ESRI Discussion Paper Series No.378

Measuring Income Inequality in Japan Using Accurate Sampling Weights

Masahiro Hori
Saeko Maeda
Fumihiko Suga

May 2023

Economic and Social Research Institute
Cabinet Office
Tokyo, Japan

Measuring Income Inequality in Japan Using Accurate Sampling Weights†

Masahiro Hori[a,b], Saeko Maeda[a], and Fumihiko Suga[a,c*]

[a] Economic and Social Research Institute, Cabinet Office, Japan
[b] Graduate of Economics, Hitotsubashi University, Japan
[c] Department of Economics, Kyushu University, Japan

April 2023

Abstract

This study attempts to provide an overview of income inequality in Japan for the 1990s and the 2000s, using the *Comprehensive Survey of Living Conditions* (CSLC) data. We calculate four income inequality measures based on eight income definitions. To measure the income inequality with a precision greater than that of the previous studies, we create the sampling weights using micro-data from the Population Census. We find that income inequality measures calculated using Population-Census weights are higher than those without weighting adjustment and those adjusted with provided weights. Although the levels of inequality measures are higher, weighting adjustments do not seem to have a significant impact on the trend of inequality measures. We also find that the level and the upward trend are less pronounced if imputed rent is considered. Moreover, we attempt to find the cause of the rise in inequality. We find that, on an equivalized disposable income basis, 31.6 to 57.4% of the rise in income inequality can be explained by the changes in the demographic structure and the composition of households for the 1990s. Among others, the aging of the population, changes in household composition, and a decrease in the number of workers had a large impact on the rise in income inequality.

Keywords: sampling weight, income inequality, Japan
JEL classifications: C83, D31, N35

---

†We are grateful to Kunio Urakawa, the discussants at the ESRI seminar, for the valuable comments. We would also like to thank Taiyo Fukai, Junya Hamaaki, Kazuhito Higa, Koichi Iwamoto, Kyogo Kanazawa, Keiko Murata, Takeshi Niizeki, and other ESRI colleagues for their support and Ralph Paprzycki for his thorough English editing service. Special thanks go to the Ministry of Health, Labour and Welfare of Japan for providing us with the microdata from the *Comprehensive Survey of Living Conditions (CSLC)*. The views expressed in this paper are those of the authors and do not represent those of the institutions the authors belong to.
* Corresponding authors: Suga.

1. Introduction

The rise in inequality has drawn growing attention, particularly after Piketty (2014) was published. In line with the global trend that Piketty (2014) pointed out, income inequality in Japan has also been rising over the last few decades. Unlike other developed countries, income distribution in Japan became unequal even during economic stagnation, and numerous studies have attempted to reveal how and why income inequality rose in Japan.

Recent discussions on growing income inequality in Japan were provoked by Tachibanaki (1998). By using the data from the *Comprehensive Survey of Living Standards* (CSLC),[1] Tachibanaki (1998) insisted that income inequality in Japan was relatively high among developed countries. However, Ohtake (2005) pointed out that the income definition used for calculating inequality measures by Tachibanaki (1998) was different from the income definition used for the calculation of income inequality in other countries. Ohtake (2005) shows that Japan's income inequality was comparable with the average of OECD countries and not so high as that of the U.S. if calculated based on an appropriate income definition. Ohtake's (2005) finding teaches us how sensitive income inequality measures are to the income definition.

Another problem associated with the measurement of income inequality is that income inequality measures, such as the Gini coefficients, sometimes differ considerably across datasets. Figure 1 shows the Gini coefficients of OECD countries, that of Japan calculated based on the *National Survey of Family Income and Expenditure* (NSFIE) data, and that calculated based on the CSLC data. As seen in Figure 1, Japan's income inequality is higher than the OECD average and not so high as that of the U.S. if calculated using the NSFIE data, while it exceeds that of the U.S. if calculated using the CSLC data.

[1] More precisely, the dataset that Tachibanaki (1998) used was Income Redistribution Survey (IRS) data. The income questionnaires were distributed to only a subsample of the CSLC respondents, and the IRS sample contains only those who received the income questionnaire.

Why are the income inequality measures calculated from the two datasets so different? One possible explanation for this discrepancy is the difference in the sampling schemes of the surveys: The way of choosing respondents or asking questions may differ between the two surveys.[2] As a result, different people respond to the survey questions differently, and the resulting income distribution and income inequality measures differ across datasets. This might also be the reason why the contribution of household composition change differs across different studies. Because inequality measures crudely capture how many rich households and poor households are there and how rich or poor they are, a sampling bias can cause a serious problem in an inequality analysis.

Our goal is to provide income inequality measures with a precision greater than that of the previous studies. The question is how we can deal with the difficulties associated with precise measurement of inequality. Our strategy is two-fold: First, to solve the complications with the income definitions, we present income inequality measures calculated based on a variety of income definitions. Second, to deal with sampling bias, we create the sampling weights using the micro-data from the Population Census, which can be regarded as providing the population distribution of the households living in Japan.[3] Most government surveys in Japan provide sampling weights with the datasets. The problem, however, is that the way of creating the sampling weight also differs across the surveys. Therefore, to correct the bias due to the difference in the sampling scheme, we have to create the sampling weight ourselves.

Our main findings are the following:

(1) The income inequality measures calculated based on the Population-Census based weights are higher than those calculated based on the provided weights, which indicates that income

[2] NSFIE and CSLC are both government surveys, but the sampling scheme is different. This is because they are conducted by different ministries.

[3] Since changing the sampling scheme of government surveys is quite difficult in general, it is common to use sampling weights to correct for such a bias arising from the difference in sampling.

inequality measures reported by previous studies using the CSLC data might be under-estimated.

(2) The levels and the upward trends in income inequality measures are less pronounced when imputed rent is included.

(3) We confirmed the previous studies' finding that income inequality has been rising, but the upward trend is less pronounced for the income definitions closer to consumption, thanks to the income redistribution by the social security system.

(4) As previous studies (e.g., Ohtake, 2005) pointed out, the changes in the composition of households contributed to the rise in income inequality in Japan. For the 1990s, 31.6 to 57.4% of the rise in income inequality is attributable to the changes in household composition.

(5) Among others, the aging of the population, changes in household composition, and the decrease in the number of workers had a great impact on the rise in income inequality.

The rest of this paper is composed as follows. Chapter 2 outlines the background and the previous literature. Chapter 3 describes the datasets that we used. Chapter 4 discusses the empirical methods. We provide the empirical results in Chapter 5, and Chapter 6 concludes.

2. Related Literature

Lise et al. (2014) provide a unified view of wage, household income, consumption, and asset inequality in Japan, using several survey data. Lise et al. (2014) show that the rise in income inequality from the 1980s to the middle of the 1990s can be attributed to the increase in the level of income above the median. The rise in income inequality after the mid-1990s, on the other hand, is attributable to the decrease in the level of income under the median. Lise et al. (2014) provide an overview of the rise in inequality in Japan over the last three decades from a wide perspective, but Lise et al. (2014) restricted the sample to households with heads aged 25-59, omitting those with heads aged 60 or older. As is pointed out by previous studies such as Ohtake (1998) and Oshio (2010), changes in household composition over the last three decades, such as the aging of the population, the decrease in household size, and the increase in the share of dual-income households among those with a younger head, had a great impact on inequality in Japan. As the variance of income within a cohort increases in age, income inequality measures increase as the share of the elderly increase, and cross-sectional income inequality can increase even if there is no change in lifetime income inequality across cohorts. Therefore, omitting households with an older head can lead to underestimating the rise in inequality.

