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# Identifying the Role of High School in Educational Inequality: A Causal Mediation Approach

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**Identifying the Role of High School in Educational Inequality:**

**A Causal Mediation Approach**

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**Keywords:**

educational attainment, family income, causal mediation, direct and indirect effects, high school

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**Abstract**

The effect of socioeconomic background on children's educational attainment has long been investigated, but the extent to which high school mediates this effect is largely unknown. This study investigates the direct effect of family income on educational attainment not mediated by the rank of high school, using data from the longitudinal surveys of ninth-grade students and their mothers as a sample in Japan ($n$ = 1,761). The results indicate that the total effects of family income on university enrollment and educational rank are substantial. Regression with residuals (RWR) analysis reveals that although high school type mediates the effects of family income on university enrollment and education rank to some extent (about 22% and 29%, respectively), the direct effects of family income are considerable. The result also suggests a positive interaction effect between family income and high school selectivity on the education rank. In other words, the higher the rank of high school, the greater the direct effect of family income on the education rank, implying a boosting advantage pattern rather than a compensatory advantage. I argue that the analytical framework used in this study can be applied to many methodological settings in sociological studies.

Research on the inequality of educational opportunity has not only been concerned with the extent and trends of the association between socioeconomic background and educational attainment but has also focused on the process of this association. Several factors link educational attainment with social background (Bourne et al. 2018; Breen and Goldthorpe 1997; Bukodi, Erikson, and Goldthorpe 2014; Jackson 2013; Morgan 2005, 2012; Weeden, Gelbgiser, and Morgan 2020). This study focuses on the hierarchical structure of high school, observed in many countries (Ballarino and Panichella 2016; Bol and van de Werfhorst 2013; Chmielewski 2014; Kariya 2011; Palardy 2013; Scheeren, van de Werfhorst, and Bol 2018), as a key factor in the association between socioeconomic background and educational attainment. Many studies have found that students' socioeconomic background is related to the types and ranks of high school they attend, and in turn, associated with educational attainment (Kariya 2011; Palardy 2013). However, little is known about the extent to which high school mediates the impact of socioeconomic background on educational attainment, especially from the causal mediation framework

(Hong 2015; VanderWeele 2015). The process of how students' socioeconomic backgrounds influence their educational attainment through high schools they attended has not been adequately described or modeled, and the identification and estimation problems associated with the estimand and the model have not been fully recognized (Lundberg, Johnson, and Stewart 2021). It should be noted that traditional methods such as regression or path analysis (structural equation models) do not provide accurate estimates of direct or indirect effects. Moreover, in the mediation analysis, the interaction effect of the socioeconomic background and rank of high school on educational attainment has rarely been investigated.

In this study, I proposed using the causal mediation method developed recently (Hong 2015; VanderWeele 2015) to investigate how high school selectivity interacts with socioeconomic background and mediates its effect on educational attainment. I applied the method to Japan's case, where not only universities but high schools are also highly stratified in terms of academic selectivity (Kariya 2011; Kariya and Rosenbaum 1987; Rohlen 1983). Public expenditure on education is relatively low (Nakazawa 2016), and the family's financial burden is high, especially for higher education, as it is viewed as a family responsibility (Kobayashi 2019). I estimated the total effect of family income on two types of educational outcomes: college enrollment and rank of education. Further, I assessed the direct effect not mediated by high school selectivity, evaluated the interaction effect, and calculated how much the mediator explains the impact of family income on educational attainment.

## HIGH SCHOOL AS A MEDIATOR

The high school system mediates educational inequality in many societies (Ballarino and Panichella 2016; Bol and van de Werfhorst 2013; Chmielewski 2014; Kariya 2011; Palardy 2013; Scheeren et al. 2018). Many countries have different types of high schools and even different tracks within the same high school (Allmendinger 1989; Gamoran and Mare 1989; Kerckhoff 2001; Scheeren et al. 2018). The socioeconomic background influences the type of school students attend, affecting their educational achievement. Therefore, the socioeconomic background has an indirect effect on educational attainment through the types of high schools, evaluated using the differences between the coefficients of socioeconomic background before and after controlling for the type of high school. This approach is referred to as the difference method (VanderWeele 2016). The other is the product method (VanderWeele 2016), which uses the product of the coefficients. However, the type of school students attend is not only influenced by socioeconomic background but also by academic performance and aspirations in junior high school and earlier (Kariya and Rosenbaum 1987), which is again influenced by socioeconomic background. With such a complex set of variables involved, it is necessary to contemplate the estimand carefully, under what conditions it is identified, and how it is estimated (Lundberg et al. 2021). Otherwise, some conventional methods may lead to erroneous estimates of both the direct and indirect effects, and hence to an incorrect understanding of the mediating role of high school in the process of educational inequality.

## INTERACTION EFFECT OF SOCIOECONOMIC BACKGROUND AND HIGH SCHOOL

The high school system may play another vital role in educational inequality based on socioeconomic background. For example, Breen and Jonsson (2000) hypothesized and tested the existing interaction effect between prior educational pathways and class origins that influences the probability of making subsequent educational transitions. The result showed that socioeconomic background's effects were strongest at arduous and unusual pathways. Bernardi and Boado (2014) also found that the difference between class origins in the success of educational transitions is much smaller among high-performing students. This stratification process pattern is discussed based on the concept of compensatory advantage (Bernardi 2014). The compensatory advantage states, "life course trajectories of individuals from privileged backgrounds are less dependent on prior negative outcomes" (Bernardi 2014:75). Concerning the role of the high school, the compensatory advantage model predicts that the effect of educational inequality caused by socioeconomic background on educational attainment after high school graduation is more remarkable among students from less selective high schools (prior negative outcomes) than those from more.[1] However, given the complex set of variables, the interaction effect of socioeconomic background and high school should be cautiously estimated. In particular, the estimand, under what conditions it is identified, and how it is estimated (Lundberg et al. 2021) should be argued before any statistical analysis. This study considered the interaction effect of socioeconomic background and the rank of high school on educational attainment to estimate the direct and indirect effects (Klein and Kühhirt 2021) and examined the heterogeneous direct effect of the socioeconomic background when the high school ranks are fixed at various values (Celli 2021; Wodtke, Alaca, and Zhou 2020; Zhou and Wodtke 2019).

## SOCIOECONOMIC BACKGROUND

The conceptualization and measurement of social origin and socioeconomic background are critical issues in understanding intergenerational inequality (Bukodi and Goldthorpe 2013). Bukodi and Goldthorpe (2013) proposed decomposing social origins into parental class, status, and education. Contrarily, the economic aspect of social origins, such as family income and wealth, is also considered an essential aspect of socioeconomic background (Hällsten and Thaning 2021). However, using these measures as a set of independent variables in the conventional regression analysis makes it difficult to interpret each coefficient (Keele, Stevenson, and Elwert 2020; Westreich and Greenland 2013). For less biased estimation and proper interpretation, it is viable to focus on one aspect of the socioeconomic background and treat it as a treatment variable while treating the other socioeconomic background variables as pre or post-treatment variables. This study focused on the family income effect on educational attainment because income-based education inequality is a topic of academic and policy interest in Japan, where public expenditure on education is relatively low (Nakazawa 2016), and the financial burden of higher education on family is high (Kobayashi 2019). In sum, the treatment variable of interest is family income, and socioeconomic background variables, such as parental education and occupation, are pretreatment confounders that affect family income and a child's educational outcomes.

## HIGH SCHOOL AND HIGHER EDUCATION SYSTEM AND INEQUALITY IN JAPAN

Japan is an appropriate case for investigating the high school's roles on educational attainment because high school and university both have a hierarchical structure and detailed ranking based on academic selectivity. Moreover, the rank of the high school an individual attends is related to the rank of university they will be enrolled in.

Japanese formal educational is based on a 6-3-3-4 school system: six years of elementary school, three years of junior high school, three years of high school, and four years of university.[2] Education is compulsory until junior high school.[3] Most students continue their education after graduating from junior high school. As of 2016, 97.8% of junior high school graduates entered high school, and 0.9% entered the college of technology (*koto senmon gakko*), which offers both upper secondary and postsecondary education in five years. The Japanese high school system is highly stratified, with a detailed pecking order concerning academic selectivity and prestige (Kariya 2011; Kariya and

Rosenbaum 1987; Rohlen 1983). Therefore, entrance examinations are essential in determining students' placement in a high school with a good ranking (Chmielewski 2014).

There are mainly three types of high school courses: general (72.9% of students enrolled), specialized (21.7%), and integrated (5.4%) courses. The proportion of high school graduates who attend a four-year university is 59.1% for general, 21.5% for specialized, and 27.8% for integrated courses. In addition to academic, vocational, or integrated streams, high schools rankings are based on prestige determined by their students' performance in university entrance examinations (Ono 2001; Stevenson and Baker 1992). Therefore, admission to university is based on academic selectivity determined by the average academic performance. Unlike within-school tracking, which is typical in the United States, tracking exists mainly between schools in Japan (LeTendre, Hofer, and Shimizu 2003). Educational institutions preparing for examination publish the standardized rank scores with a mean of 50 and a standard deviation of 10 called *hensachi* in Japanese (Goodman and Oka 2018). Students, parents, teachers, employers, and personnel can quickly check the high schools' rankings via magazines and the Internet.

Figure 1 displays the distribution of the standardized rank scores (*hensachi*) for high schools and colleges of technology by prefectures. The rank scores are widely distributed with a hierarchical structure of high schools based on the detailed rank score within each prefecture. Because the standardized rank score is higher for general courses than for integrated and vocational ones, on average, this study used only the standardized rank score as a high school characteristic and not the course types. Despite these ranks differences, the standard high school curriculum is opted by all students. The difference between high schools lies in the degree to which they focus on preparing students for entrance exams, especially for selective universities (Rohlen 1983; Stevenson and Baker 1992).

