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1. Introduction

A fundamental question in intergenerational mobility research is regarding whether economic advantages and disadvantages persist in the long run. Existing studies on intergenerational income mobility predominantly focus on the intergenerational income persistence between two consecutive generations, as formalized in the Becker-Tomes model (Becker and Tomes, 1979, 1986), which attributes income transmission to parental investments in children's human capital and the within-household transmission of endowments. Under the assumption of an AR(1) process in the transmission mechanism, in which income in any generation is influenced solely by that of the preceding generation, long-term income persistence is predicted to diminish geometrically across generations, as indicated by Borjas (2009) and Becker and Tomes (1986). For example, if the intergenerational income elasticity between two generations is 0.3, it declines to 0.09 and 0.027 in the third and fourth generations, respectively, suggesting limited long-term persistence; this is articulated by Becker and Tomes (1986): "Almost all earnings advantages and disadvantages of ancestors are wiped out in three generations."

However, recent studies have challenged this AR(1) assumption, suggesting that direct effects may occur between non-adjacent generations. For example, Solon (2014) emphasized the theoretical importance of explicitly modeling multigenerational mobility, as existing intergenerational models often fail to capture the complexities of socioeconomic status transmission beyond two generations. He proposed extensions to traditional frameworks, incorporating factors such as grandparental investment and cultural inheritance, to predict and interpret multigenerational persistence in inequality more accurately. Mare (2011) also pointed out that the influence of grandparents and other ancestors has largely been overlooked in intergenerational mobility studies, and emphasized the need to analyze persistence across three or more generations to comprehensively understand long-term economic mobility.

In recent years, empirical intergenerational mobility research has expanded to encompass educational, occupational, and income persistence over multiple generations in various national contexts. Clark (2012) used historical surname data to track the mobility of social classes in Sweden over several generations. His findings revealed surprisingly slow social mobility with persistence rates comparable with those observed in pre-industrial societies. This indicates the existence of long-run intergenerational persistence that might not be fully captured by two-generation analyses. Similarly, Chiang and Park (2015) investigated educational attainment in Taiwan and highlighted the significant role of grandparents in grandchildren's educational success, particularly in families with highly educated parents. An increasing number of studies on multigenerational income mobility are also being conducted. Long and Ferrie (2018) examined income mobility across three generations in the U.S. and Britain from 1850 to 1911. Using newly linked census data, they found that grandfathers' incomes significantly influenced grandsons' incomes, even after controlling for fathers' incomes, thus rejecting the assumption of an AR(1) process and showing that two-generation analyses overestimated true mobility.

However, some studies have confirmed the AR(1) pattern of intergenerational persistence despite the highly significant persistence coefficients between grandparents and grandchildren. Lindahl et al. (2015) employed detailed Swedish administrative data to measure lifetime earnings over three generations, alongside educational data for four generations. Their findings revealed that income persistence was only marginally inconsistent with the AR(1) hypothesis, while long-term educational persistence was stronger than that predicted by the AR(1) model. Similarly, Jia (2023a) used a representative Taiwanese household panel survey and found that grandfathers' income had no independent effect on grandsons' income. In a recent study, Modalsli and Vosters (2024) relied on Norwegian census data and found that the existence of an independent grandparental effect depended on how parental and grandparental incomes were measured. Additionally, Lucas and Kerr (2013) used Finnish census data and found no significant grandparent-grandchild income persistence.

Therefore, to determine whether income inequality persists over a longer period, two empirical questions arise: (1) Does grandparent-grandchild income persistence exist? (2) Is the grandparental effect independent? For example, can AR(1) predict three-generation intergenerational persistence? As empirical evidence on multigenerational income mobility is sparse, gathering diverse empirical evidence from countries with different inequality backgrounds, welfare policies, and cultural traditions is crucial. This study contributes to the literature on multigenerational mobility by analyzing income persistence across three generations in Japan. Japan has an intermediate level of income inequality and two-generation persistence (Clark, 2012), while most previous three-generation studies have focused on countries with higher income inequality and higher two-generation intergenerational persistence (e.g., the U.S. and Britain; Long and Ferrie, 2018; Olivetti et al., 2018), or countries with lower inequality and persistence (e.g., Finland, Norway, and Sweden; Lucas and Kerr, 2013; Lindahl et al., 2015; Engzell et al., 2020; Härtull and Saarela; 2024 Modalsli and Vosters, 2024). Using Japanese household panel data on individuals born around 1960, we extend the three-generation analysis to Japan.

We also contribute to the literature by using unique household panel surveys that track households across three generations and provide diverse individual-level information. Although the small sample size of the microdata may have limited the precision of our estimations, it has three advantages. First, we can use household IDs to efficiently identify the exact grandparent-parent-grandchild pairs, without worrying about mismatches or relying on "pseudo" matches (Olivetti et al., 2018).[1] Second, although grandparental income is

[1] Take father-son pairs in Olivetti et al. (2018) as an example: these pairs are not based on direct father-son relationships, but rather on a matching of sons who share the same name (e.g., Adam) with their fathers who also have sons named Adam. Grandfather-son pairs in Olivetti et al. (2018) are constructed using the similar method. Similarly, Long and Ferrie (2018) used names and other identification information to link children with their ancestors using a British census, but this induces problems such as unrepresentativeness, which will be reviewed in the next section.

unobservable in our data, we have detailed information on grandparental education, occupation, employment status, birth year, death year, and other characteristics, allowing us to impute grandparental income using a wide range of characteristics. Compared with previous studies that used a single feature to measure or impute income (e.g., annual income in Härtull and Saarela, 2024; multiannual income in Lucas and Kerr, 2013; Engzell et al., 2020; and Modalsli and Vosters, 2024; average income by occupation in Long and Ferrie, 2018; and Olivetti et al., 2018[2]), our use of a "compound" measurement is less vulnerable to "market luck" (Becker and Tomes, 1979, 1986) and better captures true latent economic status (Clark, 2012). To maintain consistency in measurement across the three generations, parents' and children's incomes are also imputed using education and occupation in this paper. Third, with a broad range of individual information, we can impute incomes at their mid-ages, when income better represents lifetime income, thus alleviating life-cycle bias (Haider and Solon, 2006). Additionally, we can estimate the heterogeneities in three-generation persistence by grandparents' "presence" (i.e., whether grandparents were alive before grandchildren's birth) and employment status, shedding light on the causalities underlying intergenerational persistence.