A more recent study by Kitao and Yamada (2019) used the NSFIE household data, including households with a head older than age 60, to measure inequality in income and assets. They found that the rise in income inequality in Japan can be attributed to the change in household composition, including population aging. Although they provided an overview of income inequality over the last three decades from a wide perspective, they used the NSFIE data with the weights provided with the dataset. The sampling weights provided with the NSFIE data adjust for the disproportionality of the sample with respect to household characteristics, such as the age of the household head and the area of residence. There remains, however, sampling bias because there are characteristics not considered. Hori et al. (2020) show that the income inequality measures are underestimated when the NSFIE data is not adjusted or adjusted with the provided weights.

Because the sampling weights provided with the CSLC data only correct the geographical disproportionality, weighting adjustment with the provided weight is expected to be less effective in correcting for the sampling than in the case of NSFIE. Figures 2 (a) and (b) show the age and household type distribution of the CSLC data, respectively. The left bar shows the share of each category in the raw data; the bar in the middle shows the share of each category in the data adjusted with the provided weights; the right bar shows the share of each category in the Population Census data. As can be seen from Figure 2(a), provided weight is successful in correcting for the sampling bias with respect to the age of household heads. Figure 2(b) indicates, however, that the bias in the household type distribution is not corrected.

Previous studies on income inequality in Japan teach us the importance and difficulty in precise measurement of income inequality. While most of the studies put emphasis on the source of the rise in income inequality, the method of correcting disproportionality in the sample has not been paid much attention, except for Hori et al. (2020). Thus, we follow the empirical strategy proposed by Hori et al. (2020) to provide more accurate inequality measures using the CSLC data.

3. Data Sources

This study uses the CSLC data. The CSLC data is one of the representative government surveys in Japan. Although the sample size of income data is smaller than that of the NSFIE, the CSLC data contains detailed information not provided by the NSFIE, such as nursing care and health-related issues. As we mention below, the sampling schemes of the CSLC and the NSFIE are different, and we expect that the CSLC data can collect the sample of households that are less likely to respond to the NSFIE.

3.1 CSLC

The CSLC is one of the nationally-representative surveys in Japan conducted by the Ministry of Health, Labour, and Welfare. The CSLC is an annual cross-sectional survey, but the large-scale survey is conducted only once every three years in May. We use the data from the large-scale survey conducted every three years from 1989 to 2010 to overview the transition of income inequality over the 1990s and the 2000s. We use the previous year's income to calculate the income inequality measures. Therefore, we provide inequality measures for every three years from 1988 to 2009.

A distinguishing feature of the CSLC is that the survey interviewers are those who work at public health and welfare offices or public health centers. The advantage of this feature is that the CSLC sample covers more non-standard households, such as poor single households receiving social welfare, than the other government survey. Hashimoto (2011) pointed out, however, that the response rates can differ considerably across interviewers because the survey interviewers do not go through official training.

Another important feature of the CSLC's sampling scheme is that the target districts are randomly chosen, and the target population of the survey is all of the households living in the target districts. The size of the target population of the large-scale survey is greater than 200,000 households, but the CSLC does not supplement households to compensate for the non-respondents. Therefore, even if the response rate of households with a young single male is lower than the other, for example, MHLW does not survey additional households with a young single male. Moreover, income questionnaires are distributed only to a subsample. For example, for the 2010 survey, the number of households living in the target district was 289,363, and 229,785 households responded to the survey. Among the respondent households, only 35,971 households received the income questionnaire, and 27,225 households responded. Furthermore, we apply our own sample selection criteria because there are unreliable respondents.[4]

Summary statistics of the CSLC data are provided in Table 1. The sample size has diminished, perhaps because of the decline in the response rate. We can observe the aging of household heads. Household income has decreased since the mid-1990s. Since the decrease in the mean of the equivalized income is modest, the decrease in the household income is partly due to the decrease in the household size. The household size decreased because the share of three-generation households

[4] We drop households who reported that they were working despite the fact that their earnings were zero. Moreover, we dropped households with a member older than age 65 with zero income.

declined.

3.2 Population Census

Population Census, conducted by the Ministry of Internal Affairs and Communications, is an exhaustive survey that covers all households living in Japan. We regard the household distribution of the Population Census data as the population household distribution in Japan. Unfortunately, we cannot calculate the income inequality measures by using the Population Census data because it does not collect information on households' income. The Population Census data, however, contains rich information about the family characteristics that are also available in the CSLC data. Therefore, we can take advantage of these household characteristics to define the same population groups for the Population Census and CSLC data. By using the share of each population group in the Population Census as true population distribution, we can create the sampling weights that make the distribution of the CSLC sample conform to the true population distribution.

Since we need to select the households according to the sample selection criteria of CSLC, we use the microdata of the Population Census and drop those who should be excluded under the CSLC sample selection criteria before we calculate the share of population groups. Moreover, the categories of socio-economic characteristics are defined in the same manner as we define the category for the CSLC so that responding households in the CSLC in each population group can be regarded as representing all households in that group. The Population Census is conducted every five years, and we calculate the share of households that belong to each group for the years 1990, 1995, 2000, 2005, and 2010. Then we linearly interpolate these shares.

Table 2 compares summary statistics of the Population Census and the CSLC. It shows that the sample distribution of the CSLC is disproportional. For example, single households are likely to be under-sampled, while homeowners tend to be over-sampled. Moreover, the share of nuclear households among two-or-more households is almost the same as that in the Population Census, while the share of dual-income households among nuclear households is not even when weighting adjustment with provided weight is applied.

4. Empirical Methodology

4.1 Motivation for creating the sampling weights ourselves

As we mention above, we create the sampling weights by using Population Census data to enhance the precision of income inequality measures. We employ the so-called "cell weighting" method (see, e.g., Kalton and Flores-Cervantez, 2003). The basic idea of cell weighting is that we define household groups (referred to as "weighting cells") based on household characteristics and assign the same weight to households belonging to the same cell.[5]

We apply weighting adjustment to correct for the disproportionality in the sample inclusion probability across population groups (weighting cells). If the sample inclusion probability is constant across all cells, we can obtain unbiased income inequality measures by random sampling without weighting adjustments. Unfortunately, the sample inclusion probability can differ considerably across weighting cells. For example, it is well-known that single males living alone tend not to respond to surveys, perhaps because they are likely to be absent during the daytime. Therefore, if we randomly select households and collect the information of only those who respond to the survey, households headed by a single male will be under-sampled. Then we use the sampling weights to make the sample distribution conform to the population distribution so that respondents represent similar non-respondents. For example, suppose the share of single male households in the population is 4%, but the share of corresponding

[5] The detailed procedure of calculating the weight assigned to each cell is explained in the next subsection.

households in the sample is only 2%. Then we assign heavier weights to single male households so that the share of a single male household in the adjusted sample becomes 4%. An implicit assumption behind such an adjustment is that responding households and non-responding households are so similarly distributed that we can regard responding households as representing all households in the same population group, including non-respondents. Therefore, to effectively correct the sample distribution, we would like to make the households within the same population group as homogeneous as possible.