[Insert Figure 1 here]

In 2019, 70.6% of the students enrolled in postsecondary education institutions after their high school graduation. Postsecondary education in Japan can be divided into four main categories: professional training college (*senshu gakko*), junior college (*tanki daigaku*), college of technology (for a limited number of high school graduates transferring to the 4th year), and four-year university (*daigaku*). In 2019, 16.4% of high school graduates entered professional training colleges, 4.4 % entered junior colleges, and 49.8% entered four-year universities. The International Standardized Classification of Education (ISCED) classifies high school as level 3, professional training college, junior college, and college of technology as level 5, and university as level 6. In addition to these hierarchies within postsecondary education, detailed hierarchical structures exist within universities, where educational opportunities are controlled by meritocratic entrance examinations (Stevenson and Baker 1992). A detailed hierarchical structure exists for Japanese universities based on academic selectivity and prestige (Ishida, Spilerman, and Su 1997; Kariya 2011; Takeuchi 2016), and the standardized rank score (*hensachi*) is used to indicate the selectivity of universities (mean 50 and standard deviation 10). Students (and their families) utilize the university rank score as a reference to determine which universities they are most likely to be accepted into based on their academic abilities and mock tests scores. The type of postsecondary education that individuals graduated from, and the selectivity and quality of university they graduated from, are associated with their socioeconomic status (Ishida et al. 1997; Kondo 2000; Takeuchi 2016).

Therefore, Japan's educational attainment process can be divided into two main stages: entrance examinations for high schools and postsecondary institutions. Although there are selection exams for admission in national and private junior high schools (0.7% and 7.5%) and secondary education schools (0.5%) for lower secondary education, most students take high school entrance exams.

The role of the high school system in the educational attainment process has attracted much attention from researchers in the sociology of education in Japan. Previous studies found that high school selectivity is associated with family background (Fujihara 2012; Nakanishi 2000; Nakanishi, Nakamura, and Ouchi, 1997; Ono 2001; Yamamoto and Brinton 2010). Students from less advantaged backgrounds are more likely to enroll in less selective high schools. In 2010, the "Free High School Tuition" law was implemented to reduce the economic burden of high school education on families. Mariel, Sanko, and Vega-Bayo (2021) show that although the effect of parental education and occupation on high school types have remained stable before and after the implementation of the law, the impact of wealth has weakened.

High school selectivity, in turn, affects the probability of going to college or university (Kariya 2011; Nakanishi 2000; Ono 2001:201; Takeuchi 2016; Yamamoto and Brinton 2010). Students from more selective high schools are more likely to go to universities or selective universities. For example, Kariya (2011) found that the hierarchical structure of Japanese secondary education is associated with the chance to access university education: the higher the rank of high school that students attended, the more likely they were to enroll in the university. Kariya (2011) also reported that socioeconomic background factors affect access to university education even after controlling for the rank of high school. The hierarchical structure of high schools is thought to play a key role as a gatekeeper regulating access to higher education (Kariya 2011:256). In other words, high school has been considered as a mediator linking socioeconomic background and educational attainment, but the extent of this mediation has rarely been examined.

RESEARCH QUESTIONS AND HYPOTHESIS

This paper considers two outcomes for educational attainment: (1) university enrollment indicating whether a student entered into university, and (2) rank of education indicating where a student is positioned in the education distribution. The rank of education, which I will discuss later in detail, is a measure that reflects both the vertical and horizontal stratification of education (Gerber and Cheung 2008).

Based on the above discussion, this paper addresses to what extent differences in the ranks of high schools explain the family income's effect on educational attainment.

*RQ 1 (Total Effect): What is the total effect of family income on university enrollment and education rank?*

*RQ 2 (Direct and Indirect Effects): What is the extent of the direct effect of family income on university enrollment and education rank not obtained through high school ranks? Also, what is the extent of the indirect effect created through high school ranks?*

*RQ 3 (Interaction Effect): Is the direct effect stronger for students at low-rank schools than those at high-rank schools?*

## DIRECTED ACYCLIC GRAPH FOR EDUCATIONAL INEQUALITY BY FAMILY INCOME

Based on the above discussion, I developed a directed acyclic graph (DAG), as shown in Figure 2 (Zhou and Wodtke 2019). Node $A$ is the treatment, $M$ is the mediator, $Y$ is the outcome, $X$ is a set of the pretreatment confounders, and $Z$ is a set of confounders between the mediator and the outcome, which are affected by $A$ (mediator-outcome confounders or intermediate confounders). A directed edge or an arrow from one node to the other indicates a causal effect. In the setting of educational inequality by family income and the high school education system in Japan, $A$ is family income, $M$ is the rank of high school, and $Y$ is the education outcome. $X$ includes pretreatment child and family variables, such as gender and socio-economic background, other than family income. $Z$ includes academic achievement before entering high school and subjective wealth.

The DAG in Figure 2 indicates a set of assumptions regarding causal relationships between these variables. This DAG assumes: (1) family income directly affects the rank of high school ($A \rightarrow M$) and educational attainment ($A \rightarrow Y$); (2) the rank of high school directly affects educational attainment ($M \rightarrow Y$); (3) the effects of (1) and (2) are confounded by a set of pretreatment covariates ($X$); and (4) the treatment-induced mediator-outcome confounders ($Z$) also exist. Four causal paths are linking $A$ and $Y$: (1) $A \rightarrow Y$, (2) $A \rightarrow M \rightarrow Y$, (3) $A \rightarrow Z \rightarrow M \rightarrow Y$, and (4) $A \rightarrow Z \rightarrow Y$. This DAG assumes no unobserved variables that jointly affect the treatment, outcome, or mediator (Wodtke and Zhou 2020).

[Insert Figure 2 here]

## METHODS

### *Estimand, Identification, and Estimation*

This section clarifies the estimand of interest, identification, and estimation using a statistical model (Lundberg et al., 2021). The causal mediation framework involves several direct and indirect effects (Pearl 2001; Robins and Greenland 1992; VanderWeele 2015). Generally, the indirect effect is the impact of a treatment on an outcome through the mediator, that is, through two causal paths of $A \rightarrow M \rightarrow Y$ and $A \rightarrow Z \rightarrow M \rightarrow Y$. Contrarily, the direct effect refers to a treatment impact on an outcome not mediated by the mediator ($M$), which can be denoted as $A \rightarrow Y$ and $A \rightarrow Z \rightarrow Y$ (VanderWeele, Vansteelandt, and Robins 2014).

First, I asked whether the educational attainment level of students with low family income increased if their family income increased compared to the high family income students while fixing the high schools' rankings to a predetermined level $M = m$ for every student (Pearl 2001). To clarify, my interest lies in estimating the direct effect of $A$ on $Y$ ($A \rightarrow Y$ and $A \rightarrow Z \rightarrow Y$) when the effect of $M$ is fixed at a certain value $m$. This type of estimand is called the controlled direct effects (CDE). Let $Y_i(a)$ be the potential outcome for individual $i$ when the treatment is set to $a$, the average total effect (TE) can be denoted as follows:

$$\mathrm{TE}(a, a') = E[Y_i(a) - Y_i(a')].$$

Similarly, the potential outcome for an individual $i$ when the treatment is $a$ and the mediator is $m$ can be denoted as $Y_i(a, m)$ and the average CDE is written as follows:

$$\mathrm{CDE}(a, a', m) = E[Y_i(a, m) - Y_i(a', m)].$$

There is no indirect counterpart because the mediator $m$ is fixed to be a particular value. These control direct effects are termed as "perspective" because they hypothesize intervening directly on the mediator (Pearl 2001; Rudolph et al. 2019).

Second, I considered the following estimand to describe the mediation process:

$$r\mathrm{TE}(a, a') = E\left[Y_i\left(a, G_{a|X}\right) - Y_i\left(a', G_{a'|X}\right)\right],$$

where $G_{a|X}$ denoted a randomly selected value of the mediator among those with treatment status $a$ conditional on $X$ (VanderWeele et al. 2014). Therefore, $r\mathrm{TE}(a, a')$ is called a randomized analog of the average total effect (VanderWeele et al. 2014). The $r\text{TE}$ can be decomposed into a randomized analog of natural direct and indirect effects:

$$r\text{TE}(a,a') = E\left[Y_i\left(a, G_{a|X}\right) - Y_i\left(a, G_{a'|X}\right)\right] + E\left[Y_i\left(a, G_{a'|X}\right) - Y_i\left(a', G_{a'|X}\right)\right]$$

$$= r\text{NIE} + r\text{NDE}.$$

$r\text{NIE} = E\left[Y_i\left(a, G_{a|X}\right) - Y_i\left(a, G_{a'|X}\right)\right]$ is the randomized analog of a natural indirect effect, and $r\text{NDE} = E\left[Y_i\left(a, G_{a'|X}\right) - Y_i\left(a', G_{a'|X}\right)\right]$ is the randomized analog of a natural direct effect.[4] The randomized analog of natural effects was used to derive descriptive interpretation of the mediation mechanism because the mediator values are drawn from the mediator distribution with the treatment condition of interest ($a$ or $a'$) conditional on $X$, not fixing a particular value to the mediator for all students (Pearl 2001; Rudolph et al. 2019; VanderWeele and Tchetgen Tchetgen 2017).

The $\text{CDE}$ can be identified under the following two assumptions (VanderWeele et al. 2014): (i) no unobserved confounding of the treatment-outcome conditional on $X$ ($Y(a,m) \perp A|X$), and (ii) no unobserved confounding of the mediator-outcome conditional on $A$, $X$, and $Z$ ($Y(a,m) \perp M|\{A,X,Z\}$). An additional condition is required to identify

$r$NDE and $r$NIE (VanderWeele et al. 2014): (iii) no unobserved confounding of the treatment-mediator conditional on $X$ $(M(a) \perp A|X)$ (VanderWeele et al. 2014). In addition, other conditions, such as consistency and positivity, are required for identification (Hernán and Robins 2020; Wodtke and Zhou 2020). When these assumptions are met, the $\mathrm{CDE}$, $r$NDE, $r$NIE can be identified from the observed variables.