We utilize data from the 2004–2023 Japan Household Panel Survey (JHPS) for parents and the 2019–2023 JHPS Second-Generation Supplement (JHPS-G2) for their adult children, to impute the lifetime incomes of both parents and children. Regarding the grandparents, the JHPS contains information on their occupation, education, and birth year, from which we impute their lifetime income by estimating income returns to education and occupation using data from another survey, the 1965 and 1975 Social Stratification and Social Mobility Survey (SSM).

To investigate intergenerational income persistence, we estimate the income elasticities between paternal grandfathers (G0) and fathers (G1), as well as between G0 and grandchildren (G2). Additionally, we test the AR(1) assumption to examine the existence of the direct effect of G0 on G2. We also conduct additional analyses robustness checks analysis in terms of the variables and data used to impute incomes. We also conduct instrumental variable (IV) estimation using grandparents' income as an instrument for parental income to obtain better estimates of two-generation intergenerational income elasticities. Finally, we estimate the heterogeneities of income elasticity between G0 and G2 to investigate the potential causalities underlying intergenerational persistence.

The remainder of this paper is organized as follows. Section 2 outlines the previous literature. Section 3 details the data and methods used in the analysis. Section 4 presents the results of the analysis and discusses the results. Finally, Section 5 concludes the paper.

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[2] Specifically, Olivetti et al. (2018) used occupational income by first name. Since first names contain additional information on income inequality, Olivetti et al. (2018)'s measurement would better capture the "real" economic status than Long and Ferrie (2018).

2. Previous studies

With pioneering studies of Lipset and Bendix (1959) and Featherman et al. (1975) as a foundation, numerous empirical studies have been published on the intergenerational persistence in socioeconomic outcome, such as education, occupation, income and wealth, between parent and children. Solon (1999) and Black and Devereux (2011) offer comprehensive reviews of empirical research, focusing particularly on the intergenerational elasticity of earnings. Björklund and Salvanes (2011) provide a similarly extensive overview of literature on the impact of family background on educational outcomes. In Japanese context, Ishida (1993), Ojima (1998), Imada (2000), Kondo (2000), Lefranc et al. (2014), Ueda (2015), and Kubota (2017) have also conducted intergenerational persistence of economic outcomes in Japan.

A key question is whether grandparents play a direct influence in shaping their grandchildren's economic outcomes, separate from the impact of the parents' socioeconomic status. Empirical research on multigenerational mobility has expanded in recent years, encompassing income, educational, and occupational persistence across multiple generations in various national contexts. Although there are studies such as Warren and Hauser (1997)[3] and Erola et al. (2020) found no significant influence of the grandfather's outcome on the grandson's outcome after controlling parental characteristics, there are growing literature providing robust evidence for multigenerational persistence that exceeds expectations based on traditional two consecutive generations mobility models.

Due to the challenges in obtaining accurate information on multigenerational economic outcomes, various efforts have been made to conduct empirical analysis. The availability of richer datasets has enabled more nuanced analyses of multigenerational mobility. As one of the earliest studies, Clark (2012) used historical surname data to analyze surname distribution among elites over several generations in Sweden. Their findings revealed surprisingly slow social mobility, with persistence rates comparable to those observed in pre-industrial societies in both countries. Concerning occupational mobility, Knigge (2016), utilizing marriage records from five Dutch provinces, found moderate and consistent effects of grandfathers on occupational status throughout the 19th and early 20th centuries. Interestingly, his study further suggested that grandfathers influence their grandsons through contact but also without being in contact with them. Using newly linked census data, Long and Ferrie (2018) examined occupational mobility across three generations in the U.S. and Britain during 1850–1911. They found that grandfathers' occupations significantly influenced grandsons' outcomes, even after

[3] Warren and Hauser (1997), on the other hand, used the longitudinal survey data of Wisconsin high school graduates and found no significant influence of the grandfather's occupation on the grandson's occupation once the father's occupation was controlled. But the study is limited by its geographic focus on Wisconsin, leaving open the question of whether these findings are applicable to the entire United States.

controlling for fathers' occupations, thus rejecting the assumption of an AR (1) process and showing that two-generation analyses overestimate true mobility. Modalsli (2023) used administrative data spanning up to five generations in Norway and revealed that multigenerational occupational persistence is observed not only for white-collar occupations, but also for farmers and for skilled and unskilled manual workers. They also found that substantial differences in the strength of multigenerational persistence over time.

Education is also one of the attentions for multigenerational mobility. Zeng and Xie (2014) used Chinese micro data found that the educational level of co-resident grandparents directly influences grandchildren's outcomes, while non-resident and deceased grandparents have no effect. Li and Cao (2023) also analyzed multigenerational educational mobility in China, and showed that grandparents' education positively correlates with grandchildren's education, controlling for the parents' education. Sheppards and Monden (2018), using the cross-national longitudinal data called the Survey of Health, Aging and Retirement in Europe (SHARE), investigated multigenerational educational mobility with information on all four grandparents and both parents to evaluate the different ways to model grandparental associations. In addition to finding significant correlations between grandparent's and grandchildren's educational attainment, they found that having two highly educated grandfathers showed a stronger association. They also investigate to what extent the association between grandparental education and grandchildren's educational outcomes is moderated by life span overlap and family size, and found no evidence for both. Anderson et al. (2018) systematically reviewed studies on the effects of grandparental involvement on educational outcomes, highlighting both direct and indirect impacts on educational achievement, with variations based on factors such as socioeconomic status, cultural context, and the quality of the grandparent-grandchild relationship. There are studies focusing on both educational and occupational persistence between grandparents and grandchildren, such as Braun and Stuhler (2018) in Germany and Colagrossi et al. (2020) in 28 EU countries.

Concerning intergenerational persistence of wealth, Clark and Cummins (2015) used historical surname data to track wealth mobility in the U.K. over several generations and found strikingly strong persistence of economic status at the surname level. Pfeffer and Killewald (2018) used the Panel Study of Income Dynamic (PSID) in the U.S. and explored how wealth advantages persist across multiple generations, emphasizing the strong intergenerational correlation in family wealth and the structural factors that reinforce wealth inequality. Similarly, Adermon et al. (2018) examined intergenerational wealth mobility, highlighting the critical role inheritance plays in perpetuating wealth disparities across generations in Sweden.