The question is how we can make the households within a particular cell homogeneous. Now let us refer to the variables used to define the weighting cells as "auxiliary variables." If we employ more auxiliary variables, households within a weighting cell will be more homogenous, and the responding households can be regarded as more representative. This is the primary reason why we create sampling weights ourselves. The provided weights correct only for geographical disproportionality, but there are other variables available in the Population Census and the CSLC that can be used to correct for the disproportionality of the sample. For example, we can use the number of workers and the homeownership status of the households as auxiliary variables. We can take advantage of these variables in making the sampling weights to make the households within a cell as homogeneous as possible if we create the sampling weights ourselves.

There is another advantage of creating sampling weights by ourselves. Researchers often drop households whose reported incomes are not reliable. For example, some respondents report that they are working as an employee but do not report wage income. Other respondents report that they receive a public pension, but their reported pension income is zero. Moreover, even if the answers are reliable, some households are dropped for some reason. For example, households with negative disposable income are dropped because we take a logarithm for the calculation of some income inequality measures. Thus, there are respondents who report income but are dropped according to our own sample selection criteria. The problem is that respondents not used for our analysis were part of the sample when the provided weights were created. Thus, if researchers drop the sample according to their own sample selection criteria, it is desirable to create the sampling weights on their own.

There is, however, a disadvantage of employing many auxiliary variables. As we employ more auxiliary variables and define more weighting cells, there emerge more no-observation cells. Thus we have to merge them with the neighboring cells, but the selection of the cells can be arbitrary and lack generality. Furthermore, even if there is no no-observation cell, previous studies (e.g., Kish, 1992) pointed out that finer weighting cells result in a larger variance in general. To deal with this problem, we employ a measure of variance inflation, defined as:

$$F = 1 + CV(w_{it})^2,$$

where CV is the coefficient of variation. Inflation factor F measures by what margin the sampling weight inflates the variance of the mean (see, e.g., Kish, 1992). We use F to take the variance inflation into account when we create the sampling weights.

4.2 How to create the sampling weights

As mentioned above, we use the sampling weights to compensate for non-response and non-coverage. Let s_{it} denote the population share of households in the weighting cell that household i belongs to at time t. If the sample inclusion probability is constant across households, the probability of household i to be included in the sample is s_{it}, and we do not need to use the sampling weights. However, the response probability can differ across weighting cells, and there will be over-sampled and under-sampled households in the sample. To correct for the sampling bias, we apply sampling weights. Let $\bar{s}_{it}$ denote the sample share of the households in the weighting cell that household i belongs to at time t in the CSLC data. The sampling weight for household i at time t is defined as:

$$\mathrm{w}_{\mathrm{it}} \propto \frac{s_{it}}{\bar{s}_{it}} \tag{1}$$

Households belonging to the same weighting cell have the same value for w_{it}. As mentioned above, this method is called "cell weighting." An implicit assumption behind the cell weighting adjustment is that the sample inclusion probability is constant across households belonging to the same cell. Thus, it is important to define weighting cells so that households within a weighting cell are as homogeneous as possible.

We define the weighting cells using five auxiliary variables: age ("under 40", "40-59", "over 60"), household type ("single male", "single female", "couple", "single parent with children", "parents with children", "three generations", and "the other"), number of (full-time) workers ("zero", "one", and "two or more"), area ("23 special wards in Tokyo", "designated cities", "other cities in Area 1", "other cities in Area 2", "other cities in Area 3", "other cities in Area 4"[6]), and homeownership ("renters", "small homeowners", "large homeowners").[7] Thus, there are $3 \times 7 \times 3 \times 7 \times 3 = 1{,}323$ weighting cells in total. However, there are a number of weighting cells with no observations. Moreover, as mentioned above, finer weighting cells result in a larger variance in the weights and weighted estimates. Therefore, we have to merge (or "collapse") the weighting cells.

We merge the cells in the following manner: First, we merge no-observation cells with the neighboring cell in the area-of-residence category. For example, if the cell of households headed by a male aged under 40 living in the Tokyo 23 ward area has no observation, we merge

[6] Area 1 is composed of prefectures in Hokkaido and Tohoku areas, Area 2 in Kanto area, Area 3 in Kinki and Chubu areas, and Area 4 in Chugoku, Shikoku, and Kyushu areas.

[7] Naoi and Yamamoto (2010) found that the residence distribution of the Japanese Household Panel Survey differs considerably from that of the Population Census. Since response probability can differ between those living in an apartment and those living in a house, we include a variable closely related to the type of residence. We employed homeownership rather than the type of residence because homeownership is expected to be more closely related to the richness of households.

this cell with the cell of households headed by a male aged under 40 living in the Designated City area. If the neighboring cell in the area-of-residence category has no observation, we merge the cell with the neighboring cell in the age category.[8] After we collapse all the no-observation cells, we calculate the inflation factor *F*. As mentioned above, inflation factor *F* represents the amount of variance inflation due to the weighting adjustment. Kalton and Flores-Cervantes (2003) pointed out that the inflation factor *F* depends heavily on the maximum of the weights. Thus, we merge the cell with the largest weight with the neighboring cells in the same manner as we merge no-observation cells. We repeat this "collapsing" procedure of the weighting cells as long as the value of the inflation factor *F* is higher than the inflation factor of the provided weights. As a result, the number of weighting cells remained amounts to 243.[9]

The population share of weighting cells divided by the sample share of corresponding cells for single and multi-person households are provided in Table 3(a) and 3(b), respectively. The number in each cell is $s_{it}/\bar{s}_{it}$, the inverse of the weight defined by Equation (1). Households in a weighting cell are over-sampled if this number is higher than 1; households are under-sampled if this number is lower than 1. The cells are colored in red if the households in these cells are over-sampled; the cells are colored in blue if the households in these cells are under-sampled.

As can be seen in Table 3(a), single households headed by a person younger than age 60 are likely to be under-sampled, while homeowner households headed by a head older than age 60 living in larger houses in rural are tend to be over-sampled. Table 3(b), on the other hand, shows that two-or-more-person households with no worker headed by a person aged 60 or younger tend to be under-sampled, while three-generations and other type of households headed by a person

[8] There are several exceptions. For example, the age of the household head is not important for three-generations households. Therefore, we merge no-observation cells in the three-generations category with the cells of the neighboring area category. The details of the merging policy are summarized in Appendix A.

[9] The weighting cells of younger single-households, two-or-more-person households with no workers, households with an older head and children, and households with a younger head living in a large house are likely to be collapsed with their neighboring cells because they have a small sample.

younger than age 60 tend to be over-sampled except for renter households with a worker. Moreover, households living in the Tokyo 23 wards tend to be under-sampled.

Tables 4(a) and 4(b) present the distribution of single and two-or-more-person households adjusted with the provided weights. These tables show that weighting adjustment with provided weights is effective in compensating for the under-sampled households living in Tokyo 23 wards, but there remains non-negligible disproportionality in the sample distribution even after weighting adjustment is applied. This is because the provided weights correct for the geographical disproportionality only.