Conventional analyses attempt to estimate the direct effect of $A$ by conditioning on $X$ and $M$ through stratification, regression, or path analysis. In the setting shown in Figure 2, conditioning on $M$ opens a pathway ($A \rightarrow M \leftarrow Z \rightarrow Y$), resulting in a collider bias. However, if I try to accommodate this path by conditioning on $Z$, $Z$ is between the pathway from $A$ to $Y$, blocking part of the pathway of the interest effect, which is the $Z$-mediated effect of $A$ on $Y$, resulting in an over control bias (VanderWeele et al. 2014). However, since $Z$ is also a confounder of the effect of $M$ on $Y$, failure to condition on $Z$ will result in bias (confounding).

Studies of the sociology of education and social stratification have shown that socioeconomic background is linked to educational achievement through formal and informal educational systems, but measuring the degree of mediation has not been sufficiently examined. Figure 2 corresponds to the analytical framework of many social scientific research settings; however, traditional regression analysis does not provide correct estimates of either direct or indirect effects. Recently, new methods such as the inverse probability of treatment weighting (IPTW) and structural nested mean model (SNMM) have been used to obtain direct and indirect effects even in situations mentioned in Figure 2 (see also Shi et al. 2021). Here, I used regression with residuals (RWR) to estimate the controlled direct effect and the randomized analog of the natural direct and indirect effects (Linden et al. 2021; Wodtke and Zhou 2020; Zhou and Wodtke 2019).[5] The following mediator and outcome models were used to estimate the effects:

The mediator model is about the conditional mean of the mediator conditional on treatment ($A$) and a set of pretreatment confounders ($X$). The model can be expressed as follows:

$$\mathrm{E}(M|A,X) = \theta_0 + \theta_1^T X^{\perp} + \theta_2 A,$$

where $X^{\perp} = X - E(X)$.

The outcome model concerns the conditional means of the outcome conditional on the treatment ($A$), mediator ($M$), a set of pretreatment confounders ($X$), and a set of confounders between the mediator and the outcome ($Z$). The model can be written as follows:

$$\mathrm{E}(Y|A, M, X, L) = \beta_0 + \beta_1^T X^{\perp} + \beta_2 A + \beta_3^T Z^{\perp} + \beta_4 M + \beta_5 AM +$$

$$\beta_6^T AX^{\perp} + \beta_7^T MX^{\perp} + \beta_8^T MZ^{\perp},$$

where $Z^{\perp} = Z - E(Z|A, X)$ To estimate $Z^{\perp}$, we also use the linear model of $E(Z|A, X)$ as follows:

$$E(Z|A, X) = \tau_0 + \tau_1^T X^L + \tau_2 A.$$

This model assumes the interactions of the treatment and pretreatment covariates ($AX^{\perp}$), the treatment and mediator ($AM$), the mediator and pretreatment covariates ($MX^{\perp}$), and the mediator and intermediate confounders ($MZ^{\perp}$) (Linden et al. 2021). When outcome $Y$ is a binary variable, a linear probability model with robust standard errors instead of the logistic regression model can be employed (see Appendix in Wodtke and Zhou 2020).

If the models are correctly specified, I could obtain, from the equation for the outcome regression, the control direct effect $\mathrm{CDE}(m) = \beta_2 + \beta_5 m(a' - a)$, when the treatment is changed from $a'$ to $a$, and the mediator $M$ is fixed at the value $m$ (for example, changing the value of the treatment from $a = 0$ to $a' = 1$ while fixing the mediator $m = 0.5$). The CDE indicates the causal effect of family income on university enrollment if the rank of the high school was fixed, for example, in the 25th percentile ($m = 0.25$), in the 50th percentile ($m = 0.5$), and in the 75th percentile ($m = 0.75$).

With correctly specified models, the $r$NDE, $r$NIE, and $r$TE can be obtained as follows (Wodtke and Zhou 2020):

$$r\text{NDE} = \beta_2 + \beta_5(\theta_0 + \theta_2 a)(a' - a),$$

$$r\text{NIE} = \theta_2(\beta_4 + \beta_5 a')(a' - a),$$

$$r\text{TE} = r\text{NIE} + r\text{NDE}.$$

I used the *rwrmed* package in R (Wodtke and Zhou 2020; Zhou 2019b), and to obtain the standard errors for the regression-with-residuals estimates, I used the nonparametric bootstrap (1,000 bootstrap samples).

Calculating the ratio of indirect to the total effects, the importance of the mediator to explain the treatment effects on the outcome can be examined. In general, the difference between TE and CDE cannot be interpreted as an indirect effect (VanderWeele, 2009a). However, a comparison between the TE and CDE helps understand how the rank of the high school explains the effect of socioeconomic background on educational attainment (Wodtke et al. 2020). I evaluated the extent to which the mediator eliminated the effect of family income. The proportion eliminated (PE) is defined as follows (VanderWeele 2013):

$$\mathrm{PE}(m) = \frac{\mathrm{TE} - \mathrm{CDE}(m)}{\mathrm{TE}}.$$

The numerator has no causal meaning unless interaction between the treatment and the mediator (Suzuki et al. 2014), and in such a situation, CDE can be used to assess mediation (VanderWeele 2009b).

The randomized analog of natural indirect and indirect effects provides a clearer picture of the proportion of mediation. The proportion mediated (PM) is defined as follows (VanderWeele 2013):

$$\mathrm{PM} = \frac{r\mathrm{TE} - r\mathrm{NDE}}{r\mathrm{TE}} = \frac{r\mathrm{NIE}}{r\mathrm{NDE} + r\mathrm{NIE}}.$$

Note that $r\text{TE}$ is not the total but the overall effect of the treatment on outcome. Using PM, I evaluated the extent to which the mediator explains the impact of family income on educational attainment.

### *Data*

The data used are from the panel survey of junior high school students and their mothers conducted by the Institute of Social Science, University of Tokyo, Japan. The respondents were junior high school students born between April 2000 and March 2001 and their respective mothers. Pairs of children and parents were randomly chosen from the list of an access panel constructed by a survey company across Japan. Respondents were recruited with the cooperation of households randomly selected from the Basic Resident Register. As the access to the Basic Resident Register was limited, the number of new monitors, introduced by the existing monitors, had been increased.

The first survey wave (mail survey) began in October 2015. Of 4,800 pairs of children and parents asked to participate in the survey, 1,854 pairs participated in January 2016

(45.0% response rate). Information on children before they entered high school and their parent's socioeconomic status and background was obtained. In December 2017 (equivalent to a second-year high school student), a mail survey was again conducted, and information regarding students attending the high schools was acquired. In addition, the surveys were conducted online since December 2019, and information on respondents attending postsecondary schools after their high school graduation was obtained. The data included information on the socioeconomic background (mother's response) and self-reported grades at junior high school, the standard rank score (*hensachi*), high school courses the respondent children attended, and their educational attainment till 2021.

Because of my interest in the role of high school in mediating family income's effect on educational attainment, the sample was restricted to individuals who had entered high schools after graduation from junior high school ($n$ = 1,761).

*Variable*

Two types of dependent variables $Y$ were analyzed separately. The first dependent variable, a binary variable, is whether the subject enrolled in a university (1 = enrolled in university, 0 = otherwise). The second dependent variable provides a more detailed picture of educational attainment based on the ranking of education.

Although educational attainment in Japan can consist of multiple transitions (Mare 1980; Treiman and Yamaguchi 1993), I considered the rank of a student's educational attainment by 2021 in the distribution of educational attainment for all students in the same cohort. The rank of education can be created from the distribution of (1) high school, (2) junior, technical, and professional training colleges, and (3) university, as shown in Figure 3A (c.f., Bukodi and Goldthorpe 2013). Because the Japanese university system is highly stratified based on the selectivity for enrollment as discussed above, I also considered the selectivity of the university as captured by the standardized rank score, *hensachi*, in creating the ranks.

The survey asked for information about the names of schools and faculties the students attended. Based on this information, I created a variable by assigning standardized rank scores published by Kawaijuku in 2018. Figure 3B shows the distribution of the standardized rank scores. The mean and standard deviation for the standardized rank scores of the university the child respondent attended was 49.1 and 9.19, respectively. The rank of education was created from the distribution of (1) high schools, (2) junior, technical, and professional training colleges, and (3) the standardized rank scores of the universities. Here, I assumed that even the lowest-ranked universities possess higher ranks than junior, technical, and professional training colleges in the education distribution. Because the respondents were still young (aged between 20 and 21 in 2021), this study did not consider the possibility of their attending graduate school, which may have the highest rank in the educational system. The selectivity of high schools, which is a mediator, was also not considered here. Figure 3C shows the distribution of the rank of education (mean = 0.5, SD = 0.28). This dependent variable captures the position of an individual in the distribution of education based on selectivity and measures the relative values of education (Shavit and

Park 2016). The advantage of this method is that it can utilize linear regression models rather than multinomial, nested logistic regression, or Tobit models, which are complex, and the results are difficult to interpret.

[Insert Figure 3 here]

Treatment variable $A$ is the annual family income in the third year of junior high school. The mediator $M$ is the standardized rank score of high school (*hensachi*), measured after measuring $A$ and before measuring $Y$. The rank of education, family income, and standardized rank score of the high school is transformed into ranks approximately ranging from 0 to 1, indicating the relative position of each student in the uniform distributions. This transformation makes the coefficients easy to interpret (Chetty et al. 2014; Hällsten and Pfeffer 2017). For example, the estimated coefficient of family income ($A$) on the rank of high school ($M$) measures the association between students' position in the family income distribution and the distribution of high school selectivity.

The baseline confounders (pretreatment covariates) $X$ included gender, the month of birth (April = 0, May = 2, …, March = 11), parental socioeconomic index (SEI), father's and mother's years of education, neighborhood advantage index (Wodtke, Harding, and Elwert 2011), distance to the nearest university, number of siblings, order of birth, grandparents' education, and mother's age. The treatment-induced confounders (intermediate covariates) $Z$ included a self-reported academic performance evaluation in the third year of junior high school (a principal component analysis of five variables was used to create a composite variable), children's and mothers' aspirations of attending universities, and the subjective wealth of children and mothers. For details, see Table A in the Part A of the online supplement.