Since the difficulty of accurately capturing multigenerational income information, there are few studies focusing on income for multigenerational mobility until recently. One of the studies that has received the most attention is Lindahl et al. (2015). They combined survey and administrative data from Sweden to investigate earnings and educational persistence over three generations and educational attainment over four generations. Their findings showed significantly higher multigenerational persistence than would be predicted by iterating parent-child regression estimates. Specifically, grandparents' earnings were found to predict grandchildren's earnings, conditional on parents' earnings, with the size of the coefficient on grandparents being about one-quarter that of the parents.

More recent studies, however, present a more nuanced and often inconsistent picture regarding the independent effect of grandparents' socioeconomic status. For example, Jia (2023a), using data from a nationally representative household panel survey in Taiwan, found no evidence that grandfathers' income exerted an autonomous effect on grandsons' income, once parental characteristics were taken into account. Similarly, Lucas and Kerr (2013), drawing on Finnish census data, reported negligible intergenerational persistence between grandparents and grandchildren in terms of income, with estimates approaching zero.

Further evidence from Sweden by Engzell et al. (2020), based on comprehensive tax records, also suggests that while bivariate correlations between grandparental status and grandchildren's outcomes are frequently observed, these associations largely attenuate when detailed maternal and paternal attributes are included in the analysis. This finding raises the possibility that much of the observed grandparental influence may in fact reflect unobserved or unmeasured parental factors. Adding to this complexity, Modalsli and Vosters (2024), employing Norwegian census data, highlight that the detectability of a distinct grandparental effect is highly sensitive to how both parental and grandparental incomes are operationalized, pointing to important methodological considerations in the study of multigenerational mobility.

3. Data and methods

This study utilizes data from the JHPS and JHPS-G2 conducted by the Panel Data Research Center at Keio University. The JHPS, initially launched in 2004 as the Keio Household Panel Survey, targeted 4,000 adult men and women and their spouses. The participants were selected using a two-stage stratified random sampling method to minimize selection bias. In 2015, the KHPS merged with the JHPS, which was initiated in 2009, with approximately 4,000 respondents. Additional samples were added in 2007, 2012, 2018, and 2023 to mitigate attrition. The JHPS provides longitudinal data, tracking the same individuals over time and enabling the analysis of changes in key variables, such as education and training, employment, income, assets, health, and subjective well-being. The survey interviews the spouses in married couples and poses identical questions to each. Information on fathers (G1) is extracted from the JHPS, specifically from male respondents and spouses of female respondents (i.e., males in the JHPS). The JHPS includes questions about the education, occupation, employment type, birth year, death year, etc., of the respondents' and their spouses' parents, which can be utilized as data on paternal grandfathers (G0). In the JHPS, the G0's employment conditions (occupation, etc.) refer to those when the G1 was 15 years old.

The JHPS-G2 was primarily conducted to analyze intergenerational mobility. It uses the same questions as the JHPS on education, employment, income, health, and subjective wellbeing, albeit to a lesser extent. The first wave of the JHPS-G2 was conducted in 2019 and targeted adult children (aged 18 years and older) of the 2018 JHPS respondents, regardless of whether they lived with their parents. The total number of survey targets was 5,084,[4] with 1,063 participants responding in 2019, yielding a response rate of 21 %. Information on grandchildren (G2) is extracted from the JHPS-G2.

Both G1 and G2's annual pre-tax labor incomes from their main jobs can be obtained each year from the JHPS and JHPS-G2, respectively, and this information is used to represent their incomes. One empirical challenge in estimating intergenerational income elasticity across three generations in Japan using the JHPS and JHPS-G2 datasets is the absence of information on G0's incomes. Following previous studies where higher generations' incomes are unobservable (See Jerrim et al. (2016)'s review), information on education and occupation of G0 answered by the JHPS respondents is used to impute G0's incomes. Considering that mid-career incomes (i.e., early 40s) best represent lifetime income (Haider and Solon, 2006), we impute incomes at age 45. In studies on multigenerational income mobility, measuring income consistently across three generations (See the review in Section 2) is common practice, so the incomes of G1 and G2 are also imputed based on their respective education and occupation at age 45.[5] To accomplish this, we estimate the following income equation:

$$Y_{it} = \gamma_0 + \gamma_1 X_{it} + \delta_1 X_{it}(A_{it} - 45) + \delta_1 X_{it}(A_{it} - 45)^2$$

$$+\eta_1(A_{it} - 45) + \eta_2(A_{it} - 45)^2 + \textstyle\sum_t \theta_t YD_t + \varepsilon_{it} \qquad (1)$$

where Y_{it} represents log income, X_{it} represents education and occupation, and A_{it} represents age. By controlling for the linear and quadratic terms of age centered at 45, as well as their interaction terms with education and occupation, γ_1 captures the returns to education and occupation at age 45. YD_t is the year dummy variable.

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[4] The number of the corresponding children was calculated from the JHPS data.

[5] Although we can observe the incomes of both G2 and G1 in our datasets, suggesting that using multiannual average income would be a more straightforward method, G2 are young and G1 are aging, meaning their lifetime incomes would be understated and overstated, respectively. Consequently, the persistence between G0 and G2, and that between G0 and G1 would be underestimated and overestimated, respectively.

G0's incomes are unobservable in the JHPS and JHPS-G2. Hence, equation (1) is estimated using an "alternative" micro dataset to obtain income returns for G0. Respondents in the JHPS retrospectively reported their fathers' occupations when they were 15 years old, meaning that it would have been the early 1970s when respondents born around 1959 were 15 years old. Thus, a dataset collected during that period should be used to estimate income returns for grandfathers. For this purpose, the micro dataset from the 1965 and 1975 SSM Surveys were used. Moreover, fathers of males in the JHPS were born around 1927-1928, indicating that the data collected in 1965 and 1975 covered their mid-careers. The SSM is a decennial repeated cross-sectional survey that has been conducted since 1955, with the latest available wave being in 2015. It is one of the largest and most traditional social surveys in Japan, focusing on topics such as social inequality and mobility, with a wide range of variables such as family background, education, employment, attitudes toward life and society, and income. In the SSM, each respondent's income refers to pre-tax gross income. When estimating equation (1) for G0, we restrict the sample to SSM respondents whose incomes are positive and those aged 30–59.

