

ESRI Discussion Paper Series No.358

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December 2020



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Cabinet Office
Tokyo, Japan

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In Search of Accurate Measures of Income Inequality across Japanese Households[†]

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August 2020

Abstract

Using microdata from the *National Survey on Family Income and Expenditure* (NSFIE), this study tries to provide new accurate measures of income inequality across households in Japan from 1990s to 2000s. In order to correct for potential biases in conventional measures, we use microdata from the *Population Census* to construct original sampling weights. We calculate multiple income inequality measures, such as the Gini coefficient, the relative poverty rate, the mean log deviation (MLD) of income, and the log variance (LV) of income, with our original sampling weights and find that actual income inequality across Japanese households likely is larger than suggested in earlier studies. Further, while our new estimates confirm the findings of previous studies that income inequality increased throughout the 1990s and 2000s, the rate of increase for disposable income was quite moderate due to the redistributive effects of the tax and social security system. We also find that approximately 40-50% of the increase in income inequality in the 1990s, and 30-40% of the increase in the 2000s, resulted from changes in household compositions, such as a decrease in the number of family members living together and increases in the shares of jobless households and dual-income households.

Keywords: income distribution, inequality, sampling weight adjustment

JEL classifications: D31, N35, C83

[†]This paper forms part of our microdata-based research at the Economic and Social Research Institute (ESRI) on household consumption, labor supply, and macroeconomic policies in Japan. We are grateful to Professor Tomoaki Yamada for his valuable comments on an earlier version of this paper. We would also like to thank Junya Hamaaki, Keiko Murata, Koichiro Iwamoto, and other ESRI colleagues for their support, and Ralph Paprzycki for his English editing service. Special thanks go to the Statistics Bureau of Japan for providing us with the microdata from the *National Survey on Family Income and Expenditure* (NSFIE) and the *Population Census*. The views expressed in this paper are those of the authors and do not represent those of the institutions to which the authors belong.

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1. Introduction

As more and more economies around the world mature and growth slows, there has been a growing interest in inequality within countries. A key example of this is Thomas Piketty's best-selling book *Capital in the Twenty-First Century* (2014), which provoked wide-ranging discussions about the relationship between economic growth and inequality. Macroeconomic policies can have a substantial impact not only on economic growth but also on how the fruits of such growth are distributed. Japan is no exception: with the slowdown in economic growth, concern amongst the populace about economic inequality has mounted, and both policy-makers and economists have a keen interest in grasping the extent of economic inequality in Japan and understanding the mechanisms underlying changes in inequality.

Against this background, the aim of this study is to present new and more accurate measures of the distribution of income across households in Japan using microdata from the *National Survey of Family Income and Expenditure* (NSFIE) and the *Population Census* to provide an overview of how and why income inequality changed in Japan during the two lost decades from 1990 to 2010.

Until the 1990s, it was generally thought that Japanese society was relatively equal. Much of the research published before the 1990s, such as Ishizaki (1983) and Mizoguchi and Takayama (1984), showed that the distribution of income across households in Japan was comparatively equal during the period of high-speed growth until the early 1970s. However, the notion that Japanese society was relatively equal started to be questioned with the end of relatively high growth in the early 1990s. For example, Tachibanaki (1998) challenged the conventional notion, arguing that there had been a dramatic increase in income inequality in Japan, and that Japan's income inequality could be relatively high among OECD countries. Ohtake (2005), however, pointed out that Tachibanaki (1998) overestimated income inequality in Japan because

of the misleading definition of income used in the study. He then went on to show that inequality nevertheless followed an upward trend and argued that this was largely due to population aging. Tachibanaki (2006) and Oshio (2010) subsequently showed that the growing income inequality was due not only to the effects of population aging but also to the rise in within-age-group income inequality.

More recently, following Krueger et al. (2010), who examined the distribution of income in developed countries from the 1980s to the 2000s from a macroeconomic perspective and found that most developed countries were experiencing a rise in income inequality, Lise et al. (2014) provide a comprehensive study of inequality in wages, income, consumption, and assets in Japan. While the empirical findings obtained by Lise et al. (2014) appear consistent with the findings of earlier studies reporting a rise in inequality, they cannot be regarded as sufficiently comprehensive to identify the factors underlying the widening disparities in Japan, since households over the age of 60 are not included in the sample used for their analysis. The most recent study on the subject is that by Kitao and Yamada (2019), who examine the distribution of income in Japan over the past three decades using the entire sample of households in the NSFIE and show that the rise in inequality in Japan is attributable to changes in the composition of households, such as the aging of household heads, decrease in household sizes, and the increase in dual-income households.

Given the dramatic changes in demographic structure and household composition in Japan in recent years and the fact that measures of inequality likely are significantly affected by these changes, it is essential that the distribution of the sample data used for analysis accurately represents the actual distribution of households in Japan overall. To ensure the sample distribution reflects the population distribution, earlier studies using NSFIE microdata typically employed the official sampling weights provided by the Statistics Bureau, Ministry of Internal Affairs and Communications. However, as we will demonstrate in Section 3.1 below, the sample distribution

of the NSFIE does not match the population distribution well in some critical respects even after the sampling ratios are adjusted using the officially provided sampling weights.

For this reason, we use the microdata from the *Population Census* to construct our own original sampling weights (or adjustment factors) to adjust the distribution of the sample data, so that it accurately represents the actual distribution of households in Japan. Using our original sampling weights, we calculate various measures of income inequality, such as the Gini coefficient, the relative poverty rate, the log variance (LV), and mean log deviation (MLD) of income, and find that income inequality across households in Japan is larger than suggested by earlier studies using the officially provided sampling weights. It has been argued that inequality estimates using NSFIE microdata tend to suggest a lower degree of inequality than estimates using the *Comprehensive Survey of Living Condition* (CSLC), another microdata source that has frequently been used in attempts to measure income inequality across households in Japan. It could be said that the new sampling weights constructed in this paper bridge the gap between the inequality measures calculated using the two different data sources.

On the other hand, our results indicate that the increasing trend in inequality reported in the previous studies continues to be observed when we use our own sampling weights. Moreover, we find that the pace of increase in income inequality is quite moderate when we use a concept of income that can be regarded to more closely represent individuals' utility ([standard of living/well-being]), reflecting the redistributive effects of Japan's tax and social security system. We also find that changes in household composition explain 41–50% of the rise of income inequality measures (for the equivalized disposable incomes) during the 1990s and 27–43% during the 2000s. Among other things, these results suggest that the contribution of the decrease in the size of households and the increase in the number of dual-income households is more pronounced than in earlier studies, probably because our dataset more accurately reflects these

changes in the demographic structure and composition of households.