Generally, the mediation analysis required collected data of at least two or three different time points to ensure valid temporal ordering of the variables for treatment preceding the mediator, which precedes the outcome (VanderWeele 2015). The data used here meet this criterion (also see *Note* in Figure 2). Because there are many missing values in longitudinal data, I conducted the estimation using multiple imputations using the

Amelia II program, implementing expectation-maximization with a bootstrapping algorithm (Honaker, King, and Blackwell 2011).[6] Following the recommendation by Sullivan et al. (2015), I did not delete the outcomes after multiple imputations. I assumed that the data were missing at random (MAR). The number of imputations was 80. Table 1 presents descriptive statistics.

[Insert Table 1 here]

RESULTS

*Conventional Regression Analysis*

Before the causal mediation analysis, I conducted a set of regression analyses to estimate the association and the total effects of the mediator (selectivity of high school) and treatment (family income) on the probability of university enrollment after high school graduation. To avoid misinterpretation of the coefficients (Keele et al. 2020; Westreich and Greenland 2013), I did not show the coefficients of the other variables.

First, I investigated the effect of family income on the rank of the high school. The left-hand side of Figure 4 presents the estimated coefficients of family income on the rank of high school from two models: Model 1 includes only the treatment variable (family income) in the regression model, and Model 2 involves the treatment variable and pretreatment covariates. The estimated coefficient from Model 1, indicating the total association, was 0.329 (SE = 0.024) and statistically significant, meaning that a 10 percentage point difference in the rank of family income is related to a difference in the university-going rate by about 3.3 percentage points. The estimated coefficient from Model 2 that added the pretreatment covariates to Model 1 decreased to 0.149 (SE = 0.026), indicating the TE of the family income on the rank of high school.

[Insert Figure 4 here]

Second, I estimated the effect of the rank of high school on the probability of university enrollment. The right-hand side of Figure 4 shows the estimated coefficients of the rank of high school. Model 1 includes only the rank of high school with a very high estimated coefficient of 0.922 (SE = 0.034). A 10 percentage point difference in the rank of high school is associated with a difference in the probability of university enrollment by approximately 9.2 percentage points. If I controlled family income ($A$) and other pretreatment covariates ($X$) in Model 2, the coefficient decreased to 0.762 (SE = 0.045) but still remained high. Model 3 that controlled intermediate confounders ($Z$), as well as $A$ and $X$, shows that the estimated coefficient of the rank of high school was 0.381 (SE = 0.064). This coefficient indicates the TE of the rank of high school on university enrollment is substantively different from those estimated by Models 1 and 2. The results suggest that not only the treatment variable and pretreatment covariates but also the intermediate covariates are essential in assessing the mediator's effect on the outcome.

Third, I examined the family income's effect on the probability of university enrollment. Figure 5 summarizes the coefficients of family income obtained using the conventional methods. The coefficient of family income from the model without any other variables (Model 1) was 0.480 (SE = 0.042). When the TE of family income was estimated from the model with the pretreatment variables $X$ (Model 2), the coefficient was 0.256 (SE = 0.040), indicating that a 10 percentage point increase in the income raises the college-going rate by about 2.6 percentage points. When the mediator $M$ is added into the regression model as in the conventional method (Model 3), the coefficient of family income decreased from 0.256 to 0.142 (SE = 0.049). The result from the conventional method suggested that about a half of the TE of family income is the direct effect not mediated through the rank of high school. Furthermore, when the intermediate confounders $Z$ were included in the regression model (Model 4), the coefficient of family income became 0.061 (SE = 0.053) and not significant at the 5% level, indicating no direct effect of family income. These naïve or conventional analyses simply controlling for the mediator and intermediate covariates (treatment-induced confounders) concluded that there is a small or no direct effect of family income on university enrollment.

[Insert Figure 5 here]

As explained in the "Estimands, Identification, and Statistical Models" section, Models 3 and 4 in Figure 5 estimated the biased direct effect. To estimate the direct effect without bias, I applied the regression with residuals and estimated the controlled direct effect, $\text{CDE}(a = 1, a' = 0, m) = \beta_{10} + \beta_{21}(m - 0.5)$, of family income on university enrollment. The values of $a$ and $a'$ were set to 1 (the highest rank of family income) and 0 (the lowest rank of family income), respectively, and that the rank of high school ($m$) varied from 0 to 1. I used $\beta_{21}(m - 0.5)$ instead of $\beta_{21}m$ so that $\beta_{10}$ denotes the CDE for the median of the rank of high school. The estimated coefficient was $\hat{\beta}_{10}$ = 0.205 (SE = 0.046), implying that CDE for the median of the rank of high school is larger than the direct effects estimated by Models 3 and 4 in Figure 5 (0.142 and 0.061, respectively). The $\hat{\beta}_{21}$ = 0.006 (SE = 0.163) suggests that CDE is rather constant across the ranks of high schools. Figure 6 shows the estimated CDE for university enrollment according to the rank of high school.

[Insert Figure 6 here]

The PE, fixing the mediator to the median of the rank of high school is $\mathrm{PE}(m = 0.5) = (0.256 - 0.205)/0.256 = 0.199$, indicating that the TE of family income is not largely eliminated by intervening in the rank of high school. For example, the intervention of allocating all students to high schools at the median of the selectivity rank will equal the degree to which high schools focus on college preparations. In this setting, the degree to which high schools focus on preparing students for (selective) universities was moderate. The estimated *r*TE, *r*NDE, and *r*NIE values are shown in Table 2. The estimated *r*TE was 0.263 (SE = 0.050), indicating that a 10 percentage point increase in the rank of income raises the college-going rate by about 2.63 percentage points. The estimated *r*NDE and *r*NIE were 0.205 (SE = 0.052) and 0.058 (SE = 0.018), respectively. Therefore, PM was 0.220 (= 0.058/0.263), indicating that the rank of high school mediates the overall effect of family income by about 22%.

[Insert Table 2 here]

*Decomposition of the Effects of Family Income on Rank of Education with RWR*

This section used the rank of education as the dependent variable. First, I estimated the TE of family income based on the rank of education. Figure 7 shows the results of the three regression models. Model 1 includes only the rank of high school, and the estimated coefficient was 0.649 (SE = 0.020). Model 2 adds the treatment variables and pretreatment covariates to Model 1, and the estimated coefficient of the rank of high school was 0.541 (SE = 0.024). Model 3 also includes intermediate covariates as well as treatment and pretreatment variables with an estimated coefficient of 0.334 (SE = 0.034), different from those estimated in Models 1 and 2. This result shows that the intermediate variables are important to estimate the causal effect of the rank of high school on the rank of education.

[Insert Figure 7 here]

Next, I examined the causal effect of family income on the rank of education. The result of the conventional analysis is shown in Figure 8. Model 1 includes only the treatment variable (family income) with the estimated coefficient 0.346 (SE = 0.025). Model 2 adds pretreatment covariates to Model 1, and the estimated coefficient was 0.195 (SE = 0.028), indicating the total effect of family income on the rank of education. Model 3 includes the mediator, the treatment, and pretreatment variables. Model 4 added the intermediate covariates to Model 3. The estimated coefficients of family income from Models 3 and 4 were 0.114 (SE = 0.026) and 0.075 (SE = 0.029), respectively.

[Insert Figure 8 here]

The CDE is estimated using the RWR. The estimated coefficient $\hat{\beta}_{10}$ was 0.151 (SE = 0.025). The CDE for the median of the rank of high school is larger than the direct effects estimated by Models 3 and 4 in Figure 8 (0.114 and 0.075, respectively). Moreover, the estimated coefficient for the interaction effect was $\hat{\beta}_{21}$ = 0.143 (SE = 0.090), suggesting that the effect of family income differs by the rank of high school although it was not statistically significant ($p > 0.10$). Figure 9 displays the estimated CDE on the rank of education according to the rank of high school. CDE was greater when the rank of high school was fixed at higher levels. The proportions eliminated (PE) by fixing the mediator to the $0^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $100^{th}$ percentiles were 0.079, 0.115, 0.151, 0.186, and 0.222, respectively. It indicates that the CDE of family income on the rank of education was larger when the mediator values (the rank of the high school) were set to higher values (e.g., 0.75) than lower values (e.g., 0.25). This result suggests that the TE of family income on education rank is greater in the setting where all high schools have a high degree of focus on (selective) university preparation.

[Insert Figure 9 here]

The PE fixing the mediator to the median of the rank of high school is $\mathrm{PE}(m = 0.5) = (0.195 - 0.151)/0.195 = 0.226$, indicating that the TE of family income on education rank is not largely eliminated by the intervention of high schools (about 23%). However, if no interaction assumption is violated, the direct effect cannot be used to assess mediation (VanderWeele 2009b). The estimated *r*TE, *r*NDE, and *r*NIE values are also shown in Table 2. The estimated *r*TE was 0.196 (SE = 0.029), indicating that a 10 percentage point increase in the rank of income raises the college-going rate by about 1.96 percentage points. The estimated rNDE and rNIE were 0.139 (SE = 0.027) and 0.057 (SE = 0.013), respectively. High school selectivity mediates the overall effect of family income on education rank by approximately 29% (PM = 0.057/0.196 = 0.291).

## CONCLUSIONS AND DISCUSSIONS

Although high schools have been considered key institutions in the attainment of education and in producing educational inequality based on the socioeconomic background, the extent to which it mediates the influence of socioeconomic background has not been well known. In this study, I estimated the direct and indirect effects of family income on university enrollment and education rank not mediated by the rank of high schools in Japan. To estimate the direct and indirect effects, I applied two methods: traditional regression analysis controlling for the mediators and RWR. The former explains more than half of the effect of family income. In other words, I can conclude that the high school hierarchy explains more than half of the inequality in college enrollment related to family income. However, RWR estimates indicate that high school type mediates the effects of family income on university enrollment and education rank to some extent (22% and 29%, respectively). Although the rank of high school was on the family income's pathway to educational attainment, the direct effect of family income, not through the rank of high school, is substantially large. The high school stratification system is significant in considering the inequality of educational opportunities in Japan; however, without an appropriate analysis from a proper framework, the role of this system may be incorrectly evaluated and interpreted. Overestimating the role of high schools and underestimating the impact of family socioeconomic background distorts the direction of policy interventions that need to be considered.

