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【要旨】

本論文では、教育志向の就学前施設と保育志向の就学前施設の選択が子供の発達にもたらす因果効果を推計する。因果効果の推計に際して、日本において、異なるタイプの就学前施設の供給が、地域間や時間を通じて外生的に変動したことを準実験と見なした。推計の結果、教育指向の施設の利用は、算数・数学および国語のテスト得点、社会情緒面にプラスの効果をもたらしていた。また、限界処置効果 (MTE) 曲線から、教育志向の就学前施設を利用する確率が低い子供が、潜在的利得が最大であるという、本来あるべき配分と逆の選択が生じていた。この異質性は、教育志向の就学前施設の特徴 (教育志向、教育時間の標準の短さ、ピア効果) により生じていると推察される一方で、保育志向の就学前施設を利用することの利得はより均一であると推察される。

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Education-Oriented and Care-Oriented Preschools Implications on Child Development*

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Abstract

This paper estimates the causal effect of education-oriented vs. care-oriented preschools on child development. We use a unique quasi-experiment from Japan that exploits plausibly exogenous regional and temporal variation in the relative availability of different preschools. We find that attendance at an education-oriented preschool is associated with significant improvements in mathematical and linguistic achievement that manifest later in adolescence. Positive effects can also be found for socioemotional measures. Ascending marginal treatment effect (MTE) curves suggest an inverse selection pattern: children that are least likely to enroll in the education-oriented preschool gain the most from it. This heterogeneity is mainly due to specific features of education-oriented preschools (i.e., educational orientation, shorter operating hours, and peer effects), while gains from enrollment in care-oriented preschools appear more homogeneous.

JEL Classification: C26, H75, I26, J13
Keywords: Early childhood education and care, Child development, IV methods, Marginal treatment effect

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1 Introduction

It is well known that experiences in early childhood are critical to children's cognitive and noncognitive development (Carneiro and Heckman 2003; Cunha et al. 2006; Knudsen et al. 2006). A large body of research has shown that both targeted and universal early childhood education and care (ECEC) programs have positive effects on a wide range of child outcomes.[1] In recent years, the focus of policy makers has shifted from simply improving access to ECEC to the importance of quality aspects of ECEC institutions. As a result, OECD countries such as the United States or Germany have adopted policies (i.e., the *Zero to Five Plan* and the *Gute-KiTa Gesetz* (Act on good early childhood education and care)) that explicitly address quality issues such as better-qualified staff and better-equipped facilities.

The positive impact of ECEC found in previous studies is often explained by the fact that disadvantaged children would experience worse care if they were not enrolled in such an institution (Cascio and Schanzenbach 2013; Cornelissen et al. 2018). Similarly, the most advantaged children show no or even negative treatment effects, because they would receive high-quality child care even without ECEC (Felfe et al. 2015). Therefore, it is important for policy makers to understand which aspects of ECEC institutions and counterfactual care arrangements are most effective in promoting child development in order to design appropriate policies.

This paper exploits a unique feature of the Japanese preschool system to estimate the causal effect of an education-oriented against a care-oriented preschool on children's cognitive and socioemotional development in adolescence. Before children go to elementary school, almost all of them attend either an education-oriented or a care-oriented preschool. In contrast to most studies examining the effectiveness of targeted and universal ECEC programs, we can compare two high-quality preschool institutions and therefore know exactly the features of the counterfactual preschool setting.[2] Education-oriented preschools are half-day facilities that provide about four hours educational instruction per day, while care-oriented preschools are full-day facilities that provide care for parents who are unable to provide care for their child for work or other reasons. Evaluating treatment effects of this differential preschool enrollment allows us to draw more precise conclusions about the specific features of ECEC that are responsible for developmental gains.

Because OLS estimates are likely to be biased due to selective enrollment, we exploit

[1]Targeted programs in the United States are Head Start (Currie and Thomas 1995; Garces et al. 2002; Ludwig and Miller 2007; Deming 2009; Carneiro and Ginja 2014), the High/Scope Perry Preschool program (Heckman et al. 2010b; 2013), and the Abecedarian project (Barnett and Masse 2007; Campbell et al. 2014). Similarly, universal preschool programs in Uruguay, Argentina, Norway, Denmark, Germany, and Japan have been studied by Berlinski et al. (2008; 2009), Havnes and Mogstad (2011; 2015), Gupta and Simonsen (2016), Cornelissen et al. (2018), Rossin-Slater and Wüst (2020), and Kawarazaki (2022).

[2]Some notable exceptions are Bernal and Keane (2011), Gupta and Simonsen (2010; 2016), Feller et al. (2016), and Danzer et al. (2020).

plausibly exogenous regional and temporal variation in the availability of preschools to identify the treatment effect of attending an education-oriented against a care-oriented preschool using instrumental variable (IV) methods. In particular, treatment effects on mathematical and linguistic ability scores, as well as on the socioemotional measure of behavioral problems SDQ, derived from the Strengths and Difficulties Questionnaire (Goodman 1997), and a quality of life (QOL) measure, based on the KINDL^R questionnaire (Ravens-Sieberer et al. 2006), will be examined using unique Japanese survey data. By further estimating the marginal treatment effect (MTE), we are able to identify the subpopulation that benefits the most from enrollment in an education-oriented preschool, allowing us to better understand the mechanisms through which these developmental gains operate.

To identify the causal effect, we instrument the preschool decision with the relative availability of preschool slots in an IV approach.[3] We ensure conditional exogeneity of the instrument by controlling for an extensive set of child, parental, and municipality characteristics, as well as regional fixed effects, cohort fixed effects, and region-specific linear time trends. We also discuss in detail potential threats to identification and show that the historical development of preschools in Japan is independent of the regional distribution of skills and human capital (Cameron and Taber 2004), selective migration between municipalities is not a threat in our context (Kawarazaki 2022), there are no unobserved municipality characteristics that could affect our instrument, internal migration of parents and demand for child care does not drive the (relative) supply (Kawarazaki 2022), and there are no compositional changes in enrollment patterns over time. This extensive discussion ensures that the relative availability of preschool slots is a valid instrument for the preschool decision.

Our results show that enrollment in an education-oriented instead of a care-oriented preschool is associated with strong developmental gains in linguistic achievement. These estimates are robust to the exclusion of ability proxies (i.e., parental education and income), the use of a stricter treatment definition, and the use of an adjusted version of the instrument that is less susceptible to potential demand-side influences. Implementation of permutation tests following Bertrand et al. (2004) for the reduced-form estimates further supports the finding of significantly positive effects. In assessing treatment effects at different ages, we find that cognitive gains (i.e., mathematical and linguistic) materialize at a later stage of compulsory schooling (aged 12 to 15), which seems surprising in the light of previous research. In particular, Currie and Thomas (1995) show that the cognitive benefits from Head Start fade early, rationalizing this finding with the worse environment which treated children would return after completing the program (see also Currie and Thomas 2000). Although this explanation makes sense in the context of Head Start, schools in Japan are more homogeneous and of similar quality. This implies that disad-

[3]See Loeb et al. (2007), Berlinski et al. (2008; 2009), and Cornelissen et al. (2018) for a similar strategy.

vantaged children who enrolled in an education-oriented preschool face the same school and neighborhood conditions as their advantaged peers. Within this equal environment, positive effects from early investments lead to long-lasting improvements, as suggested by the theory of dynamic complementarities (Cunha and Heckman 2007).

In the next step, we extend our analysis by estimating MTE curves (Björklund and Moffitt 1987; Heckman and Vytlacil 1999; 2001; 2005; 2007) to allow the treatment effects to vary with unobserved characteristics that are responsible for children being less likely to attend an education-oriented preschool (i.e., distaste for treatment, Cornelissen et al. 2016). These MTE curves show an increasing pattern, suggesting substantial heterogeneity: children who are least likely to attend an education-oriented preschool benefit the most from it. By decomposing this inverse selection pattern into the unobserved parts of the outcomes when untreated and treated, respectively (Brinch et al. 2017), we find that all children benefit similarly from attending a care-oriented preschool with respect to linguistic ability and the QOL score, while returns to enrollment in an education-oriented preschool are positive only for high-resistance children. This finding suggests that characteristics of education-oriented rather than care-oriented preschools explain the results. In an extensive discussion, we then argue that the educational orientation, shorter operating hours and thus a reduction in maternal labor supply which allow for more interaction with the mother, and stronger peers are the most likely channels.

Our study contributes to the literature in several ways. First, previous literature has examined quality aspects of schools that are conducive to children's development, such as smaller class sizes (Angrist and Lavy 1999), stronger peers (Hanushek et al. 2003; Bifulco et al. 2011; Sacerdote 2011; Burke and Sass 2013), and better-qualified teachers (Rockoff 2004; Rivkin et al. 2005; Kane et al. 2011). In contrast, studies on the effectiveness of such aspects in preschools are still scarce. Evidence from project STAR suggests that smaller class sizes in preschool have a positive short-term impact on test scores, but also improve long-term outcomes such as the likelihood of college attendance, while teacher characteristics seem to play a minor role (Krueger 1999; Chetty et al. 2011). Using a reform in the German child care system, Felfe and Zierow (2018) find that a switch from half-day to full-day care is associated with negative effects on socioemotional well-being. In contrast, attending preschool together with high-ability peers seem to have positive spillover effects (Henry and Rickman 2007; Neidell and Waldfogel 2010). In addition, Claessens et al. (2014) find that advanced content covered in preschool benefits all children's school readiness.[4] Although we cannot quantify the contribution of these aspects to our treatment effects, our analysis confirms that previously studied quality aspects of preschools also play a large role in our context. The institutional setting in which we know all characteristics of the treatment but also the control institution allows us to interpret our treatment effects as results stemming from differences between the two

[4]See also the discussion in Duncan and Magnuson (2013).

preschools, suggesting that educational orientation, shorter operating hours, and peer effects explain our results.

Second, we add to the literature by estimating longer-term effects of universal preschools for children aged 6 to 15. While many studies assess short-term outcomes prior to school enrollment (e.g., school readiness, Cornelissen et al. 2018), there is limited evidence on the durability of such effects. Berlinski et al. (2008) estimate the effect of preschool attendance on the educational attainment of children aged 15 in Uruguay. Felfe et al. (2015) estimate the impact of an expansion of high-quality child care in Spain on reading achievement and grade retention among children aged 15. Similarly, Gupta and Simonsen (2016) find positive effects of center-based child care on the linguistic achievement for children aged 15 to 16. In contrast, Kuehnle and Oberfichtner (2020) do not find any effect of earlier enrollment in day care for children aged 15 in Germany, and Fort et al. (2020) even find negative effects of day care in Italy on a measure of intelligence and personality traits for children aged 8 to 14.[5] We add to these studies by estimating the impact for different age groups to obtain a complete picture of the evolution of gains in adolescence. Since this period is critical for acquiring the skills needed to succeed in the labor market, it is important to evaluate the effectiveness of earlier investments not only in the short run but also in the long run.[6]

Third, to our knowledge, we are the first to examine differential effects of the two preschool institutions in Japan on child development. In a recent paper, Yamaguchi et al. (2018b) find positive effects on behavioral aspects of enrollment in care-oriented preschools at early ages compared to home care. Because these outcomes are measured at age 3.5 and enrollment in education-oriented preschools is generally limited to children aged 3 to 5, differential effects between education-oriented and care-oriented preschools are not considered. In addition, Kawarazaki (2022) examines the long-term effects of attending preschool at age 4 and shows that the positive effects on future earnings are mainly due to an increase in educational attainment. We complement these studies by estimating the differential effects of preschool institutions on cognitive and socioemotional development in adolescence. We provide a more detailed picture of the features of the Japanese preschool system that contribute to a child's development in recent years, which complements the short-term analysis of Yamaguchi et al. (2018b) and the long-term analysis of Kawarazaki (2022).

The remainder of this paper proceeds as follows. In Section 2, we describe Japan's preschool system in more detail and explain the institutional background of education-oriented and care-oriented preschools. In Section 3, we describe the data sources used for the empirical analysis. In particular, the cognitive and socioemotional measures are

[5]Studies assessing educational attainment and labor market outcomes of adults are Havnes and Mogstad (2011; 2015) for Norway, Rossin-Slater and Wüst (2020) for Denmark, and Kawarazaki (2022) for Japan.

[6]By the age of 15, Japanese children take high school entrance exams to enroll in better-ranked schools.

presented, and the instrumental variable as well as the control variables are described. Descriptive statistics are also provided. In Section 4, we introduce our estimation strategy and discuss the identifying assumptions. In Section 5, we present the results from our first-stage Probit regression, OLS and 2SLS regressions, and MTE estimations. In Section 6, we discuss possible channels and mechanisms that could explain our results. Finally, Section 7 concludes.

2 Background and Institutional Setting

Preschools in Japan are divided into half-day kindergartens (*youchien*) and full-day nursery schools (*hoikuen*), which are distinguished by different purposes and characteristics.[7] Originally, kindergartens were intended to promote the mental and physical development of children by providing a sound educational environment. The Ministry of Education, Culture, Sports, Science, and Technology (MEXT) sets the curriculum and teachers must be certified by the ministry.[8] The curriculum is broadly defined in the *Course of Study for Kindergarten* guideline, but usually consists of about four hours per day, covering topics such as reading Hiragana characters, writing, recognizing numbers and geometry, playing music together, and drawing. Therefore, we refer to kindergartens in this paper as *education-oriented preschools*. Nursery schools, on the other hand, were originally designed to care for children whose parents (or equivalents) were unable to provide care for work or other reasons. The Ministry of Health, Labour, and Welfare sets guidelines for nursery schools, and these providers must be certified as "child care providers" by the ministry.[9] Therefore, we refer to nursery schools in this paper as *care-oriented preschools*. Children aged 3 to 5 can attend an education-oriented preschool while children aged 0 to 5 can attend a care-oriented preschool (Abumiya 2011).[10]

Although both institutions are overseen by different ministries and teachers/caretakers receive the certificate from the respective ministry, both institutions must meet strict requirements and are therefore considered to be of similar high quality (e.g., Kawarazaki 2022). This also implies similarly low monthly tuition rates ranging from US$ 290 to US$ 425 for care-oriented preschools in 2009 and around US$ 452 for education-oriented

[7] Although most kindergartens do not operate on a full-day basis, some facilities have expanded their services to working mothers in order to maintain the number of children enrolled, also offering child care until the evening (Ishikida 2005; Imoto 2007). For a detailed discussion of the differences between kindergartens and nursery schools, see Ben-Ari (2005) and Hegde et al. (2014).