The remainder of this study is organized as follows. Chapter 2 provides an overview of the two data sources used in this study. Chapter 3 presents our empirical methodology. It starts by explaining the need for weighting adjustments and our approach for creating sampling weights. It then defines our inequality measures and finally describes our method for decomposing changes in inequality into contributing factors. Chapter 4 presents the results of our calculations of four income inequality measures and then identifies the factors responsible for the increases in income inequality across households. Chapter 5 concludes.

2. Data Sources

This study tries to understand income inequality across households in Japan by taking advantage of microdata from two fundamental statistical surveys, the *National Survey of Family Income and Expenditures* (NSFIE) and the *Population Census*, both conducted by the Ministry of Internal Affairs and Communications.

2.1 National Survey of Family Income and Expenditures (NSFIE)

To study the extent of income distribution across households in Japan, we use the microdata from the NSFIE, which is a fundamental statistical survey of the Japanese government and one of the most widely used nationally representative surveys on households' income, consumption, and asset holdings in Japan. Around 50,000 households with two or more persons and around 5,000 single-person households are surveyed every five years. In order to grasp changes in the income distribution in 10-year intervals, we use data from three waves of the NSFIE (1989, 1999, and 2009).

Sample households of the NSFIE are selected in the following manner. First, after sample

cities, towns, and villages have been selected,¹ the survey districts (or unit areas) are randomly chosen from the selected cities, towns, and villages. Then, survey respondent households are randomly drawn from the survey districts. Those in hospital or other institutions or living in a dormitory are not surveyed. Similarly, households headed by a foreigner or a single student and those living with four or more live-in employees are excluded from the survey.

An important feature of the sampling scheme of the NSFIE is that if the target household does not respond to the survey, another household in the same survey district is surveyed in place of the non-responding household. This sampling scheme is quite different from that of the *Comprehensive Survey of Living Conditions (CSLC)*, which is also a fundamental statistical survey often utilized to examine income inequality in Japan. Sample households of the CSLC are selected through one-stage cluster sampling, where survey districts are randomly selected and all households in the survey districts are subject of the survey. Therefore, unlike in the case of the NSFIE, a household that refuses to respond to the CSLC cannot be supplemented by another household in the same survey district. As pointed out by Sano et al. (2015), this can lead to non-negligible differences between the statistics obtained from the NSFIE and those obtained from the CSLC.

The fact that non-responding households in the CSLC cannot be supplemented leads to differences in the extraction rate across survey districts. One might therefore expect the NSFIE sample to be more representative than the CSLC sample. However, earlier studies such as Hashimoto (2011) highlight that the CSLC is better able to capture non-standard households such as poor single households receiving social welfare services than the NSFIE, since enumerators for the CSLC work at public health and welfare offices or public health centers. Therefore, it is not necessarily clear which of the two government statistics, the NSFIE or the CSLC, should be used to

¹ To be precise, all cities are surveyed, but for towns and villages, only some are randomly selected for the survey.

obtain an accurate picture of income inequality in Japan.

Table 1 presents summary statistics of the raw NSFIE samples for the three survey years we are interested in. As can be easily seen, the NSFIE samples clearly reflect the aging of the population and shrinking of household sizes. Turning to income variables, while household income increased from 1989 to 1999, it shows a sharp contraction between 1999 and 2009.² This pattern – an increase between 1989 and 1999 and a decrease between 1999 and 2009 – can be observed both for before- and after-tax disposable income. Moreover, both before- and after-tax income in 2009 were lower than in 1989. One possible reason for the decline in household incomes is the shrinking size of households due to the trend toward single-person and nuclear family households. To control for the effect of changes in household size, we therefore calculate equivalized household incomes, that is, household income divided by the square root of the number of household members. However, we still find a sharp fall from 1999 to 2009, although on an equivalized basis household incomes in 2009 were larger than those in 1989.

2.2 *Population Census*

The *Population Census* is an exhaustive survey that covers all households in Japan. Therefore, the household distribution of the *Population Census* data can be regarded as the true distribution of households in Japan. Unfortunately, we cannot calculate income inequality measures using data from the *Population Census*, since it does not contain information about household incomes. The *Population Census* does, however, provide several variables on household characteristics that are also available in the NSFIE. We can therefore use these characteristics to define household groups in the *Population Census* and NSFIE. Using the share of each population group in the *Population Census* as the true household distribution, we can create sampling weights (adjustment factors)

² To remove the effects of price changes, income variables are deflated by the 2009 base year consumer price index (CPI).

that make the distribution of the NSFIE household sample consistent with the true household distribution in Japan. We provide an outline of how we create the sampling weights from the NSFIE data in the following section.

Before using the *Population Census* data to represent the population for the NSFIE sample, we apply the sample selection criteria of the NSFIE and exclude those that are hospitalized or live in a dormitory, households headed by a foreigner, etc. We then choose several household characteristics obtainable from both the *Population Census* and the NSFIE and define household groups based on combinations of the selected characteristics. Finally, we calculate the share of each household group in each of the two surveys and calculate the ratios between the two shares, which we use as the sampling weights for households in each of the household groups in the empirical analysis.

Part (A) of Table 2 presents summary statistics of the *Population Census*. As mentioned, the *Population Census* covers all households in Japan. As can be seen, the number of households increased from around 40 million in 1990 to around 50 million in 2010, even though population growth came to a halt during this period. Reflecting the aging of the population, the average age of the household head rose from 48 years in 1990 to slightly less than 55 years in 2010. The shares of elderly households, jobless households, and single-person households substantially increased. On the other hand, the share of homeowner households remained more or less unchanged at around 60%. Finally, other notable trends are the increasing share of nuclear family households among two-or-more-person households and the increasing share of dual-income households among nuclear family households.

Next, Part (B) of Table 2 shows summary statistics of the NSFIE sample presented in a manner comparable with those calculated from the *Population Census* shown in Part A. Section (B-1) shows summary statistics for the raw NSFIE data, while Section (B-2) presents those for

the NSFIE data adjusted using the officially provided sampling weights. Section (B-1) indicates that there are clear sample biases in the NSFIE raw data. Roughly speaking, large family households and homeowner households are overrepresented in the NSFIE samples, while single-person and jobless households are underrepresented. Section (B-2) suggests that some of the biases, including those observed in the number of family members and in the share of single-person households, are corrected through the weighting adjustments using the officially provided weights. However, other biases such as in the shares of nuclear family households, dual-income households, and homeowner households, remain even after the adjustments using the officially provided weights.