In the Japanese case, the conventional method overestimates the mediating role of high school rank. Because high school selectivity is highly associated with academic performance and is based on entrance exams and grades at junior high schools, personality traits and aptitude are rarely considered (Kariya and Rosenbaum 1987). An educational plan should be designed based on the student's academic performance in junior high school or earlier to decide what kind of high school they attend accordingly (Kariya and Rosenbaum 1987). Thus, the role of the high school is overestimated if I do not consider the impact of grades and educational plans, which are influenced by students' socioeconomic backgrounds.

To clarify the direct and indirect effects, it is essential to consider intermediate confounders of the mediator-outcome affected by the treatment. In the case of educational attainment, it is necessary to understand how family income affects the rank of high school and educational attainment without mediating the rank of high school. Grades and educational aspirations at junior high school, which are affected by family income, strongly affect the rank of high school and educational attainment. The results suggest that these two factors intensely mediate the effect of family income on educational attainment and that high school ranks mediate only to a limited extent.

I also estimated the interaction effect of family income on high school selectivity. High school selectivity not only mediates some portion but also modifies the effect of family income, especially on the rank of education, although the latter's effect is statistically uncertain. The result of mediation analysis for estimating the controlled direct effect indicates no evidence supporting the compensatory advantage model. Instead, the socioeconomic background advantage is greater in the scenario where students attended more selective high schools (prior positive outcome) than the less selective ones. This process can be described as a boosting advantage or augmentation effect rather than a compensatory advantage (Bernardi and Gil-Hernández 2021; Chiang and Park 2015). Interestingly, while using the conventional regression model to investigate the interaction effect between the treatment and mediator on university enrollment, the coefficient was −0.318 (SE = 0.114) when controlled for the pretreatment covariates ($X$) (adding the interaction term in Model 3 in Figure 5), and −0.081 (SE = 0.114) when controlled for the mediator-outcome confounders ($Z$) in addition to $X$ (adding the interaction term in Model 4 in Figure 5). This result suggests a compensatory advantage. I found a positive interaction effect between the treatment and mediator in the analysis of education rank as the outcome. The coefficient was 0.035 (SE = 0.066) when controlled for only $X$ (adding the interaction term in Model 3 in Figure 8) and 0.155 (SE = 0.065) when controlled for $X$ and $Z$ (adding the interaction term in Model 4 in Figure 8). This result was similar to that obtained from the RWR, suggesting a boosting advantage. This additional analysis indicates that the conventional regression method to examine the interaction effect between the treatment and mediator may incorrectly evaluate the impact of family income on educational attainment, especially on university enrollment.

So, why does family income have a greater impact on education rank when the rank of high schools is higher? As shown in Figure 1, high schools with various levels of selectivity exist within each prefecture; however, the higher-ranked universities, like the former imperial universities and highly selective national and private universities, are located in metropolitan areas. Even if high-rank schools are dedicated to preparing students for highly selective universities, students will have to move to a metropolitan area to enter a higher-ranked university (Hozawa 2016). Therefore, if a student's family cannot afford the costs, they will go to a nearby university (which may not be a high-rank university). If the family can afford it, students will attend a university with the highest rank possible by taking several entrance exams. The geographic location of universities may create an interaction between the high school rank and socioeconomic background, that has an impact on education rank.

Finally, I highlight the effectiveness of the analytical framework of this study compared to other sociological studies. As shown in Figure 2, the analytical framework used in this study can be applied to many methodological settings in sociological studies (Klein and Kühhirt 2021; Zhou 2019a). The problems of traditional mediation analysis (e.g., hierarchical regression analysis) have not been adequately considered, although some methodological studies have repeatedly pointed them out (Breen 2018; Elwert and Winship 2014; Lundberg et al. 2021). Fortunately, an increase in methodological studies on causal mediation analysis by sociologists has been seen recently (e.g., Brand et al. 2019; Klein and

Kühhirt 2021). In addition, methods and tutorials for performing the mediation analysis in popular statistical software such as Stata and R have been introduced (Linden et al. 2021; Shi et al. 2021; Wodtke et al. 2020; Wodtke and Zhou 2020; Zhou and Wodtke 2019). However, unobserved confounders of the treatment-outcome, treatment-mediator, and mediator-outcome may produce bias in the estimates of total, direct, and indirect effects, which is also the case in this study (for an example of the sensitivity analysis, see the Part B of the online supplement). The assumptions that identify direct and indirect effects should be carefully examined theoretically and empirically.

Future research on the role of high school in educational attainment should pay more attention to the new method of mediation analysis to estimate the correct direct and indirect effects of the treatment variable and the interaction effect and then derive policy implications. Such attempts are essential in clarifying the relationship between social inequality and institutional arrangements (Kerckhoff 1995).

Notes

1. It also predicts that the effect of high rank on educational outcomes is greater for those from less advantaged backgrounds than those from more advantaged backgrounds.
2. See https://www.mext.go.jp/en/policy/education/overview/index.htm for details on the Japanese education system.
3. 4.5% of junior high schools are combined with high schools, called secondary education schools (*chuto kyoiku gakko*).
4. The natural direct and indirect effects cannot be identified in the presence of treatment-induced confounders $Z$, as shown in Figure 2 (VanderWeele et al. 2014; Wodtke et al. 2020; Wodtke and Zhou 2020).
5. I also estimated the $r$NDE, $r$NIE, and $r$TE using the g-formula approach (Robins 1986) instead of regression with residuals (RWR). For details, see Part B of the online supplement.
6. The auxiliary variables (20 variables) were used in multiple imputations processes to increase the prediction accuracy of missing data.

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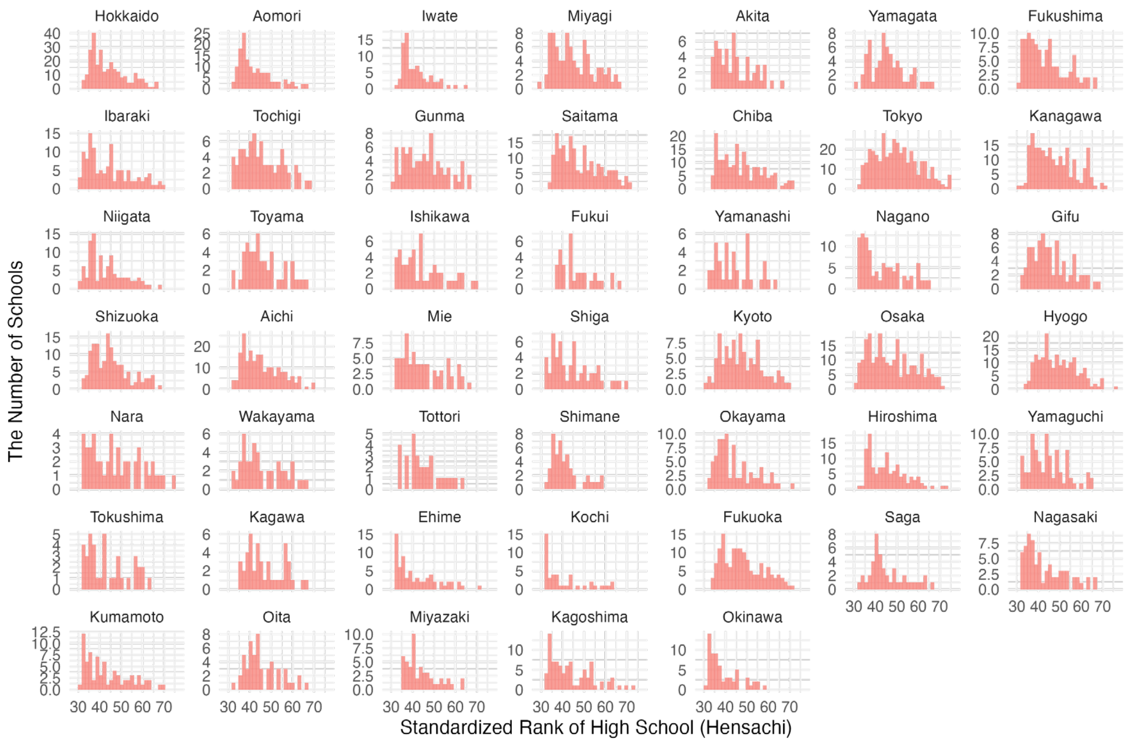


Figure 1. Distributions of A High School Rank Score (*Hensachi*) by Prefectures

*Note*: $N$ = 4,656. The rank score (*hensachi*) was extracted from https://www.trygroup.co.jp/exam/high/ TRY GROUP Corporation (April 19, 2016). The rank score can be obtained for high schools and technical colleges.

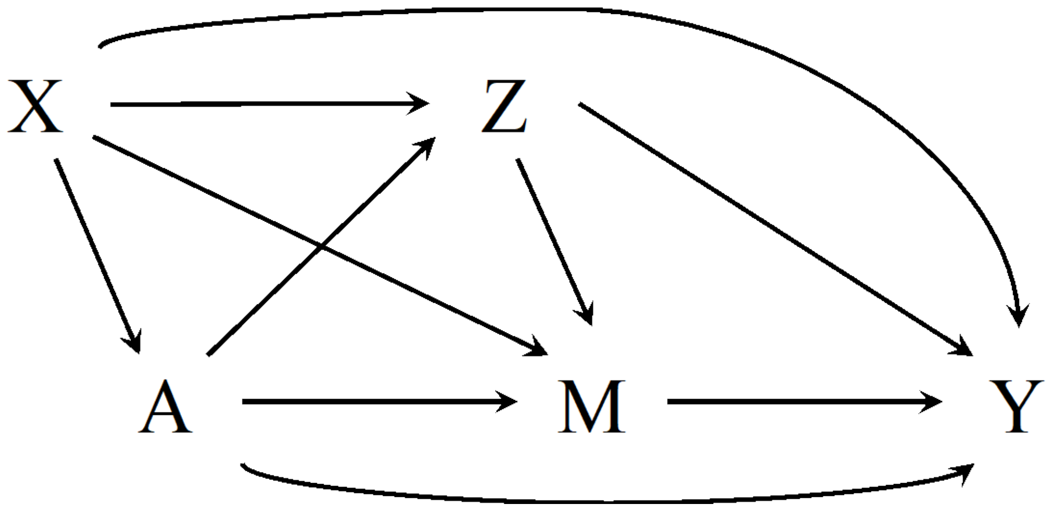


Figure 2. A Directed Acyclic Graph (DAG) for Mediation Analysis

*Note*: The outcome $Y$ = educational attainment in 2021 (university enrollment or the rank of education); the mediator $M$ = the rank of high school in 2017; the treatment $A$ = family income in 2015, the pretreatment confounders $X$ = demographic and socioeconomic characteristics such as gender, parental SEI, years of father's education, years of mother's education, neighborhood advantage index, distance to the nearest university, number of siblings, birth order, maternal grandparents' education, and mother's age, which were collected in 2015. $Z$ = the mediator-outcome confounder affected by exposure $A$ (the treatment-induced intermediate confounders) such as performance in the third year of junior high school, the child's aspiration to go to university, and the mother's aspiration for the child to go to university, and subjective wealth of the child and mother, which were collected in 2015.

