbance on the system, the magnitude, the direction and duration of the shock.

Let that an N-dimensional multiple time series {Y1}, {Y2} …, {Yt} with $Y_t = (Y_{1t}Y_{2t} \dots Y_{nt})'$ is available that is known to be generated by a stationary, stable VAR(p) process in a standard form (Lütkepohl,2005, p.69, eq.3.1.1).

$$Y_t = V + \mathrm{A}_1 Y_{t-1} + \cdots + \mathrm{A}_p Y_{t-p} + U_t \tag{1}$$

where

$\mathrm{V} = (v_1 v_2 \dots v_n)'$ is a (n × 1) vector of intercept terms;

$\mathrm{A}_i (i = 1,2, \dots, p)$ are (K × K) coefficient matrices;

U_t is a white noise with nonsingular covariance matrix Σu;

p is the maximum lag order of the model.

It can be known from the above formula that VAR(p) model is a model with multiple variables ($Y_{1t}Y_{2t} \dots Y_{nt}$) as dependent variables and with multiple variables ($Y_{1t-1}Y_{2t-2} \dots Y_{nt-p}$) of the largest p-order lagged variables as independent variables, which contains N equations totally. The VAR model is mainly used to analyze the dynamic relationship between multiple endogenous variables. "Endogenous" refers to the study of the interaction between multiple variables, while "dynamics" refers to p-order lags. Therefore, the VAR model is called as a dynamic model that analyzes the dynamic relationship between multiple endogenous variables and contains n dynamic equations with feedback mechanism.

The most important feature of the VAR model is that the model is not based on strict economic theories. In the modeling process, there are three things needed to be clarified: first, the choice of the lag order p; second, which variables can enter the model (there is

Granger causality between the required variables); third, the ordering of the variables is determined.

3.2. Stationarity and Unit Root Test

So far, when we analyze time series, an underlying assumption exists based on econometric theory, that is, series involved in models have stationary properties. Otherwise, t-test, F-test and other hypothesis test are incredible and are prone to spurious regressions. Therefore, when analyzing time series, the first concern is whether the series is stationary or not?

Suppose a random time series $\{X_t\}$ ($t = 1, 2...$) is generated by a stochastic process, and each value of $\{X_t\}$ is randomly derived from a probability distribution. If the following conditions are satisfied:

Condition1: the mean of $\{X_t\}$ is a time-independent constant;

Condition2: the variance of $\{X_t\}$ is a time-independent constant;

Condition3: the covariance of $\{X_t\}$ is a constant only related to the interval and time-independent;

the series $\{X_t\}$ is said to be stationary, and the random process is a stationary stochastic process.

White noise, with properties of zero mean, constant variance and serial uncorrelation, is the simplest stationary random time series.

In addition to observe stationary of a time series directly by graphs, it is more accurate and important to use statistics for stationary testing. The unit root test is a commonly-used instrument for stationarity tests.

We already know that random walk sequences

$$X_t = X_{t-1} + \mu_t \quad (2)$$

is nonstationary, where μ_t is white noise, and the sequence can be recognized as a stochastic model

$$X_t = \rho X_{t-1} + \mu_t \quad (3)$$

in the case of parameter $\rho = 1$. That is to say, if regression is performed on $Xt = \rho X_{t-1} + \mu_t$ (3) and it is found that $\rho=1$, the random variable Xt can be proved to have a unit root. Obviously, a time series with a unit root is random walk series, while random walk sequences are nonstationary. Therefore, to determine whether a time series is stationary, we can determine whether it has a unit root by equation $Xt = \rho X_{t-1} + \mu_t$ (3). This is the unit root test of time series stationarity.

In this study, the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) unit root test is applied for this purpose. The ADF test is completed by the following three models:

$$\text{Model 1} \quad \Delta X_t = \delta X_{t-l} + \sum_{i=l}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t \quad (4)$$

$$\text{Model 2} \quad \Delta X_t = \alpha + \delta X_{t-l} + \sum_{i=l}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t \quad (5)$$

$$\text{Model 3} \quad \Delta X_t = \alpha + \beta t + \delta X_{t-l} + \sum_{i=l}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t \quad (6)$$

The t in model 3 is a time variable that represents a certain trend (if exists) of the time series over time. The null hypothesis is that N_0: $\delta=0$, that is, there is a unit root. The difference between model 1 and the other two models is whether it contains constant items and trend items. As long as the test result of one of the models rejects the null hypothesis, the time series can be considered as stationary. When the test results of the three models cannot reject the null hypothesis, the time series is considered to be nonstationary.

3.3. Granger Causality/Block Exogeneity Wald Test

3.3.1. Granger Causality

The Granger causality test was first proposed in 1969 by C.W.J. Granger(1969). It is a statistical hypothesis test in which the causality is not a traditional causal relationship, but a test from a statistical point of view, that is, the test result is expressed by a probability or a distribution function. The Granger test uses the F-statistic to test whether the lagged value of X significantly affects Y. If the effect is not significant, then X is said not to Granger-cause Y; if the effect is significant, then X is said to Granger-cause Y. Similarly, this can also be used to check that Y is the "Granger causality" of X and verify that the lagged value of Y affects X. In other words, under the condition that the occurrence of all other events is fixed, if the occurrence of one event X has no influence on the probability of the occurrence of another event Y, and the two events are successive in time (X occurred first, and Y followed). Then we can say that X Granger-cause Y. (Enders, 2003, p.283-284)

In brief, the Granger causality test examines the chronological order of the sequences statistically. It does not mean that there is a real causal relationship between them, and whether there is a causal relationship needs to be judged based on theories, experience and models.

3.3.2. Block Exogeneity Wald Test

A block exogeneity test is used to examine whether a variable can be incorporated into a VAR system. In practice, the Block Exogeneity Wald test blocks all lags of one variable off equations of the other variables and uses likelihood ratio statistic for hypothesis testing. The likelihood ratio statistic is given as follow:

$$(\mathrm{T} - \mathrm{c})(\log|\Sigma_r| - \log|\Sigma_u|) \tag{7}$$

where

the statistic has a χ^2 distribution with degrees of freedom equal to the number of restrictions in the system;

Σ_u and Σ_r are the variance/covariance matrices of the systems respectively;

T

c

Given

3.4.

For

3.4.1.