3. Empirical Methodology

3.1 Motivation for creating our own sampling weights

The cursory analysis in the previous section suggests that the officially provided sampling ratios fail to adequately adjust for sample biases in the NSFIE. This means that any measures of inequality in Japan will also be biased. Therefore, in order to correctly measure inequality in Japan using the NSFIE, it is necessary to construct sampling weights that adequately reflect the population of households in Japan. Against this background, this section presents a more detailed assessment of the officially provided sampling weights and explains our strategy for creating our own sampling weights.

To assess the effectiveness of the sample adjustment using the officially provided sampling weights, we proceed as follows. We calculate the shares of households in our NSFIE sample by age category and household type (in terms of household composition) with and without the adjustment based on the official weights and compare them with the actual shares calculated from the *Population Census*. Figure 1(a) shows the household shares by household heads' age

category. Since the provided weights correct for differences in extraction rates across the age categories, the share of each age category (observed in the NSFIE sample) gets closer to the actual household share observed in the *Population Census* after the adjustment. On the other hand, Figure 1(b), which examines the shares of households by household type, reveals that the provided sampling weights fail to correct for differences in extraction rates across household types. While the adjustment based on the provided sampling weights successfully corrects for the difference in extraction rates between one-person and two-or-more-person households, it fails to correct for differences in extraction rates across household types among two-or-more-person households. However, to correctly measure income inequality in Japan, it is necessary to accurately capture changes in the demographic structure and composition of households and correct for differences in extraction rates across different types of two-or-more-person households, i.e., households with and without children, three generation households, and so on.

We therefore construct new sampling weights using the distribution of households in the *Population Census* to correct for possible differences in extraction rates across household groups with various characteristics. Of course, if sample extraction rates are identical across all household groups, sample adjustment would not be necessary. Unfortunately, however, extraction rates differ substantially across household groups with different characteristics, as can be seen from Figure 1.

The basic idea of making adjustments using weights is to correct for such differences in extraction rates to ensure that the sample distribution reflects the population distribution and respondents represent the total population, including non-respondents. For example, if the share of single male households in the population is 4%, but the corresponding share of households in the sample is only 2%, sampling weights are used so that single male households responding to the survey are counted twice when calculating sample statistics such as average income or some

income inequality measures as estimates of population parameters.

An implicit assumption underlying such an adjustment is that responding households and non-responding households in a particular household group are so similarly distributed that we can regard responding households as representing not only respondents but also non-respondents in the same household group. However, even when we focus on single-person male households only, reality unfortunately is not that simple. For instance, response rates likely depend on the age of the household head, and younger single males are less likely to respond to the survey than older ones. This means that the share of retirees among single-person male households in the sample is likely to be higher than in the population overall. And since retirees living off their pension tend to have a lower income than working-age single males, the average income of respondents, for example, will be lower than that of non-respondents, meaning that the sample will understate the average income of single-person male households.

These considerations suggest that, in order for household groups in the sample to be representative, they should be as homogeneous as possible. The most straightforward way to make households within a group as homogeneous as possible is to define household groups based on multiple household characteristics. We therefore define detailed household groups based on a number of characteristics and assign the same weight to households belonging to the same household group. We will refer to these detailed household groups and weights as "weighting cells. For instance, if we define weighting cells based on age and household type categories, we can assign a smaller weight to older male single-person households and a larger weight to younger male single-person households. Variables such as age and household type categories used for the detailed definition of weighting cells are called "auxiliary variables," and the more auxiliary variables we employ to define the weighting cells, the more homogeneous are households within a cell likely to be and hence the more representative are respondents within the cell likely to be.

The auxiliary variables used to define the sampling weights officially provided with the NSFIE data consist only of age, the distinction between single-person and two-or-more-person households, and the area where respondents live. However, it is possible to employ a larger number of auxiliary variables on the basis of information available in both the *Population Census* and the NSFIE. For example, we can use household composition variables such as the number of workers in the households and the homeownership status of households. Setting the weighting cells ourselves based on arbitrarily selected auxiliary variables allows us to take advantage of the rich information available in the *Population Census* and the NSFIE to make sample households within each weighting cell as homogeneous as possible. However, as pointed out in some earlier studies (e.g., Kalton and Flores-Cervantes, 2003), there is also a disadvantage to finely defining weighting cells based on a large number of auxiliary variables. If weighting cells are defined too finely, there is a higher probability that the number of observations in some weighting cells is zero. In that case, no-observation cells have to be merged with neighboring weighting cells and the selection of cells to be combined becomes arbitrary and lacks generality. Furthermore, even if all cells with zero observations can be eliminated, there can still be cells with a small number of observations that are assigned a much larger weight than other cells. It is known that the existence of such cells often leads to larger variance of the calculated sample statistics, such as the mean of a selected variable or some inequality measures.

Bearing these considerations in mind, in the following section we explain how we construct our original sampling weights to correct for the bias in the sample data while avoiding an unnecessary increase in the variance of sample statistics.

3.2 Method for creating sampling weights

We employ the so-called “cell weighting” method to create our sampling weights (adjustment

factors).³ Let $s_{j,t}$ denote the share of households belonging to weighting cell j , which is defined based on a combination of variables representing household characteristics, in total households in Japan at time t . If response rates do not differ across weighting cells, the sample share of households in a weighting cell in total sample households in the NSFIE will be $s_{j,t}$ and we do not need to use sampling weights to make the sample data representative. However, in practice, response rates might differ across weighting cells, and there may be over- or undersampled household groups in the sample dataset.

Let $\hat{s}_{j,t}$ denote the sample share of households in weighting cell j at time t in the total sample households in the NSFIE data. We define the adjustment factor for households in weighting cell j at time t as follows:

$$w_{j,t} \equiv \frac{s_{j,t}}{\hat{s}_{j,t}} \quad (1)$$

Households belonging to the same weighting cell j will be given the same weight, $w_{j,t}$. An implicit assumption behind this cell weighting adjustment is that the probability that households are included in the sample (i.e., respond to the survey) is identical for all households with the characteristics corresponding to a particular weighting cell. Therefore, it is important to define weighting cells in a way that ensures that households within a weighting cell are as homogeneous as possible.

We define weighting cells using five auxiliary category variables: age of household head (under 40, 40–59, 60 or over), household type (single male, single female, couple, single parent with child(ren), parents with child(ren), three generations, and other), number of (full-time) workers (zero, one, and two or more), area of residence (23 special wards of Tokyo, designated cities,⁴ other municipalities in Area 1, other municipalities in Area 2, other municipalities in Area

³ Kalton and Flores-Cervantes (2003) review several alternative weighting methods to make weighted sample estimates conform to the population parameters.

⁴ In Japan, a designated city, also known as a government ordinance city, is a city that has a population greater than 500,000 and has been designated as such by order of the cabinet.