[8] The educational standard for the kindergarten curriculum and teachers was originally established in 1900 in the *Elementary School Order* and further specified in 1926 in the *Kindergarten Order*.

[9] The minimum standard for nursery schools and child care providers was first set in 1947 in the *Child Welfare Act*, which established that protection and nurture of children who lack sufficient care is the responsibility of the government.

[10] In 2002, some districts began allowing children as young as 2 to attend an education-oriented preschool as well (Ishikida 2005). Imoto (2007) provides an excellent overview of the origins and development of the Japanese preschool system.

preschools in 2010 (Ministry of Health, Labour and Wealth 2009; Ministry of Education, Culture, Sports, Science and Technology 2010).[11]

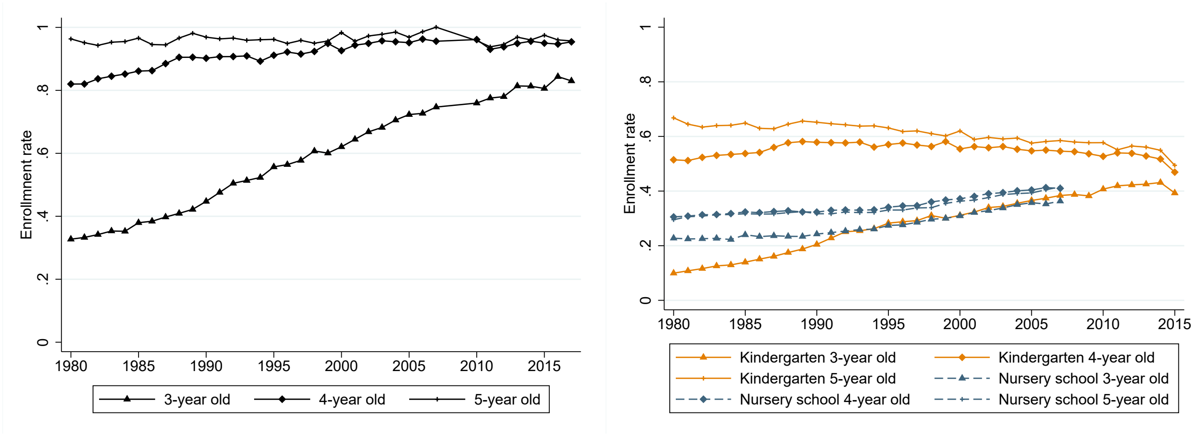
Although parents would in principle have the option to educate their children at home, most families choose to enroll them in one of these two preschools.[12] Graph 1 presents the enrollment rate of children in both preschools over time. Figure (a) shows that in recent years more than 90% of four and five-year-old children are enrolled in a preschool, although the share is lower for three-year-olds. This figure has been largely constant for four- and five-year-old children over the past 30 years, although it has increased significantly for three-year-old children, highlighting the improved supply. Figure (b) shows that education-oriented preschools are the predominant choice among four- and five-year-old children, although three-year-old children are evenly distributed between education-oriented and care-oriented preschools. In recent years, however, more children have been enrolled in care-oriented preschools, resulting in a narrowing of the gap in enrollment rates between the two alternatives. This is not surprising given the steady increase in maternal labor force participation, which has led to an increasing demand for full-time preschools (Imoto 2007). Figure A1 in the appendix shows this trend graphically.

In principle, the decision-making process of parents consists of two steps. First, parents decide whether or not to enroll their child in a preschool. Second, they choose between a care-oriented and an education-oriented preschool, depending on availability and preferences. In reality, however, almost all children enroll in one of the two institutions, so the small group of children who do not enroll in any preschool is negligible for our analysis and we can focus exclusively on the second-step decision (see Figure 1).

Traditionally, care-oriented and education-oriented preschools served different purposes, leading to selective enrollment based on status and perception. The targeting of care-oriented preschools to children who lack sufficient care led to the perception that these preschools were less prestigious than education-oriented preschools (Ben-Ari 2005). As a consequence, children from working-class families would go to a care-oriented preschool while upper-class families who value education more would send their children to an education-oriented preschool. Although in recent years these traditional differences are diminishing, they are still present today. Apart from these preference differences, low-income families, where both parents need to work full time, would in practice send their children to a care-oriented preschool early because they need to go back to work to earn sufficient income, while high-income families can wait until the child is old enough to send

[11] Tuition rates vary depending on whether the facility is private and on the location.

[12] In fact, only ten children in our data set were never enrolled in any preschool. Moreover, Kachi et al. (2020) show that only 9% of children aged 3, 3% of children aged 4, and 2% of children aged 5 were never enrolled in any preschool.



(a) Preschools in General, 1980–2017 (b) Kindergartens and Nursery Schools, 1980–2015

Figure 1
Enrollment in Preschools Over Time

Source: Authors' calculations using data from Statistics Bureau, Ministry of Internal Affairs and Communications (2020), Ministry of Education, Culture, Sports and Technology (MEXT) (2020), and OECD (2020). *Note*: Figure (a) shows enrollment rates in either kindergartens (i.e., education-oriented preschools) or nursery schools (i.e., care-oriented preschools). No data is available for 2008 and 2009. Figure (b) shows enrollment rates at different ages by preschool type. No data is available for nursery school enrollment rates for 2008 to 2015.

him or her to an education-oriented preschool.[13] The descriptive evidence from Figure 2 shows this choice pattern clearly, in which wealthier and better-educated families tend to prefer the education-oriented over the care-oriented preschool.

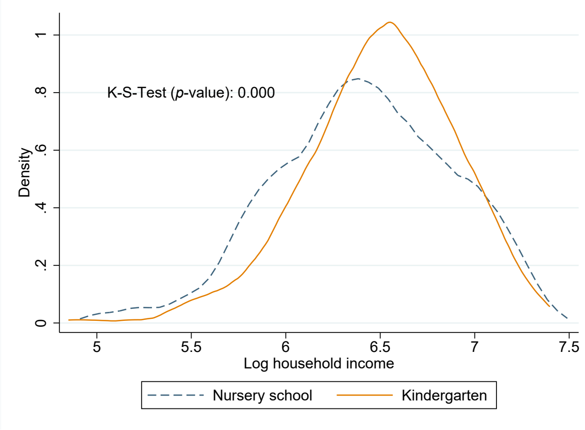
3 Data

3.1 JCPS and KHPS/JHPS

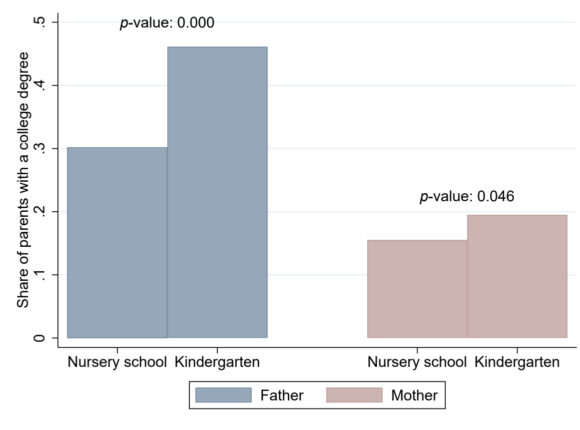
We use data from the Japanese Child Panel Survey (JCPS), Keio Household Panel Survey (KHPS), and Japan Household Panel Survey (JHPS). The JCPS is a nationally representative longitudinal parent-child survey of children enrolled in elementary schools (grades 1 to 6, aged 6 to 12) and lower secondary schools (grades 7 to 9, aged 12 to 15) and was designed as a complementary survey to the KHPS/JHPS, two comprehensive household surveys initiated in 2004 (KHPS) and 2009 (JHPS).[14] The JCPS consists of a child questionnaire that captures a child's cognitive ability by achievement tests for math, Japanese,

[13]In principle, parents can decide to switch between the two institutions. However, because this process involves switching costs and parents might have to wait again for vacancies at another facility, they typically leave their child in the facility where he or she was first enrolled.

[14]Households with children in the JHPS 2010/2012 were invited to participate in the JCPS 2010/2012, while households with children in the KHPS 2011/2013 were invited to participate in the JCPS 2011/2013. In 2014, 2016, and 2018, households from both surveys were participating in the JCPS. For details, see Akabayashi et al. (2016).



(a) Distribution of Household Income



(b) Differences in Parental Education

Figure 2
Household Differences in Preschool Choices

Source: Authors' calculations using data from JCPS and KHPS/JHPS. *Note*: Figure (a) shows kernel density estimates for the log household income using a bandwidth of 0.1 and an Epanechnikov kernel for households with children enrolled in a nursery school (i.e., care-oriented preschool) and a kindergarten (i.e., education-oriented preschool), respectively, together with the p-value from a Kolmogorov-Smirnov test of equality of distributions (Kolmogorov 1933; Smirnov 1933). Figure (b) shows the share of fathers and mothers having a college degree, respectively, separately for households with children enrolled in a nursery school or a kindergarten together with p-values from t-tests of mean equality.

and reasoning, as well as a parent questionnaire that collects information about the school and home environment, educational expenditures, and social environment. Information on the socioeconomic background, residence, and parental education are included in the KHPS/JHPS. Our final sample consists of seven waves of the JCPS from 2010, 2011, 2012, 2013, 2014, 2016, and 2018, together with additional household information from the KHPS/JHPS. In addition, we use regional information at the municipality level from the Statistics Bureau, Ministry of Internal Affairs and Communications (2020) to construct our instrument and some control variables (see Section 3.2).

3.2 Variables

Outcome Variables

Our goal is to estimate the causal effect of differential preschool types on cognitive and socioemotional outcomes during the 9 years of compulsory education (i.e., adolescence). As measures of cognitive abilities, we use information from a mathematical and Japanese ability test in the JCPS. The Japanese assessment consists of vocabulary as well as reading and writing of Kanji characters. The math assessment consists of calculations and word problems concerning numbers and the manipulation of figures.[15] Because every item of the tests is vertically equated across grades using item response theory, we estimate the individual latent math and Japanese theta scores from all participants (see Yamaguchi et al. 2019). These cognitive scores are standardized by grade with a mean of zero and a unity standard deviation.

As socioemotional measure, we build on the scores for behavioral difficulties based on the parents' responses to the Strengths and Difficulties Questionnaire (SDQ) (Goodman 1997).[16] The SDQ is a questionnaire for parents to evaluate a child's strengths and difficulties along five subscales, namely, conduct problems, emotional symptoms, hyperactivity, peer relationships, and prosocial behavior. We use the parent report version of the SDQ, that was first provided in the 2011 wave of the JCPS.[17] Each of these subscales consists of five items with 3-point Likert scales. Our socioemotional measure, which we will call SDQ throughout the paper, is derived from the sum of the subscales conduct problems, emotional symptoms, hyperactivity, and peer relationships, and is standardized by grade such that it has a mean of zero and a unity standard deviation.[18] We rescaled the SDQ score such that higher values imply less behavioral problems and therefore a better socioemotional development.

We also use a quality of life (QOL) measure obtained from the child questionnaire for children enrolled in the third grade and above. Two editions of the KINDL^{R} (Ravens-Sieberer et al. 2006)[19] were used, namely, the elementary school children's edition and the junior high school children's edition (Matsuzaki et al. 2007). KINDL^{R} measures QOL based on six subscales, namely, physical health, emotional well-being, self-esteem, family, friends, and school. It is a 24-item Likert scale that measures each of these areas through four items, which was included in the child's questionnaire. The total score represents a child's general QOL score, which is standardized by grade such that it has a mean of zero and a unity standard deviation. The SDQ as well as the QOL serve as measures of the socioemotional development in our empirical analysis.

Although we observe outcomes for the same children at different grade levels (see Figure B2 in the appendix), the decision to attend a preschool is made only once. When we use the pooled sample for estimation, the same child is used more than once in the first

[15]The reliability and validity of the ability tests in the JCPS were verified by Shikishima et al. (2013).

[16]This measure of socioemotional skills was also used by Gupta and Simonsen (2010) to evaluate the introduction of universal kindergarten in Denmark. This measure is often labeled *noncognitive ability*. However, because the SDQ is a behavioral screening questionnaire that allows cognitive skills to affect a child's behavior, we refer to this skill as *socioemotional skill*.

[17]There are also versions of the SDQ for self-completion (Goodman et al. 1998), adding an impact supplement (Goodman 1999), and using only a three-subscale division (Goodman et al. 2010).

[18]The reliability and validity of this scale was confirmed by Stone et al. (2010). In addition, Matsuishi et al. (2008) show that the Japanese version of the SDQ questionnaire is approximately as reliable as the original English one.

[19]KINDL^{R} is a health-related QOL scale for children developed by Bullinger (1994) and Ravens-Sieberer and Bullinger (1998).

stage. Therefore, using the panel structure of the data (i.e., using the pooled sample) does not add additional information to the first-stage estimation. Instead, we take individual-specific averages for each outcome variable for children who were surveyed more than once at different time points, providing us with a cross-sectional data set.

Treatment Variable

Our binary treatment variable will take on the value 0 if a child attended a care-oriented preschool and 1 if a child attended an education-oriented preschool.[20] Only a few children attended both preschool alternatives for some time. These children are categorized as having attended a care-oriented preschool if the years spent in this institution exceed the years spent in an education-oriented preschool, but they are categorized as having attended the latter if the years spent in an education-oriented preschool are at least as many as the years spent in a care-oriented preschool. Robustness of our results with respect to a stricter treatment definition is evaluated in the appendix in Tables H8 to H11.

Because of institutional differences, the preschool decision directly affects the age of enrollment and thus the length of attendance. Figure 3 shows that, on average, children who attend a care-oriented preschool enroll at an earlier age than children that attend an education-oriented preschool. The implication of this difference for the interpretation of our results will be discussed in Section 5.2.