In order to figure out how effectively weighting adjustments correct for the disproportionality in the sample distribution, we calculate the ratio of the population to sample share $s_{it}/\bar{s}_{it}$ by category for each auxiliary variable. The charts in the first column of Figure 3 show the ratio calculated without sampling weights; the charts in the second column show the ratio calculated with the provided sampling weights; the charts in the last column show the ratio calculated with our original sampling weights created from the Population Census. If the weighting adjustment works perfectly, the ratio of the shares should be equal to one. As seen in Figure 3, however, the ratios of the shares deviate from one for age and area categories even if we use our original sampling weights.[10] This is because we merged no-observation cells and cells with extremely high w_{it} with the neighboring cells in area-of-residence or age categories. Although the weighting adjustment is not perfect, Figure 3 clearly shows that our original sampling weights are more successful in conforming the sample distribution to the population distribution than the provided weights, particularly with regard to household characteristics such as the number of workers, homeownership, and household type to evaluate the effectiveness of

[10] In particular, households living in Tokyo 23 wards and Designated cities are under- and over-sampled because the number of households living in the Tokyo 23 wards is quite small, and we merged the cells of those living in Tokyo 23 wards with the cells of those living in designated cities.

the weight adjustment.

Figure 3 shows that adjustment with our original sampling weights is successful in adjusting for the disproportionality with respect to the auxiliary variables. This may appear to be trivial because the weights are designed to make the sample distribution conform to the population distribution with respect to the auxiliary variable. Thus, to check the external validity, we calculate the share of self-employed households with no weighting adjustment and with adjustments with provided weights and our original weights. The bottom charts in Figure 3 reveal that weighting adjustment with our original sampling weights is effective in correcting for the disproportionality with respect to the characteristics not employed as auxiliary variables.

4.3 Definition of Income

Previous studies such as Ohtake (2005) show that income inequality measures are sensitive to the definition of income, and it is important to present income inequality measures based on a variety of income definitions to assess the role of the tax and social security system in reducing inequality. Therefore, we assess the income inequality for each of the following four income definitions: Initial income, pretax income, disposable income, and disposable income with imputed rents. Initial income is defined as pretax income excluding pension income and social security benefits; Pretax income is defined as pretax income including pension income; Disposable income is defined as after-tax income including pension income and social security benefits. Moreover, we calculate income inequality measures based on disposable income plus imputed rents.

Because our ultimate interest is to assess the inequality of households' welfare, it is desirable to use the income definition that is close to the actual resource for consumption. For example, the United Nations Canberra Group recommends Haig-Simons income definition, which includes not only cash income but also imputed rents of owned houses, capital gain/loss, and in-kind employee benefits. Larrimore et al. (2021) show that the rise in inequality in the U.S. from 1989 to 2016 is much less pronounced when they assess income inequality based on the Haig-Simons income definition. Thus we provide income inequality measures based on disposable income plus imputed rents. [11]

Although we cannot include non-cash income flow other than imputed rents, including imputed rents can have a significant impact on the level and the trend in the inequality measures. As we mentioned above, previous studies, such as Ohtake (2005) and Kitao and Yamada (2019), suggest that the rise in inequality in Japan is attributable to the aging of the population. Because the homeownership rate of households with an older head is quite high in Japan, the rise in inequality can be moderate if we include imputed rents as a part of income.

Furthermore, previous studies have shown that the levels of income inequality measures can differ considerably between household income and equivalized income. Thus we calculate the income inequality measures for each of the 4×2 income definitions. Since our Population-Census-based weights do not allow for family size explicitly, we apply the raking method to modify our weights.[12].

4.4 Income Inequality Measures

To assess income inequality from a wide perspective, we calculate several income inequality measures commonly employed by previous studies. First, we present the Gini coefficients, which are regarded as one of the most common income inequality measures. Gini coefficient G represents the area between the 45-degree line and the Lorenz curve and can be written as:

[11] Because the information about capital gain/loss and in-kind employee benefits are not available, we include only imputed rents. The CSLC data does not contain imputed rents. The NSFIE data contains imputed rents calculated by the Statistical Bureau, and we use them to estimate the imputed rents. For a detailed procedure of estimation, see Appendix B.

[12] To verify if this modification affects our results, we present income inequality measures calculated based on equivalized income using the household-level weights (household size is not considered) and the individual-level weights (household size is considered).

$$G = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|y_i - y_j\right|$$

Where y_i is the income of individual i, μ is the mean of income, and n is the number of observations.

The Gini coefficient is useful in that it summarizes the overall trend in income inequality. However, it is difficult to figure out whose income changed when the Gini coefficient changed. Therefore, we draw the Lorenz curve and calculate the income share of the top, middle, and bottom 10% of households. By doing so, we can show whether richer/poorer households became richer/poorer when the Gini coefficient changed. We also present the kernel density of the income distributions to show visually how income distribution changed. Moreover, to shed light on the most disadvantaged households, we present relative poverty rates, defined as the share of households with income below half of the median income.

The Gini coefficients, Lorenz curves, 10% share, kernel density, and relative poverty rates are informative about how the change in income distribution affects income inequality. However, those statistics do not reveal why income inequality changed. To investigate the cause of the increase/decrease in income inequality, we present log variance (LV) and mean log deviation (MLD) for the purpose of factor decomposition of income inequality.[13]

The log variance *LV* is defined as:

$$\mathrm{LV} = \frac{1}{n}\sum_{i=1}^{n}\left(\log y_i - \overline{\log y}\right)$$

Suppose there are *J* population groups. As Ohtake and Saito (1998) show, LV can be written as:

$$\mathrm{LV} = \mathrm{V}(\mathrm{s_t}, \sigma_\mathrm{t}, \mathrm{Y}_t) \qquad (1)$$

where $\mathrm{s_t} \equiv \{s_{t1}, s_{t2}, \dots, s_{tJ}\}$ is the vector of the population share of each population group, $\sigma_\mathrm{t} \equiv$

[13] As noted in prior research, such as Oshio et al. (2006), LV and MLD tend to be particularly sensitive to changes in the income distribution at the lower quantiles, whereas the Gini coefficient is more responsive to shifts in the income distribution around the mean.

$\{\sigma_{t1}, \sigma_{t2}, \dots, \sigma_{tJ}\}$ is the vector of the variances within each population group, and $\mathrm{Y_t} \equiv \{\bar{y}_{t1}, \bar{y}_{t2}, \dots, \bar{y}_{tJ}\}$ is the vector of the average income of each population group. Using Equation (2), we can calculate the contribution of each factor: The contribution of the change in population share is given by $\mathrm{V}(s_{t+1}, \sigma_t, Y_t) - \mathrm{V}(s_t, \sigma_t, Y_t)$; the contribution of the change in within-variation is given by $\mathrm{V}(s_t, \sigma_{t+1}, Y_t) - \mathrm{V}(s_t, \sigma_t, Y_t)$; the contribution of the change in between-variation is given by $\mathrm{V}(s_t, \sigma_t, Y_{t+1}) - \mathrm{V}(s_t, \sigma_t, Y_t)$.