3, and other municipalities in Area 4⁵), and homeownership (“renters”, “small homeowners”, and “large homeowners”). This means that, in theory, there are a total of 1,512 ($=3 \times 8 \times 3 \times 7 \times 3$) weighting cells. However, if we define cells in this manner, we end up with at least several weighting cells that do not contain any observations. Moreover, as mentioned, using more finely defined weighting cells with only a small number of observations tends to result in larger variances in the weights and weighted estimates. We therefore decided to collapse cells with insufficient numbers of observations by merging them with their neighboring cells.

In order to avoid collapsing cells arbitrarily, we use the following variance inflation factor F proposed by Kish (1992):

$$F = 1 + cv^2 \quad (2),$$

where cv is the coefficient of variation of sampling weight $w_{j,t}$. Inflation factor F measures the ratio of the increase in the variance (of the mean of a selected variable) due to the adjustment (or weighting). That is, the variance of the mean of a variable becomes F times larger if weighting adjustment is applied. We use this inflation factor F to take the variance inflation effect of sample adjustment into account when we create our original sampling weights.

More concretely, we merge cells with insufficient numbers of observations with their neighboring cells in the following manner. We start by merging cells with no observations with the neighboring cell in the area of residence category. If the neighboring cell in the area of residence category has no observations, we merge the cell with the neighboring cell in the age category.⁶ After we have collapsed all cells with no observations, we calculate the inflation factor F . As mentioned above, inflation factor F represents the extent to which the variance increases

⁵ Area 1 is composed of prefectures in Tohoku and Hokkaido, Area 2 is composed of those in Kanto, Area 3 is composed of those in Kinki and Chubu, and Area 4 is composed of those in Chugoku, Shikoku, and Kyushu.

⁶ There are several exceptions. For example, the age of the household head is not important for three-generation households. We therefore merge no-observation cells in the three-generations category with the neighboring cell in the area category. Details of our merging procedure are provided in Appendix A.

due to the use of the sampling weights. Kalton and Maligalig (1991) found that the inflation factor F depends heavily on the maximum of the sampling weights. We therefore merge the cell with the largest sampling weight with the neighboring cell, following the same steps that we took to merge cells with no observations. We repeat this procedure of collapsing the weighting cells until the value of the calculated inflation factor F becomes smaller than the inflation factor calculated with the officially provided sampling weights.

Table 3 shows the final weighting cells that we end up with following the described procedure and the inverse of the sampling weight ($1/w_{i,t}$) for each weighting cell i calculated based on the NSFIE raw data (without sampling ratio adjustments) for 2009.⁷ Specifically, Table 3(a) is for single-person households, while Table 3(b) is for two-or-more-person households. The number in each cell is derived as the inverse of equation (1), $\hat{s}_{i,t}/s_{i,t}$, where $\hat{s}_{i,t}$ denotes the sample share of weighting cell i at time t calculated from the NSFIE data, while $s_{i,t}$ is the population share of the same weighting cell calculated from the *Population Census* data. If the figure shown in a weighting cell exceeds one and the cell is shaded in a reddish color, this means that households in the weighting cell are over-sampled. In contrast, if the figure in the weighting cell is less than one and the cell is shaded in a blue color, households in the weighting cell are undersampled. As can be seen in Table 3(a), single households, particularly those consisting of a young male, tend to be undersampled. Turning to two-or-more-person households, shown in Table 3(b), we find that couples with children tend to be over-sampled. Moreover, homeowner households appear to be over-sampled, while renters are undersampled. This is perhaps because renters likely live in an apartment, and those living in an apartment tend not to respond to the survey. Furthermore, households living in the 23 Tokyo wards and the designated cities are under-sampled because of the survey design of the NSFIE.

⁷ The tables for 1989 and 1999 are reported in Appendix B.

Next, Table 4 presents $\hat{s}_{i,t}/s_{i,t}$ for each weighting cell i calculated based on the NSFIE data after sampling ratio adjustments with the officially provided sampling weights. Again, Table 4(a) is for single-person households, while Table 4(b) is for two-or-more-person households. These tables, which contain many red and blue cells, indicate that sampling ratio adjustments using the provided sampling weights do not always yield satisfactory outcomes (if the adjustment is successful, all the ratios (\hat{s}_{it}/s_{it}) should be close to one and there should be no colored cells). Comparing Table 4(a) with Table 3(a) indicates that the official adjustment weights compensate for the undersampling of single-person households and correct for the disproportionality in the sample distribution across areas of residence. However, there remains considerable disproportionality in the sample distribution even after the adjustment with the official sampling weights, since important household characteristics other than age, gender, household type (single-person vs. two-or-more-person), and area of residence are not used.

To check how effectively our sampling weights correct for the disproportionality in the sample distribution, we calculate the ratio $\hat{s}_{j,t}/s_{j,t}$ for each category j at time t , where $\hat{s}_{j,t}$ is the share of category j in the sample at time t and $s_{j,t}$ is the share of category j in the population at time t . Each row in Figure 2 shows the ratio for each category of each auxiliary variable, that is, age of household head, household type, number of (full-time) workers, area of residence, and homeownership. The charts in the left column show the ratios calculated based on the NSFIE data without weighting adjustments; the charts in the middle column show the ratios calculated based on the NSFIE data adjusted with the officially provided sampling weights; and the figures in the right column show the ratios calculated based on the NSFIE data adjusted using our *Population Census*-based sampling weights.

If the sampling weights worked perfectly, the ratios based on the adjusted NSFIE data, i.e., those in the middle and right columns, should equal one. As can be seen in Figure 2, however,

the ratios often deviate from one even after the sampling ratio adjustments. In the case of the adjustments with the officially provided sampling weights reported in the center column, the adjustments appear to have had the intended effect only with regard to the distribution of areas of residence, which is reported in the fourth row. For the other variables, especially in the case of household types, the adjustment is far from satisfactory. In comparison, the sampling weights we constructed in this study have the intended effect with regard to four out of the five variables, as can be seen in the right column. Only the result with regard to the area of residence looks inferior to that reported in the center column (with the officially provided sampling weights), as we had to merge the 23 Tokyo wards category with the designated cities category in our procedure of merging cells with no observations and with extremely high sampling weights, i.e., w_{it} , with their neighboring cells. Therefore, while the weighting adjustment is not perfect, our original sampling weights appear to be successful in making the sample distribution conform more closely to the population distribution.⁸

3.3 *Definition of income*

Previous studies such as Ohtake (2005) showed that income inequality measures are sensitive to the definition of income. Moreover, those studies also showed that presenting income inequality measures based on a variety of income definitions is important for evaluating the role of tax and social security systems in reducing inequality. We therefore examine inequality with regard to each of the following four income definitions: (i) initial income, (ii) pre-tax income, (iii) disposable income, and (iv) disposable income with imputed rent. Initial income is defined as pre-tax income including neither pension income nor social security benefits; pre-tax income is

⁸ In order to evaluate the effectiveness of weighting adjustment, we calculate the share of self-employed households. Since job type is not used as an auxiliary variable, we can check the external validity of the weighting adjustment. Figure B2 in Appendix B shows the result. As can be seen, unfortunately, the provided weights perform better for 1989 and 1999.

income before taxes but including pension income and social security benefits; disposable income is after-tax income including pension income and social security benefits;⁹ and disposable income with imputed rent is after-tax income including pension income and social security benefits plus imputed rent.