Instrumental Variable

Our identification strategy requires an instrumental variable that affects the preschool decision but is exogenous to our cognitive and socioemotional measures after including control variables. In particular, we exploit regional and temporal variation in the availability of care-oriented and education-oriented preschool slots across Japan as arguably exogenous variation (Akabayashi and Tanaka 2013).

We use information on children's enrollment in either institution at the time of a child's birth t in municipality c as measure of the local availability of these preschool alternatives.[21] Using municipalities as the level of aggregation allows us to consider finer differences between geographic units than in previous studies.[22] Information at the mu-

[20]We exclude from our analysis children who only experienced home care and children who attended a child care center, because the distinction between education and child care is less clear for this relatively new institution. This applies to only ten children (0.60%) in our sample.

[21]It is reasonable to assume that enrollment corresponds to actual availability, because in most regions there is a high demand for early child care slots and parents apply for these places months in advance, although not every child receives a place.

[22]Japan is divided into 1,719 municipalities and Tokyo's 23 special wards, resulting in 1,741 regional units. Previous studies of Yamaguchi et al. (2018b) and Kawarazaki (2022) use variation at the prefectural level for identification (i.e., 47 prefectures). Because of the stratification of the survey, only 337 municipalities are covered in the final data set.

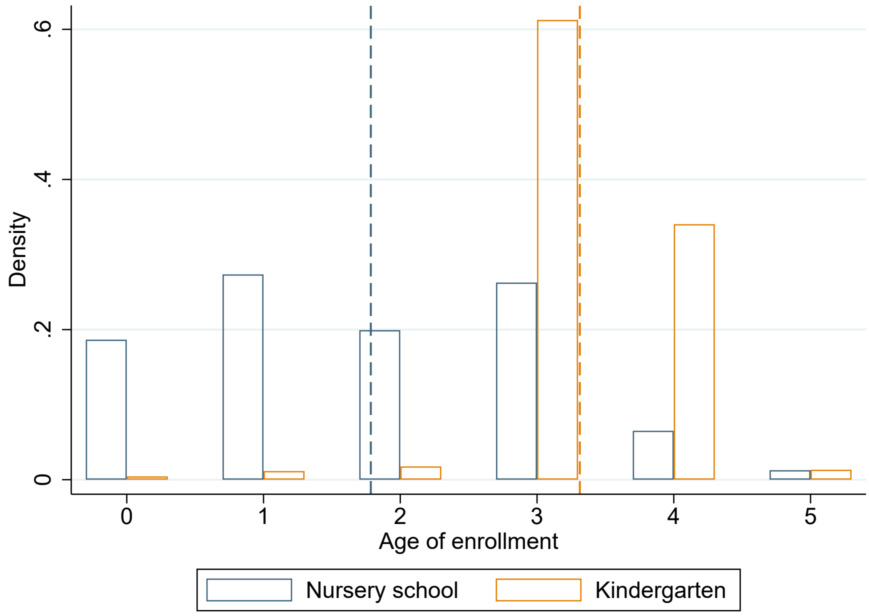


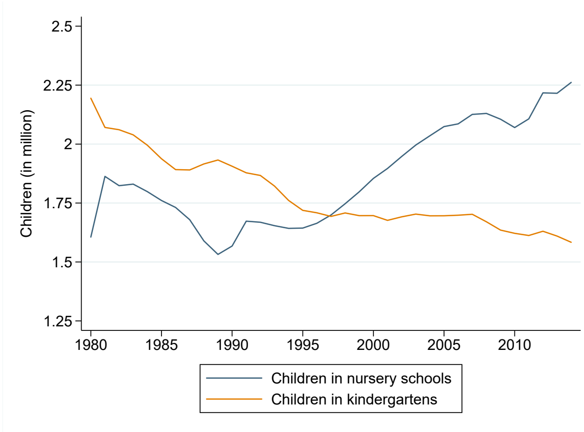
Figure 3
Distribution of Age of Enrollment

Source: Authors' calculations using data from JCPS and KHPS/JHPS. *Note*: This graph shows the distribution of age of enrollment for children attending a nursery school (i.e., care-oriented preschool) and a kindergarten (i.e., education-oriented preschool), respectively. The dashed lines show the corresponding sample means.

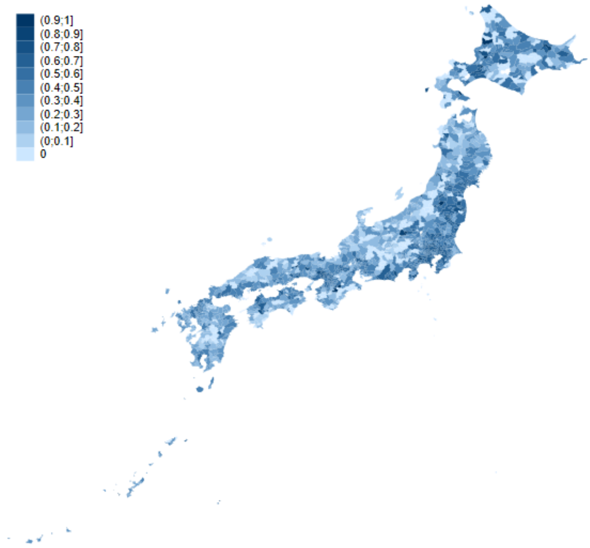
nicipality level is more likely to affect parents' preschool decision than larger aggregates because changes in the availability of preschool slots are only relevant if they are close to home. We then construct our instrument as the number of education-oriented preschool slots relative to the number of all preschool slots in a municipality at the time of a child's birth, that is,

$$Z_{ct} = \frac{\#\text{ Education-oriented preschool slots}_{ct}}{\#\text{ All preschool slots}_{ct}}. \tag{1}$$

Although this share increased in some prefectures (e.g., Kōchi), it decreased in most others (e.g., Tokyo). Figure (a) in Figure 4 depicts this temporal development across Japan from 1980 to 2016, while Figure (b) depicts the regional variation in our instrument Z for 2006, the year in which a large share of children in our sample started preschool education. Figure (a) shows a declining trend in the number of education-oriented preschool slots over time, although the number of care-oriented preschool slots has been steadily increasing since the mid-1990s. This reflects the trend that preferences are shifting in favor of full-day preschools. Figure (b) provides some suggestive evidence that in 2006, regions with a higher population density, such as the large cities Sapporo, Tokyo, and Osaka, have a higher share of education-oriented preschool slots than rural areas, depicted by the darker in contrast to the lighter color.



(a) Temporal Variation



(b) Regional Variation

Figure 4
Regional and Temporal Variation in Preschool Slots

Source: Authors' calculations using data from Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: Figure (a) shows the development of the number of children enrolled in kindergartens (i.e., education-oriented preschools) and nursery schools (i.e., care-oriented preschools), respectively. Figure (b) shows the regional distribution of children enrolled in kindergartens (i.e., education-oriented preschools) relative to the total number of preschool children in 2006. The year 2006 was chosen because the largest share of children in our sample started their preschool education in 2006.

Control Variables

In addition to the control variables necessary to maintain the conditional independence assumption of our IV strategy, we control for several variables that are likely to affect the preschool decision or our outcome variables. We control for child characteristics such as the gender, a dummy for being born in the first quarter of a year,[23] and the number of siblings. In addition, we control for parental characteristics such as the mother's age at birth of the child, dummies for each parent having graduated from a college, dummies for household income quartiles, and a dummy for the grandfather's college education. We also include characteristics on the municipality level such as the child per kindergarten ratio, the child per nursery school ratio, the population density, the female employment rate,[24] the local unemployment rate, and the per capita income.[25]

Our preferred specification includes fixed effects for prefectures to control for institu-

[23]Children born in the first quarter of a year must go to school on 1st April when turning 6 years old and are therefore relatively younger than their classmates.

[24]Our measure of the female employment rate is the share of employed women in the total female working population.

[25]Cameron and Heckman (1998; 2001) and Cameron and Taber (2004) point out the importance of controlling for local labor market conditions in models with schooling decisions.

tional and structural differences between administratively divided regions as well as the birth year of the child. Furthermore, Mazumder (2008) and Stephens and Yang (2014) emphasize the importance of controlling for regional time trends to estimate causal effects of educational choices (i.e., when the model is based on regional variation in schooling laws). They show that many results are very sensitive to this common trend assumption. Therefore, we also include prefecture-specific linear time trends in our model to allow for systematic changes in prefectures over time.

3.3 Descriptive Statistics

Table 1 provides descriptive statistics of the cognitive and socioemotional ability measures, the instrument, and covariates for children who attended a care-oriented and an education-oriented preschool, respectively.

These descriptive statistics suggest that, on average, children who attended an education-oriented preschool have significantly higher mathematical and linguistic ability and also score higher on the SDQ score. However, no significant mean difference can be found for the QOL score. As expected, children who attend an education-oriented preschool instead of a care-oriented preschool are born in municipalities with a significantly higher share of education-oriented preschool slots among all preschool slots. This can be taken as first evidence for the relevance of our instrument.[26] Although there are no significant differences in gender or quarter of birth between education-oriented and care-oriented preschool children, the former have slightly more siblings on average. In terms of household characteristics, we can confirm our observations from Figure 2. Children who attend an education-oriented instead of a care-oriented preschool are more likely to come from households with high-educated parents and with higher incomes on average. These children also appear to have better-educated grandfathers. Finally, there are significant differences with respect to the child per kindergarten ratio, the population density, the unemployment rate, and the per capita income. Education-oriented preschool children come, on average, from more densely populated areas, municipalities with a higher child per kindergarten ratio, and municipalities with a better economic performance. This observation is in line with the fact that larger (and wealthier) cities such as Sapporo, Tokyo, and Osaka have a higher share of education-oriented preschool slots than rural areas (see Figure 4).

[26] Throughout the paper, we will use the terms "relative preschool enrollment" and "relative preschool availability" interchangeably.

Table 1
Summary Statistics

	Care orientation			Educational orientation			
	(1) Obs.	(2) Mean	(3) SD	(4) Obs.	(5) Mean	(6) SD	(7) $p > \|t\|$
Panel A: Outcome variables							
Math score	552	−0.173	0.95	1128	0.048	0.87	0.000
Japanese score	552	−0.160	0.97	1128	0.022	0.87	0.000
SDQ score	491	−0.116	0.96	1023	−0.010	0.95	0.040
QOL score	417	−0.018	0.95	924	−0.027	0.88	0.860
Panel B: Instrumental variable							
Relative preschool enrollment	552	0.451	0.16	1128	0.551	0.13	0.000
Panel C: Child characteristics							
= 1 if female	552	0.500	0.50	1128	0.460	0.50	0.120
= 1 if born in first quarter	552	0.241	0.43	1128	0.229	0.42	0.580
# siblings	552	2.022	0.89	1128	2.177	0.79	0.000
Panel D: Household characteristics							
Mother age at birth	552	30.344	5.13	1128	30.412	4.29	0.780
= 1 if mother has college	552	0.155	0.36	1128	0.195	0.40	0.050
= 1 if father has college	552	0.302	0.46	1128	0.461	0.50	0.000
= 1 if HH in 1st income quartile	552	0.257	0.44	1128	0.152	0.36	0.000
= 1 if HH in 2nd income quartile	552	0.315	0.47	1128	0.336	0.47	0.390
= 1 if HH in 3rd income quartile	552	0.236	0.42	1128	0.338	0.47	0.000
= 1 if HH in 4th income quartile	552	0.192	0.39	1128	0.174	0.38	0.360
= 1 if grandfather has college	552	0.176	0.38	1128	0.216	0.41	0.060
Panel E: Regional characteristics							
# children per kindergarten	552	145.360	59.75	1128	160.076	56.73	0.000
# children per nursery school	552	98.864	23.68	1128	98.287	20.06	0.600
Inhabitants per ha	552	37.878	45.56	1128	50.218	46.66	0.000
Female empl. rate	552	0.953	0.01	1128	0.952	0.01	0.450
Unemployment rate	552	0.055	0.01	1128	0.054	0.01	0.040
Per capita income in 1,000 Yen	552	1461.618	293.55	1128	1577.394	323.10	0.000

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents summary statistics for variables for children who attended a care-oriented and an education-oriented preschool, respectively. The last column shows p-values from a t-test of mean equality.

4 Identification Strategy

4.1 Ordinary Least Squares Regression

For the empirical analysis, we first estimate a standard OLS regression assuming exogeneity of the treatment decision conditional on the inclusion of control variables as a benchmark. In particular, we estimate the following equation,

$$Y_{ic} = \alpha + \beta D_{ic} + X'_{ic}\lambda + \gamma_p + \delta_t + \zeta_p t + \epsilon_{ic}, \tag{2}$$

where α is a constant and Y_{ic} corresponds to either the math score, Japanese score, SDQ score, or QOL score for child i who was born in municipality c. Treatment status is captured by D_{ic} and equals one if children attended an education-oriented preschool and zero if they attended a care-oriented preschool. If the OLS assumptions are met, β corresponds to the causal effect of attending an education-oriented preschool compared to a care-oriented preschool. Control variables are summarized by the vector X_{ic}, while λ is the corresponding coefficient vector. γ_p are prefecture fixed effects, δ_t are cohort fixed effects, and ζ_p are prefecture-specific linear time trends. Finally, ϵ_{ic} is an error term.

4.2 Instrumental Variable Regression

If parents choose a preschool alternative based on individual-specific and municipality-specific unobserved characteristics which in turn may be correlated with a child's cognitive and socioemotional development, this selection pattern would lead to inconsistent estimates of β in Equation (2) from OLS. To circumvent this problem, we follow an IV strategy.