According

$Yt=V+A1Yt-1+\ldots+ApYt-p+Ut$ (1), taking a VAR (2) model with two endogenous variables as an example to illustrate how the residual error item transfers the impact to endogenous variables. Let a two-variable VAR (2) model as follow:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + U_{1t} \quad (8)$$

$$X_t = B_1 X_{t-1} + B_2 X_{t-2} + U_{2t} \quad (9)$$

If the above system is shocked by some disturbance, one-unit standard deviation change (impact) will occur to the innovation U_{1t}, which not only makes Y_t change (respond) immediately, but also affects the value of X_t through Y_{t-1} and Y_{t-2}. And it will correspondingly affect the subsequent values of Y_t and X_t, which is called lagged response. Similarly, some disturbance to the innovation U_{2t} can also cause similar shock chain reaction.

Accordingly, the impulse response function describes the response of an endogenous variable to a residual shock which is called innovation. Specifically, it describes the dynamic effects on the current and future values of endogenous variables after being imposed one-standard-deviation magnitude impact (from internal or external system) on the random disturbance.

The difficulty with handling impulse response functions is that the residuals are not completely uncorrelated. When the residuals are related, their common parts are not easy to identify. The non-strict approach to deal with this problem is to attribute the common part to the disturbances of the first equation of the VAR system. Therefore, changing the order of the equations in the VAR model can result in very different impulse responses, especially when using the orthogonalized impulse response (OIR) method which was established by Sims (1980).

3.4.2. Variance Decomposition

The impulse response function is to observe the response of each variable in the model to the shock over time, while the variance decomposition is to further evaluate the contribution of each endogenous variable to the variance of prediction.

The main idea of variance decomposition is to decompose the fluctuation (k-step ahead forecast error) of each endogenous variable (assume existing N variables in total) into N components associated with the innovation of the subequation based on conditional expectation. The main application of variance decomposition is how much impact is caused by the variable itself and how much impact is caused by the other variables in the system, which helps to understand the relative importance of each innovation to endogenous variables in the system. (Enders, 2003, p. 278-280)

Similar to the impulse response function, the result of variance decomposition is also strongly influenced by the order of variables in the VAR model due to the Cholesky decomposition method. Therefore, in the analysis of variance decomposition, Cholesky ordering is crucial, which can refer to the results of Granger causality/Block Exogeneity Wald test.

Chapter 4: Indicator Construction and Data Description

In order to study the impact of Japan's democratic changes on evolution of industrial structure, I specified the issue as the dynamic relationship between population aging and industrial structure, and constructed some representative indicators based on official statistics to measure population aging and industrial structure, which served for the econometric modelling of the following sections and benefited to search empirical linkages between them.

4.1 Indicator Construction

4.1.1 Measurement of Population Aging

Population aging is defined as a process which is due to declining fertility rates and increasing the elderly population and is often used to describe demographic transition in the age structure. Regarding elderly population, there is no unified criterion, but 60+ years or 65+ years is generally used to define elderly population (Kowal & Dowd, 2001). Referring to classification of Japan statistics bureau, this paper adopted people aged 65 and over to represent the elderly population and used the ratio between the elderly population and the total population to represent democratic changes.

$$\text{Aged Population Ratio} = \frac{\text{Population Aged 65 and Over}}{\text{Total Population}} * 100\% \tag{10}$$

4.1.2 Measurement of Industrial Structure

The evolution of industrial structure is a complex process, but fundamentally speaking, its essence is a process that leads to the continuous replacement among different industrial sectors. Comprehensively considering the relevant research results, the purpose of this study and the representativeness and availability of the measurement indicators, I adopted two indicators to examine the transition of industrial structure from two dimensions. One is defined as rationalization of industrial structure; the other is defined as industrial structure upgrading.

4.1.2.1 Rationalization of Industrial Structure

The rationalization of industrial structure essentially refers to the process that is closely related to the coordination between input and output. On the one hand, the indicator reflected whether the development of various industries is coordinated; on the other hand, it reflects whether the use of resources is rational (Gan, Zheng & Yu,2011).

Taking into account the availability of data (easy access to continuous statistical data), this study considers labor force (employment) as input and gross domestic product (GDP) as output, which is measured by means of structural deviation index. (Gan et al., 2011) The equation is given in the following:

$$SD = \sum_i \left|\frac{Y_i / L_i}{Y/L} - 1\right| = \sum_i \left|\frac{Y_i / Y}{L_i / L} - 1\right| \qquad (i = 1, 2, 3) \tag{11}$$

where Y and L represent output and employment respectively, and i represents three-sector industry (primary industry, secondary industry and tertiary industry). Y/L can indicate the productivity level. When Yi/Li is equaled to Y/L, it means that each industrial productivity level equals the average productivity level of the whole country. In other words, if SD equals 0, the output is complete coupled to employment. The greater the value of SD is, the greater the degree of deviation between output and employment is. Since the economic imbalance is a normal state, the SD value is generally greater than 0.

However, considering the limitations of the equation （2）, there is a problem with this indicator. That is, the indicator cannot distinguish the importance of deviation degree of each industry and neglects the importance of each industry within an economy. Therefore, this paper adopted an improved structure deviation index. Based on the above equation (2), the industrial weight is introduced and a structural deviation correction index is constructed (Guan & Ding, 2012).

$$SDC = \sum_i w_i \left|\frac{Y_i/L_i}{Y/L} - 1\right| = \sum_i w_i \left|\frac{Y_i/Y}{L_i/L} - 1\right| \quad (i = 1, 2, 3) \qquad (12)$$

where w represents the industrial weight and is measured by output.

4.1.2.2 Upgrading of Industrial Structure

The process of industrial structure upgrading refers to constantly changing of industrial structure from low level to high level. With respect to the measurement of upgrading of industrial structure, the general literature used the proportion of non-agricultural output as a measure of the upgrading of industrial structure according to Petty-Clark's law. Although the increase in the proportion of non-agricultural output is a rule of traditional economic development, each of the three major industries presents different development trends with the economic development. In the context of the third industrial revolution, informatization has increasingly become the theme of the contemporary era. It has not only changed our way of life but also penetrated into all aspects of economic activities. The most significant feature is that it has promoted the development of the service industry and has emerged a trend of economic servitization. In view of economic service-oriented process, the growth rate of the tertiary industry is faster than the growth rate of the secondary industry (Wu, 2013).

In this context, the traditional measurement methods cannot completely reflect this trend of economic structure development. Therefore, this paper adopts Wu's (2013) statement and uses the ratio of the tertiary industry's output value to the secondary industry's output value as a measure of industrial structure upgrading. The calculation formula is given as follows:

$$\mathrm{SU} = {}^{Y_3}/_{Y_2} \tag{13}$$

where Y3 represents output of tertiary industry and Y2 represents output of secondary industry. This indicator can clearly reflect whether the industrial structure is moving in the direction of servitization. If the SU value is in a rising state, it means that the economy is advancing in the service-oriented process and the industrial structure is constantly upgrading (Gan et al., 2011).