For G1, equation (1) is estimated using the data of males in the 2004–2023 JHPS. We restrict the sample to those with a positive income and aged 25–64 years. For G2, equation (1) is estimated using the 2019–2023 JHPS-G2. We restrict the sample to respondents aged 20–64 years with positive labor income, who are neither students nor female part-time workers. Considering the relatively small sample size of JHPS-G2, the 2019–2023 JHPS data is also incorporated into the estimation of equation (1) for G2. As earnings data are less informative for females (Lindahl et al., 2015), we also estimate income returns only for male G2 (grandsons). In this case, information from males in the 2019–2023 JHPS and JHPS-G2 datasets is used.

After estimating γ_0 and γ_1, log incomes at age 45 are imputed using equation (2). First, we calculate the imputed log income for each individual by multiplying the returns to education and occupation at age 45 by their respective education and occupation levels. We then compute the average imputed log income across all available survey waves for each individual. This procedure addresses the challenge of missing income data for G0 while ensuring consistency in income measurements across the three generations.

$$\hat{Y}_i = \frac{1}{T}\sum_t(\hat{\gamma}_0 + \hat{\gamma}_1 X_{it}) \qquad (2)$$

Intergenerational income elasticity (IGE) between G0 and G1 is estimated by estimating the following equation:

$$\hat{Y}_{1i} = \alpha_1 + \beta_1 \hat{Y}_{0i} + \mu_1 \qquad (3)$$

where $\hat{Y}_{0i}$ and $\hat{Y}_{1i}$ refer to the imputed log income of G0 and G1, respectively. β_1 is the IGE between G0 and G1. The IGE between G0 and G2 is estimated by estimating the following equation:

$$\hat{Y}_{2i} = \alpha_2 + \beta_2 \hat{Y}_{0i} + \mu_2 \tag{4}$$

where $\hat{Y}_{2i}$ refers to the imputed log income of G2, and β_2 is the IGE between G0 and G2. If β_2 statistically exceeds zero, it indicates that intergenerational income persistence between G0 and G2 exists.

To test whether G0 exerts an additional effect on G2, we test the null hypothesis that $\beta_2 \leq \beta_1^2$. If it is rejected at conventional levels, this would indicate that intergenerational persistence is not an AR(1) process. Here, the variables on the right-hand side (i.e., G0's income) are the same as in equations (3) and (4). Therefore, the potential bias in the estimations of β_1 and β_2 (such as attenuation bias due to measurement error) should be at the same magnitude (Modalsli and Vosters, 2024). Thus, the test results would accurately reflect the true relationship between β_2 and β_1^2.

4. Results

4.1 Descriptive statistics

Table 1 presents the descriptive statistics for the sample used to estimate income returns. The top panel provides information on the age in the survey year, birth year, and log income. Column (1) shows that the average age of the 2019–2023 JHPS-G2 respondents, as well as the 2019–2023 JHPS respondents and their spouses, is 44.7, with an average birth year of 1975.5. Among these individuals, the average age and birth year of the males are 45.8 and 1974.3, respectively, as shown in Column (2). These individuals are used to estimate the income returns for grandchildren (G2) and grandsons (male G2). As Column (3) shows, the average age of 2004–2023 JHPS male respondents and the spouses of female respondents is 47.8, with an average birth year of 1964.7. These individuals are used to estimate income returns for fathers (G1). Column (4) shows that the average birth year of JHPS paternal grandfathers (G0) is 1927.5. Column (5) shows that the average age and birth year of the 1965 and 1975 SSM respondents are 42.2 and 1928.3, respectively. These individuals are used to estimate the income returns for G0. The log income information is presented in the third row of the top panel.

The bottom panel shows the distributions of education and occupation. Several patterns are observed. First, from the grandfathers' generation to the grandchildren's generation, the percentage of individuals who have only a lower secondary degree dropped from around 50% to around 2%, while that of individuals who have at least a tertiary degree increased from around 10% to nearly 50%, representing an overall enhancement in education level. Second, the percentage of workers in the agricultural or manufacturing sector dropped from nearly 50% to approximately 25%, representing a shift in the economic structure. Note that compared to the SSM occupation classification, the JHPS occupation classification has an additional category of "information technology related occupation." We merged this category into professional occupation, which is why the percentage of professional occupations is relatively high (over 20%) in the 2019–2023 sample. Third, the distributions of education and occupation for grandfathers in the JHPS and individuals in the SSM are similar. For instance, approximately 1/2, 1/3, and 10% of them have lower secondary, upper secondary, and at least tertiary degrees, respectively, and approximately 17%–18% and 30% of them are engaged in agricultural and manufacturing work, respectively. The JHPS grandfathers and SSM individuals are broadly comparable, indicating that they can be regarded as randomly drawn from the same underlying population.

Table 1 Descriptive statistics for the sample used to estimate income returns

	(1) JHPS and JHPS-G2 2019-23	(2) JHPS and JHPS-G2 2019-23 males	(3) JHPS 2004-23 males	(4) Fathers of JHPS 2004-23 males	(5) 1965 and 75 SSM respondents
age	44.65 (11.52)	45.83 (11.37)	47.78 (10.28)	N/A	42.19 (8.77)
birth year	1975.48 (11.60)	1974.28 (11.45)	1964.73 (11.39)	1927.54 (16.13)	1928.33 (9.97)
log (income)	6.02 (0.65)	6.10 (0.66)	6.11 (0.63)	N/A	4.64 (0.95)
education					
middle school (ref.)	1.87%	2.19%	5.00%	48.22%	55.13%
high school	37.79%	39.76%	44.98%	36.01%	30.13%
junior college	12.67%	8.17%	7.68%	2.30%	4.74%
universities	47.68%	49.87%	42.34%	13.47%	10.01%
occupation					
agriculture	1.37%	1.51%	2.31%	17.94%	18.39%
mining	0.04%	0.05%	0.05%	0.50%	0.58%
sales	12.59%	13.69%	12.89%	13.07%	11.16%
service	9.10%	9.13%	8.45%	5.17%	2.46%
management	7.82%	8.48%	9.90%	10.48%	10.03%
clerk	14.72%	11.46%	11.50%	6.71%	12.80%
transporting & communicating	6.39%	7.27%	7.57%	7.98%	5.59%
manufacturing	22.38%	24.86%	25.54%	27.44%	30.61%
professional	23.53%	21.30%	19.52%	8.67%	7.08%
security	2.06%	2.25%	2.28%	2.04%	1.31%

Note: Numbers in parentheses are standard deviations.