The mean log deviation MLD is defined as:

$$\mathrm{MLD} = \frac{1}{n}\sum_{i=1}^{n} \log\left(\frac{\mu}{y_i}\right).$$

Mookherjee and Shorrocks (1982) proposed a factor-decomposition of the change in MLD:

$$\Delta MLD \approx \sum_{j=1}^{J} \bar{s}_j \Delta MLD_j + \sum_{j=1}^{J} \overline{MLD}_j \, \Delta s_j$$

$$+ \sum_{j=1}^{J} (\bar{\lambda}_j - \overline{ln\,\lambda_j}) \Delta s_j + \sum_{j=1}^{J} (\bar{\theta}_j - \bar{s}_j) \Delta \, ln\, \bar{y}_j$$

where a bar above a variable indicates the average of the variable at time *t* and *t*+1. The first term can be regarded as the contribution of the change in within-variation; the sum of the second and third terms can be regarded as the contribution of the change in population share; the last term can be regarded as the contribution of the change in between-variation. The advantage of the factor decomposition of MLD over the factor decomposition of LV is that the sum of the three factors is approximately equal to the total change in MLD.

5 Results

5.1 Income Inequality by Weights

Figure 4 shows the Gini coefficients of various income definitions. Solid (blue) lines represent the Gini coefficients calculated without weighting adjustment, while dashed (orange) and dotted (gray) lines represent the Gini coefficients adjusted with the provided sampling weights and those adjusted with our original sampling weights, respectively. Three charts on the top of Figure 4 represent Gini coefficients calculated based on household income, while those in the middle and bottom show Gini coefficients calculated based on equivalized income. As can be seen from Figure 4, weighting adjustment with our original sampling weights has different effects on different income definitions. Moreover, we use modified weights for equivalized incomes to allow for household size. Thus, Figure 4 includes the Gini-coefficients calculated based on equivalized income weighted with household-level weights (household size is not considered) and individual-level weights (household size is considered). The charts in the middle of Figure 4 show Gini coefficients calculated based on equivalized incomes adjusted with household-level weight, while the charts at the bottom of Figure 4 show those adjusted with individual-level weights.

First, let us compare the Gini coefficients calculated without weighting adjustment (solid blue line) and those calculated with the provided weights (dashed orange line). It appears that Gini coefficients are slightly lower in 2000 and 2003 when weighting adjustment is applied, but the difference is quite small and negligible for the other years. Next, let us compare the Gini coefficients calculated using the provided weights and those calculated with the Population-Census-based weights. As can be seen from Figure 4, the Gini coefficients calculated with the Population-Census-based weights are higher than those calculated with the provided weights. This is perhaps because single households and jobless households tend to be under-represented even after being adjusted with the provided weights. The relative poverty rates, MLD, and LV by sampling weights are shown in Figures 5, 6, and 7. The effects of weighting adjustments are almost the same as those of Gini coefficients shown in Figure 4.

As we can see in Figures 4 to 7, there is an upward trend in income inequality when the inequality measures are calculated based on initial income. However, the trend is less pronounced when pensions and taxes are considered. This indicates that income redistribution via tax and social security system effectively reduces the impact of the rise in income inequality in Japan. The income inequality measures calculated with and without weights shift almost in parallel. Thus, it appears that weighting adjustment does not affect the trend.

Previous studies using the CSLC data, such as Oshio (2010), report that the trend of income inequality during the 2000s is flat, while those using the NSFIE data (e.g., Hori et al., 2020) report an upward trend. There appears to be an upward trend for some income inequality measures based on initial and disposable income, while the trend is not clear for those based on pretax income.[14].

5.2 Lorenz Curve, and Top and Bottom 10% share

In order to take a closer look at what is behind the rise in income inequality, we draw the Lorenz curve in Figure 8. Apparently, the Lorenz curves became more curved, and this is the reason for the increase in Gini coefficients. From Figure 8, however, it is difficult to know whether poor households became poorer or rich households became richer.

In order to figure out at which level income distribution became unequal, we draw the top, middle, and bottom 10% share in Figure 9.[15] The upward trend of the top 10% share is more pronounced than the downward trend of the bottom 10% share. Thus, it appears that richer households' share of income increased, but it is not always the case because the top 10% share can increase when all households become poorer. Therefore, we should look over the whole distribution of income.

5.3 Kernel density of income distribution

[14] We construct a 95% confidence interval of the Gini coefficient and find that the increase in the Gini coefficient from 2000 to 2009 is not statistically significant.
[15] The middle 10% share is defined as the share of income owned by 45-55 percentile households.

In order to directly look at the income distribution, we draw kernel densities in Figures 10(a) and 10(b). Figure 10(a) shows the income distribution from 1988 to 2000, while Figure 10(b) shows the income distribution from 2000 to 2009. Apparently, the pattern of the changes in the income distribution for the 1990s is different from that of the 2000s. During the 1990s, both the level and variance increased. As a result, income inequality increase, reflecting the increase in the dispersion of income. On the other hand, the income level decreased during the 2000s, and the increase in the share of poor households resulted in a rise in income inequality measures. As can be seen from Figure 10(b), the shift of income distribution during the 2000s is less pronounced for the disposable income with imputed rents. This is perhaps because the share of low-income households increased during the 2000s, but many of them were homeowners. Thus, many of the low-income households in 2010 received housing services from their own home, and their living standards were not as low as they might appear.

5.4 Contribution of the Household Composition Change

Thus far, we have provided an overview of the transition of income inequality and income distribution itself for a variety of income definitions. Henceforth we focus on the change in income inequality from 1988 to 2000 and 2000 to 2009 and attempt to reveal the cause of the rise in income inequality. As mentioned above, previous studies suggested that changes in the demographic structure and composition of households played a key role in the rise of inequality in Japan. Among the household characteristics that we used to define the household groups, we focus on age, household type, number of workers, and area because these characteristics are more relevant to important demographic changes, such as aging of the population, household nuclearization, and increase in the share of dual-income households.

First, in order to figure out by what margin changes in the demographic variables used for the definition of weighting cells can collectively account for the rise in income inequality, we calculate the income inequality measures holding the share of each cell constant at the 1988 and 2000 levels. To obtain income inequality measures for 2000 and 2009 holding the share of each cell at the 1988 level, we use the sampling weights $w_{j,t}^{1988} = \frac{s_{j,1988}}{\bar{s}_{j,t}}$ (t=2000, 2009) instead of $w_{j,t} = \frac{s_{j,t}}{\bar{s}_{j,t}}$ to calculate the income inequality measures. We can create the sampling weights that hold the share of each cell at the 2000 level in the same manner. The results are shown in Figures 11(a) to 11(d).

The dashed lines illustrate what would happen to the income inequality measures if the share of each weighting cell is held fixed at the level of the 1988 Population Census. As can be seen in Figures 11(a) to 11(d), the rise in income inequality during the 1990s would be moderate if the household composition stayed constant. For the income inequality measures calculated based on equivalized disposable income (with and without imputed rents), the contribution of the change in the household composition ranges from 31.6% to 57.4%. Thus, the rise in income inequality in the 1990s can be explained by the changes in household composition to a decent extent, such as the aging of the population and the nuclearization of households. This result is consistent with the finding of Hori et al. (2020). The dotted lines, on the other hand, illustrate how income inequality would shift for the 2000s if the population share was fixed at the 2000 level. They indicate that income distribution would stay constant or even become equal if there were no changes in household composition. Thus, for the 2000s, the changes in household composition account for the rise in income inequality for the most part, which is not consistent with the results of Hori et al. (2020), which reports that only a small fraction of the rise in inequality during the 2000s is attributable to changes in the demographic structure and composition of households. It is difficult to find the cause of this discrepancy, but one possible reason is that the change in inequality was modest during the 2000s. Another possibility is the difference in the survey years. Hori et al. (2020) decomposed the change from 1999 to 2009, while we decomposed the change from 2000 to 2009.