4.2 Data Description

In this study, I mainly used annual data related to the population structure and industrial structure in Japan covering the period from 1955 to 2016. All secondary data is sourced from Statistics Bureau of Japan (Ministry of Internal Affairs and Communications) and Cabinet Office. Since the above constructed indicators are not directly accessible from the official statistics released by Japan, I first collected demographics classified by age group, gross domestic product (GDP) and employment classified by economic activities. Subsequently, I calculated the three indicators aforementioned based equation $\text{Aged Population Ratio} = \frac{\text{Population Aged 65 and Over}}{\text{Total Population}} * 100\%$ (10), $\text{SDC} = \sum_i w_i \left|\frac{Y_i/L_i}{Y/L} - 1\right| = \sum_i w_i \left|\frac{Y_i/Y}{L_i/L} - 1\right| \quad (i = 1, 2, 3)$ (12) and $\text{SU} = Y_3/Y_2$ (13).

Since Japan's industrial classification has been revised several times since 1955, I mainly use the Japan Standard Industrial Classification (Rev. 13, October 2013) as the benchmark to adjust the industrial classification before 1995 so that the data in different years can be comparable, ensuring that the industrial classification is consistent before and after. As for gross domestic product(GDP), in order to ensure that the industry's total share is equal to 100%, coverage of GDP used in this paper does not include statistical discrepancy, taxes and duties on imports.

After the above adjustment, final calculation results of the three constructed indicators (time series) are illustrated as follows:

Table 1: Final Calculation Results of Three Variables

Series / Year	APR	SDC	SU
1955	0.05317	0.33428	1.39437
1956	0.05367	0.35544	1.28090

1957	0.05421	0.33397	1.24395
1958	0.05504	0.30781	1.32966
1959	0.05603	0.29625	1.25442
1960	0.05727	0.31088	1.13813
1961	0.05834	0.29521	1.12246
1962	0.05932	0.27399	1.17767
1963	0.06070	0.25487	1.17933
1964	0.06189	0.24764	1.17904
1965	0.06291	0.22542	1.25417
1966	0.06480	0.20784	1.30523
1967	0.06649	0.19265	1.26894
1968	0.06804	0.18532	1.25381
1969	0.06925	0.18199	1.22155
1970	0.07068	0.20475	1.18138
1971	0.07166	0.18892	1.22220
1972	0.07339	0.17375	1.25832
1973	0.07506	0.15421	1.21759
1974	0.07684	0.15150	1.29328
1975	0.07923	0.14809	1.43838
1976	0.08136	0.14361	1.45299
1977	0.08375	0.14154	1.52569
1978	0.08613	0.14077	1.52060
1979	0.08875	0.13463	1.53315
1980	0.09100	0.12925	1.55260
1981	0.09337	0.12534	1.66486
1982	0.09560	0.12176	1.71540
1983	0.09764	0.11576	1.80191
1984	0.09938	0.10919	1.77527
1985	0.10303	0.10728	1.77677
1986	0.10579	0.10362	1.82913
1987	0.10898	0.10065	1.85576
1988	0.11231	0.09613	1.81876
1989	0.11614	0.09090	1.78908
1990	0.12077	0.08583	1.75722
1991	0.12556	0.08157	1.79068
1992	0.13039	0.08908	1.89003
1993	0.13527	0.10862	2.01924
1994	0.14038	0.07964	2.15014
1995	0.14555	0.07027	2.10879
1996	0.15110	0.06604	2.10500
1997	0.15661	0.06383	2.17380
1998	0.16215	0.06098	2.25135

1999	0.16726	0.05906	2.32408
2000	0.17365	0.05671	2.33739
2001	0.17962	0.05663	2.50929
2002	0.18534	0.05722	2.61551
2003	0.19038	0.05502	2.62292
2004	0.19467	0.05436	2.63052
2005	0.20162	0.05501	2.63340
2006	0.20800	0.05200	2.63403
2007	0.21451	0.05093	2.62092
2008	0.22029	0.04933	2.71757
2009	0.22654	0.05148	3.04918
2010	0.23024	0.04476	2.84062
2011	0.23274	0.04298	2.99580
2012	0.24134	0.04067	2.97544
2013	0.25035	0.03978	2.95990
2014	0.25936	0.04022	2.87504
2015	0.26648	0.05561	2.72996
2016	0.27251	0.07177	2.68390

Notes:

APR: Aged population ratio

SDC: Rationalization of industrial structure

SU: upgrading of Industrial structure

From Table 1, it can be seen that after the second world war, the rate of the elderly population in Japan continuously increases, especially after 1970 when Japan officially entered the aging society[1]. Since then, the rate of population aging has accelerated noticeably. In 1994, Japanese society entered the aged society, that was, from the aging society to the aged society, it took Japan 24 years (1970-1994) . But it took only 13

[1] The World Health Organization (WHO) and the United Nations define the concept of "aging society" as a society whose population aged 65 years or above account for more than 7% of the total population, the concept of "aged society" as a society whose population aged 65 years or above account for more than 14% of the total population, and the concept of "super-aged society" as a society whose population aged 65 years or above more than 21% of the total population.

years（1994-2007）from the aged society to the super-aged society. Regarding changes in industrial structure，since 1955 Japan's industrial structure has been undergoing a remarkable process of transition not only in the dimension of rationalization but also in the dimension of upgrading. At present, the value of the structural deviation index (SDC) tends towards 0，which suggests that the output of various industries in Japan is basically consistent with the input of labor force.

The upgrading indicator of the industrial structure also shows that the proportion of the tertiary industry to the secondary industry rises over time, and Japan is in the way of accelerating servitization. Obviously, after the completion of the industrialization since the 1970s (Kohama, 2007), Japan's service-oriented industrial structure has accelerated.

Chapter 5: Empirical Results

In this study, EViews10 program is used as econometric instrument. All the results illustrated in this chapter are output directly derived from EViews program or compiled from EViews output.

Before model identification, I observed the behavior of the three time series (APR, SDC and SU) which will be diagnosed by the model.