The fourth definition, which includes imputed rent as a part of disposable income, may be unfamiliar even to scholars in the field of income distribution studies. However, an owned home can be regarded as an asset that yields a return equivalent to housing rent. It therefore seems logical to also consider a definition of income that includes imputed rent when comparing homeowner households with renting households. As the homeownership rate in Japan increases with the age of household heads, excluding imputed rent could exaggerate the increase in income inequality due to population aging.

In addition to the four definitions above, we use the corresponding equivalized incomes by dividing income by the square root of the number of household members. Equivalized income is useful for comparing income across households with different numbers of members. Thus, we will calculate income inequality measures for each of the 4×2 income definitions.

3.4 *Income inequality measures*

To assess income inequality from a broad perspective, we calculate several income inequality measures that are commonly employed in studies in this field. The first is the Gini coefficient, which is one of the most widely used measures of income inequality. The Gini coefficient, G , represents the area between the 45-degree line and the Lorenz curve and is calculated as follows:

$$G = \frac{1}{2n^2\bar{y}} \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j| \quad (3)$$

⁹ As the NSFIE does not contain questions about tax and social security, we had to estimate the amount of tax and social security payments to derive disposable income based on the previous year's pre-tax income and family composition in the manner suggested by the Ministry of Internal Affairs and Communications (2015).

where y_i is the income of individual i , \bar{y} is the mean of income, and n is the number of observations.

The Gini coefficient is useful for summarizing the overall trend in income inequality. However, the Gini coefficient is not the only measure of income inequality and is not necessarily well suited for understanding how the income distribution is changing. Therefore, to examine inequality from a range of perspectives, we also calculate several other income inequality measures, namely, the relative poverty rate, the mean log deviation (MLD), and the log variance (LV) of household incomes. The relative poverty rate, which is defined as the share of households whose income falls below half of the median income, helps to shed light on the most disadvantaged households. The last two measures, the MLD and LV, not only measure income dispersion but also have the advantage that they make it possible to decompose the observed changes in dispersion, as shown in the next section.

In addition to the income inequality measures above, we also created charts of the Lorenz Curve, the income shares of the top, middle, and bottom 10% of households, and the kernel density of the income distribution to visually show how the income distribution changed. The charts of the kernel density of the income distribution help to clarify which part of the income distribution has changed in which direction.

3.5 Decomposition of the MLD and LV

Income inequality measures such as the Gini coefficient and depictions of the income distribution such as the Kernel density are informative about how the income distribution is changing. However, these measures do not necessarily tell us something about the causes of such changes. To investigate the causes of changes in income inequality, decomposing changes in the mean log deviation (MLD) and the log variance (LV) of household income is useful.

The mean log deviation (MLD) of household income is defined as

$$MLD = \frac{1}{n} \sum_{i=1}^n \log \left(\frac{\bar{y}}{y_i} \right) = \frac{1}{n} \sum_{j=1}^J \sum_{k=1}^{n_j} \log \left(\frac{\bar{y}}{y_{kj}} \right) \quad (4),$$

where \bar{y} is the overall mean of income, y_{kj} is the income of household k belonging to household group j , and $n = \sum_{j=1}^J n_j$. Mookherjee and Shorrocks (1982) proposed decomposing changes in the MLD as follows:

$$\begin{aligned} \Delta MLD \approx & \sum_{j=1}^J \bar{s}_j \Delta MLD_j + \sum_{j=1}^J \overline{MLD}_j \Delta s_j + \sum_{j=1}^J (\bar{\lambda}_j - \ln \bar{\lambda}_j) \Delta s_j \\ & + \sum_{j=1}^J (\bar{\theta}_j - \bar{s}_j) \Delta \ln \bar{y}_j \quad (4') \end{aligned}$$

where Δ is the difference operator between times t and $t+1$, and a bar above a variable indicates the average of the variable at times t and $t+1$, i.e., $\bar{s}_j = \frac{s_{t,j} + s_{t+1,j}}{2}$. Overall changes in inequality can be decomposed into (1) the contribution of changes in within-variation (the first term), (2) the contribution of changes in population shares (the sum of the second and third terms); and (3) the contribution of changes in between-variation (the last term).¹⁰

Next, the log variance (LV) of household income is defined as

$$LV = \frac{1}{n} \sum_{i=1}^n (\log y_i - \overline{\log y}) \quad (5),$$

where $\log y_i$ is the log income of household i , $\overline{\log y}$ is the average of log income, and n is the number of observations. Supposing that there are J household groups such that $\sum_{j=1}^J n_j = n$, Ohtake and Saito (1998) show that the LV can be rewritten as a function of s_t , σ_t , and Y_t :

¹⁰ The advantage of using the MLD over using the LV for decomposing changes is that the sum of the three components is approximately equal to the total change in the MLD.

$$LV = V(s_t, \sigma_t, Y_t) = \sum_{j=1}^J s_{tj} \sigma_{tj}^2 + \sum_{j=1}^J s_{tj} (\overline{\log y_{tj}})^2 - \left(\sum_{j=1}^J s_{tj} \overline{\log y_{tj}} \right)^2 \quad (5')$$

where $s_t \equiv \{s_{t1}, s_{t2}, \dots, s_{tj}\}$ is a vector of the population shares of the different household groups, $\sigma_t \equiv \{\sigma_{t1}, \sigma_{t2}, \dots, \sigma_{tj}\}$ is a vector of the standard deviations within household groups, and $Y_t \equiv \{\overline{\log y_{t1}}, \overline{\log y_{t2}}, \dots, \overline{\log y_{tj}}\}$ is a vector of the average log incomes within household groups, where t denotes the point in time and j the population group.

Using Equation (4'), we can calculate the contribution of each factor. The contribution of changes in population shares is given by $V(s_{t+1}, \sigma_t, Y_t) - V(s_t, \sigma_t, Y_t)$; the contribution of changes in within-variation is given by $V(s_t, \sigma_{t+1}, Y_t) - V(s_t, \sigma_t, Y_t)$; and the contribution of changes in between-variation is given by $V(s_t, \sigma_t, Y_{t+1}) - V(s_t, \sigma_t, Y_t)$.