5.5 Factor-Decomposition of Income Inequality Measures

Income inequality measures calculated with fixed population shares reveal that the changes in the household composition, such as the aging of household heads, the nuclearization of households, and the increase in dual-income households, collectively played an important role in the rise of income inequality. The next question we consider is which of these changes are important. To answer this question, we decompose the changes in the MLD and the LV with respect to household characteristics. Since the composition effects can be regarded as the contribution of household composition change, let us focus on the composition effects. Moreover, we mainly focus on the decomposition of the change during the 1990s because the amount of the change in MLD and LV during the 2000s is modest.

The decomposition of the changes in the MLD and the LV with respect to age are displayed in Figures 12(a) and 12(b), respectively. The composition effect is greater for household initial income than for the other income definitions because initial income does not contain pension income, and the variability of income received by older people is exaggerated. Because the contributions of the composition effect differ considerably across income definitions, let us focus on the income definitions closer to the actual resource of consumption. The contribution of the change in age-composition effect during the 1990s is 38.4% for the MLD based on disposable income without imputed rents and 28.2% for the MLD based on disposable income with imputed rents.[16]

[16] Since decomposed factors of the LV do not sum up to the whole amount of the change in LV, we calculate the rate of contribution only for the MLD.

To figure out how age composition has changed, we calculate the share of households belonging to each age category, shown in Figure 16. It clearly shows an upward trend in the share of households with a head older than age 60. Thus, the composition effects shown in Figures 12(a) and 12(b) are attributable to population aging.[17]

The between effect also had a non-negligible positive effect on the rise in inequality during the 1990s. This indicates that the income dispersion across age groups increased. In order to see the income differential across age groups, we calculate the mean of income for each category of age, household type, and number of workers. Figures 17(a)-(c) show the mean of income of each category of age, household type, and number of workers, respectively. The between effect during the 1990s perhaps reflects the fact that, as can be seen in Figure 17(a), household income increased only for households with a head age 30s to 50s during the 1990s, which led to the rise in income differential across age categories. For the 2000s, the contribution of the composition effect is inconclusive. For initial income, the composition effect is positive, and it offsets the negative within effect. For disposable income, however, the composition effect has a sizable positive impact only for MLD of the disposable income without imputed rents, and it is even negative for the LV of the disposable income with imputed rents. The results appear to be inconsistent results perhaps because, as noted above, the amount of the change in inequality for the 2000s was relatively small for disposable income.

Figures 13(a) and 13(b) show the decomposition of the changes in the MLD and LV with respect to household type. The contribution of household type composition effect calculated based on the disposable income without imputed rents is 18.6% for the 1990s and 24.7% for the 2000s, while that calculated based on the disposable income with imputed rents is 18.0% for the

[17] The aging of the population leads to an increase in income inequality because income inequality is high among households with an elderly head in Japan. Income inequality among the elderly can be lower in countries with higher welfare and higher tax burden.

1990s and 40.0% for the 2000s. Thus, the magnitude of the contribution for the 1990s is smaller than that of the composition effect for the decomposition with respect to age.[18] To see how the composition of household type changed, let us take a look again at Figure 16. As can be seen from the charts in the second row, there are upward trends in the shares of households with fewer members (single and couple) and downward trends in the shares of households with more members (couple-with-children and three-generations). Since single and couple households contain more households with an older head and the variability of income is increasing in age, the increase in the share of the households with fewer members contributes to the rise in income inequality. Thus, the composition effect shown in Figures 13(a) and 13(b) can be interpreted as the effect of the nuclearization of households. The between effect was relatively small for the decomposition with respect to household type, perhaps because the mean of income of different household types shifted mostly in parallel, as shown in Figure 17(b).

The decompositions of the MLD and LV with respect to the number of workers are presented in Figures 14(a) and 14(b). The magnitude of composition effects of the number of workers is comparable to those of the decomposition with respect to age. The contribution of the change in the number of workers calculated based on the disposable income without imputed rents is 19.6% for the 1990s and 46.7% for the 2000s, while those calculated based on the disposable income with imputed rents are 16.7% for the 1990s and 51.2% for the 2000s. Figure 16 shows the share of households by the number of workers. As can be seen, the share of no-worker households increased, while the share of households with two or more workers decreased. This is perhaps because of the aging of the population and the nuclearization of households.

A distinguishing feature of the decomposition with respect to the number of workers is

[18] The contribution of the change in household composition during the 2000s is greater than that during the 1990s. This is merely because the total amount of the change in MLD and LV during the 2000s was small.

that the between effect has a sizable negative impact for the 2000s. This implies that the income gap between households with different numbers of workers shrank in the 2000s. In order to verify this hypothesis, we present the mean of income by the number of workers in Figure 17(c). It shows that the average income of households with no workers increased, perhaps because of the increase in pension beneficiaries among elderly households, while the average income of households with two or more workers declined. As a result, the income gap shrank, which resulted in the negative effects during the 2000s.

Figures 15(a) and 15(b) present the MLD and LV decomposition with respect to areas. Apparently, the composition and between effects have no effect on the rise in income inequality. Therefore, we can conclude that area of residence does not play an important role in explaining the rise in income inequality.

5.6 Income inequality by household characteristic

Within-effects can be interpreted as the part of the rise in income inequality not explained by the change in the composition of households nor the change in the differences in average income across household groups. Although within-effects do not inform us of why income inequality rose, we can at least figure out in which category the rise in income inequality occurred. Thus, we calculate the income inequality for each category of household characteristics.

Figures 18(a) to (d) present income inequality measures by age category. As previous studies such as Oshio (2010) pointed out, income distribution became unequal for the younger group and more equal for the oldest group, particularly after 2000. The rise in income inequality among younger households might be caused by the factors associated with the labor market, such as the collapse of traditional Japanese employment and wage system (e.g., Hamaaki et al., 2012). The decrease in income inequality among the oldest group is perhaps because of the increase in the share of pension beneficiaries.

Figure 19(a)-19(d). show income inequality measures by household types. Income inequality increased for most of the household types except for couple households. The level and upward trend of inequality among single-parent-and-children households are remarkable.

Figure 20(a)-20(b) presents income inequality measures by the number of workers. On a household income basis, income inequality rose throughout the 1990s and 2000s for all of the measures. On an equivalized income basis, on the other hand, changes in income inequality are modest for households with workers, while income inequality declined for households with no workers. This is perhaps because the share of poor households with no workers decreased because of the increase in the share of pension-beneficiary households.

Finally, we present income inequality measures by area in Figure 21(a)-21(b). Income inequality increased in both urban and rural areas, but the rates of increase seem slightly higher in urban areas than in rural areas.