After imputing the incomes for G0, G1, and G2, we merge the JHPS with JHPS-G2 using household IDs to estimate the IGE. The descriptive statistics for the matched sample are shown in Table 2. The distributions of age, birth year, education, and occupation in the matched sample are similar to those in the income regression sample. In the matched sample, we identify 215 G0-G1 pairs and 264 G0-G2 pairs to estimate the intergenerational elasticity in our basic specification.

Table 2 Descriptive statistics for the matched sample used to estimate IGE

	(1) G2 (all grandchildren)	(2) Male G2 (grandsons)	(3) G1 (fathers)	(4) G0 (grandfathers)
age	36.20 (10.24)	35.37 (10.39)	65.97 (9.52)	N/A
birth year	1984.53 (10.05)	1985.33 (10.16)	1954.90 (9.19)	1922.90 (12.35)
imputed income at age 45	6.25 (0.20)	6.32 (0.21)	6.32 (0.21)	3.99 (0.27)
education				
middle school (ref.)	0.00%	0.00%	7.28%	57.59%
high school	38.15%	39.10%	45.77%	30.98%
junior college	12.80%	3.11%	8.02%	2.41%
universities	49.05%	57.79%	38.93%	9.02%
occupation				
agriculture	0.88%	1.19%	3.11%	20.71%
mining	0.00%	0.00%	0.00%	0.35%
sales	11.06%	13.04%	10.79%	13.45%
service	13.57%	11.86%	13.69%	5.13%
management	2.21%	3.95%	13.07%	10.44%
clerk	27.73%	15.81%	8.92%	5.31%
Transporting & communicating	1.33%	3.56%	7.88%	9.03%
manufacturing	11.50%	22.13%	24.90%	26.90%
professional	30.68%	25.69%	14.73%	7.96%
security	1.03%	2.77%	2.90%	0.71%

Note: 1) Standard deviations are shown in parentheses.

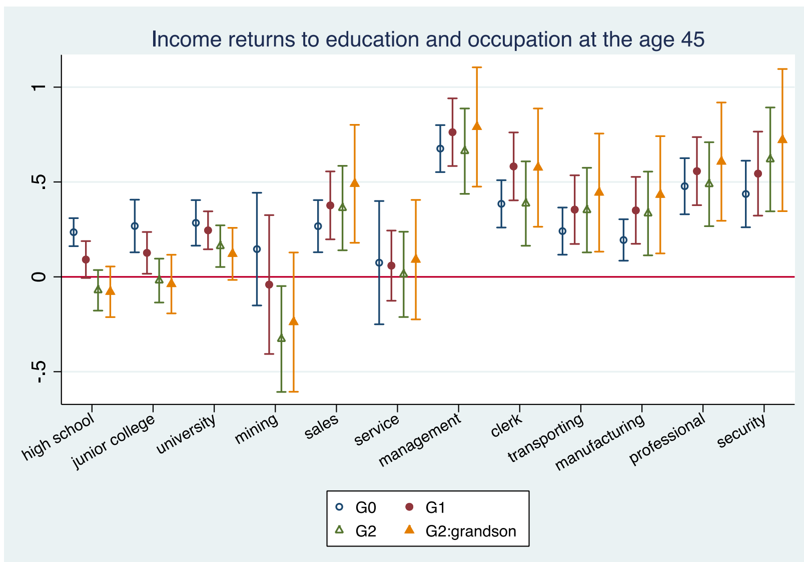
2) After calculating the average value of imputed income at age 45 ($\hat{Y}_i$), we merge the 2023 JHPS-G2 with the 2023 JHPS. For JHPS-G2 respondents whose latest participation year is Y (Y = 2019, 2020, 2021, or 2022) but who attrite from JHPS-G2 after year Y, we merge Y's JHPS-G2 with Y's JHPS. We use all these matched observations to boost the sample size. Since all observations in our matched sample are from 2019 and later, G1 is relatively old in the matched sample. For example, an individual aged 45 in 2010 (2004) would be in their mid-50s (early-60s) after 2019.

4.2 Income returns at age 45

We first present the estimation results for γ_1, which represent returns to education and occupation at age 45. In

Figure 1, the dots indicate point estimates, whereas the lines represent 90% confidence intervals. Most estimates are significant at conventional levels, except for returns to upper secondary education and junior college for G2 and returns to mining and service occupations. Additionally, we observe that, from the grandfathers' generation to the grandchildren's generation, income returns to education have decreased, while returns to occupation have increased. This suggests that income inequality due to education has diminished, whereas inequality arising from occupation has increased.

Figure 1 Income returns to education and occupation at age 45



Note: Lines represent 90% confidence intervals.

4.3 IGEs between generations

(1) Estimation results

In Table 3, Columns (1) and (2) present the IGE estimates between G0 and G1 and G0 and G2, respectively. In Column (1), we find that the IGE between G0 and G1 is 0.35, indicating that a 1 percent increase in grandfathers' income is associated with a 0.35 percent increase in fathers' income.

In Column (2), we find that the IGE between G0 and G2 is 0.147 (P<0.01), indicating that a "grandparental effect" does exist. The estimated IGE between G0 and G2 exceeds the square of the IGE between G0-G1 ($0.147>0.35^2 \fallingdotseq 0.123$). However, the null hypothesis $\beta_2 = \beta_1^2$ cannot be rejected at conventional significance levels, indicating that the IGE follows the prediction of an AR(1) process. In other words, the inequality persists over two generations, but the "additional" grandparental effect on grandchildren is weak.

Although not shown in Table 3, when we estimate the IGE between G0 and G2 controlling for G1's income, the estimated coefficient falls to 0.06 and is no longer statistically insignificant (P=0.358), suggesting that the grandfathers' income affects grandchildren's income primarily through fathers' income.