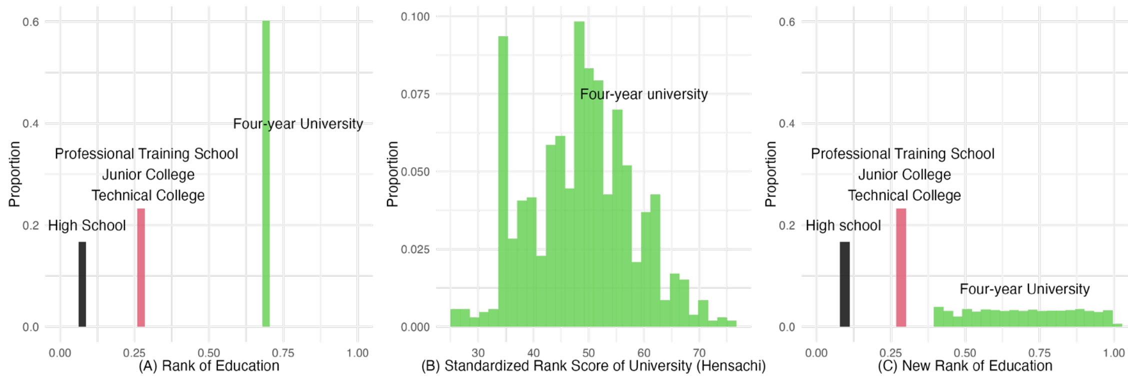


Figure 3. Distributions of (A) Educational Attainment, (B) Selectivity of University (Hensachi), and (C) the Rank of Education

*Note*: Multiple imputations are used for missing values. Distributions are obtained from one of the imputed data sets. When *Hensachi* score is as labeled 'Border Free (universities where anyone can pass an entrance exam and enroll),' I assigned the lowest value of the rank score (hensachi) minus one (34 = 35 – 1).

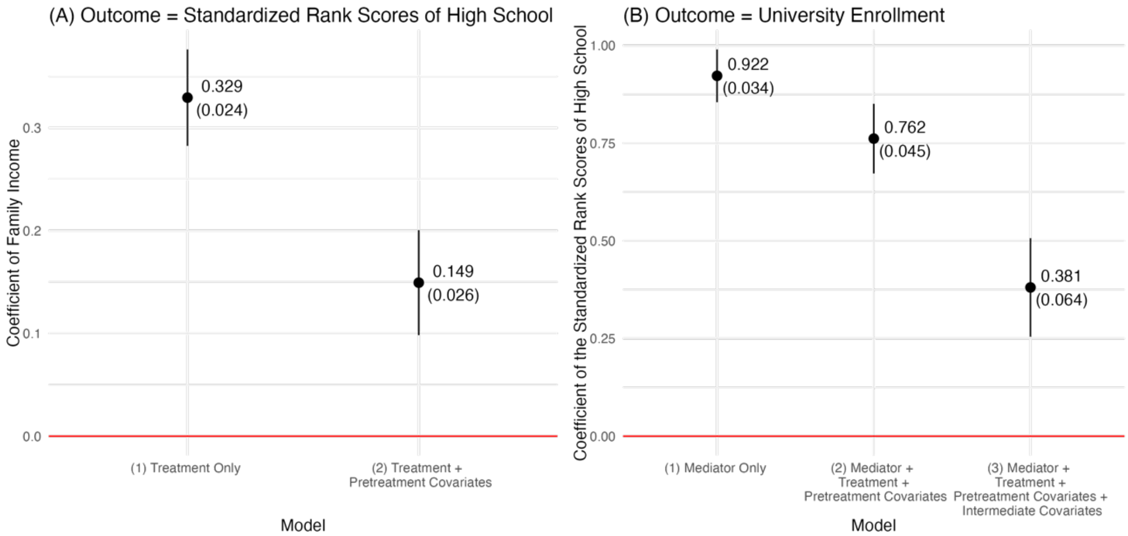


Figure 4. Estimated Coefficients of (A) Family Income on the Selectivity of High School and (B) Selectivity of High School on the Probability of University Enrollment

*Note*: Calculations are combined across 80 imputed data sets.

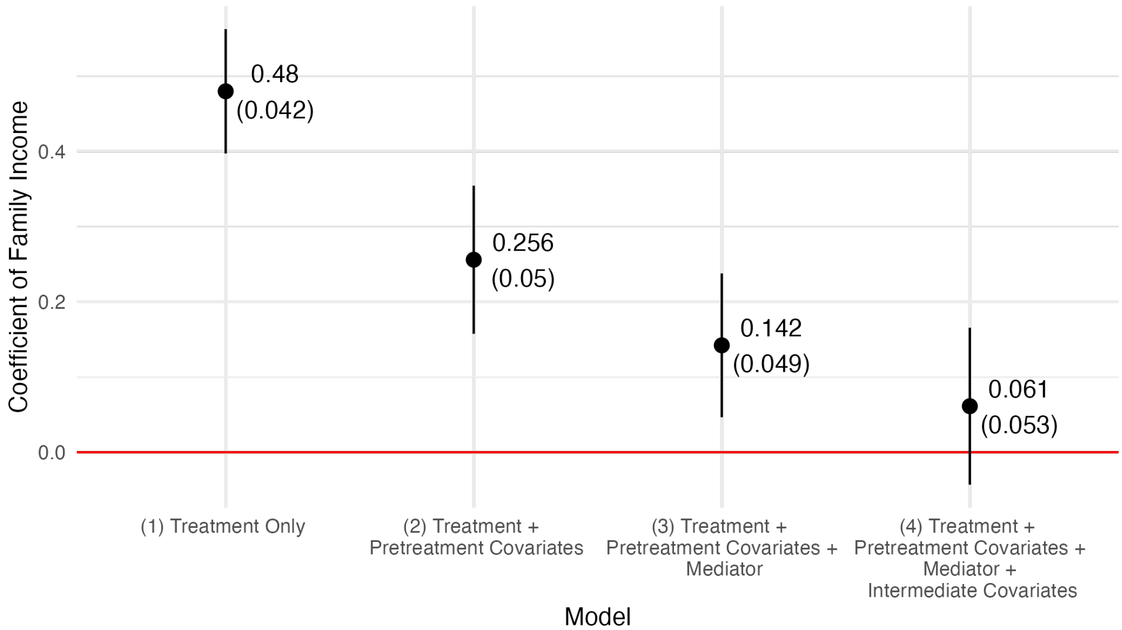


Figure 5. Estimated Coefficients of Family Income on the Probability of University Enrollment

*Note*: Calculations are combined across 80 imputed data sets.

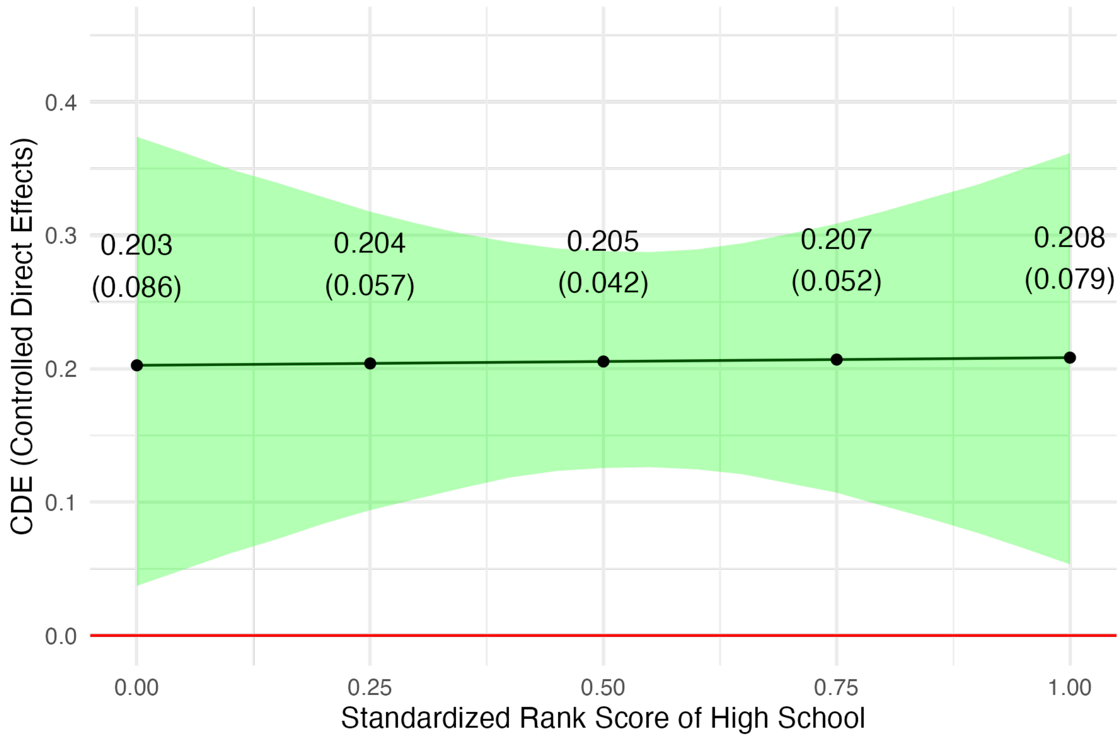


Figure 6. Estimated Controlled Direct Effects of Family Income on University Enrollment by the Percentile Rank of High School Selectivity

*Note*: Calculations are combined across 80 imputed data sets. These values indicate controlled direct effects. Bootstrap standard errors (bootstrap samples = 1,000) are in parentheses. Ribbon indicates the 95% confidence intervals obtained using non-parametric bootstrap standard errors.