4. Results

4.1 Income inequality measures

Figure 3 shows the trend in the Gini coefficient calculated based on household income data from the 1989, 1999 and 2009 NSFIE. The eight line graphs in the figure correspond to the eight income definitions described in Section 3.3. The four line graphs in the upper row show the Gini coefficient for household income, while those in the lower row show the Gini coefficient for equivalized income. There are three lines in each line graph: the blue line shows the Gini coefficient calculated using the raw NSFIE data, the orange line shows that using data adjusted with the officially provided sampling weights, and the gray line shows that using data adjusted with our sampling weights constructed from the *Population Census* data.

As mentioned in the introduction, it has been argued that inequality estimates such as the Gini coefficient obtained using the NSFIE data tend to be lower than those obtained using

other widely used statistics such as the CSLC data.¹¹ If the differences between the Gini coefficient calculated based on NSFIE data and other data sources result from sampling biases, we would expect the value of the Gini coefficient to increase when we apply sampling weights that are closer to reality. And, broadly in line with this expectation, the Gini coefficient tends to be higher after the weighting adjustments, that is, the orange and gray lines in Figure 3 tend to be above the blue line showing the result for the unadjusted data. Moreover, if we compare the two results after adjustments, the Gini coefficient calculated based on our weights (gray lines) is generally higher than that calculated based on the officially provided sampling weights (orange lines), except in the case of equalized initial income.¹²

Unlike the level of the Gini coefficient, developments over time in the Gini coefficient do not appear to be substantially affected by the sampling weights. That is, the results based on our newly calculated sampling weights confirm the increase in inequality pointed out in many earlier studies¹³ and show a similar pace of increase. Further, redistributive mechanisms such as social security benefits and taxes have the effect of reducing inequality to a considerable extent and, moreover, have slowed the increase in inequality. While equalization has the effect of reducing the level of Gini coefficients, the upward trend of the Gini coefficient calculated for equalized income generally looks steeper after the sampling weight adjustment than before the adjustment. Finally, a new finding of this study is that both the level and the upward trend of the Gini coefficient are reduced by taking imputed rent into account. This latter finding suggests that

¹¹ For example, using NSFIE data, Kitao and Yamada (2019) report a Gini coefficient of 0.336 for household pre-tax income in 1989, while Oshio et al. (2006), using CSLC data, obtain a Gini coefficient of 0.353. Using NSFIE data with the provided weights, we obtain a Gini coefficient of 0.334, which is very close to that reported by Kitao and Yamada (2019).

¹² Figure B2 in Appendix B shows how income distribution changes when weighting adjustment is applied. As can be seen from the graph, the Gini coefficients calculated with our original weights tend to be higher than those calculated with the provided weights and without weighting adjustment, because the poorer households tend to be under-sampled.

¹³ The Gini coefficients we obtain increase from 1989 through 2009, which is in line with Ministry of Internal Affairs and Communications (2015), the official report by the Statistics Bureau of the Ministry of Internal Affairs and Communications. On the other hand, in the results reported by Kitao and Yamada (2019), who utilizes the same dataset, the Gini coefficients for some reason levelled off from 1999.

the Gini coefficients reported in earlier studies, which do not take imputed rent into account, likely somewhat overstate inequality in Japan.

Next, Figures 4, 5, and 6 present similar charts for the relative poverty rate, the MLD, and the LV, respectively, from 1989 to 2009. The figures exhibit patterns similar to those for the Gini coefficient presented in Figure 3: the three income inequality measures tend to be higher when calculated with our *Population Census*-based sampling weights. Meanwhile, although an upward trend in the inequality measures can be observed for all income definitions, the pace of increase is considerably larger for initial income.

In sum, we can conclude that existing studies, which typically use the officially provided sampling weights, appear to underestimate income inequality in Japan. Moreover, income inequality widened during the 1990s and 2000s. However, the upward trend in income inequality is not very steep when we look at equivalized disposable income (with or without imputed rents). Finally, the more the definition of income shifts from one focusing on initial income (before any redistributive mechanisms) to one that can be regarded as more closely reflecting individuals' utility (standard of living), the lower the level of inequality and the less pronounced the upward trend in inequality tends to be.

4.2 Lorenz curve, top, middle, and bottom 10% share, and kernel density of income distribution

In order to understand the reasons for the increase in income inequality during the 1990s and 2000s, we examine the Lorenz curve, the top, middle, and bottom 10% shares, and the Kernel density in this section. Based on the reasoning outlined above, we assume that the sample distribution adjusted with the *Population Census*-based sampling weights most closely reflects the actual distribution of income in Japan and will therefore focus on the results obtained using those weights only.

Figure 7 shows the Lorenz curves for the income distribution across households in 1989, 1999, and 2000. To save space, Figure 7 as well as most of the figures below show the results for four of our eight income definitions only, namely, household initial income, household disposable income, equivalized disposable income, and equivalized disposable income plus imputed rent.¹⁴ As the mathematical definition of the Gini coefficient is based on the Lorenz curve, changes in the shape of the Lorenz curve provide a first indication of the reasons for an increase in the Gini coefficient. Figure 7 shows that the Lorenz curve became more convex over time, implying that poorer households became poorer or richer households became richer, or both. Taking a closer look, the change in the shape of the Lorenz curve does not show a particularly strong bias in either direction.

To examine this point more carefully, we show the income share of the top 10% households (gray line), the middle 10% households (red line), and the bottom 10% households (blue line) in Figure 8. We can observe a clear increase in the income share of the top 10% households and a decline in the income share of the bottom 10% households in the charts for the two equivalized incomes,¹⁵ while the share of the middle 10% households looks broadly constant over the two decades. Therefore, the observed patterns for the top and bottom 10% shares suggest that the increase in income inequality resulted from both the poor getting poorer and the rich getting richer.

Finally, to more visually examine why the income shares changed, Figure 9 shows the Kernel densities of household incomes. Interestingly, while the inequality measures suggest that there is no clear difference between the increase in inequality from 1989 to 1999 and that from

¹⁴ We choose household initial income, household disposable income, and equivalized disposable income (without imputed rents), since these measures are widely used in the literature. We employ equivalized disposable income plus imputed rent since among the eight measures this can be regarded to most closely reflect individuals' utility.

¹⁵ The bottom 10% share in the initial income chart is close to zero since the majority of households in the bottom 10% are those living on their pension only, which by definition is not included in households' initial income.