5.7 Comparison with Hori et al. (2020)

We construct the sampling weights following the procedure employed by Hori et al. (2020). We apply the same weighting adjustment to the CSLC, while Hori et al. (2020) uses the NSFIE. If the gap between the income inequality measures calculated with the two data is partly attributable to the difference in the sample distributions, the gap is expected to shrink if the sample distribution is adjusted with a sampling weight created in the same manner. Thus let us compare the results obtained in this study and Hori et al. (2020)

As mentioned above, income inequality measures calculated using the CSLC data tend to be higher than those calculated using the NSFIE data if the data are weighted with the provided weights. We find that the gap between the Gini coefficients calculated using the CSLC and NSFIE data with the provided weights is 0.0485, while the gap shrinks to 0.0408 if adjusted with our original weights. The gap shrinks only slightly because even the income inequality measures calculated with the CSLC data tend to be higher if the weighting adjustment with our original weights is applied. This is partly because the CSLC undersamples single households.

The levels of income inequality measures calculated using the CSLC and NSFIE tend to be higher when weighting adjustments with our original weights are applied. However, the weighting adjustment with our original sampling weight does not have a significant change in the trend of the inequality measures. We also find that 31.6 to 57.4% of the change in inequality measures during the 1990s are attributable to the changes in the composition of households, which is comparable with the corresponding figures in Hori et al. (2020). For the changes in the income inequality measures during the 2000s, however, we draw different conclusions. Hori et al. (2020) found that approximately 20-30% of the change in the 2000s is attributable to the changes in the composition of households, while we find that more than 100% can be explained by the changes in the composition of households. This discrepancy is perhaps due to the fact that the amount of the change in the 2000s is small. Another difference that can cause this discrepancy is that we decompose the change from 2000 to 2009, while Hori et al. (2020) decompose the change from 1999 to 2009.

6 Conclusion

This study attempts to measure income inequality in Japan during the 1990s and 2000s with a precision greater than that of previous studies. We use the CSLC data to calculate four representative income inequality measures based on eight income definitions. To precisely measure the income inequality in Japan, we create sampling weights using the microdata from the Population Census.

We find that the level of income inequality measures becomes higher if we apply weighting adjustment using the Population-Census based weights. We confirmed previous studies' findings that there was an upward trend in income inequality in the 1990s. We also confirmed the finding of previous studies that the pattern of the change in income distribution was quite different for the 1990s and 2000s: the rise in income inequality during the 1990s was caused by the increase in the variability of income, while the rise in income inequality during the 2000s was caused by the increase of poorer households.

A comparison of the level and pace of increase in inequality measures across the eight income definitions revealed that the rise in income inequality is less pronounced for income definitions closer to the actual source of consumption. This is largely due to the redistributive mechanisms such as the tax and social security system. Moreover, we show that the upward trend in inequality measures and the effect of the aging of the population are less pronounced if we include the imputed rents because the majority of older households are homeowners. This indicates that omitting imputed rents can exaggerate the level and the upward trend in income inequality.

References

Hamaaki, J., Hori, M., Maeda, S., & Murata, K. (2012). Changes in the Japanese employment system in the two lost decades. *ILR Review*, 65(4), 810-846.

Hashimoto, H. (2011). Kongo no Kokumin Seikatsu Kisochousa no Arikata ni tsuite no Ichikousatsu (Dai 3 pou). *Kousei no Shihyou*, 58(4), 33-39

Hori, M., Maeda, S., & Suga, F. (2020). In Search of Accurate Measures of Income Inequality across Japanese Households. *ESRI Discussion Paper Series*, 358.

Kalton, G., & Flores-Cervantes, I. (2003). Weighting methods. *Journal of official statistics*, 19(2), 81.

Kish, L. (1992). Weighting for unequal Pi. *Journal of Official Statistics*, 8(2), 183.

Kitao S. and Yamada T. (2019). Dimensions of Inequality in Japan: Distributions of Earnings, Income and Wealth between 1984 and 2014. *RIETI Discussion Paper Series* (2019-034).

Larrimore, J., Burkhauser, R. V., Auten, G., & Armour, P. (2021). Recent trends in U.S. income distributions in tax record data using more comprehensive measures of income including real accrued capital gains. *Journal of Political Economy*, 129(5), 1319-1360.

Lise, J., Sudo, N., Suzuki, M., Yamada, K., & Yamada, T. (2014). Wage, income and consumption inequality in Japan, 1981–2008: from boom to lost decades. *Review of Economic Dynamics*, 17 (4), 582-612.

Mookherjee, D., & Shorrocks, A. (1982). A decomposition analysis of the trend in U.K. income inequality. *The Economic Journal*, 92(368), 886-902.

Naoi, M. & Yamamoto, K. (2010). Nihon Kakei Panel Chousa no Hyouhon Sekkei to Daihyousei (Sample Design of JHPS and Its Representativeness). *Joint Research Center for Panel Studies Discussion Paper Series*.

Ohtake, F. (2005). *Nihon no Fubyoudou (Inequality in Japan)*. Nihon Keizai Shinbun sha, Tokyo (in Japanese).

Ohtake, F., & Saito, M. (1998). Population aging and consumption inequality in Japan. *Review of Income and Wealth*, 44(3), 361-381.

Oshio, T. (2010) *Saibunpai no Kousei Bunseki (Welfare Analysis of Redistribution)*. Nihon Hyouron Sha, Tokyo (in Japanese).

Oshio, T., Tajika, E., & Fukawa, T. (2006) *Nihon no Shotoku Bunpai (Income Redistribution in Japan).* The University of Tokyo Press (in Japanese)

Piketty, T. (2014). *Capital in the Twenty-First Century*, Cambridge Massachusetts: Belknap Press

Sano, S., Tada, S. & Yamamoto, M. (2015). Setai Chousa no Houhou to Chousa Setai no Seishitsu – Setai Kousei, Nenrei, Gakureki ni kansuru Hikaku– (Methods of Househould Survey and the Characteristics of the Households –Comparison of Family Composition, Age, and Educational Attainment), *Financial Review*, (122), 4-24.

Tachibanaki, T. (1998). *Nihon no Keizai Kakusa: Shotoku to Shisan kara Kangaeru (Economic Inequality in Japan: Consideration from the Viewpoint of Income and Assets)*. Tokyo: Iwanami Shinsho.

Table 1: Summary statistics (CSLC)

	Comprehensive Survey of Living Conditions							
	1988	**1991**	**1994**	**1998**	**2000**	**2003**	**2006**	**2009**
Number of households	36,009	34,073	31,487	28,509	28,298	23,365	21,663	24,271
Age of household head (mean)	48.4	49.2	50.1	51.5	53.0	54.5	55.5	56.5
	(14.1)	(14.3)	(14.8)	(15.1)	(15.4)	(15.7)	(16.1)	(16.1)
Number of family members (mean)	3.4	3.3	3.1	3.0	3.0	2.9	2.8	2.7
	(1.6)	(1.6)	(1.6)	(1.5)	(1.6)	(1. 5)	(1.5)	(1.4)
Household pre-tax income (mean)	600.8	638.4	657.6	644.4	609.0	591.9	580.9	562.6
	(511.9)	(550.8)	(567.6)	(562.9)	(541.8)	(468.3)	(495.3)	(488.1)
Household disposable income (mean)	499.5	524.4	537.4	528.0	502.2	493.4	465.4	455.2
	(378.0)	(373.9)	(414.7)	(409.7)	(404.9)	(370.4)	(383.3)	(384.4)
Equivalized pre-tax income (mean)	332.3	359.9	376.9	374.9	358.5	349.8	351.7	347.1
	(283.6)	(300.6)	(312.8)	(311.5)	(302.8)	(359.6)	(281.0)	(278.8)
Equivalised disposable income (mean)	276.0	295.5	307.2	306.9	295.6	291.5	281.6	280.8
	(204.8)	(197.3)	(223.7)	(222.2)	(222.6)	(202.4)	(215.7)	(216.6)

Notes: Figures in parentheses are standard deviations.
Equivalized income here is defined as income divided by the square root of the number of family members.