Column (3) shows the estimated IGE between G0 and male G2 (grandsons). The estimated value is 0.176 (P<0.01), confirming the persistence between grandfathers and grandsons. However, the AR(1) test results fail to reject the null hypothesis $\beta_2 = \beta_1^2$, when assuming that the IGE between G0 and G1 for grandsons is similar to that for all grandchildren.[6]

Table 3 Main estimation results

	(1) G1	(2) G2 (all)	(3) G2 (grandsons)
G0	0.35051***	0.14667***	0.17576***
	(0.05734)	(0.0437)	(0.06326)
Constant	4.90258***	5.65287***	5.61336***
	(0.23552)	(0.17763)	(0.2599)
χ^2 statistic for $H_0: \beta_2 = \beta_1^2$	N/A	0.20 (P=0.66)	0.56 (P=0.45)
Observations	215	264	139
R-squared	0.18876	0.04288	0.0542

Notes: 1) Robust standard errors (clustered on households) are shown in parentheses.
2) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

(2) Comparison to the existing studies

Compared with previous Japanese two-generation studies on intergenerational income mobility (IGM), the "grandfathers" in our analysis correspond to the "fathers" or "parents" (born around the late 1920s) in those studies, while the "fathers" in our analysis correspond to the "sons" or "children" (born around the late 1950s). In this analysis, the incomes of both grandfathers and fathers are imputed using their education and occupation, whereas in previous Japanese two-generation IGM studies that relied on imputed incomes (Ueda, 2009; Lefranc et al., 2014; Jia, 2022; Jia, 2023b), only the fathers' incomes were imputed. Despite these methodological differences, our findings are consistent: the IGE between individuals born in the late 1920s and those born in the late 1950s is approximately 0.35. A detailed comparison is presented in Table 4.

[6] As the number of matched grandfather-father pairs is less than 100 for grandsons, we do not use the estimate of IGE between G0 and G1 for grandsons.

Table 4 Two-generation Japanese IGM studies using imputed value

	Data	Measurement of children's income	Measurement of parental income	Estimated IGE
Ueda (2009)	Japanese Panel Survey of Consumers 1993–2004	Original value	Imputed by education, occupation, etc.	Above 0.40
Lefranc et al. (2014)	SSM 1965–2005			0.35
Jia (2022)				0.40
Jia (2023b)				

Note: Ueda (2009) focused only on married sons, while Jia (2022) excluded self-employed sons from the sample. In addition to education and occupation, some of these studies also used firm size (Ueda, 2009; Lefranc et al., 2014; Jia, 2022), self-employment status (Lefranc et al., 2014; Jia, 2022), living area, and birth cohort (Lefranc et al., 2014) for imputation. Ueda (2009) and Lefranc et al. (2014) also reported results for daughters, whereas we only summarize results for sons here.

The existence of intergenerational persistence between G0 and G2 generations in Table 3 is consistent with the findings of Lindahl et al. (2015), Long and Ferrie (2018), Olivetti et al. (2018), and Jia (2023a). Then, compared with them, how large is the IGE between G0 and G2 in Japan? Our estimates of 0.147 for all grandchildren and 0.176 for grandsons are lower than those of Olivetti et al. (2018) (approximately 0.2) and are comparable to those of Long and Ferrie (2018) (0.158 for Britain and 0.145 for the U.S.). Although our study uses imputed income based on both education and occupation—which arguably better captures latent economic status than Long and Ferrie (2018), who used only occupational income—our estimates remain broadly comparable. This suggests that intergenerational persistence between G0 and G2 may not be particularly strong in Japan. Unlike some of the previous studies (Lindahl et al., 2015; Long and Ferrie, 2018; Olivetti et al., 2018), our findings suggest that the intergenerational income mobility converges to the AR(1) process, indicating that grandfathers' income primarily affects grandchildren's income indirectly. A detailed comparison is presented in Table 5.

Table 5 Three-generation IGM studies (selected)

	Sample	Data	Measurement of grandparental income	Measurement of children's income	Estimated IGE b/w 3 generations	AR(1) process
Lucas and Kerr (2013)	Finland	Census data	Multiannual average income		Insignificant	Not shown
Lindahl et al. (2015)	Sweden (Malmö)		Residual income		0.184	No
Long and Ferrie (2018)	Britain and the U.S.		Average income by occupation		0.158 (Britain) 0.145 (U.S.)	No

Olivetti et al. (2018)	U.S.		Average income by occupation and first name		Around 0.2	No
Jia (2023a)	Taiwan	Household panel data	Multiannual average income	Imputed income by education and occupation	0.139	Yes
Modalsli and Vosters (2024)	Norway	Census data	Multiannual average income		Not shown	Depends on measurement

Note: Modalsli and Vosters (2024) simultaneously regressed G2's income on G1's and G0's incomes and found that the coefficient on G0's income becomes insignificant when G1's income is averaged more than 20 years. Some of the above studies also investigated the three-generation persistence of education (Lindahl et al., 2015) and occupation (Long and Ferrie, 2018).

4.4 Robustness checks

(1) Latent economic status hypothesis

As Lindahl et al. (2015) stated, education is less sensitive to market luck, suggesting that income imputed from education may better capture latent economic status than income imputed from occupation. To test this possibility, we impute the incomes of three generations using either education or occupation alone and repeat the estimation presented in Table 3. The results are summarized in Table 6.

Table 6 Testing the implication of latent economic status hypothesis

	(1-1)	(1-2)	(1-3)	(2-1)	(2-2)	(2-3)
Impute income by		Occupation			Education	
	G1	G2 (all)	G2 (grandsons)	G1	G2 (all)	G2 (grandsons)
G0	0.23467***	0.05548*	0.10979**	0.25413***	0.11518***	0.13431***
	(0.06794)	(0.02982)	(0.05545)	(0.03865)	(0.03852)	(0.04459)
Constant	5.37274***	5.99509***	5.85438***	5.29252***	5.79752***	5.81866***
	(0.27418)	(0.12105)	(0.22417)	(0.15631)	(0.15535)	(0.1804)
χ^2 statistic for $H_0: \beta_2 = \beta_1^2$	N/A	0.00 (P=0.99)	0.84 (P=0.36)	N/A	1.89 (P=0.17)	2.51 (P=0.11)
Observations	237	318	163	274	400	218
R-squared	0.08402	0.00999	0.02364	0.17263	0.02421	0.03939

Notes: 1) Robust standard errors (clustered on households) are shown in parentheses.
2) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In the first three columns, incomes are imputed using only occupation. While we find a significant IGE between G0 and G2, the estimates are smaller: 0.055 for all grandchildren and 0.110 for grandsons. In the last three columns, incomes are imputed using only education. The IGE between G0 and G2 is 0.115 for all grandchildren and 0.134 for grandsons. These estimates are larger than those derived from occupational income, but remain smaller than those derived from incomes imputed using both education and occupation. In summary, educational income, which is less likely to be affected by external shocks, better captures long-term economic status, and consequently results in less attenuation of intergenerational persistence. However, the results based on education alone are still smaller than those in Table 3, emphasizing the importance of using a "compound" measure, such as income imputed by both education and occupation.