The identification strategy exploits regional and temporal variation in the supply of educational opportunities, which follows a long tradition in economic research.[27] We assume that the relative availability of preschool slots Z in a municipality significantly affects the parental decision about which preschool their child should attend. If there are only few children enrolled in education-oriented preschools in municipality c compared to care-oriented preschools, parents are more inclined to choose the latter because children in the neighborhood are also enrolled in that preschool. Also, because there are relatively few education-oriented preschools in this municipality, the commuting distance to a care-oriented preschool is relatively short. The same argument applies to a relatively higher share of children enrolled in education-oriented preschools compared to

[27] Since Duflo (2001), countless papers have used variation in supply-side factors to instrument educational decisions within an IV framework. In the context of a child's cognitive and socioemotional development, Loeb et al. (2007), Berlinski et al. (2008; 2009), and Cornelissen et al. (2018) followed this strategy. Yamaguchi et al. (2018b) and Kawarazaki (2022) used an instrument similar to ours at the prefectural level to explain the preschool decision in Japan.

care-oriented preschools. Following this argument, we can interpret the instrument as a cost-shifter leaving potential outcomes unchanged. This reasoning leads to the expectation of a positive correlation between Z and D. The empirical results in Section 5.1 show that the coefficients have the correct sign and that F-statistics are significantly larger than the rule-of-thumb F-statistic of 10 (Staiger and Stock 1997).

Our IV estimation strategy yields consistent estimates only if the instrument is valid. In addition to being relevant, it must be conditionally exogenous to a child's cognitive and socioemotional development measured by our outcome variables. In particular, after controlling for confounding factors that are associated with the preschool decision, variation in the local availability of preschool slots must be independent of unobserved factors that affect the outcome variables.

A concern raised by Cameron and Taber (2004) in the context of estimating returns to education is that the geographic distribution of educational facilities may coincide with the distribution of cognitive abilities and human capital. Historically, the kindergarten movement in the late 1800s was strongly influenced by the ideas of Friedrich Fröbel and the Christian missionaries who brought these ideas to Japan (Nishida 2015). Therefore, many kindergartens (i.e., education-oriented preschools) were established by Christian missionaries and organizations. Although nowadays more pragmatic aspects, such as the local demand, are taken into account when opening preschools, we can evaluate the historical relationship between Christian settlement, the opening of kindergartens, and the distribution of abilities using data from the Japan Imperial Ministry of Education (1902), Ministry of War (1917), Bassino et al. (2009), and Oda (2017).[28] Figure C3 in the appendix shows a positive relationship between the number of kindergarten teachers as a proxy for the number of preschool facilities and the number of Christian facilities in 1900, supporting the previous argument that the opening of kindergartens was related to Christian settlement. However, this geographic pattern was unrelated to the distribution of abilities measured by social, mathematical, and linguistic test scores from 1917. We find a similar pattern using the GDP per capita in 1909 provided by Bassino et al. (2009) as a potential confounder for Christian settlement and the development of human capital in a region. Although the GDP per capita was positively correlated with the number of kindergarten teachers, there is no effect on test scores, relaxing the concern that Christian settlement, even if it was not random, is itself, as well as factors that may underlie it, independent of the regional distribution of cognitive abilities. This evidence supports our identification strategy in the sense that, at least historically, the regional distribution of kindergartens is not related to the regional distribution of cognitive abilities and human

[28]The establishment of nursery schools (i.e., care-oriented preschools) began slightly later (i.e., around 1900, Imoto 2007) and was rather driven by the local demand for child care.

capital.[29]

Another potential threat is that highly-educated parents might move to municipalities with a better supply of education-oriented preschool slots because of their own educational orientation, while at the same time their children might perform better in school. This would lead to an upward bias of our IV estimates if we cannot control for the ability of parents. However, the rich information provided by the KHPS/JHPS allows us to control directly not only for the parents' educational attainment and their economic success, but also to control for the educational attainment of the grandfather, thereby capturing ability of two generations. Moreover, internal migration between municipalities is generally low,[30] and in Table D1 in the appendix we show that parental characteristics (i.e., ability proxies) are unrelated to the instrument, supporting the assumption that better-educated parents do not move to municipalities with more education-oriented preschools. This exogeneity of the instrument with respect to household characteristics is also confirmed by Table H7 in the appendix, which reports results from 2SLS regressions excluding these ability proxies. They show that the estimated treatment effects are virtually unchanged from our main specification.

Although it is likely that we can control for most confounding child and parent characteristics by using the rich information from the JCPS and KHPS/JHPS, there may be municipality characteristics that are correlated with the relative availability of preschool slots and a child's cognitive and socioemotional development. Ideally, one would control for municipality fixed effects to account for differences in initial conditions. Because we have only a few observations in each municipality, this strategy would remove too much variation in the instrument. Therefore, we add further control variables to capture the economic development of municipalities over time and to account for initial differences at a higher regional level. First, preferences for investments into one preschool alternative might depend on the financial resources of a municipality, which are likely to be correlated with a child's academic achievement. Therefore, we control for the per capita income in a municipality. Second, one of the main drivers behind the expanding supply of care-oriented preschool slots (see Figure 4) is the steady increase in female labor supply in recent years (see Figure A1 in the appendix). Therefore, we add a control for the local female employment rate. Third, prefectures may simply differ in their preschool preferences and education policies, which affects a child's outcomes through the provision of regionally varying financial resources. Therefore, we control for prefecture fixed effects and allow for differential trends across prefectures.

[29]When we regress our instrument on the social, mathematical, and linguistic test scores at the prefectural level (results available upon request), we cannot find any relationship, further relaxing the concern of Cameron and Taber (2004).

[30]Based on data from Statistics Bureau, Ministry of Internal Affairs and Communications (2020), we find that only about 4% of the total population moved from one municipality to another in any given year between 1996 and 2017. Yamaguchi et al. (2018a;b) also show that selective migration is a minor threat when estimating the effect of child care enrollment on child and parental outcomes in Japan.

Even if parents do not move based on their own education and financial resources, they could still be attracted by potentially unobserved municipality characteristics that affect the local availability of preschool slots. To investigate this potential threat, we use regional information from Statistics Bureau, Ministry of Internal Affairs and Communications (2020) to estimate a flexible panel fixed effects model of Z on municipality characteristics that are potentially correlated with the parents' location decision. These characteristics consist of the set of variables that are used as covariates in both stages in the main analysis (see Section 3.2), as well as other municipality characteristics that correspond to the unobservables we are testing for. Table D2 in the appendix shows that municipality characteristics that are excluded from the main analysis but are potentially correlated with the parents' location decision are unrelated to the relative preschool availability.

Another potential threat to identification is that parental preferences could influence the local supply of preschools through lobbying, for example, leading to the conclusion that our instrument would be endogenous to demand-side factors.[31] Although this potential threat is indirectly rejected by Table D1, we additionally check the robustness of our main results to an alternative instrument that is less prone to short-time fluctuations in demand-side factors. In particular, instead of using the number of preschool slots, we use the number of preschools to create the alternative instrument $Z_{ct,alt}$, which is defined as the number of education-oriented preschools in municipality c at the time of a child's birth t divided by the total number of preschool facilities, that is,

$$Z_{ct,alt} = \frac{\text{\# Education-oriented preschools}_{ct,alt}}{\text{\# All preschools}_{ct,alt}}. \tag{3}$$

The idea behind this approach is that the number of facilities cannot be easily adjusted because establishing a new facility requires time and is costly. Tables H8 to H11 in the appendix show that our main results hardly change when using this instrument instead, further supporting our identification strategy.

Finally, even after controlling for prefecture-specific linear time trends, compositional changes in enrollment patterns over time could bias our results. In particular, it is possible that more and more children from advantaged backgrounds will attend an education-oriented instead of a care-oriented preschool. We can test this threat by examining whether the correlation between the instrument and individual as well as parental characteristics is stable across birth cohorts. Therefore, Table D3 in the appendix presents results of regressions of individual and parental characteristics on interactions of the instrument with birth cohorts. We do not find evidence of compositional changes over time. There is little, if any, change in mothers' education.

Another important assumption that is often omitted from the discussion of IV strate-

[31] Kawarazaki (2022), however, shows that demand for child care has not affected supply in Japan.

gies, but is important for the interpretation of 2SLS estimates as local average treatment effects (LATEs), is monotonicity in the spirit of Imbens and Angrist (1994). This assumption implies that an improvement in the local availability of education-oriented preschool slots at each Z must increase the probability of sending a child to this institution for some children, while not reducing this probability for any child. If we follow the reasoning from before and interpret the relative availability of preschool slots as cost-shifter, it is reasonable to assume that monotonicity holds in our context. In Appendix E, we also provide evidence of monotonicity by presenting first-stage estimates for several subsamples showing that the effect is always strongly positive. Furthermore, we use partitions of Z to allow for a flexible first stage showing that more and more children are shifted into a kindergarten at different levels of Z.

4.3 Marginal Treatment Effect

Using a continuous instrument to identify the treatment effect in an IV strategy complicates the interpretation of this estimate as LATE. This effect is representative for compliers changing treatment status for changes at different values of the instrument, and the overall effect is obtained by attaching different weights to complier-specific treatment effects (Cornelissen et al. 2016). Because this treatment effect hides interesting patterns by aggregating treatment effects for different groups of compliers, we use our continuous instrument to estimate the marginal treatment effect (MTE, Björklund and Moffitt 1987; Heckman and Vytlacil 1999; 2001; 2005; 2007), which is the treatment effect for individuals at different margins of treatment take up. This allows us to estimate a flexible relationship between preschool education and children's cognitive and socioemotional development, identifying the subgroup that gains the most from enrolling in an education-oriented preschool.

Parents choose to enroll their children in a care-oriented preschool ($D = 0$) or an education-oriented preschool ($D = 1$). The cognitive or socioemotional outcome during adolescence is Y_0 if the child attended a care-oriented preschool and Y_1 if the child attended an education-oriented preschool. These potential outcomes can be written as the sum of a function of the observed characteristics $X\lambda_j$ and unobserved characteristics U_j, with $j = \{0, 1\}$:[32]

$$Y_j = X\lambda_j + U_j \quad \text{with } \mathbb{E}[U_j \mid X] = 0, \quad j = \{0, 1\}. \tag{4}$$

Because we only observe children in one treatment state but not the other at the same time, we write the equation of the observed outcome Y based on the switching regression

[32]For clarity, we omit indices and assume that X also includes prefecture fixed effects, cohort fixed effects, and prefecture-specific linear time trends.

model of Quandt (1972) as

$$
\begin{aligned}
Y &= (1-D)Y_0 + DY_1 \\
&= Y_0 + D(Y_1 - Y_0) \\
&= X\lambda_0 + D\left[X(\lambda_1 - \lambda_0) + U_1 - U_0\right] + U_0,
\end{aligned} \tag{5}
$$

where the last line follows from replacing Y_1 and Y_0 with Equation (4). Treatment effect heterogeneity in Equation (5) arises either from different valuations of observed characteristics, $\lambda_1 \neq \lambda_0$, or differences in unobserved characteristics, $U_1 \neq U_0$, the latter being called unobserved gain from treatment.

The latent net benefit of treatment D^* is defined as

$$
D^* = \tilde{Z}\beta_d - V, \tag{6}
$$

where $\tilde{Z} \equiv (X, Z)$ implies that there is at least one excluded instrument Z, and V denotes unobserved characteristics that reduce the likelihood of choosing an education-oriented instead of a care-oriented preschool, often called resistance or distaste for treatment (e.g., Cornelissen et al. 2016).

Parents choose an education-oriented preschool if the net benefit from observed characteristics exceeds the unobserved resistance or distaste for it:

$$
D = \begin{cases} 0 & \text{if } \tilde{Z}\beta_d < V \\ 1 & \text{if } \tilde{Z}\beta_d \geq V. \end{cases} \tag{7}
$$

By applying the cumulative distribution function (cdf) of V to both sides of Equation (7), the left-hand side becomes $F_V(\tilde{Z}\beta_d) \equiv P(\tilde{Z})$, the propensity score,[33] and the right-hand side becomes $F_V(V) \equiv U_D$, the quantiles of unobserved resistance or distaste for treatment. This model assumes that $\tilde{Z}$ is statistically independent of (U_0, U_1, V) given X.[34]

The MTE is the average gain from treatment for children who are indifferent between care-oriented and education-oriented preschools at different U_D for fixed X:

$$
\begin{aligned}
\text{MTE}(X, U_D) &= \mathbb{E}\left[Y_1 - Y_0 \mid X, U_D\right] \\
&= X(\lambda_1 - \lambda_0) + \mathbb{E}\left[U_1 - U_0 \mid U_D\right].
\end{aligned} \tag{8}
$$

[33]The propensity score can be estimated using standard binary choice models such as Probit and Logit regressions.

[34]Vytlacil (2002) shows that additive separability between $\tilde{Z}$ and V implies monotonicity because changes in the instrument Z and hence in the propensity score $P(\tilde{Z})$ shift individuals either into or out of treatment, but never both simultaneously.

Therefore, treatment effect heterogeneity arising from X affects the intercept of the MTE curve, while its slope depends on heterogeneity in $U_1 - U_0$. Heckman and Vytlacil (2007) show that the MTE can be recovered by taking the first derivative of $\mathbb{E}\left[Y \mid X, P(\tilde{Z})\right]$ with respect to the propensity score:

$$\begin{aligned}
\text{MTE}(X, U_D) &= \frac{\partial \mathbb{E}\left[Y \mid X, p\right]}{\partial p} \\
&= \frac{\partial \left[X\lambda_0 + X(\lambda_1 - \lambda_0)p + \Pi(p)\right]}{\partial p} \\
&= \underbrace{X(\lambda_1 - \lambda_0)}_{observed} + \underbrace{\frac{\partial \Pi(p)}{\partial p}}_{unobserved},
\end{aligned} \tag{9}$$

where p is the estimated propensity score and $\Pi(p)$ is a flexible function of it.

In our main specification, we model $\Pi(p)$ as a polynomial of p of degree $K = 2$,[35] where p is estimated using a Probit regression. We also test sensitivity of our results by allowing a more flexible shape of the MTE curve. In particular, we estimate the MTE using a polynomial of degree 3 and 4 and by following the semiparametric approach described in detail in Carneiro et al. (2011).

5 Results

5.1 First-Stage Selection Equation

In a first step, we estimate a Probit regression to test the strength of the relationship between the relative preschool availability and the preschool choice. Average partial effects of this Probit regression for different sets of control variables are presented in Table 2. This model is then used to calculate predicted probabilities used to estimate the MTE (see Section 5.3).