1999 to 2009, the shifts in the Kernel densities between 1989 and 1999 on the one hand and 1999 and 2009 on the other look quite different. While the rise in income inequality from 1989 to 1999 resulted from income increases for middle-income households and above (indicated by the fact that the broken orange line lies to the right of the solid blue line), the rise in income inequality from 1999 to 2009 resulted from a decline in the income of low-income households (indicated by the fact that the dotted gray line lies to the left of the broken orange line). These findings are in line with the results reported by Oshio (2010).

4.3 Contribution of changes in household composition

Examining the Lorenz curve, the 10% shares, and the Kernel densities allowed us to determine the changes in the income distribution that caused the rise in the income inequality measures. However, the findings so far are not very informative in terms of what socioeconomic factors play a role in the rise in income inequality.

Some earlier studies, such as Ohtake (2005), have shown that the rise in income inequality during the 1990s can be largely attributed to the aging of the population. Other studies, such as Tachibanaki (1998) and Iwamoto (2000), argue that the nuclearization of households and the increase in labor force participation of wives are important. To examine to what extent the rise in the income inequality measures can be explained by changes in the distribution of household characteristics, we calculate the Gini coefficient, the relative poverty rate, the MLD, and the LV, using sampling weights created in a manner such that the share of each household group (or each weighting cell) remains constant at the 1989 and 1999 levels. For example, to obtain income inequality measures for 1999 and 2009 holding the share of each household group at the 1989 level, we use the sampling weights $w_{j,t}^{1989} = \frac{s_{j,1989}}{\hat{s}_{j,t}}$ ($t=1999, 2009$) instead of $w_{j,t} = \frac{s_{j,t}}{\hat{s}_{j,t}}$ to calculate the income inequality measures.

The blue lines in Figure 10 show the Gini coefficient (Figure 10(a)), the relative poverty rate (10(b)), the MLD (10(c)), and the LV (10(d)) for 1989, 1999, and 2009 calculated with our original *Population Census*-based sampling weights. The orange dashed lines show the four income inequality measures calculated using the 1989 household group shares, and the gray short-dashed lines use the 1999 household group shares.

Starting with household initial income and household disposable income, when household group shares are held constant at the 1989 levels, the increases in inequality observed earlier more or less disappear, especially from 1989 to 1999 (i.e., the orange line is horizontal from 1989 to 1999). Turning to household disposable income and the equivalized incomes, i.e., the third and fourth columns, while the increase in the inequality measures does not disappear when using the 1989 household group shares, the extent of the increase is considerably smaller than in the earlier estimates. Looking, for instance, at the Gini coefficient for equivalized disposable income, 50.3% of the increase from 1989 to 1999 and 32.1% of that from 1999 to 2009 is accounted for by changes in the shares of household groups.¹⁶ Similar patterns can be observed for the other inequality measures, with changes in household group shares explaining between 41.2% and 50.3% of the increase in these measures for the equivalized disposable incomes during the 1990s and between 27.5% and 43.3% during the 2000s. The results indicate that the changes in household group shares (or weighting cells), especially during the 1990s, played an important role in the rise in income inequality.

4.4 Decomposition of MLD and LV

The analysis in the preceding section keeping household group shares fixed showed that changes

¹⁶ For example, while the value of the Gini coefficient for household disposable income increased from 0.2753 in 1989 to 0.2959 in 1999, the value of the Gini coefficient for 1999 would be 0.2855 if the population group shares had remained unchanged from 1989. Thus, the change in population group shares accounts for approximately 50% ($\hat{=} \{1 - (0.2855 - 0.2753) / (0.2959 - 0.2753)\} \times 100$) of the increase in the Gini coefficient.

in household shares in terms of their characteristics such as the age of the household head and the household type explain a sizeable part of the increase in income inequality, especially during the 1990s. The next question is which household characteristics play an important role in the increase in inequality. In particular, we want to know to which extent factors such as the aging of the population, the nuclearization of households, the increase in dual-income households, and concentration of the population in urban areas contribute to the rise in income inequality. To examine these issues, we decompose changes in the MLD and LV into the contribution of changes in the following four household characteristics: the age of the household head, the household type, the number of workers in the household, and the area of residence.¹⁷

Employing the approaches described in Section 3.5, we decompose changes in the MLD and LV into the following three parts: (1) the composition effect, the (2) between effect, and (3) the within effect. The composition effect represents the contribution of changes in the share of households falling into each category to changes in income inequality; the between effect represents the contribution of changes in income differences across categories; and the within effect represents the contribution of changes in income inequality within each category. We can assess the relative importance of population aging, changes in household types, including the nuclearization of households, the increase in dual-income households (or increase in the labor force participation of wives), and changes in the area of residence such as the growing concentration of the population in urban areas by looking at the composition effect obtained from the decomposition with respect to age, household type, number of workers, and area of residence, respectively.

Figures 11(a) and 11(b) present the decomposition of changes in the MLD and LV, respectively, with respect to age. The figures show that the aging of the population, represented

¹⁷ We do not examine the role of homeownership, since in this study we are not interested in the effect of homeownership.

by the composition effect in the bar charts, played a significant role in the increase in inequality in household initial income. Almost half of the increase in the 2000s and roughly 60–70% of the increase in the 1990s is accounted for by the population-aging effect. On the other hand, when we look at the effect on equivalized disposable income (without and with imputed rent), which takes redistributive mechanisms and the number of household members into account, the part that can be explained by population aging is substantially smaller than in the case of household initial income. Specifically, for the 1990s, the population-aging effect accounts for at most 17% of the change in the MLD and LV for equivalized disposable income, while for the 2000s it accounts for less than 7%.

Next, Figures 12(a) and 12(b) present the decomposition of changes in the MLD and LV with respect to household types.¹⁸ Regarding the effect of changes in the shares of household types, we can observe relatively robust effects across different income definitions. Even for equivalized disposable income (without and with imputed rent), the household-type effect accounts for about 25–31% of the increase in income inequality during the 1990s and 21–29% during the 2000s.

Figures 13(a) and 13(b) show the decomposition of changes in the MLD and LV with respect to the number of workers in the household. We find that the composition effect of changes in the number of workers is slightly larger than that of changes in the shares of household type. Even for the equivalized disposable income, changes in the number of workers in the household account for 30–31% of the rise of income inequality during the 1990s and 33–39% during the 2000s.

Finally, Figures 14(a) and 14(b) present the decomposition with respect to the area of residence. The figures indicate that the rise in income inequality is almost entirely due to the

¹⁸ As mentioned in Section 3.2, households are classified into seven types (single male, single female, couple without children, single parent with children, couple with children, three generation, and the other households).

within effect, which implies that changes in the area of residence such as households moving to urban areas is not a major factor underlying the rise in income inequality.