Finally, the finding that intergenerational persistence converges to an AR(1) process remains unchanged.

(2) Other data sources for grandfather's income

Next, we use the average income by occupation from a nationally representative dataset, the Employment Status Survey (ESS) conducted by the Ministry of Internal Affairs and Communications, to represent grandfathers' incomes. The ESS aims to capture the employment status in Japan, covering topics such as income, firm size, occupation, industry, employment type, and demographic information. For our analysis, we use the 1974 aggregated ESS data for the following reasons. First, grandfathers in the current analysis were in their mid-40s during the early 1970s, and fathers born in the late 1950s reported their fathers' occupations when they were 15 years old, which was also the case in the early 1970s. Second, the occupational categories in the 1974 ESS align with those in the JHPS, JHPS-G2, and SSM, and no missing income information exists for the listed occupations. We exclude self-employed individuals because the average income data for three self-employed occupations (mining, transport, communication, and security) were unavailable. Table 7 presents the average income by occupation from the 1974 ESS. In our analysis, we consolidate skilled and unskilled manual workers into a single category, manual workers.

Table 7 ESS occupation categories and average earning

1974 ESS occupation	1974 ESS occupational mean earning (in 10,000 JPY)	JHPS and JHPS-G2 occupation	SSM occupation
agriculture	113.5	agriculture	agriculture
mining	137.3	mining	mining
sales	169.0	sales	sales
service	123.0	service	service
management	344.7	management	management

clerk	178.2	clerk	clerk
transporting and communicating	149.2	transporting and communicating	transporting and communicating
skilled manual worker	137.2	manual worker	manual worker
unskilled manual worker	119.1		
professional	199.2	IT	professional
		professional (excluding IT)	
security	165.6	security	security

Table 8 presents the estimation results. As G0's income is measured as the average income by occupation, G1 and G2's incomes are imputed solely based on occupation to maintain consistency in the measurement. We find evidence of a G0-G2 IGE, although it is less substantial and significant, indicating the presence of intergenerational persistence between G0 and G2. Meanwhile. the null hypothesis that intergenerational persistence follows an AR(1) process cannot be rejected.

Table 8 Using average earning by occupation in 1974 ESS to represent G0's income

	(1) G1	(2) G2 (all)	(3) G2 (grandsons)
G0	0.1878***	0.03622*	0.06912*
	(0.04847)	(0.02119)	(0.03815)
Constant	5.3621***	6.03314***	5.94219***
	(0.24709)	(0.10977)	(0.19652)
χ^2 statistic for $H_0\colon \beta_2 = \beta_1^2$	N/A	0.00 (P=0.97)	0.72 (P=0.40)
Observations	237	318	163
R-squared	0.09286	0.00724	0.01708

Notes: 1) Robust standard errors (clustered on households) are shown in parentheses.
2) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

(3) Instrument variable estimation to recover long-term intergenerational persistence

As discussed above, income or education measures latent economic status with error (market luck), implying that two-generation analyses relying on a single index (e.g., intergenerational income persistence between parents and children) may underestimate the true persistence of economic status (Clark, 2012; Lindahl et al., 2015). One way to address this issue is to use grandparents' income as an instrumental variable (IV) for parental income (Lindahl et al., 2015). Using grandparents' income as an IV for parental economic status helps capture the effects of latent factors, such as endowments, culture, or genetics, which may not be fully reflected in parental income but would affect grandchildren through their effect on parental income.

A crucial assumption of this latent economic status model is that the market luck in each generation is i.i.d. and does not directly "transmit" to subsequent generations. While this assumption is likely to hold (for example, a recession in the late 1920s is unlikely to "cause" prosperity in the late 1980s), we cannot completely rule out the possibility that grandparents influence their grandchildren directly (e.g., through human capital investment or upbringing). Nonetheless, our finding that grandparents' income has no additional effect on grandchildren's income, as indicated by the AR(1) test results, supports the validity of the exclusion restrictions (Modalsli and Vosters, 2024).

Table 9 OLS and IV estimations of IGE between G1 and G2

	(1)-OLS G2 (all)	(2)-IV G2 (all)
G1	0.29797***	0.54255***
	(0.08299)	(0.16999)
Constant	4.35438***	2.8002***
	(0.52875)	(1.07654)
χ^2 statistic for the equality of OLS and IV estimates	N/A	1.91 (P=0.17)
Observations	160	128
R-squared	0.0979	0.1395
First-step results		
		G1
G0		0.31742***
		(0.06533)
Constant		5.02851***
		(0.26639)
Observations		128
R-squared		0.1625

Notes: 1) Robust standard errors (clustered on households) are shown in parentheses.
2) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Due to the small sample size of male G2, we present the results only for all grandchildren. In the top panel, the OLS estimate is 0.30, which is similar to the IGE between G0 and G1in Table 3 (0.35). In contrast, the IV estimate increases to 0.54, suggesting that traditional two-generation analyses may underestimate the true intergenerational transmission of economic status. In other words, this result may indicate that grandparents directly influence grandchildren and such a direct effect would potentially inflate the IV estimates. However, the χ^2 statistic for the null hypothesis of equality between the OLS and IV estimates for the IGE between G1 and G2 is 1.91 (P=0.17), indicating no significant difference between the two estimates. This finding suggests that the two-generation OLS analyses sufficiently capture the real intergenerational transmission of inequality in our research setting, which is consistent with our findings of AR(1) process. In addition, we do not detect a significant difference between the IGE from G0 to G1 (0.32, the first-step results in Table 9) and the IV estimates of the IGE from G1 to G2 (the χ^2 statistic is 1.86 (P=0.17)).