The relative availability of education-oriented preschool slots within a municipality significantly influences parents' preschool choice. As expected, results show that an increase in this share by 1 percentage point leads to a substantial increase in the probability of choosing an education-oriented over a care-oriented preschool by 0.63 to 0.92 percentage points on average. This strong positive relationship is highly significant and leads to a partial χ^2-statistic of 20.11 in our preferred specification (Column (3)).[36] Thus, we can conclude that our instrument meets the relevance criterion and any remaining bias in our

[35] This approach has been used by empirical applications of Cornelissen et al. (2018) and Felfe and Lalive (2018), among others.

[36] If we run a linear probability model instead and test for weak instruments, we obtain a partial F-statistic of 19.18 in our preferred specification (Column (3)), which is well above the rule-of-thumb threshold of 10 (Staiger and Stock 1997).

Table 2
First-Stage Probit Regression

	Educational vs. care orientation		
	(1)	(2)	(3)
Relative preschool enrollment	0.923***	0.842***	0.632***
	(0.088)	(0.108)	(0.138)
Control variables		✓	✓
Prefecture fixed effects			✓
Cohort fixed effects			✓
Prefecture-specific linear time trends			✓
χ^2-stat	83.696	52.605	20.107
p-value	0.000	0.000	0.000
Observations	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents average partial effects from first-stage Probit regressions of enrollment in an education-oriented against a care-oriented preschool on the relative preschool availability and a set of control variables described in Section 3.2. χ^2-tests of significance of the coefficient on the instrument are conducted and the results are presented at the end of the table. Table F5 in the appendix presents full estimation results. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

2SLS estimates will be small.

The full estimation results in Table F5 in the appendix also show that children with more siblings, from households with a more educated father and higher income, and from municipalities with a low unemployment rate are more likely to enroll in an education-oriented instead of a care-oriented preschool. These findings are consistent with our observations from the descriptive statistics and confirm that parents from different backgrounds have different preferences for their children's preschool education. Those from advantaged backgrounds place more emphasis on the educational orientation and tend to send their children to this institution rather than to a care-oriented preschool.

5.2 Estimation Results Based on OLS and 2SLS

Our main analysis starts with benchmark OLS regressions of our cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool based on Equation (2) in Columns (1), (3), (5), and (7) of Table 3.

These regressions suggest a positive relationship between educational orientation and the cognitive development. Children who attended an education-oriented preschool have

Table 3

OLS and 2SLS Regressions

	Math		Japanese		SDQ		QOL	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Educational vs. care orientation	0.187***	0.324	0.193***	0.871**	0.102	0.608	−0.005	0.747
	(0.055)	(0.344)	(0.056)	(0.386)	(0.067)	(0.404)	(0.065)	(0.514)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture-specific linear time trends	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1680	1680	1680	1680	1514	1514	1341	1341

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from OLS and 2SLS regressions of the cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Table G6 in the appendix presents full estimation results. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

on average 0.19 SD higher scores in math and Japanese than children who attended a care-oriented preschool instead. The coefficients for the regressions of the SDQ score and the QOL score are 0.10 and −0.01, respectively, indicating little or even no relationship between the educational orientation and the socioemotional development.

As it is likely that these estimates are biased estimates of the true causal effect, in Columns (2), (4), (6), and (8) we present results from 2SLS regressions instrumenting the preschool decision with the relative preschool availability. The effect of the educational orientation on the math score almost doubles when estimating a 2SLS instead of an OLS regression. This coefficient, however, is not statistically significant anymore. Even more, the effect on the Japanese score rises to 0.87 SD, suggesting significant improvements in cognitive development.[37] Somewhat smaller and not statistically significant anymore are the effects of the educational orientation on the SDQ score and the QOL score. Children who attended an education-oriented instead of a care-oriented preschool have on average a 0.61 SD higher SDQ score and a 0.75 SD higher QOL score.

These treatment effects seem quite large compared to similar studies evaluating preschool programs in various countries. Considering that children in our sample attend the education-oriented preschool for an average of 2.7 years, the annualized returns are 0.12 SD on the math score, 0.32 SD on the Japanese score, 0.23 SD on the SDQ score, and 0.28 SD on the QOL score, respectively. These effect sizes are very similar to, for instance, annualized returns to universal pre-primary education on test scores in Argentina (0.23 SD, Berlinski et al. 2009).

Although we suspected estimates from OLS to be biased upwards because of positive selection into treatment, it appears that they understate the true causal effect. While treatment effects from OLS are also identified by always-takers, treatment effects from 2SLS are identified by compliers that enroll in an education-oriented preschool due to a shift in the instrument. If the returns are heterogeneous such that high-resistance children have higher returns than low-resistance children, and these high-resistance children receive a larger weight than low-resistance children in the 2SLS estimation, effects from 2SLS are larger than those from OLS. This explanation is supported by the IV weights obtained from the MTE curves in the next subsection (see Figure L7 in the appendix), which assign larger weight to high-resistance children with large treatment effects.[38]

The full estimation results in Table G6 in the appendix show that girls perform better in Japanese and show less behavioral problems, that relatively young age is associated with negative effects on mathematical and linguistic ability, and that the number of siblings has a negative effect on the cognitive development as well as on the QOL score. Although parental education is positively related to the cognitive development, there is no

[37]The effect on the Japanese score also survives a correction for multiple hypothesis testing following Romano and Wolf (2005).

[38]We thank an anonymous referee for pointing this out.

effect on the socioemotional development. Finally, a higher household income significantly improves the cognitive and socioemotional development of children.

In the discussion of the identification strategy, we emphasized that our results are robust if a stricter treatment definition is used instead, that is, all children who attended both types of preschools for a short time period are excluded from the analysis. Columns (4) to (6) in Tables H8 to H11 in the appendix show that the 2SLS estimates remain virtually unchanged. Furthermore, using the relative number of preschool facilities as instrument instead of available slots in Columns (7) to (9) in Tables H8 to H11 in the appendix further support our main results, as the 2SLS estimates remain largely unchanged, although the coefficients increase slightly.

The comparatively large standard errors of our 2SLS estimates may raise concerns about statistical inference in the small sample. Therefore, as a further sensitivity check, we estimate reduced-form regressions of our outcome variables on relative preschool availability and compare these effects with the distribution of placebo treatment effects based on the permutation test suggested by Bertrand et al. (2004). It is not possible to perform this exercise with the fully specified 2SLS regression because random assignment of the instrument would lead to a weak instrument problem in the first stage and thus to highly biased estimates in the second stage. Instead, evaluating inference of reduced-form estimates can serve as a check for the existence of positive effects. Given that the assumptions of a valid instrumental variable hold (see Section 4), positive reduced-form effects suggest improved child development as a result of improved availability of education-oriented preschools, which operates through enrollment in them. For the permutation test, we randomly assign birth years and municipalities to children (without replacement) and estimate the placebo treatment effect of the relative preschool availability on the outcomes for these children. This procedure is repeated 3000 times so that we can obtain an exact finite sample distribution of hypothetical effects against which we can compare the actual reduced-form estimates. Figure I5 in the appendix shows the results. We find that our reduced-form estimates are positive and statistically significant for all outcome variables at least at the 5% level, suggesting that our positive treatment effects are not due to chance.

Although these results suggest strong improvements in children's socioemotional development after attending an education-oriented preschool, these developmental gains could also be driven by gains from cognitive improvements, as these children are exposed to less stress and pressure due to better performance in math and Japanese. Therefore, we disentangle the effects on our socioemotional measures by repeating the same 2SLS regressions for the subscales of the SDQ score in Table J12 and the QOL score in Table J13 in the appendix. We find that the positive effect on the SDQ score is mainly driven by improvements in the subscales emotional symptoms and peer relationships, although the effect on the former is not statistically significant. For the QOL score, however, we are not able to find the driving subscale behind the positive effect due to large standard errors. This suggests that positive effects for this socioemotional measure might be driven by the improved cognitive ability instead.

5.3 Who Gains from an Education-Oriented Preschool?

To shed more light on the distribution of these positive effects, we will estimate MTE curves in the next step to allow for heterogeneity in the effect based on the unobserved resistance to treatment. This allows us to draw conclusions about which children gain more (or less) from enrolling in an education-oriented instead of a care-oriented preschool.

Estimation of the MTE requires common support of the propensity score over the full unit interval, that is, treated and untreated observations with predicted probabilities of treatment for all values between zero and one. Figure 5 shows these predicted probabilities from a first-stage Probit regression for children who attended a care-oriented preschool in blue and children who attended an education-oriented preschool in orange.

The estimated propensity score is more evenly distributed for children who attended a care-oriented preschool and has a high probability mass around zero. In contrast, our model assigns a high predicted probability of treatment to children who attended an education-oriented preschool. Although we have a remarkable common support over the interval $[0.10, 0.95]$, there are few observations that fall in the lower range of the propensity score. Therefore, we restrict the estimation of the MTE to percentile intervals of the propensity score with at least three treated and untreated observations, which leaves us with a practical common support of $[0.32, 0.93]$.

In the next step, this propensity score is used to parametrically model $\Pi(p)$ as a polynomial of degree $K = 2$ and obtain estimates for the MTE for the math, Japanese, SDQ, and QOL score, respectively. These MTE curves are presented in Figure 6. Although these curves can be obtained for the full unit interval of the unobserved resistance by extrapolation based on the parametric assumption, we believe that this strategy only confuses about the population we are able to draw conclusions about. Furthermore, extreme values at low/high quantiles of the unobserved resistance could bias the MTE curve due to its parametric shape. Therefore, we focus only on the MTE obtained from the practical common support defined above. This means that we cannot draw conclusions about the average treatment parameters in the population and we refer to the average treatment parameters obtained from the MTE curves presented in Table 4 as $\widetilde{\text{ATT}}$, $\widetilde{\text{ATE}}$, and $\widetilde{\text{TUT}}$, to distinguish them from their population counterparts.[39]

The MTE curves for cognitive and socioemotional development show an increasing pattern, suggesting inverse selection on gains. Children who are least likely to attend an

[39] For estimation, we use the Stata code provided by Cornelissen et al. (2018), which is an enhanced version of the `margte` command of Brave and Walstrum (2014).

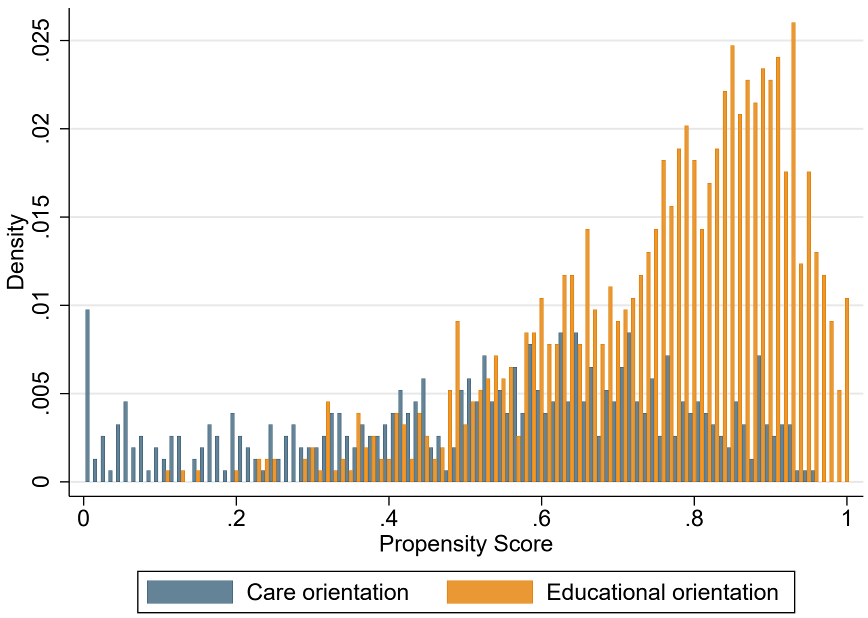


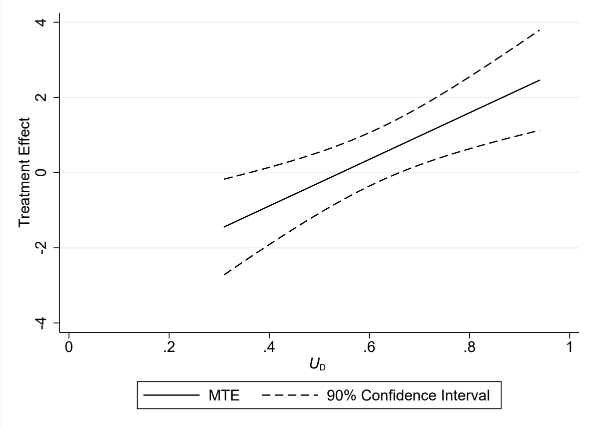
Figure 5
Common Support

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This graph shows the distribution of the propensity score summarized in 0.01-intervals. The propensity score is obtained from a Probit regression of enrollment in an education-oriented against a care-oriented preschool on the relative preschool availability and a set of control variables described in Section 3.2, prefecture fixed effects, birth year fixed effects, and prefecture-specific linear time trends. The instrument is interacted with all child and household characteristics.