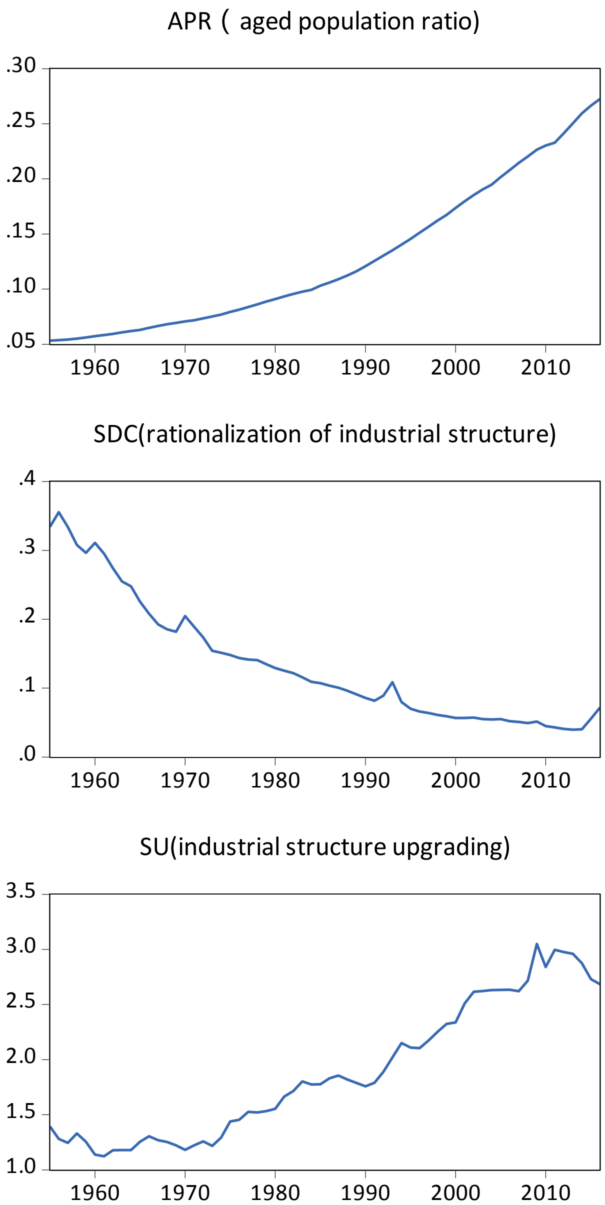

Figure 1: Behavior of Three Variables

Figure 1 exhibits the line graphs of the selected three variables. In the graph of aged population ratio (APR), there is a relatively stable increasing trend over the whole period. Rationalization of industrial structure (SDC) remains a declining tendency over time accompanied with a violent fluctuation every several decades. From the long-run view, the sequence of industrial structure upgrading (SU) rises with fluctuation for more than 50 years and starts to decline after 2011.

From Figure 1, it can be preliminarily judged that all the time series may be nonstationary with time trend. So, I performed ADF unit root test for further quantitative inspection.

5.1 Results of Unit Root Test

Table 2：Augmented Dickey-Fuller (ADF) Unit Root Test on APR, SDC and SU in Level

series	t-statistic			p-values			results	stationarity
	Intercept and Trend	Intercept	None	Intercept and Trend	Intercept	None		
APR	0.224778	3.504548	4.171267	0.9977	1	1	accept H_0	nonstationary
SDC	-0.674927	-3.182693	-4.60912	0.9703	0.0259	0	reject H_0	stationary
SU	-3.043878	-0.016138	1.870442	0.1292	0.9531	0.98	accept H_0	nonstationary

Notes: The null hypothesis is that the series has a unit root.

The lag length of ADF unit root test is chosen automatically by Eviews program based on Schwarz Info Criteria.

Table 2 indicates results of ADF unit root test on the three series APR, SDC and SU in levels. From results of p-values in Table 2, I conclude that APR and SU sequences are nonstationary in levels and SDC sequence is stationary in level.

Sequence stationarity is an important premise for building a stable VAR model. Therefore, in order to follow VAR specification, the above three sequences need to be transferred into proper forms to remove non-stationarity. In general, there are two mathematical ways for data transformation. One is logarithm, and the other is differencing. Since the three sequences are proportional data, they are not suitable for logarithmic transformation, so I perform differencing form. And then, rerun the unit root test on the three new sequences in form of difference.

Table 3：Augmented Dickey-Fuller (ADF) Unit Root Test on APR,SDC and SU in First-difference

series	t-statistic			p-values			results	stationarity
	Intercept and Trend	Intercept	None	Intercept and Trend	Intercept	None		
ΔAPR	-5.180921	-0.012502	1.845926	0.0004	0.9529	0.9833	reject H_0	stationary
ΔSDC	-8.127108	-6.502658	-5.594419	0.0000	0.0000	0.0000	reject H_0	stationary
ΔSU	-7.585252	-7.640796	-7.154610	0.0000	0.0000	0.0000	reject H_0	stationary

Notes: The null hypothesis is that the series has a unit root.
The lag length of ADF unit root test is chosen automatically by Eviews program based on Schwarz Info Criteria.

As emphasized in chapter 3, as long as the test result of one of test equations rejects the null hypothesis, the time series can be considered as stationary. Table 3 indicates that the three new variables (ΔAPR, ΔSDC and ΔSU) are stationary series, which means their original series are integrated of first order, written by notation I (1).

Taking results of Table 2 and Table 3 into account together, the original series SDC and the three first-difference series (ΔAPR, ΔSDC and ΔSU) are stationary, which means they satisfy the premise of VAR modeling. From the perspective of model specifications, the above four stationary sequences are all suitable for VAR system. However, from an economic point of view, it is more appropriate to select three sequences in form of difference for the following VAR modeling. Based on that, I construct a VAR model with three endogenous variables (ΔAPR, ΔSDC and ΔSU).

5.2 Model Identification and Diagnostics

VAR model will be overparameterized when lag length is too large, while the model will be misspecified if lag length is too small (Enders, 2003). There are two common ways to determine lag length. One is to refer to likelihood ratio statistics (LR), the other is based on various information criteria such as final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hanna-Quinn information criterion (HQ). This paper adopts the latter method.

Table 4: VAR Lag Order Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	512.5513	NA	2.51e-12	-18.19826	-18.08976	-18.15620
1	556.1452	80.95998	7.29e-13	-19.43376	-18.99975*	-19.26549*
2	563.2228	12.38591	7.84e-13	-19.36510	-18.60559	-19.07064
3	574.2264	18.07725*	7.35e-13	-19.43666	-18.35165	-19.01600
4	584.1098	15.17809	7.23e-13*	-19.46821*	-18.05769	-18.92135
5	591.0877	9.968481	7.95e-13	-19.39599	-17.65997	-18.72294

Notes: Indicates lag order selected by the criterion; each test at 5% level;
LR: sequential modified LR test statistic;
FPE: Final prediction error ;
AIC: Akaike information criterion ;
SC: Schwarz information criterion;
HQ: Hannan-Quinn information criterion.

According to indication of Table 4, VAR (1), VAR (3) and VAR (4) are selected by different criteria. Therefore, I conduct three-variable VAR models with lag 1, lag 3 and lag 4 and exanimate them by stability test, residual normality test and autocorrelation LM test respectively.