Table 2: Summary statistics (Population Census)

	(A) *Population Census*			(B) *Comprehensive Survey of Living Conditions*					
				(B-1) Raw data			(B-2) Adjusted data		
	1990	**2000**	**2010**	**1988**	**2000**	**2009**	**1988**	**2000**	**2009**
Number of households	39,283,207	45,046,024	48,886,982	36,099	28,298	24,271			
Average number of family members	3.0	2.7	2.5	3.4	3.0	2.7	3.4	3.0	2.7
	(1.6)	(1.5)	(1.4)	(1.6)	(1.6)	(1.4)	(1.6)	(1.5)	(1.4)
Mean of age of household head	49.1	52.0	55.1	48.4	53.4	56.7	48.4	53.0	56.5
	(15.1)	(16.3)	(17.1)	(14.0)	(15.5)	(16.1)	(14.0)	(15.5)	(16.2)
Share of self-employed households	15.6%	12.2%	8.7%	16.9%	13.0%	9.8%	16.9%	12.7%	9.6%
Share of jobless households	12.1%	20.2%	28.5%	11.2%	18.9%	24.9%	11.1%	18.4%	25.0%
Share of elderly households (age > 60)	23.9%	32.1%	41.4%	18.7%	30.9%	41.1%	18.6%	30.2%	41.0%
Share of single households	20.9%	25.5%	29.2%	11.7%	17.7%	20.1%	11.8%	17.7%	20.6%
Share of home-owner households	61.0%	61.7%	63.9%	71.4%	72.0%	74.1%	70.8%	69.8%	72.4%
Share of nuclear family households among two-or-more-person households	49.6%	50.5%	53.3%	49.3%	48.9%	52.9%	49.6%	50.3%	54.1%
Share of dual-income households among nuclear family households	41.6%	41.8%	45.9%	39.0%	52.0%	54.1%	38.9%	49.7%	52.5%

Notes: 1. Figures in parentheses are standard deviations.
2. The "Adjusted data" in the columns on the right show the sample statistics of the adjusted data using the sampling weights officially provided by the Ministry of Health, Labour and Welfare for the CSLC micro data.
3. Nuclear family households in the denominator here are limited to households with household heads aged 60 years or younger.

Table 3(a): Inverse of the adjustment factors *($1/w_{j,t} \equiv \hat{s}_{j,t}/s_{j,t}$)* by weighting cell :

Single-person households in the raw 2009 CSLC data

<table>
<tr><th colspan="3" rowspan="2">CSLC 2009</th><th colspan="3">Renter</th><th colspan="3">Home-owner</th></tr>
<tr><th>-40</th><th>41-60</th><th>61-</th><th>-40</th><th>41-60</th><th>61-</th></tr>
<tr><td rowspan="14">Single male</td><td rowspan="7">No worker</td><td>Designated cities</td><td colspan="2" rowspan="7">0.0745</td><td rowspan="5">0.5758</td><td colspan="2" rowspan="7">0.2096</td><td rowspan="2">0.8886</td></tr>
<tr><td>Tokyo 23 wards</td></tr>
<tr><td>Other cities in Area 1</td><td rowspan="3">1.0839</td></tr>
<tr><td>Other cities in Area 2</td></tr>
<tr><td>Other cities in Area 3</td></tr>
<tr><td>Other cities in Area 4</td><td rowspan="2">1.0219</td><td rowspan="2">1.4083</td></tr>
<tr><td>Other cities in Area 5</td></tr>
<tr><td rowspan="7">One worker</td><td>Designated cities</td><td rowspan="2">0.2586</td><td rowspan="2">0.5650</td><td rowspan="7">0.8564</td><td rowspan="2">0.1991</td><td>0.5372</td><td rowspan="2">0.5802</td></tr>
<tr><td>Tokyo 23 wards</td><td>1.1007</td></tr>
<tr><td>Other cities in Area 1</td><td>0.2510</td><td>0.4597</td><td rowspan="3">0.5597</td><td>0.6598</td><td rowspan="3">1.7448</td></tr>
<tr><td>Other cities in Area 2</td><td>0.4113</td><td>0.5750</td><td>1.0609</td></tr>
<tr><td>Other cities in Area 3</td><td>0.2824</td><td>0.4390</td><td>0.7903</td></tr>
<tr><td>Other cities in Area 4</td><td>0.4235</td><td>0.9893</td><td rowspan="2">1.0052</td><td>0.9719</td><td rowspan="2">2.1024</td></tr>
<tr><td>Other cities in Area 5</td><td>0.4746</td><td>1.4201</td><td>1.8322</td></tr>
<tr><td rowspan="14">Single female</td><td rowspan="7">No worker</td><td>Designated cities</td><td colspan="2" rowspan="7">0.1174</td><td rowspan="2">0.7442</td><td colspan="2" rowspan="5">0.3405</td><td rowspan="2">0.7771</td></tr>
<tr><td>Tokyo 23 wards</td></tr>
<tr><td>Other cities in Area 1</td><td rowspan="3">0.7768</td><td rowspan="3">1.1841</td></tr>
<tr><td>Other cities in Area 2</td></tr>
<tr><td>Other cities in Area 3</td></tr>
<tr><td>Other cities in Area 4</td><td rowspan="2">1.3438</td><td colspan="2" rowspan="2">0.7638</td><td rowspan="2">1.6847</td></tr>
<tr><td>Other cities in Area 5</td></tr>
<tr><td rowspan="7">One worker</td><td>Designated cities</td><td rowspan="2">0.3130</td><td>0.8625</td><td rowspan="7">1.1377</td><td rowspan="7">0.3086</td><td>0.6134</td><td rowspan="2">0.6377</td></tr>
<tr><td>Tokyo 23 wards</td><td>0.4450</td><td>0.4676</td></tr>
<tr><td>Other cities in Area 1</td><td>0.3315</td><td rowspan="3">0.8312</td><td>0.8242</td><td rowspan="3">1.3002</td></tr>
<tr><td>Other cities in Area 2</td><td>0.6802</td><td>1.0650</td></tr>
<tr><td>Other cities in Area 3</td><td>0.2273</td><td>1.1705</td></tr>
<tr><td>Other cities in Area 4</td><td>1.1256</td><td rowspan="2">1.1749</td><td>0.9265</td><td rowspan="2">2.1544</td></tr>
<tr><td>Other cities in Area 5</td><td>0.5929</td><td>1.5631</td></tr>
</table>