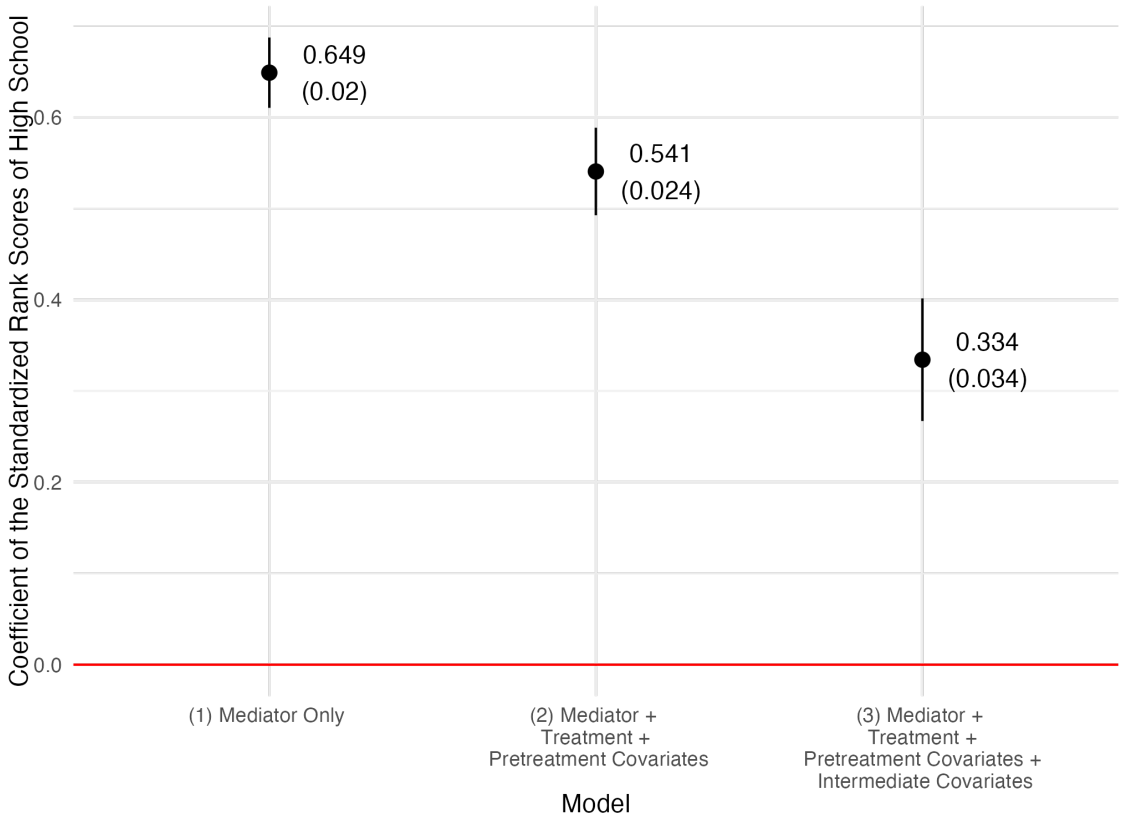


Figure 7. Estimated Coefficients of Selectivity of High School on the Percentile Rank of Education

*Note*: Calculations are combined across 80 imputed data sets.

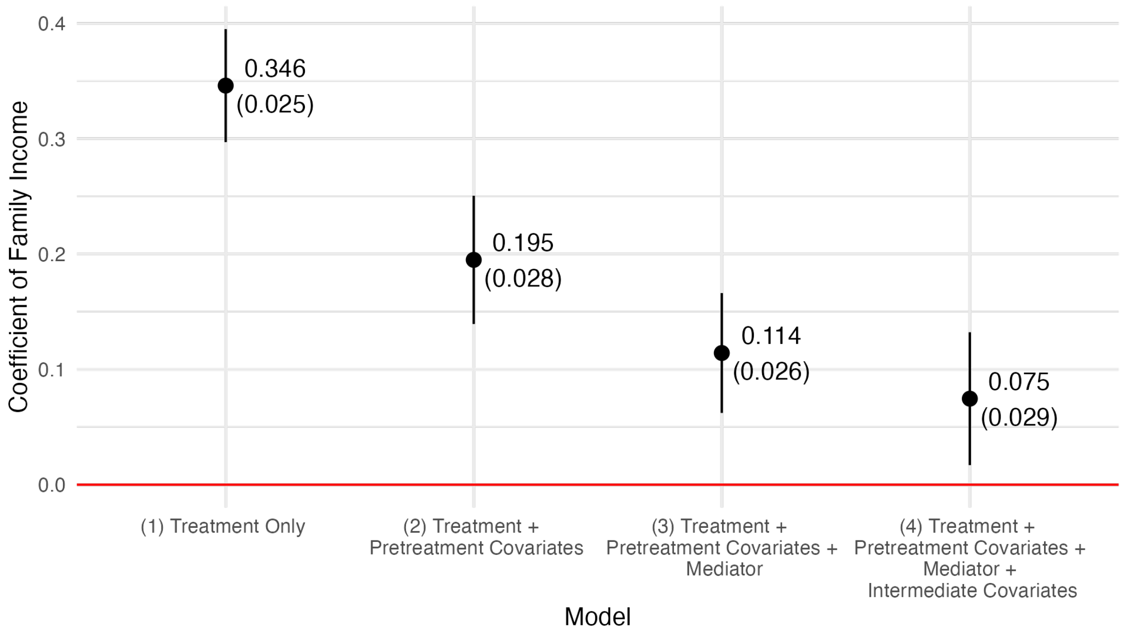


Figure 8. Estimated Coefficients of Family Income on the Percentile Educational Rank

*Note*: Calculations are combined across 80 imputed data sets.

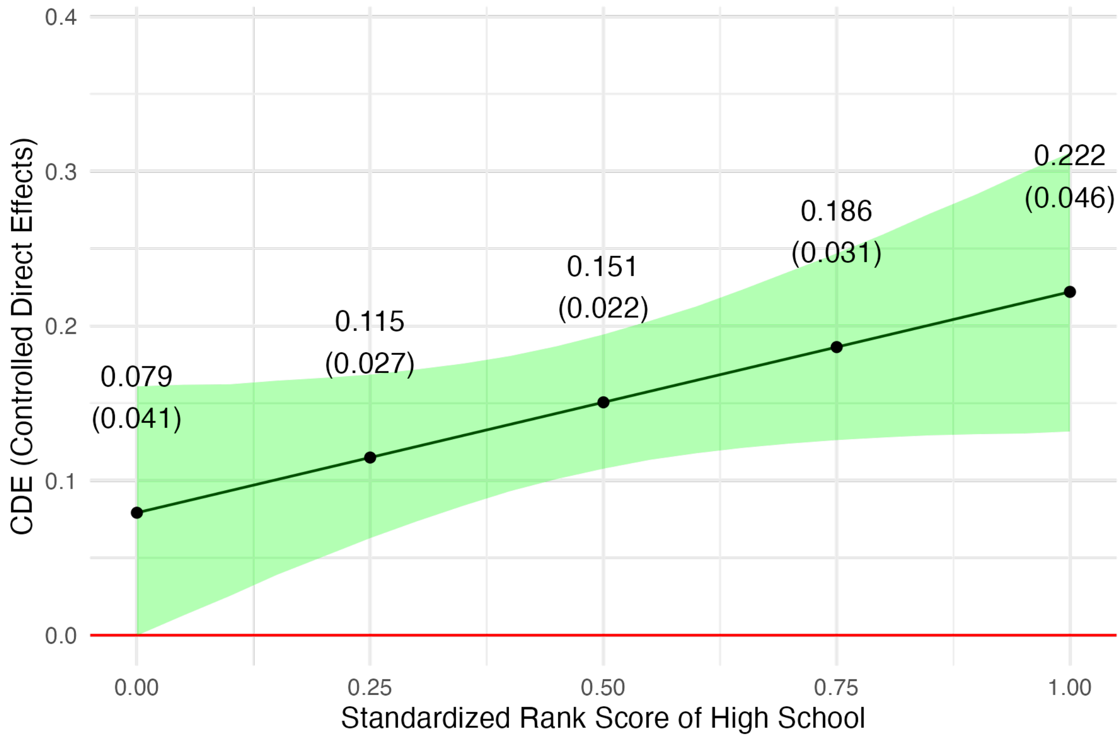


Figure 9. Estimated Controlled Direct Effects on the Percentile Educational Rank by the Percentile Rank of High School Selectivity

*Note*: Calculations are combined across 80 imputed data sets. These values indicate controlled direct effects. Bootstrap standard errors (bootstrap samples = 1,000) are in parentheses. Ribbon indicates the 95% confidence intervals obtained using non-parametric bootstrap standard errors.