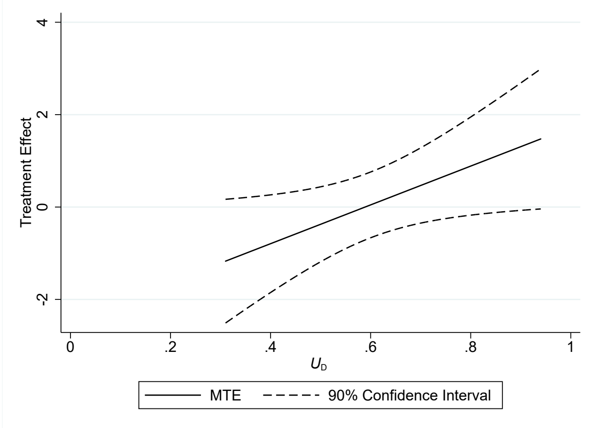
education-oriented preschool based on their unobserved characteristics benefit the most from attending it, while children who have a lower resistance for treatment do not exhibit any positive gains. These unobserved characteristics most likely correspond to lower ability or less emphasis parents place on their children's education (or distaste against education), even after controlling for socioeconomic background. This implies that the educational orientation plays a minor role in the cognitive and socioemotional development of children who have a higher ability or come from households that place more emphasis on education. These children likely know most of the content taught in the education-oriented preschool, or they learn it at home and therefore do not benefit from this type of institution.[40]

This selection pattern can be tested statistically under the null hypothesis that the slope of the MTE curve, and hence the first derivative of the unobserved part of Equation (9), is constant. This is the same as testing for no effect heterogeneity based on unobserved characteristics, or equivalently for no selection on gains. Results from this test for each

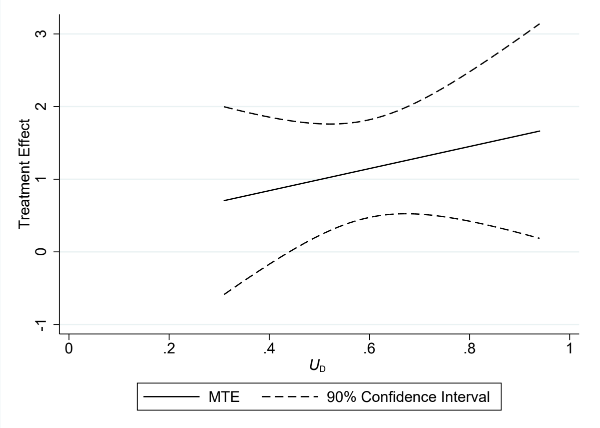
[40]For a similar argument in the context of mathematical instruction in kindergarten, see Engel et al. (2013).



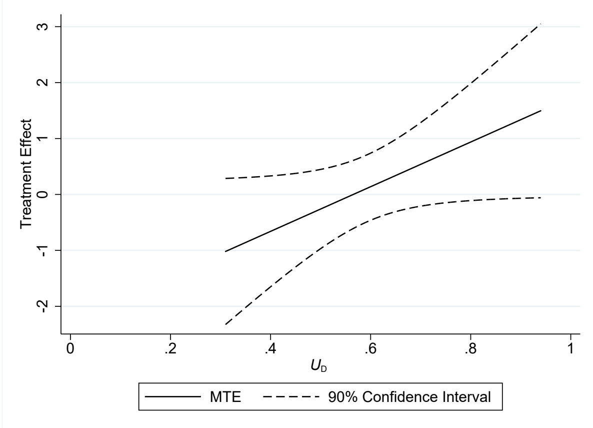
(a) Math



(b) Japanese



(c) SDQ



(d) QOL

Figure 6
MTE Curves

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: These graphs show MTE curves from a parametric MTE specification with $K = 2$ and their 90% confidence intervals. Covariates are held constant at their means. Confidence intervals are obtained from a municipality level clustered bootstrap with 299 replications.

outcome variable are presented in Table 4. In fact, we can show that for the math and Japanese score an inverse selection pattern can be statistically detected, that is, p-values below conventional critical values allow us to reject the null hypothesis of no selection on gains.

Our parametric specification of the MTE using a polynomial of degree $K = 2$ is a common choice in applied work (e.g., Cornelissen et al. 2018). However, alternative specifications are also possible, and one should test the robustness of this choice with respect to more flexible relationships. Therefore, we reestimate the parametric MTE specification using polynomials of degree 3 and 4, respectively, as well as a semiparametric specification (e.g., Carneiro et al. 2011), and compare these curves to our main specification in Figure K6 in the appendix. Allowing a more flexible relationship, the shape of the MTE curves for the math and QOL score hardly changes. Most remarkably, the semiparametric curve resembles the parametric curve for the math score, while for the QOL score it is very similar but somewhat steeper. More flexible parametric specifications for the Japanese score suggest a stronger increase in the treatment effect for higher values of U_D. However, the semiparametric curve is flatter, suggesting more moderate treatment effects for higher values of U_D. Our main specification lies in between those two extreme shapes, but covers the increasing pattern of the other parametric specifications. Therefore, we believe that our preferred specification is a good and reliable choice for the Japanese score. In contrast, different specifications for the SDQ score suggest different shapes and a flat or inverse U-shape rather than an increasing curve. Thus, we should be careful in interpreting the inverse selection pattern in the case of the SDQ score, even though the different specifications still confirm strong positive effects.

In estimating average treatment parameters, we can draw conclusions about clearly specified subpopulations and learn about their behavior, which is not possible if we only rely on simple 2SLS estimates. Therefore, Table 4 presents estimates of the $\widetilde{\text{ATT}}$, $\widetilde{\text{ATE}}$, and $\widetilde{\text{TUT}}$ of attending an education-oriented instead of a care-oriented preschool on children's cognitive and socioemotional development.[41] The inverse selection pattern suggests that children randomly drawn from the population of education-oriented preschool attendees ($\widetilde{\text{ATT}}$s) do not gain at all from it with respect to the math, Japanese, and QOL score. A similar, albeit more positive, picture arises for children randomly drawn from the overall population. The $\widetilde{\text{ATE}}$s suggest slightly positive returns to the educational orientation with respect to the math score, while they are close to zero for the Japanese and QOL score. Interestingly, those children who attended a care-oriented preschool would benefit the most if they had attended an education-oriented preschool instead. The $\widetilde{\text{TUT}}$s suggest gains of around 1.58 SD for the math score and strong but not statistically significant gains for the Japanese and QOL score. Only with respect to the SDQ score all children would gain in a similar way, regardless of whether they are from the population of education-oriented preschool attendees or care-oriented preschool attendees.

5.4 Which Preschool Drives Heterogeneity?

In this subsection, we use the approach suggested by Brinch et al. (2017) to split up heterogeneity of the MTE ($\mathrm{E}(U_1 - U_0 \mid U_D = u_d)$) in the unobserved parts of the outcomes when untreated ($\mathrm{E}(U_0 \mid U_D = u_d)$) and when treated ($\mathrm{E}(U_1 \mid U_D = u_d)$). This allows us to shed further light on the inverse selection pattern (i.e., why children with a high resistance for treatment gain while those with a low resistance do not). Therefore, in Figure 7, we

[41]Figure L7 in the appendix shows the weights used to calculate the $\widetilde{\text{ATT}}$s and $\widetilde{\text{TUT}}$s from the MTE curves. The $\widetilde{\text{ATE}}$ gives equal weights to all values of the MTE curve, and therefore these weights are not presented.

Table 4
Average Treatment Parameter

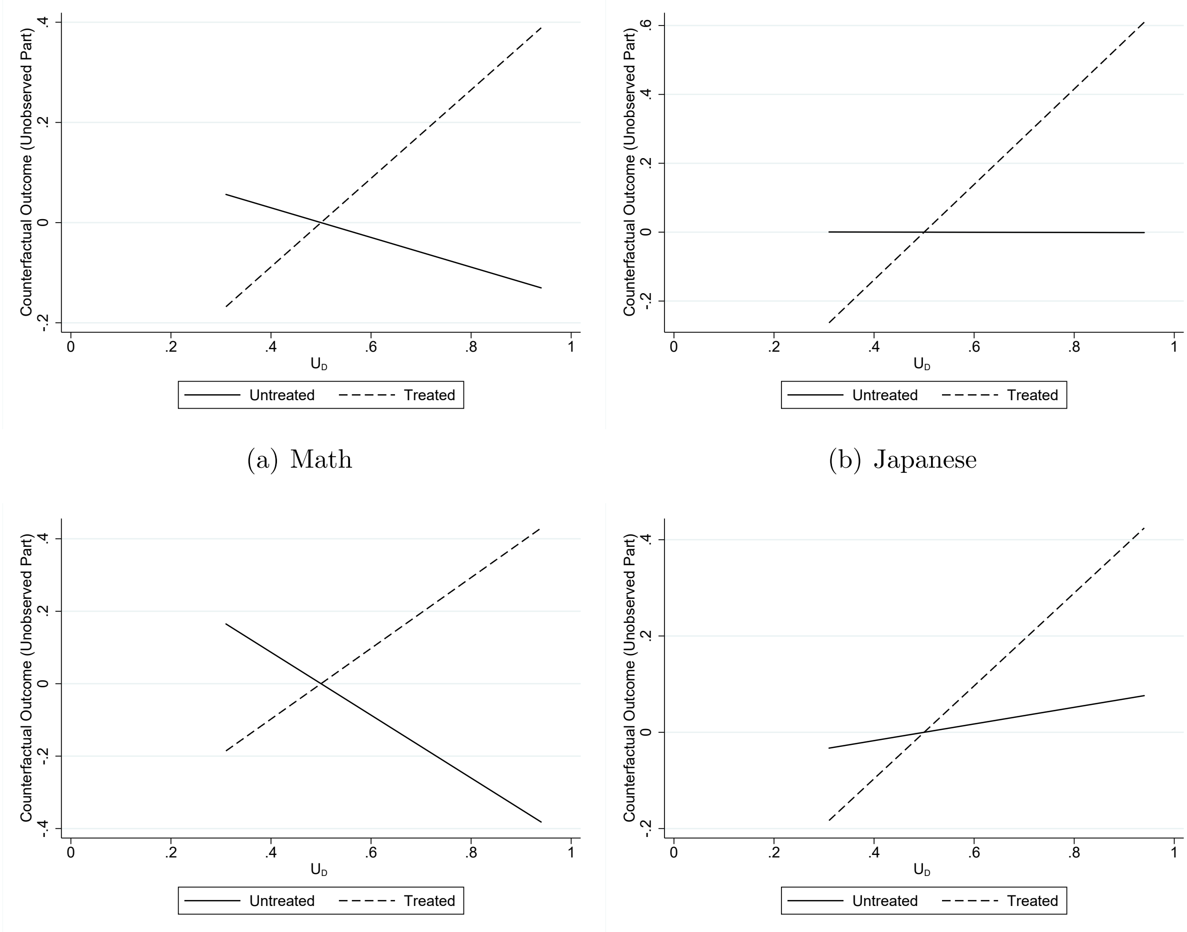
	Math	Japanese	SDQ	QOL
	(1)	(2)	(3)	(4)
$\widetilde{\text{ATT}}$	-0.214	-0.376	1.007**	-0.167
	(0.482)	(0.482)	(0.442)	(0.405)
$\widetilde{\text{ATE}}$	0.507	0.152	1.184***	0.239
	(0.431)	(0.437)	(0.414)	(0.374)
$\widetilde{\text{TUT}}$	1.582***	0.935	1.461***	0.877
	(0.537)	(0.594)	(0.560)	(0.575)
p-value for test of heterogeneity	0.004	0.079	0.515	0.112

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents estimates of the ATT, ATE, and TUT from a parametric MTE specification with $K = 2$. For details of the calculation of these parameters, see Appendix L. Standard errors are obtained from a municipality level clustered bootstrap with 299 replications and are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

plot the unobserved parts of the outcomes when untreated and when treated, respectively, against the unobserved resistance for treatment.

For math, the curve in the untreated state is slightly falling, while it is almost flat for the Japanese and the QOL score. This implies that high-resistance children have only slightly worse math development than low-resistance children from attending a care-oriented preschool, while there are almost no differences for the linguistic ability and the QOL score.[42] This emphasizes the high-quality care that applies equally to all children enrolled in a care-oriented preschool. In contrast, for all outcome variables, the curve in the treated state is strongly increasing, implying that especially high-resistance children benefit from attending an education-oriented preschool. These differences can explain the inverse selection pattern and hence the heterogeneity in returns. Although children can expect essentially the same returns from attending a care-oriented preschool, regardless of whether they are more or less likely to enroll, attending an education-oriented preschool leads to strong positive developmental gains only for high-resistance children. Those are the children whose unobserved characteristics, such as lower ability, make them less likely to enroll in the education-oriented preschool. These children lack behind their higher-ability peers when they start preschool, and therefore can catch up by attending an education-oriented preschool. This finding suggests that specific aspects of education-oriented preschools rather than aspects of care-oriented preschools are responsible for the positive treatment effect of high-resistance children. Therefore, it is very likely that the

[42]Because of the instability of the corresponding MTE curve (see Figure K6), we should not overinterpret the falling curve for the SDQ score.



(a) Math (b) Japanese

(c) SDQ (d) QOL

Figure 7
Counterfactual Outcomes by Treatment Status

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This graph shows the unobserved part of the cognitive and socioemotional ability measures separately for treated and untreated children, based on the approach suggested by Brinch et al. (2017).

educational orientation as one of the main features of kindergartens is responsible for these gains.[43]

5.5 Short-Term vs. Long-Term Effects

One aspect that is widely discussed in the context of early childhood education is the durability of positive effects. In a seminal work, Currie and Thomas (1995) show that cognitive gains from Head Start fade early (see also Hill et al. 2015). In contrast, Heckman et al. (2010b) and Carneiro and Ginja (2014) find that noncognitive gains remain

[43]In Section 6, however, we discuss possible features other than the educational orientation that could explain parts of the treatment effect.

remarkably stable into adolescence.[44] The question of whether or not effects fade has very different implications for the long-term evaluation of early childhood interventions.

The unique structure of the JCPS allows us to assess the evolution of effects over time to test the hypotheses of declining cognitive and stable socioemotional gains in the context of two high-quality preschool institutions. In particular, we repeat the IV strategy with samples for children in the first three years of elementary school (aged 6 to 9), in the last three years of elementary school (aged 9 to 12), and in lower secondary school (aged 12 to 15). This allows us to evaluate effect heterogeneity over the course of compulsory schooling in Japan. Results are presented in Figure 8 (and Table M14 in the appendix).