Our finding that the OLS estimate of the IGE between G1 and G2 is approximately 0.3 aligns closely with Akabayashi and Naoi (2021), who used the same dataset to estimate the IGE between two generations corresponding to G1 and G2 in our study and found a value of 0.29. A key difference is that Akabayashi and Naoi (2021) used household income to measure G2's income, whereas we use imputed labor income based on education and occupation at age 45. Furthermore, to measure G1's income, they used imputed labor income based solely on education at age 45.

(4) Heterogeneities of the IGE between G0 and G2

Lastly, we examine heterogeneities of the IGE between G0 and G2 by focusing on the potential mechanism: direct investment in G2's human capital by G0 and the transmission of family-specific endowments. A smaller IGE when grandfather passed away before grandchildren's birth may indicate that direct human capital investment from grandfather to grandchildren contributes to intergenerational persistence, since such investment would have been precluded in those cases. To test this, we include an interaction term between G0's income and a dummy variable indicating G0's death before G2's. Similarly, if the IGE is larger among self-employed families, this may indicate that family-specific endowments (such as family business-specific skills or the family business itself) are stably transmitted over generations. To access this, we include an interaction term between G0's income and a dummy variable indicating G0 was self-employed. The estimation results are presented in Table 10.

Columns (1-1) and (1-2) of Table 10 show the estimated coefficients of the interaction term between G0's income and G0's death before G2's birth is negative, which is consistent with our intuition that a lack of contact reduces intergenerational persistence. However, these estimates are relatively small (-0.059 for all G2 and -0.096 for male G2) and insignificant, implying that even though G0 may not have met G2 in life, their economic status still transmits stably to G2, thus weakening the case for a direct G0 effect through human capital investment. This finding aligns with Jia's (2023a) results from Taiwan. Additionally, more than half of the studies on three-generation persistence in education found that G0's (dis)appearance or co-residence with G2 does not significantly affect G0-G2 persistence (see Anderson et al., 2018, for a review). Columns (2-1) and (2-2) of Table 10 also show no heterogeneity of the IGE between G0 and G2 based on whether the grandfathers are self-employed. Although the estimated coefficients for the interaction term are large (0.134 for all G2 and 0.215 for male G2), they are insignificant.

These results, showing little heterogeneity related to grandfather's death or self-employment, are consistent with our earlier findings in Table 3 that support an AR(1) process, suggesting that the transmission from grandfather to grandchildren is limited.

Table 10 Heterogeneities in IGE between G0 and G2

	(1-1)	(1-2)	(2-1)	(2-2)
	G2 (all)	G2 (grandsons)	G2 (all)	G2 (grandsons)
G0	0.15927***	0.1995***	0.11847**	0.12168*
	(0.04251)	(0.05507)	(0.05187)	(0.06941)
G0's death	0.19471	0.35204		
	(0.54178)	(0.77127)		
G0×G0's death	-0.05881	-0.09597		
	(0.13625)	(0.19189)		
G0 is self-employed			-0.50607	-0.8318
			(0.38073)	(0.61533)
G0×G0 is self-employed			0.13378	0.21548
			(0.09521)	(0.15334)
Constant	5.60706***	5.52244***	5.7602***	5.82668***
	(0.17378)	(0.22945)	(0.21334)	(0.28822)
Observations	260	136	264	139
R-squared	0.05079	0.06233	0.05275	0.07176

Notes: 1) Robust standard errors (clustered on households) are shown in parentheses.
2) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Concluding

Recent studies on intergenerational mobility have increasingly turned attention to the role of grandparents in shaping their grandchildren's economic outcomes, beyond the influence of parents' socioeconomic status. This growing body of research, which spans income, education, and occupation across three or more generations, has produced mixed findings depending on national and institutional contexts. However, in the case of Japan, such multigenerational analyses remain scarce, leaving an important empirical and theoretical gap in the literature.

To address this gap, we analyzed intergenerational income mobility across three generations in Japan by estimating intergenerational income elasticities between grandfathers and fathers, as well as between grandfathers and grandchildren, using representative Japanese household panel datasets, JHPS and JHPS-G2. We imputed the income at age 45 for each generation to reduce life-cycle bias and better approximate permanent income across generations. Practically, for each father and grandchild, we estimated the returns to education and occupation using their actual pooled income information from the JHPS and JHPS-G2, and predicted their income at age 45. Although grandfathers' income is unobserved in these datasets, we imputed their income at age 45 by applying the same approach to an alternative micro dataset from the 1965 and 1975 SSM surveys, where we similarly estimated the returns to education and occupation. The richness of the individual-level data allowed us to impute income using a wide array of characteristics, including education, occupation, employment status, and birth and death years—resulting in a compound measure that is more robust to short-term income fluctuations caused by "market luck" and better reflects long-term economic status.

We found significant intergenerational income elasticity between grandfathers and grandchildren in Japan across various settings. Our finding is consistent with the results of previous studies, and the elasticities are lower than those reported by Olivetti et al. (2018) for the U.S., and comparable to those of Long and Ferrie (2018) for the U.S. and Britain. However, we found that the intergenerational persistence of income converged to an AR(1) process, implying that the direct effect of grandfathers on grandchildren is weak in Japan. As a robustness check, we conducted IV estimations using grandfathers' income as an instrument for fathers' income to obtain better estimates of two-generation intergenerational income elasticities. Although the IV estimate was higher than the OLS estimate, the statistical test indicated no significant difference, suggesting that any direct effect of grandfathers on grandchildren is limited or statistically indistinguishable in our data.

As the first empirical study on multigenerational mobility in Japan, our analyses provide the following implications for intergenerational persistence in Japan: First, two-generation analysis seems to adequately capture the long-term intergenerational transmission of inequality. Second, grandparental investment in grandchildren's human capital appears to be trivial. One important caveat is that the small sample size may limit the precision of our estimations, making it difficult to draw strong conclusions. Hence, we cannot rule out the possibility that two-generation analysis overestimates mobility. Additionally, we cannot rule out the possibility that grandparents actively contribute to their grandchildren's human capital accumulation, or that strong intrahousehold inheritance of endowment traits exists. In fact, our estimated figures are consistent with all of these possibilities.

Several questions remain. For instance, is there statistical evidence of long-term persistence and intrahousehold inheritance of endowments? How do other indices of economic status, such as education and occupation, persist across multiple generations? To answer these questions, using census data with a larger sample size and including additional indices in the analysis would be a promising approach to gain a deeper understanding of intergenerational transmission of inequality in Japan.

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