Table 5: VAR Model Selection

model to be estimated	hypothesis tests		
	stability	normality	autocorrelation
VAR(1)	pass	pass	pass
VAR(3)	pass	do not pass	pass
VAR(4)	pass	pass	pass

From Table 5, both VAR (1) and VAR (4) pass all hypothesis tests. Considering that the lag length of VAR (1) is relatively small, it is more likely to cause misspecification. Hence, I finally select VAR (4) with three variables (ΔAPR, ΔSDC and ΔSU) as the optimal model and employ it for the following empirical analysis. The estimation result of VAR(4) is shown in Table 6. Results of stability test, residual normality test and autocorrelation LM test for VAR(4） are presented in Figure 2, Table 7 and Table 8 respectively.

Table 6: Vector Autoregression Estimates

	DSU	DSDC	DAPR
DSU(-1)	0.011698	-0.012095	0.000696
	(0.15186)	(0.01521)	(0.00154)
	[0.07704]	[-0.79516]	[0.45102]
DSU(-2)	0.030314	-0.006215	-0.005723
	(0.15756)	(0.01578)	(0.00160)
	[0.19239]	[-0.39379]	[-3.57398]
DSU(-3)	-0.113429	-0.018715	0.004266

	(0.16899)	(0.01693)	(0.00172)
	[-0.67121]	[-1.10560]	[2.48376]
DSU(-4)	0.021498	0.015468	0.003764
	(0.18504)	(0.01853)	(0.00188)
	[0.11618]	[0.83456]	[2.00171]
DSDC(-1)	0.614461	0.053360	-0.009322
	(1.48638)	(0.14888)	(0.01511)
	[0.41339]	[0.35840]	[-0.61712]
DSDC(-2)	0.495257	-0.174056	-0.005645
	(1.44129)	(0.14437)	(0.01465)
	[0.34362]	[-1.20566]	[-0.38538]
DSDC(-3)	-1.065662	-0.165379	0.021790
	(1.37883)	(0.13811)	(0.01401)
	[-0.77288]	[-1.19745]	[1.55510]
DSDC(-4)	-0.273628	0.223815	0.009413
	(1.34570)	(0.13479)	(0.01368)
	[-0.20334]	[1.66046]	[0.68835]
DAPR(-1)	-19.99258	-0.909592	0.770705
	(13.6142)	(1.36366)	(0.13835)
	[-1.46851]	[-0.66702]	[5.57058]
DAPR(-2)	11.72371	2.739233	0.003085
	(18.3666)	(1.83968)	(0.18665)
	[0.63832]	[1.48897]	[0.01653]
DAPR(-3)	-10.20004	0.805270	-0.199794
	(15.9977)	(1.60240)	(0.16257)
	[-0.63759]	[0.50254]	[-1.22894]
DAPR(-4)	22.72584	-0.554159	0.324225
	(12.9019)	(1.29231)	(0.13111)
	[1.76143]	[-0.42881]	[2.47285]
C	0.016771	-0.011199	0.000563
	(0.04255)	(0.00426)	(0.00043)
	[0.39416]	[-2.62769]	[1.30094]
R-squared	0.128497	0.361288	0.876473
Adj. R-squared	-0.109186	0.187094	0.842784
Sum sq. resids	0.333579	0.003347	3.44E-05
S.E. equation	0.087071	0.008721	0.000885
F-statistic	0.540623	2.074052	26.01646
Log likelihood	65.63691	196.7907	327.2136
Akaike AIC	-1.846909	-6.448796	-11.02504
Schwarz SC	-1.380950	-5.982837	-10.55908
Mean dependent	0.025079	-0.003938	0.003798
S.D. dependent	0.082674	0.009673	0.002232

Determinant resid covariance (dof adj.)	4.35E-13
Determinant resid covariance	2.00E-13
Log likelihood	590.7014
Akaike information criterion	-19.35794
Schwarz criterion	-17.96007
Number of coefficients	39

Note:Standard errors in ( ) & t-statistics in [ ]

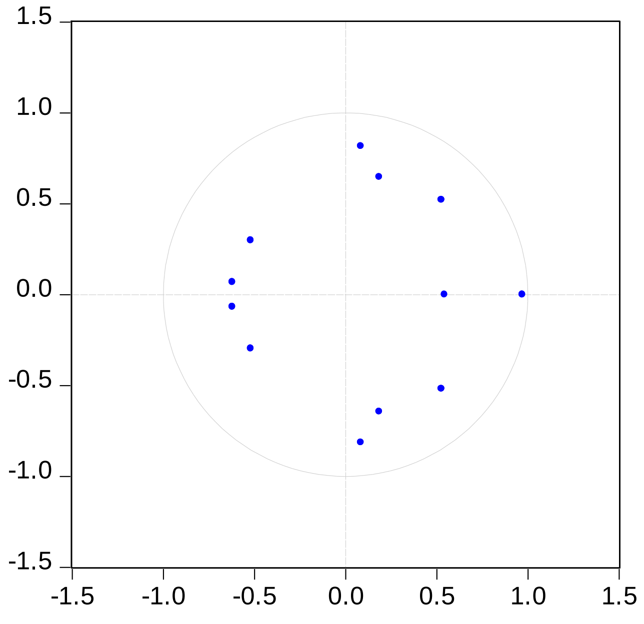

Figure 2: Stability Test on VAR(4)

Notes: No root lies outside the unit circle.

VAR satisfies the stability condition.

Table 7: VAR Residual Normality Tests

Component	Skewness	Chi-sq	df	Prob.*
1	0.163780	0.254828	1	0.6137
2	0.647366	3.981282	1	0.0460
3	0.292485	0.812704	1	0.3673
Joint		5.048813	3	0.1683

Notes:Cholesky (Lutkepohl) Orthogonalization;

Null Hypothesis: Residuals are multivariate normal.

Table 8: VAR Residual Serial Correlation LM Tests

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	9.853817	9	0.3624	1.110579	(9, 95.1)	0.3630
2	9.080451	9	0.4299	1.019345	(9, 95.1)	0.4304
3	7.567294	9	0.5783	0.842896	(9, 95.1)	0.5787
4	14.66145	9	0.1007	1.694075	(9, 95.1)	0.1010

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	9.853817	9	0.3624	1.110579	(9, 95.1)	0.3630
2	19.02714	18	0.3902	1.070034	(18, 102.3)	0.3927
3	31.22746	27	0.2619	1.185567	(27, 97.0)	0.2685
4	41.98012	36	0.2276	1.201237	(36, 89.4)	0.2414

*Edgeworth expansion corrected likelihood ratio statistic.