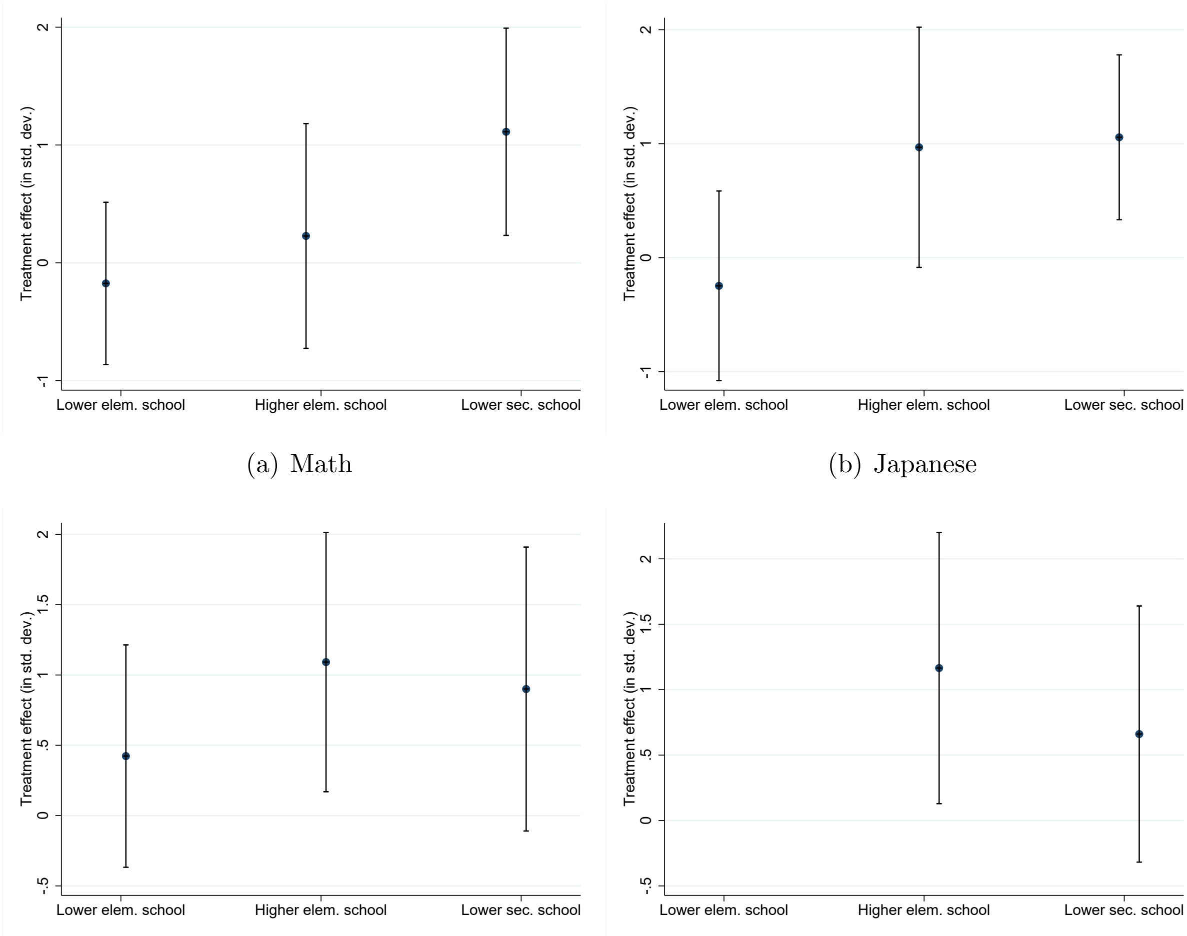
The results are surprising in the light of previous research. Attending an education-oriented preschool before elementary school has almost no effect on mathematical and linguistic development in the first three years of elementary school, while cognitive scores increase strongly thereafter. Effects range from -0.17 to 1.11 SD on mathematical achievement and from -0.25 to 1.06 SD on linguistic achievement. These results demonstrate that education-oriented preschools have an increasingly positive impact on children's cognitive development over time. In contrast, the findings on the evolution of effects on socioemotional outcomes are mostly in line with previous research. It appears that the positive effects on our socioemotional measures are mostly stable over time, at most decreasing slightly at the end of the observation period.

One potential explanation for increasing positive effects on cognitive development is selective panel attrition. This problem could arise if children attending an education-oriented preschool and performing poorly in the early grades dropped out of the survey in later waves, leading to an upward bias over time.[45] We can test for this by estimating a Probit regression of a dummy variable indicating whether children in the lower grades at survey wave s would drop out at survey wave $s+1$ on the cognitive achievement in those lower grades as well as child and parental characteristics. Results of this exercise can be found in Table N15 in the appendix. We find no evidence of high- or low-achieving children to be more or less likely to drop out of the survey in either the sample of care-oriented preschool children or the sample of education-oriented preschool children, providing evidence against the selective panel attrition explanation.

Another explanation is rooted in the differences between the Japanese and the U.S. school system. Diminishing positive cognitive effects in the United States were explained by the worse environment to which treated children would return after completing the program (e.g., Currie and Thomas 2000). In Japan, on the other hand, schools are more homogeneous and have similar quality across the country. Therefore, disadvantaged children who attended an education-oriented preschool will experience the same school and

[44] Similar results were found from the Perry Preschool program (e.g., Schweinhart et al. 2005; Heckman et al. 2010a; Conti et al. 2016).

[45] In general, the same pattern could arise if high-performing children attending a care-oriented preschool dropped out over time. However, this is unlikely to happen.



(a) Math (b) Japanese

(c) SDQ (d) QOL

Figure 8
Effect of Preschool Types Over Time

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This graph shows results from 2SLS regressions of the cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. These regressions are conducted separately for children in the first three years of elementary school, the last three years of elementary school, and lower secondary school. There are not enough observations for the QOL score at lower elementary school. Table M14 in the appendix presents full estimation results together with F-statistics from tests of weak instruments in the first stage. The whiskers indicate 90% confidence intervals based on robust standard errors clustered at the municipality level.

neighborhood environment as advantaged children. Within this rather equal environment, the early investment into human capital can bear fruits and lead to longer-lasting improvements in the cognitive development, as suggested by the theory of dynamic complementarities (Cunha and Heckman 2007).

6 Educational Orientation or Other Channels?

Although we cannot directly test the conjecture that the educational orientation and the structured curriculum of education-oriented preschools are the main drivers behind the treatment effect, our results point to this interpretation. In particular, in Section 5.4 we concluded that specific aspects of education-oriented preschools, such as the structured curriculum, are responsible for the positive treatment effect, rather than aspects of care-oriented preschools. Studies in the United States argue in a similar way, although they cannot identify the characteristics of the counterfactual care that children would experience in absence of the targeted programs.[46] In this section we discuss other potential channels and mechanisms through which our treatment effect might also operate.

A key difference between education-oriented and care-oriented preschools are operating hours (full-day vs. half-day). While mothers of care-oriented preschoolers are able to work full-time, mothers of education-oriented preschoolers often work part-time at best. A large literature shows that the use of child care instead of informal care alternatives leads to an increase in maternal labor supply and reduces child-mother interaction (e.g., Gelbach 2002; Baker et al. 2008; Lefebvre and Merrigan 2008; Nollenberger and Rodríguez-Planas 2015; Yamaguchi et al. 2018a;b). Thus, the positive effect of educational orientation could be explained by the additional interaction with the mother in the afternoon, which care-oriented preschoolers do not have.[47] Using data from KHPS/JHPS and estimating difference-in-differences regressions of parental labor supply on the relative availability of preschool slots, we find a strong negative effect of the relative availability of education-oriented preschool slots on maternal labor supply, while paternal labor supply is largely unaffected (see Figure O8 in the appendix).[48] Similarly, there is a strong positive effect on time spent at home for child care. Both results suggest that the interaction with mothers may partially explain the treatment effect.

One could further argue that enrolling children in different preschool alternatives could have an impact on parental behavior, leading to potential multiplier effects. For example, Gelber and Isen (2013) find that Head Start led to greater parental engagement in terms of time spent reading, math activities, and days spent with the child (for Japan, see Yamaguchi et al. 2018b). If attending an education-focused preschool also improves parental behavior, this, along with afternoon interaction, could enhance the positive impact on the

[46]For example, Barnett and Masse (2007) argue that the Abecedarian project's returns are higher than Perry's because of the additional hours of instruction. Similarly, Schweinhart (2007) expresses the opinion that the HighScope curriculum is the main reason for Perry's success (see also Heckman et al. 2010b; Conti et al. 2016). See also the discussion in Duncan and Magnuson (2013).

[47]Although we cannot test this, parents might also use the afternoons to send their children to extracurricular activities that have a positive impact. This means that the positive effects cannot necessarily be explained by the interaction with parents alone.

[48]Because we do not observe preschool enrollment for these children, our estimates are intention-to-treat (ITT) estimates.

child's cognitive and socioemotional development. Although we cannot test this hypothesis directly, we follow the same strategy as before and estimate the effect of the relative preschool availability on education expenditures and total expenditures (see Figure O8 in the appendix) as proxies for behavioral change. We cannot find clear evidence for a change in spending behavior, relativizing the behavioral channel.

Another possible channel through which education-oriented preschools could lead to developmental gains is through interaction with stronger peers. Henry and Rickman (2007) find positive spillover effects of peers in Head Start on children's cognitive development (see also Neidell and Waldfogel 2010). Throughout the paper we have seen that children from more advantaged backgrounds are more likely to be enrolled in education-oriented preschools. Therefore, it is possible that children attending this preschool are simply learning from each other and that the positive effect is ultimately due to interaction with stronger peers. This could explain why children who are less likely to attend an education-oriented preschool and are therefore of lower ability or come from households that place less value on education gain more from it than their peers who are more likely to attend it (see Figure 6). This explanation is also supported by the strong positive effect on peer relationships (see Table J12).

Finally, because the two institutions are supervised by different ministries and teachers/caretakers receive the certificate from the respective ministry, it is possible that teachers in education-oriented preschools are better qualified than caretakers in care-oriented preschools, suggesting that the treatment effect is due to this difference in institutional quality. For example, the results of Guarino et al. (2006) show that teacher qualifications and instructional practices play an important role in the effectiveness of kindergartens on the cognitive development of children in the United States.[49] Although we cannot empirically test this hypothesis given our data, both teachers and caretakers are generally well-trained and therefore of similar high quality (e.g., Kawarazaki 2022), and possible differences between the two groups contribute only slightly to the treatment effect.

7 Conclusion

This paper uses a unique feature of the Japanese preschool system to estimate the causal effect of an education-oriented against a care-oriented preschool on children's cognitive and socioemotional development in adolescence. Relying on plausibly exogenous regional and temporal variation in the relative availability of preschool slots, we estimate 2SLS regressions of a measure of mathematical and a linguistic ability, the socioemotional measure of behavioral problems SDQ, and a quality of life measure on children's preschool attendance.

[49]In contrast, Palardy and Rumberger (2008) show that teacher qualifications play a minor role compared to instructional practices in first grade of elementary school.

Our main findings suggest strong developmental gains, particularly in linguistic ability, which materialize at a later stage of adolescence. Although previous research has shown that cognitive gains from targeted programs such as Head Start fade soon after the program ends (Currie and Thomas 1995), we can explain our results with the homogeneous high-quality schooling across Japan, as opposed to the more heterogeneous environments in the United States, where disadvantaged but treated children experience the same environment as their advantaged but nontreated peers. This finding is consistent with the theory of dynamic complementarities (Cunha and Heckman 2007) and underscores the importance of the post-treatment period for the effectiveness of preschool programs in the long run.

To further examine heterogeneity of this treatment effect, we estimate the MTE and find an inverse selection pattern: children who are least likely to attend an education-oriented preschool are those who benefit the most. This finding can most likely be explained by aspects of education-oriented preschools as opposed to care-oriented preschools, such as the educational instruction. Children with high resistance are less gifted or come from households that place less emphasis on education. These children benefit from the additional instruction that advantaged children can replace with knowledge and skills acquired in their home environment. Nevertheless, shorter hours of operation leading to a reduction in maternal labor supply and allowing more interaction with the mother, as well as interaction with stronger peers, could serve as further explanations. Thus, we welcome future research on the channels and mechanisms through which our estimated treatment effect might operate to gain a deeper understanding of the forces behind these developmental gains.

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A Female Employment Rate

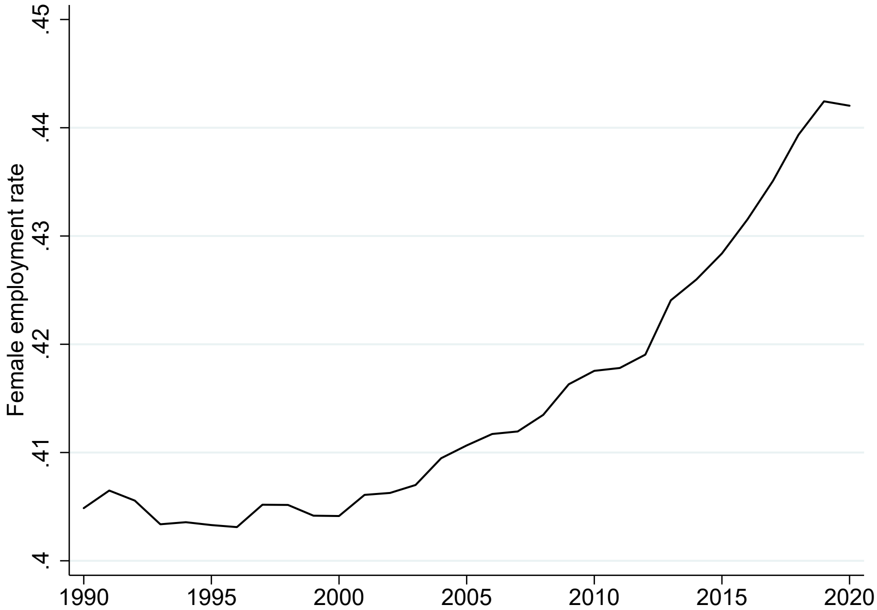


Figure A1
Female Employment Rate Over Time

Source: Authors' calculations using data from The World Bank (2022). *Note*: This graph shows the female employment rate over time for Japan, calculated as the share of working women among all women aged 15 or above.