To sum up, we find that changes in the distribution of household types, such as the nuclearization of households, and changes in the number of workers in the household, which probably reflect women's participation in the labor market, are at least as important as the aging of the population in accounting for the increase in income inequality during the 1990s. Moreover, changes in the distribution of household types and changes in the number of workers in the household appear to have been even more important than the aging of the population in explaining the rise in income inequality during the 2000s.

4.5 Household and population shares by category

The decomposition of changes in the MLD and LV in the previous section indicated that changes not only in the shares of household groups defined by household head age but also in those defined by household type and the number of workers in the household are important in explaining the increase in income equality. To examine the underlying changes in household demographics, the charts in the left column of Figure 15 show developments in the share of households falling into each of the different groups for the auxiliary categories, such as the share of households with a household head falling into a certain age group in the total number of households. Similarly, the right column presents developments in the share of individuals falling into each of the groups in the total population.

Starting with the charts for age, the share of households with a head aged 60 or older increased during the observation period, while the shares of households with a younger head decreased. The chart on the right for individuals indicates that these changes in household demographics mirror developments in population demographics. As for the shares by household

type, a clear increase in the share of households without children and a sharp decrease in the share of three-generation households can be observed. Regarding shares by the number of workers in the household, we find that the share of households without a worker rapidly increased. On the other hand, the share of households with two-or-more workers declined despite the increase in the share of dual-income households among economically active households. This is perhaps because the effect of the increase in dual-income households was offset by the increasing share of retired households. Finally, regarding the shares by the area of residence, surprisingly, the share of urban dwellers appears to have changed little during the observation periods.

4.6 Income inequality by household category

While the decomposition of changes in the MLD and LV presented in Section 4.4 revealed that the rise in inequality, particularly that during the 2000s, to a great extent is attributable to the within-effects, it is difficult to identify the factors causing these within effects. However, it is possible to at least identify the categories of household characteristics for which income inequality increased by calculating the income inequality measures by category.

Figure 16 presents the Gini coefficients (16(a)), the relative poverty rates (16(b)), the MLD (16(c)), and the LV (16(d)) by age category, i.e., those in their 20s, 30s, 40s, 50s, 60s, and 70s and over. The charts indicate that income inequality tends to widen the older the head of household, as highlighted in previous studies. Moreover, the upward trend is more pronounced for household initial income, while the slopes look flatter for disposable income and equivalized disposable incomes. These findings suggest that redistributive mechanisms such as the tax and social security system play an important role in mitigating income inequality across different age groups. Looking at changes over the years, while inequality among households with a head under 60 increased during the observation period, inequality among households with a head aged 70 or

over narrowed. This probably implies that the increase in within-age-group income inequality during the 2000s largely resulted from changes in the labor market environment, but redistributive mechanisms had the effect of considerably mitigating the increase in within-age-group income inequality.

Figure 17 presents the four income inequality measures by household type. Income inequalities look smaller for nuclear family households consisting of parents and children as well as three-generation households, while they are generally larger for other types of households, especially households without children and single-parent households. As the shares of nuclear family households and three-generation households have been shrinking, such changes in family structure likely also account for the increases in income inequality. This can be interpreted as suggesting that while the redistributive policies successfully mitigated income inequalities across most household types, this is not the case for single-parent households. Meanwhile, looking at trends, a rise in income inequality can be observed across all types of households, with the increase most pronounced for single-parent households.

Turning to the number of workers in the household (Figure 18), income inequality appears to be larger among households without a worker than other households. This indicates that the increasing share of households without a worker is one of the factors contributing to the increase in inequality in Japan. Next, looking at developments over time, while no clear increasing trend of income inequality can be observed among households without a worker, income inequality appears to have increased among households with at least one worker, except when the relative poverty rate is used as the inequality measure. The relative poverty rate followed a decreasing trend for households without a worker, while it slightly increased for households with at least one worker when income is defined on an equivalized basis.

Finally, Figure 19 presents the Gini coefficient, the relative poverty rate, the MLD, and

the LV by area of residence. We find that income inequality increased in both urban and rural areas. While the pace of increase in inequality during the 2000s appears to be slightly faster in urban than in rural areas, these patterns suggest that changes in the area where households reside had little impact on inequality overall.

5. Conclusion

Using microdata from the NSFIE, this study presented new and more accurate estimates of the income distribution across households in Japan to examine how and why income inequality changed during the two lost decades from 1989 to 2009. Given the dramatic changes in Japan's demographic structure and composition of households in recent decades, it is crucially important that the distribution of the sample data used to investigate income inequality faithfully reflects the actual distribution of households. To make the sample distribution conform to the population distribution, we used sampling weights that we newly created using microdata from the *Population Census*.

Calculating four income inequality measures using our original *Population Census*-based sampling weights, we found that income inequality across households in Japan is larger than suggested by earlier studies using NSFIE microdata. Furthermore, we found that income inequality in Japan increased both during the 1990s and 2000s. However, the upward trend in inequality was moderate when looking at inequality measures based on equivalized disposable income, showing that the tax and social security system in Japan play an important role in reducing the level of and growth in income inequality.

We also examined the Lorenz curves, the top and bottom 10% shares, and the Kernel density of the income distribution to understand what factors underlie the increase in income inequality during the 1990s and 2000s. From the Lorenz curves and the top and bottom 10%

shares we found that the rise in income inequality resulted from both the poor getting poorer and the rich getting richer. Further, from the Kernel density we found that the rise in income inequality from 1989 to 1999 resulted from a rise in the income of middle- and upper-income households, while a similar rise in income inequality from 1999 to 2009 resulted from a decline in the income of poorer households.

Finally, decomposing changes in the MLD and LV, we found that although the aging of the population substantially contributed to the increase in initial income inequality, it played little role in the increase in inequality calculated for equivalized disposable income, especially in the 2000s. Instead, changes in the distribution of household types, such as increases in single-person households and the nuclearization of households, and changes in the number of workers in the household appear to be more important than the aging of the population in explaining the increase in equivalized income inequality. Our estimates indicate that changes in demographic structure and household composition played a greater role than suggested in previous studies, probably because our data, as a result of using sampling weights we constructed based on the *Population Census*, are able to capture such changes more accurately than the data used in earlier studies.

As noted in the introduction, earlier studies report that the values of income inequality measures calculated based on the NSFIE data tend to be lower than those calculated based on other datasets such as the CSLC data. This study revealed that earlier studies using the NSFIE data might underestimate income inequality. A task for the future therefore is to examine whether income inequality measures calculated based on the NSFIE data and on the CSLC data indeed become closer if our *Population Census*-based sampling weights are used. Moreover, our sampling weights could be used to investigate inequality in other dimensions such as wealth and consumption to gain a more comprehensive understanding of economic inequality in Japan.

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