5.3 Results of Granger Causality/Block Exogeneity Wald Test

Results of the Block Exogeneity Wald test indicate that the two variables DAPR and DSDC are not exogenous, since the joint p-values for each equation of those variables are 0.0003 and 0.0745, which reject the null hypothesis at a 10% significance level. The variable DSU is an exogenous due to its joint p-value accepts the null hypothesis of excluding DAPR and DSDC from the equation of itself at the 0.1 significance level. Above results help to answer the ordering of variables in the following structural analysis (IRF and variation decomposition)(see

Table 9).

Results of pairwise Granger causality test show that there is unidirectional Granger causality from DAPR to DSDC with the p-value of 0.0171 which fails to reject the null hypothesis. Similarity, there is one-way Granger causal relationship of DSU on DAPR with rejection to the null hypothesis at a 5% level. Tentatively, it seems like DAPR shows a weaker sign of Granger causality on DSDC than that from DSU to DAPR. And the test also provides evidence that DSDC doesn't Granger-cause DAPR and DSU (see

Table 9).

Table 9: VAR Granger Causality/Block Exogeneity Wald Test

Dependent variable: DSU			
Excluded	Chi-sq	df	Prob.
DSDC	1.193225	4	0.8792
DAPR	4.681998	4	0.3215
All	6.345640	8	0.6086
Dependent variable: DSDC			
Excluded	Chi-sq	df	Prob.
DSU	2.965466	4	0.5636
DAPR	12.02874	4	0.0171
All	14.29009	8	0.0745
Dependent variable: DAPR			
Excluded	Chi-sq	df	Prob.
DSU	28.19354	4	0.0000
DSDC	4.395492	4	0.3551
All	29.52623	8	0.0003

Note: The null hypothesis is that all lags of one variable can be excluded from each equation in the VAR system.

In summary, the Granger causal relationship between the three variables can illustrate as follows:

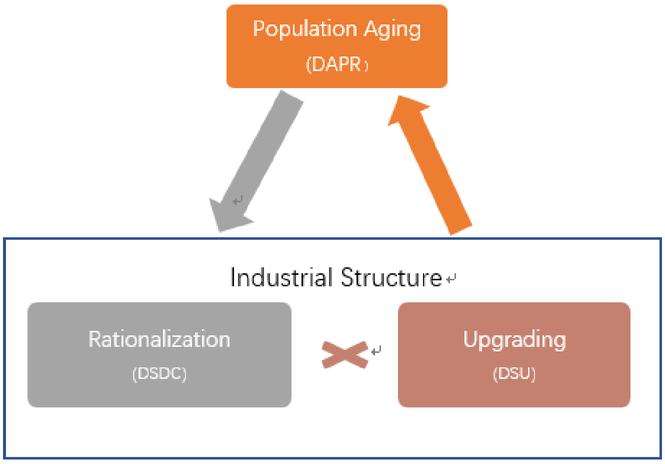

Figure 3 Granger Causal Relationship between Variables

5.4 Results of Impulse Response Function

Since this study uses the orthogonalized impulse response (OIR) method, prior to performing the impulse response function, the Cholesky ordering is determined in advance with reference to results in Table 9. The order of the variables is as follows: DSU, DAPR and DSDC. Based on the causal direction of Figure 3, this study focuses on the shock of changes of aging population(DAPR) on changes of rationalization of industrial structure(DSDC) (see Figure 4) and the response of changes of population aging(DAPR) to changes of the upgrading of industrial structure(DSU)(see Figure 5).

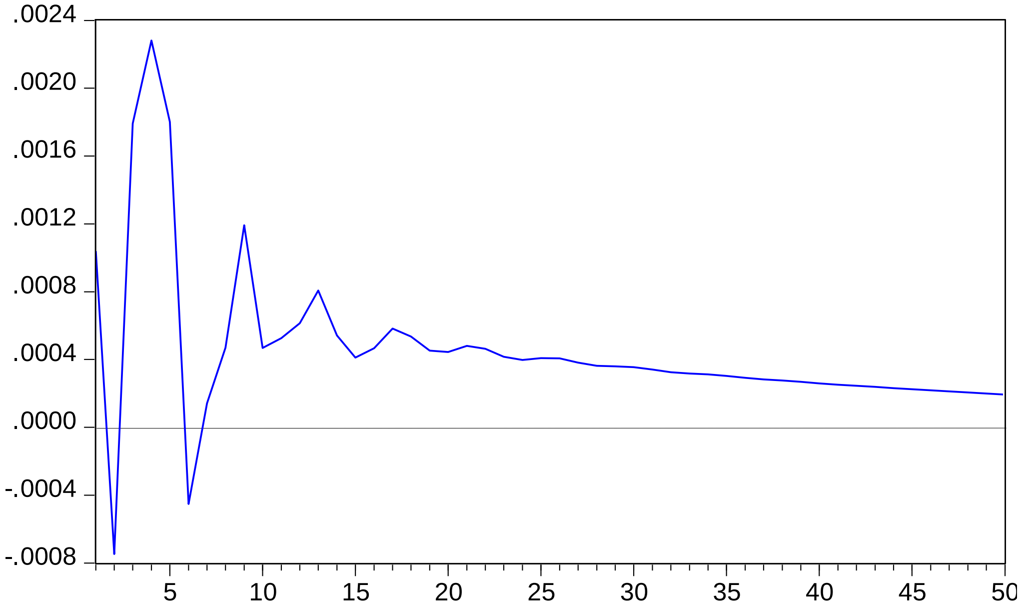

Figure 4 Response of DSDC to DAPR Innovation Using Cholesky (D.F. adjusted) Factors

Figure 4 presents the long-run effect on population aging(DAPR) as a shock to rationalization of industrial structure(DSDC). The shock of population aging on the rationalization of the industrial structure is intense in the first ten periods. After the 10th period and before the 25th period, the impulse effect gradually weakens in a small fluctuation. After the 25th period, the impulse effect gradually disappears. In the first ten periods of sharp fluctuations, the second period has the largest negative effect, followed by the sixth period. The fourth period has the largest positive effect, followed by the ninth period. There is a rapid increase from the second period to the fourth period, while there is a sharp decline from the fourth period to the sixth period. And a rapid rise occurs from the sixth period to the ninth period. After the seventh period, although there are fluctuations, the effect maintains positive. In the long run, the impact of changes of aging population on the rationalization of industrial structure is positive most of the time.