**Table 1.** Descriptive Statistics

| Node | Variable | Mean | SD |
|---|---|---|---|
| $Y$ | University enrolment | 0.598 | 0.490 |
| $Y$ | Education rank | 0.500 | 0.286 |
| $A$ | Family income (rank) | 0.500 | 0.288 |
| $M$ | High school selectivity (rank) | 0.500 | 0.289 |
| $X_1$ | Women dummy | 0.508 | |
| $X_2$ | Parental SEI / 10 | 5.224 | 0.921 |
| $X_3$ | Father's years of education | 14.101 | 2.081 |
| $X_4$ | Mother's years of education | 13.563 | 1.459 |
| $X_5$ | Neighborhood advantage index (PCA) | 0.564 | 0.255 |
| $X_6$ | Distance to the nearest University (logged) | 1.309 | 1.108 |
| $X_7$ | Number of siblings | 1.417 | 0.817 |
| $X_8$ | Order of birth | 1.818 | 0.789 |
| $X_9$ | Maternal grandparents' education | 0.239 | 0.426 |
| $X_{10}$ | Mother's age / 10 | 4.522 | 0.392 |
| $X_{11}$ | Birth month | 5.330 | 3.392 |
| $Z_1$ | GPA at 9th grade (PCA) | -0.001 | 2.089 |
| $Z_2$ | Child's university aspirations at 9th grade | 0.652 | |
| $Z_3$ | Mother's university aspirations for the child at 9th grade | 0.685 | |
| $Z_4$ | Student's subjective wealth | 3.344 | 0.946 |
| $Z_5$ | Mother's subjective wealth | 2.897 | 0.809 |

*Note*: Calculations are combined across 80 imputed data sets. $N = 1{,}761$. $Y$ = outcome; $A$ = treatment; $M$ = mediator; $X_1$ to $X_{11}$ = pretreatment covariates; $Z_1$ to $Z_5$ = post-treatment covariates.

**Table 2.** The Decomposition of the Effect of Family Income on University Enrollment and Education Rank by the Regression with Residuals (RWR)

| Estimand | Coef. | B.S.E. |
|---|---|---|
| Dependent variable: university enrollment | | |
| $r$TE | 0.263 | 0.050 |
| $r$NDE | 0.205 | 0.052 |
| $r$NIE | 0.058 | 0.018 |
| Dependent variable: education rank | | |
| $r$TE | 0.196 | 0.029 |
| $r$NDE | 0.139 | 0.027 |
| $r$NIE | 0.057 | 0.013 |

*Note*: $N = 1{,}761.$ $r$TE, $r$NDE, and $r$NIE are the randomized interventional analogs of the total, direct, and indirect effects. B.S.E. = bootstrap standard errors from 1,000 bootstrap samples.

**Supplement**

**Part A: Details of the Variables**

**Table A.** Details of the Variables

| Node | Variable | Year | Value |
|---|---|---|---|
| $Y$ | University enrolment | 2021 | Binary: 1 = enrolled in university, 0 = otherwise |
| $Y$ | Rank of education | 2021 | Continuous. See main text and Figure 3. |
| $A$ | Family income (logged) | 2015 | Continuous. 5, 25, 37.5, 62.5, 87.5, 112.5, 137.5, 175, 225, 275, 325, 375, 425, 500, 600, 700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500, 1600, 1700, 1800, 1900, 2000, 2100 (unit: million yen) |
| $M$ | High school selectivity | 2017 | Continuous. The rank score (*hensachi*) was extracted from: https://www.trygroup.co.jp/exam/high/ TRY GROUP Corporation (April 19, 2016). The rank score can be obtained not only for high schools but also for technical colleges. The rank score ranges from 32 to 75. |
| $X_1$ | Women dummy | 2015 | Binary. 1 = Women, 0 = Men |
| $X_2$ | Parental SEI / 10 | 2015 | Continuous. Parental SEI was based on father's SEI. If father's SEI was not available, mother's SEI was used. |
| $X_3$ | Father's years of education | 2015 | Continuous. It ranges from 9 (junior high) to 18 years (graduate school). |
| $X_4$ | Mother's years of education | 2015 | Continuous. It ranges from 9 (junior high) to 18 years (graduate school). |
| $X_5$ | Neighborhood advantage index (the 1st principal scores) | 2015 | Continuous. A composite measure of the following five socio-economic characteristics of census basic unit block and municipality of the 2010 and 2015 Population Census by the principal component analysis: (1) unemployment rate, (2) professional and managerial workers rates, (3) four-year university graduates rates, (4) junior high school graduates rate, and (5) divorce rate. |
| $X_6$ | Distance to the nearest Univ (logged) | 2015 | Continuous. The units are kilometers. |
| $X_7$ | Number of siblings | 2015 | Continuous. It ranges from 0 to 5. |
| $X_8$ | Order of birth | 2017 | Continuous. It ranges from 1 to 6. |
| $X_9$ | Grandparents' education | 2015 | Binary. 1 = if maternal grandfather or grandmother went to junior college or university, 0 = otherwise. |

| | | | |
|---|---|---|---|
| $X_{10}$ | Mother's age / 10 | 2015 | Continuous. Mother's age in 2015 ranges from 33 to 58. |
| $X_{11}$ | Birth month (April = 0) | 2015 | Continuous. 0 = April,…, 11 = March |
| $Z_1$ | GPA at 9th grade (the 1st principal scores) | 2015 | Continuous. A composite measure of self-reported grade of (1) all subjects, (2) Japanese, (3) mathematics, (4) science, (5) social studied, and (6) English created by the principal component analysis. Eigenvalue for the 1st and 2nd components were 4.421 and .494, respectively. |
| $Z_2$ | Child's university aspiration at 9th grade | 2015 | Binary. 1 = university or more, 0 = otherwise. |
| $Z_3$ | Mother's university aspiration for the child at 9th grade | 2015 | Binary. 1 = university or more, 0 = otherwise. |
| $Z_4$ | Student's subjective wealth | 2015 | Continuous. 0 = Poor, 1 = Somewhat poor, 2 = Average, 3 = Somewhat rich, 4 = Rich. |
| $Z_5$ | Mother's subjective wealth | 2015 | Continuous. 0 = Poor, 1 = Somewhat poor, 2 = Average, 3 = Somewhat rich, 4 = Rich. |

**Part B: The G-Formula Approach and Sensitivity Analysis**

I estimated the controlled direct effect (CDE), randomized analog of the total effect (*r*TE, overall effect), and natural direct and indirect effects (*r*NIE and *r*NDE) using the g-formula approach (Robins 1986) instead of regression with residuals (RWR). I used the *CMAverse* package in R to estimate these effects (Shi et al. 2021). The *CMAverse* imputes potential outcomes such as $E[Y(a,m)]$, $E[Y(a',m)]$, $\mathrm{E}\left[Y\left(a', G_{a'|X}\right)\right]$, $\mathrm{E}\left[Y\left(a, G_{a|X}\right)\right]$, $\mathrm{E}\left[Y\left(a, G_{a'|X}\right)\right]$, and $\mathrm{E}\left[Y\left(a', G_{a|X}\right)\right]$ and then calculates the causal estimands *r*TE, *r*NIE, and *r*NDE (Shi 2021). The results in Table B are quite similar to those in Table 2.

A sensitivity analysis was also conducted to assess the impact of potential unmeasured or unobserved confounders ($U$) that were associated with both the mediator ($M$) and outcome ($Y$) on the observed causal effects. For the sensitivity analysis, I used E-values because they are simple and easy to compute (Ding and Vanderweele 2016; Smith and VanderWeele 2019; VanderWeele and Ding 2017). The definition of the E-value is "the minimum strength of association, on the risk ratio scale, that an unmeasured confounder would need to have with both the treatment and outcome, conditional on the measured covariates, to fully explain away a specific treatment-outcome association" (VanderWeele and Ding 2017:269). The mediational analog to the E-value shows the minimum size of the parameters for the confounder-mediator and the confounder-outcome relationships to explain the effect of interest including the direct and indirect effects (Smith and VanderWeele 2019).

Because the treatment variable, the rank of family income, is continuous, the risk ratio[1]

[1] If the causal estimand is about a difference in a continuous outcome, the standardized effect size *d* was used to obtain the risk ratio ($RR$) for the E-value ($= RR +$

and E-value vary depending on the degree of change in the values of the treatment (VanderWeele, Ding, and Mathur 2019). I obtained the E-values for a change in the treatment from 0 (the lowest rank of family income) to 1 (the highest rank of family income). Table A2 (the 3rd and 4th columns) shows the E-values for each estimate obtained by the *CMAverse*. The E-value for *r*TE was 2.615, and that for the lower limit of the confidence intervals was 2.101. If an unmeasured confounder was associated with both the rank of high school ($M$) and university enrollment ($Y$), and the approximate risk ratios were 2.615-fold or more for each, the observed *r*TE was completely explained. For the lower limit of the confidence intervals, the approximate risk ratios of 2.101-fold or more for each variable could suffice to shift the lower limit of the confidence intervals to zero. The E-values for *r*TE, *r*NDE, and *r*NIE indicate that the E-values for the *r*NIE were relatively low, suggesting that the indirect effect of family income on educational attainment through the rank of high school was sensitive to unmeasured or unobserved confounders of the mediator-outcome association. *r*TE and *r*NDE were more robust for such confounders.

For another method of sensitivity analysis, see Wodtke and Zhou (2020).

**Table B.** Decomposition of the Effect of Family Income on University Enrollment and Education Rank Using the G-formula Approach

| Estimand | Estimate | B.S.E. | E-value | E-value (LL) |
|---|---|---|---|---|
| Dep.: university enrollment | | | | |
| *r*TE | 0.256 | 0.050 | 2.615 | 2.101 |
| *r*NDE | 0.204 | 0.051 | 2.303 | 1.817 |

$\sqrt{RR * [RR - 1]}$). For detail, see Smith and VanderWeele (2019) and VanderWeele and Ding (2017).

| | | | | |
|---|---|---|---|---|
| *r*NIE | 0.051 | 0.015 | 1.431 | 1.270 |
| Dep. education rank | | | | |
| *r*TE | 0.195 | 0.029 | 3.156 | 2.585 |
| *r*NDE | 0.135 | 0.027 | 2.470 | 2.047 |
| *r*NIE | 0.061 | 0.013 | 1.724 | 1.507 |

*Note*: $N = 1{,}761$. The *r*TE, *r*NDE, and *r*NIE are randomized interventional analogs of total, direct, and indirect effects, respectively. B.S.E. = bootstrap standard errors from 1,000 bootstrap samples. E-value (LL): E-value for the lower limit of the confidence intervals.

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