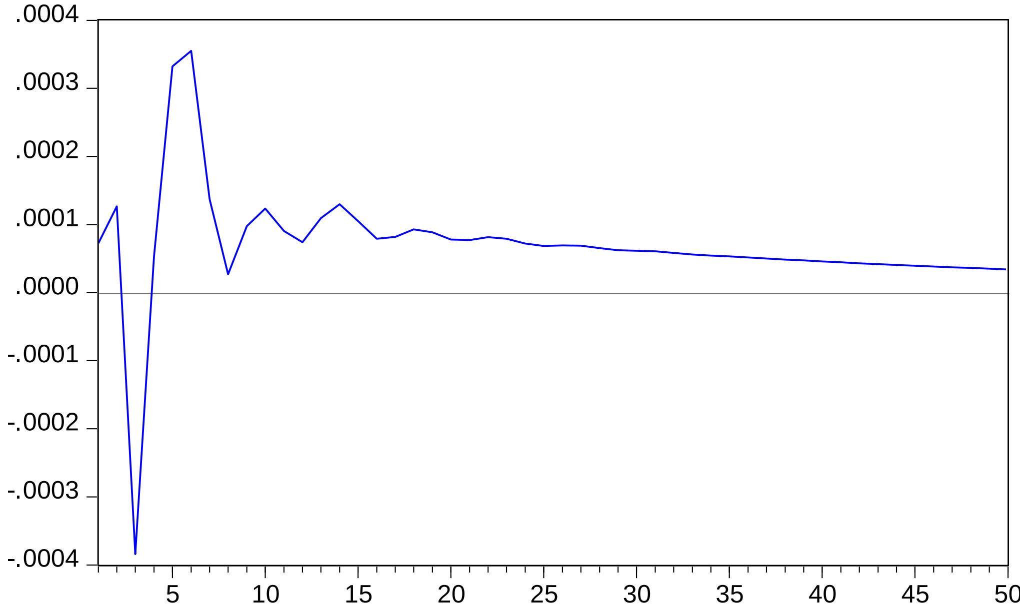

Figure 5 Response of DAPR to DSU Innovation Using Cholesky (D.F. adjusted) Factors

Figure 5 suggests population aging(DAPR) respond to the shock of the upgrading of industrial structure(DSU) in the long run. Compared with Figure 4, the biggest difference in Figure 5 is that the duration of the impulse effect is relatively shorter than that in Figure 4. In Figure 5,the response of population aging to the upgrading of the industrial structure is intense in the first eight periods. After the eighth period and before the 25th period, the impulse effect gradually weakens in a small fluctuation. After the 25th period, the impulse effect gradually disappears. In the first eight periods of sharp fluctuations, the third period has the largest negative effect and the sixth period has the largest positive effect. There is a rapid increase from the third period to the sixth period. From the sixth to eighth periods, although the effect has dropped significantly, it is still in the positive range. Similar to Figure 4, in the long run, the response of changes of aging population to the upgrading of industrial structure is positive most of the time.

5.5 Results of variance decomposition

Based on results from Figure 4 and Figure 5, since both shock of DAPR on DSDC and response of DAPR to DSU significantly weaken after the 25th period, I implement variance decomposition of 50 periods in long run to further evaluate the contribution rate of each variable.

According to Table 10, changes of rationalization of industrial structure (DSDC) are mainly explained by itself by shock of DAPR (population aging). The proportion in the variance of rationalization of industrial structure (DSDC) continuously decreases over the time, accounting for 96.99% in the first year and 74.4% in the 50th year. In other words, the impact of population aging on the change of industrial structure is increasing over time and its contribution rate increase from 1.5% in the first year to 19.2% in the 50th year. It implies that population aging can interpret more than nearly 20 percent of changes of rationalization of industrial structure at most in the case of this study.

Table 11 represents how much response of population aging (DAPR) is caused by the shock of upgrading of industrial structure. In the first period, population aging accounts for nearly the whole variance of per se. Different from Table 10, the impact of changes of structural upgrading (DSDU) on the population aging presents an upward tendency with a sharp fluctuation, peaking in the 7th period with the variance of 17.7%, then it presents a downward tendency with a stable fluctuation, finally reaching the variance of 14.1%. In other words, the response of population aging on the shock of structural upgrading fluctuates over time and the proportion of the response can peak at more than 15 percent over 60 years around.

Table 10 Variance Decomposition of DSDC Using Cholesky (d.f. adjusted) Factors (%)

Period	S.E.	DSU	DSDC	DAPR
1	0.000885	1.585201	96.99642	1.418379
2	0.001120	3.314164	94.59362	2.092215
3	0.001293	3.218227	90.99091	5.790859
4	0.001337	3.179905	85.94155	10.87855
5	0.001422	3.101856	83.33756	13.56058
6	0.001520	3.449496	82.97015	13.58035
7	0.001553	4.020892	82.50172	13.47739
8	0.001583	5.439590	81.09999	13.46042
9	0.001622	5.672174	79.73438	14.59344
10	0.001668	5.788959	79.45782	14.75322
11	0.001702	5.880562	79.15833	14.96110
12	0.001728	5.986896	78.76799	15.24512
13	0.001754	6.167241	78.10852	15.72423
14	0.001783	6.170565	77.87988	15.94955
15	0.001808	6.160579	77.75677	16.08265
16	0.001828	6.192167	77.56223	16.24560
17	0.001848	6.269823	77.23853	16.49165
18	0.001868	6.282129	77.01152	16.70635
19	0.001887	6.272910	76.86409	16.86300
20	0.001904	6.274837	76.71315	17.01202
21	0.001919	6.302075	76.51746	17.18047
22	0.001934	6.320223	76.34245	17.33733
23	0.001948	6.322404	76.21235	17.46525
24	0.001961	6.325888	76.09243	17.58168
25	0.001973	6.338012	75.95882	17.70317
26	0.001984	6.349410	75.82814	17.82245
27	0.001995	6.353835	75.71787	17.92830

28	0.002005	6.357094	75.61910	18.02381
29	0.002014	6.363685	75.51957	18.11675
30	0.002023	6.371385	75.42166	18.20695
31	0.002031	6.376500	75.33342	18.29008
32	0.002039	6.380167	75.25369	18.36615
33	0.002046	6.384641	75.17693	18.43843
34	0.002053	6.389759	75.10228	18.50796
35	0.002059	6.394002	75.03280	18.57320
36	0.002065	6.397338	74.96904	18.63363
37	0.002071	6.400721	74.90885	18.69043
38	0.002076	6.404375	74.85114	18.74448
39	0.002081	6.407742	74.79678	18.79548
40	0.002086	6.410603	74.74627	18.84313
41	0.002090	6.413290	74.69885	18.88786
42	0.002094	6.416011	74.65382	18.93017
43	0.002098	6.418607	74.61126	18.97014
44	0.002102	6.420934	74.57140	19.00766
45	0.002105	6.423086	74.53401	19.04290
46	0.002109	6.425180	74.49868	19.07614
47	0.002112	6.427189	74.46529	19.10752
48	0.002115	6.429045	74.43391	19.13704
49	0.002117	6.430764	74.40443	19.16481
50	0.002120	6.432401	74.37663	19.19097

Note: Cholesky Ordering is DSU DAPR DSDC

Table 11 Variance Decomposition of DAPR Using Cholesky (d.f. Adjusted) Factors (%)

Period	S.E.	DSU	DSDC	DAPR
1	0.008721	0.668245	0.000000	99.33176
2	0.008844	1.694715	0.511128	97.79416
3	0.009147	10.09155	1.117232	88.79122
4	0.009611	9.602294	1.466043	88.93166
5	0.009901	13.95843	2.892986	83.14859
6	0.009969	17.66756	4.127144	78.20529
7	0.010015	17.71736	4.076614	78.20602
8	0.010103	17.07716	3.924722	78.99811
9	0.010192	16.62865	3.744090	79.62726
10	0.010210	16.26378	3.662899	80.07332
11	0.010229	15.89781	3.639307	80.46288
12	0.010254	15.61306	3.593150	80.79379
13	0.010300	15.53726	3.548530	80.91421

14	0.010317	15.57223	3.533686	80.89409
15	0.010325	15.48616	3.522949	80.99089
16	0.010338	15.32790	3.490072	81.18203
17	0.010361	15.19902	3.449064	81.35192
18	0.010377	15.11763	3.418228	81.46414
19	0.010387	15.03615	3.400467	81.56339
20	0.010397	14.94420	3.383604	81.67220
21	0.010411	14.86977	3.364197	81.76604
22	0.010424	14.81910	3.346774	81.83413
23	0.010433	14.77062	3.333148	81.89623
24	0.010441	14.71334	3.320127	81.96653
25	0.010451	14.65828	3.306234	82.03549
26	0.010460	14.61372	3.293250	82.09303
27	0.010468	14.57507	3.282499	82.14243
28	0.010475	14.53615	3.273032	82.19082
29	0.010482	14.49862	3.263705	82.23767
30	0.010489	14.46589	3.254747	82.27937
31	0.010495	14.43693	3.246733	82.31634
32	0.010501	14.40893	3.239505	82.35157
33	0.010507	14.38174	3.232608	82.38565
34	0.010512	14.35690	3.226022	82.41708
35	0.010517	14.33456	3.219981	82.44546
36	0.010522	14.31364	3.214488	82.47187
37	0.010526	14.29365	3.209343	82.49701
38	0.010530	14.27502	3.204459	82.52052
39	0.010534	14.25795	3.199902	82.54215
40	0.010538	14.24204	3.195697	82.56226
41	0.010541	14.22697	3.191772	82.58126
42	0.010544	14.21282	3.188070	82.59911
43	0.010548	14.19970	3.184599	82.61570
44	0.010550	14.18748	3.181370	82.63115
45	0.010553	14.17598	3.178355	82.64567
46	0.010556	14.16516	3.175521	82.65932
47	0.010558	14.15505	3.172858	82.67209
48	0.010561	14.14561	3.170367	82.68403
49	0.010563	14.13674	3.168036	82.69523
50	0.010565	14.12839	3.165848	82.70576

Note: Cholesky Ordering is DSU DAPR DSDC.

Chapter 6: Conclusions

This study empirically investigated the interaction between population aging and transition of industrial structure based on industry-level data of post-war Japan from 1955 to 2016 under the vector autoregression (VAR) framework. There are five main findings in this study:

First, empirical results reveal the existence of a long-term interaction between population aging and changes in the industrial structure. Different measurement angles of the change of industrial structure lead to different direction. When measurement taken from the perspective of input-output coordination (defined as rationalization of the industrial structure in this study), changes in the aging of the population can cause changes in the industrial structure, which is consistent with many related economic theories and relevant researches. If measured from the perspective of the service-oriented process of industrial structure (defined as upgrading of industrial structure in this study), the aging of the population can be affected by the servitization process of the industrial structure. This is a relatively novel conclusion drawn from the empirical analysis of this study compared with the other relevant studies.

Second, empirical analysis indicates that the one-way effect from population aging to changes of industrial structure is primarily caused by changes in productivity level among different industries or shifts in employment structure among different industries. In other words, differences in labor input between industries caused by changes in the employment population brought about by aging, finally affect transition of the industrial structure. However, with respect to the effect of service-oriented transition of the industrial structure in promoting population aging, this study cannot come to a further conclusion what the impact mechanism is, since this study just take three main industries into account. To further understand the influencing mechanism, the sector-, subsector- and even the micro-level data should be involved into the research.

Third, in the case of post-war Japan, the visible impact of aging population on the rationalization of the industrial structure lasts for about 25 years, and the relatively significant effect appeared in the first ten years whose projection to the history of economic development in post-war Japan is the 1960s. Japan in the1960s was undergoing a process of transition from a developing country to an industrialized country. Accordingly, it means that the industrial structure especially in terms of labor input is more sensitive to the effect of the population aging in the process of industrialization. Similarity, the notable effect of industrial upgrading（or industrial servitization）on the aging of the population occurs in the first decade. It implies that in the process of the industrial structure toward the tertiary industry (or service sectors), the promotion to population aging is relatively significant in the previous decade.

Fourth, the degree of influence of aging population on the rationalization of the industrial structure continuously strengthen over time， while the degree of effect of industrial upgrading（or economic servitization） on the population aging is fluctuating, which means it gradually increases and then declines after peaking. That means that the duration of impact of population aging on industrial structure is longer than that of industrial structure on the population aging.

Last, although this study has demonstrated the existence of certain interrelationships between the aging of the population and the industrial structure from the perspective of the econometric model, the extent of the effects of these correlations is not strong based on empirical evidence. For the rationalization of industrial structure, although the aging of the population has an impact on it, this impact only accounts for at most one-fifth of the total impact (based on data of this paper), that is, other influences may come from the industrial structure per se or other external factors, such as industrial policies, special events, economic environment and so on. The influence of these factors on the industrial structure is not included in the measurement of this study. Therefore, if further research proposes to consider the impact of other factors besides the aging of the population, it suggests including dummy variables in the model system for specified testing. Similarly, with respect to the upgrading of industrial structure, although the aging of the population has an active response to it, the response only accounts for at most 15 percent of the total response (based on data of this paper), that is, other influences may come from internal demographic changes or another external factor.

In summary, the empirical evidence confirms a long-run mutual relationship between population aging and changes in the industrial structure. The influence of population aging on the transition of industrial structure is mainly caused by different productivity among industries, which continuously strengthen over time. The transition of industrial structure has an enhancement effect on the aging of society in the service-oriented process of industrial structure and the effect path has an inverted U-shaped tendency.

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