B Distribution of Outcome Observations Across Grades

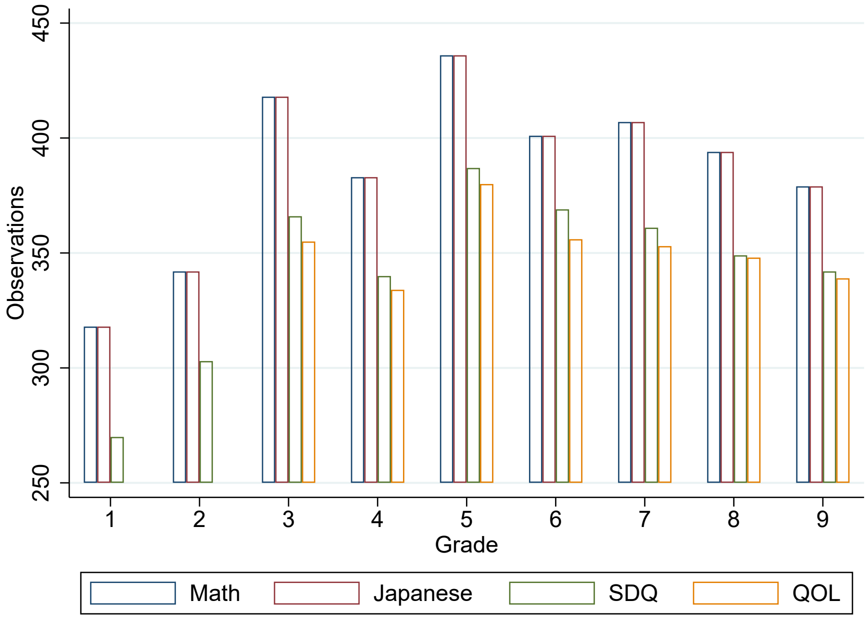
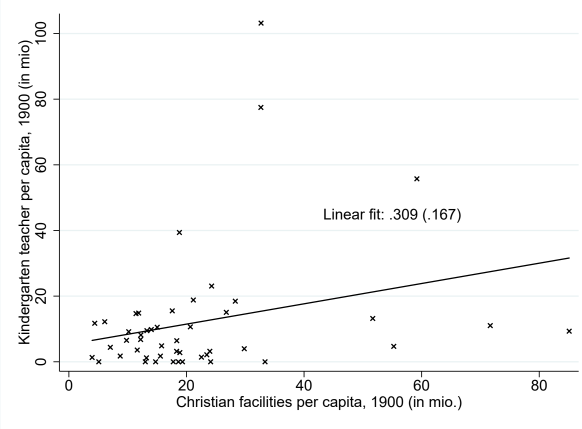


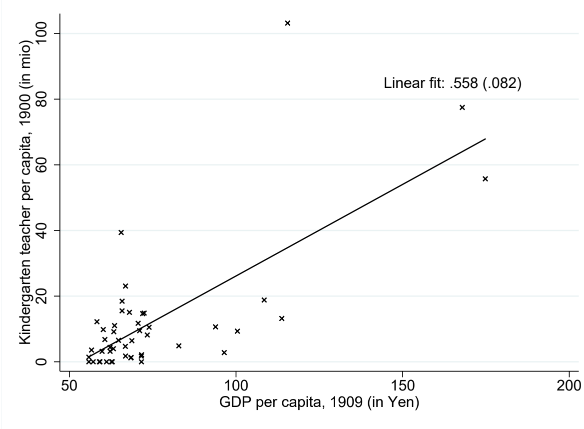
Figure B2
Distribution of Outcome Observations Across Grades

Source: Authors' calculations using data from JCPS and KHPS/JHPS. *Note*: This graph shows the number of observations for each outcome variable across grades. One child might be measured several times at different grades. These observations are used to obtain the individual-averaged outcome variables used in the main analysis.

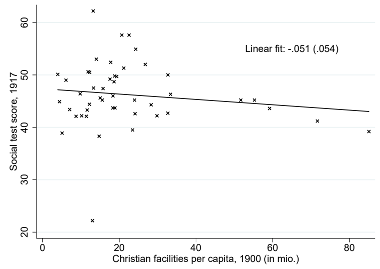
C Historical Relationship Between Christianity and Kindergartens



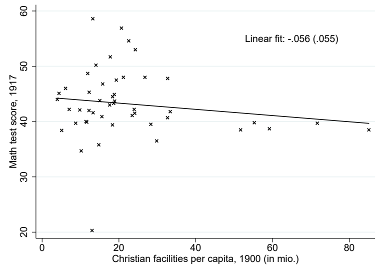
(a) Kindergarten teachers and Christianity



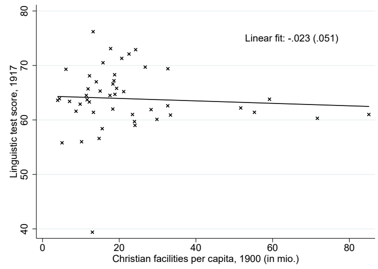
(b) Kindergarten teachers and GDP



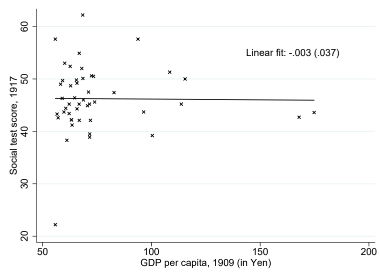
(c) Social score and Christianity



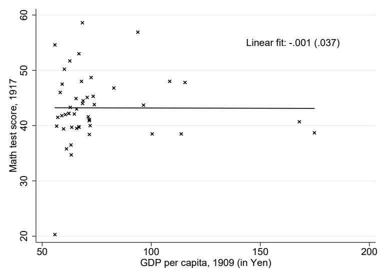
(d) Math score and Christianity



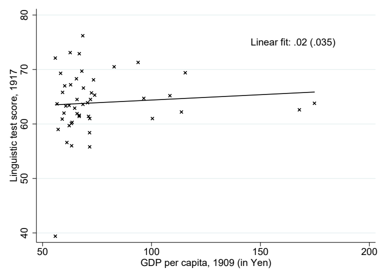
(e) Linguistic score and Christianity



(f) Social score and GDP



(g) Math score and GDP



(h) Linguistic score and GDP

Figure C3

Christian Facilities, GDP, Kindergartens, and Test Scores

Source: Authors' calculations using data from Imperial Bureau of Statistics of Japan (1898; 1903), Japan Imperial Ministry of Education (1902), Ministry of War (1917), Bassino et al. (2009), and Oda (2017). *Note*: These graphs show the relationship between outcomes described below and the number of Christian facilities per capita in a prefecture in 1900 or the GDP per capita in 1909. Figures (a) and (b) use the number of kindergarten teachers per capita on the ordinate. Figures (c) and (f) use the social test score on the ordinate, Figure (d) and (g) use the math test score on the ordinate, and Figure (e) and (h) use the linguistic test score on the ordinate. Each figure presents a linear fit, where the estimated coefficient is presented in the upper right corner with its standard error given in parentheses.

D Instrument Validity – Placebo Analyses

Table D1

Potential Relationsip between Parental Characteristics and Relative Preschool Availability

	Relative preschool availability		
	(1)	(2)	(3)
Mother age at birth	-0.002^{**}	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
= 1 if mother has college	0.007	0.003	0.009
	(0.012)	(0.009)	(0.008)
= 1 if father has college	0.023^{**}	0.003	-0.000
	(0.010)	(0.008)	(0.006)
= 1 if HH in 2nd income quartile	0.019	0.001	0.003
	(0.013)	(0.012)	(0.008)
= 1 if HH in 3rd income quartile	0.034^{**}	0.007	0.013
	(0.014)	(0.011)	(0.008)
= 1 if HH in 4th income quartile	0.027	-0.011	-0.008
	(0.019)	(0.017)	(0.011)
= 1 if grandfather has college	-0.001	-0.004	-0.002
	(0.013)	(0.011)	(0.007)
Further municipality characteristics		✓	✓
Prefecture fixed effects			✓
Cohort fixed effects			✓
Prefecture-pecific linear time trends			✓
F-stat of test of joint significance	2.791	0.988	1.920
p-value of test of joint significance	0.008	0.440	0.066
Observations	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from regressions of the relative preschool availability on household characteristics. Further municipality characteristics are described in Section 3.2. F-tests for joint significance of the presented coefficients are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

Table D2

Potential Determinants of Preschool Availability

	Relative preschool availability		
	(1)	(2)	(3)
Share of children	2.924***	1.374***	−0.392
	(0.347)	(0.508)	(0.594)
Per capita educ. expendit. in 1,000 Yen	0.004	−0.010	−0.027
	(0.015)	(0.026)	(0.024)
Per capita local taxes in 1,000 Yen	−0.024	−0.106***	−0.076*
	(0.017)	(0.034)	(0.046)
Per capita health expendit. in 1,000 Yen	0.024	−0.008	−0.013
	(0.033)	(0.029)	(0.029)
Per capita crimes	0.990***	0.449***	0.110
	(0.206)	(0.142)	(0.146)
Industrial area in ha	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)
Further municipality characteristics		✓	✓
Municipality fixed effects	✓	✓	✓
Year fixed effects			✓
Prefecture-pecific linear time trends			✓
F-stat of test of joint significance	35.636	7.539	1.094
p-value of test of joint significance	0.000	0.000	0.364
Observations	15240	12416	12416

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from panel fixed effects models of the relative preschool availability in a municipality on various municipality characteristics. Further municipality characteristics are described in Section 3.2. Because some variables are not available in all years, these regressions are based on data from 2000 to 2008, covering the birth year of around 60% of the children in our sample. F-tests for joint significance of the presented coefficients are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

Table D3
Test for Unobserved Compositional Changes

	= 1 if female		= 1 if mother has college		= 1 if father has college		= 1 if HH in 3rd or 4th income quartile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Z \times 1995$	−0.713	−0.939	0.426	0.550	0.882**	0.866*	0.703	0.576
	(0.498)	(0.575)	(0.374)	(0.480)	(0.428)	(0.517)	(0.578)	(0.612)
$Z \times 1996$	0.306	0.305	−0.349*	−0.252	−0.138	0.106	−0.149	−0.033
	(0.325)	(0.363)	(0.207)	(0.283)	(0.404)	(0.462)	(0.309)	(0.390)
$Z \times 1997$	0.324	0.239	0.140	0.249	0.052	0.284	0.152	0.123
	(0.317)	(0.335)	(0.194)	(0.248)	(0.352)	(0.374)	(0.385)	(0.428)
$Z \times 1998$	0.019	−0.063	−0.233	−0.122	−0.962***	−0.844**	−0.375	−0.267
	(0.305)	(0.341)	(0.232)	(0.259)	(0.271)	(0.327)	(0.277)	(0.307)
$Z \times 1999$	−0.039	−0.142	0.046	0.074	−0.209	−0.087	−0.505*	−0.404
	(0.302)	(0.330)	(0.179)	(0.232)	(0.296)	(0.324)	(0.299)	(0.359)
$Z \times 2000$	0.074	0.033	−0.471*	−0.213	−0.158	0.023	0.182	0.421
	(0.304)	(0.317)	(0.242)	(0.268)	(0.305)	(0.351)	(0.330)	(0.366)
$Z \times 2001$	−0.266	−0.362	0.240	0.296	−0.163	−0.166	−0.267	−0.197
	(0.297)	(0.304)	(0.213)	(0.253)	(0.293)	(0.327)	(0.296)	(0.331)
$Z \times 2002$	−0.238	−0.323	0.043	0.102	0.463	0.396	0.022	0.154
	(0.268)	(0.290)	(0.258)	(0.272)	(0.285)	(0.336)	(0.292)	(0.347)
$Z \times 2003$	0.096	−0.050	−0.185	−0.059	−0.208	−0.219	0.198	0.349
	(0.262)	(0.295)	(0.139)	(0.186)	(0.240)	(0.275)	(0.252)	(0.294)
$Z \times 2004$	0.070	−0.207	0.124	0.266	0.230	0.086	−0.019	0.068
	(0.289)	(0.335)	(0.172)	(0.220)	(0.239)	(0.279)	(0.282)	(0.335)
$Z \times 2005$	−0.151	−0.316	−0.602**	−0.559*	−0.287	−0.440	0.562	0.689*
	(0.363)	(0.408)	(0.270)	(0.295)	(0.343)	(0.369)	(0.342)	(0.378)
$Z \times 2006$	−0.019	−0.207	0.460*	0.522	0.334	0.059	0.053	0.030
	(0.379)	(0.396)	(0.238)	(0.318)	(0.312)	(0.381)	(0.361)	(0.394)
$Z \times 2007$	−0.219	−0.194	0.279	0.425	0.781***	0.539*	0.163	0.276
	(0.361)	(0.390)	(0.214)	(0.286)	(0.253)	(0.323)	(0.315)	(0.395)
$Z \times 2008$	0.304	0.174	0.901**	1.023**	0.646	0.252	0.138	0.146
	(0.493)	(0.478)	(0.368)	(0.442)	(0.464)	(0.520)	(0.498)	(0.583)
$Z \times 2009$	0.080	−0.015	0.743**	0.707	0.325	0.228	0.014	0.435
	(0.446)	(0.516)	(0.317)	(0.449)	(0.417)	(0.526)	(0.442)	(0.544)
$Z \times 2010$	0.914	1.229*	0.367	1.179	−0.432	0.057	0.204	0.309
	(0.589)	(0.708)	(0.549)	(0.848)	(0.634)	(0.695)	(0.626)	(0.714)
$Z \times 2011$	−0.151	−0.273	0.301	0.483	0.804	0.798	−0.281	0.266
	(0.507)	(0.586)	(0.540)	(0.503)	(0.567)	(0.489)	(0.477)	(0.609)
Further municipality characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effects		✓		✓		✓		✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture-specific linear time trends		✓		✓		✓		✓
χ^2-stat of test of joint significance	0.596	0.784	2.207	1.692	2.282	1.440	0.774	0.716
p-value of test of joint significance	0.895	0.712	0.004	0.043	0.003	0.115	0.724	0.787
Observations	1680	1680	1680	1680	1680	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note:* This table presents results from linear probability models of individual and parental characteristics on the instrument interacted with birth cohorts. Further municipality characteristics are described in Section 3.2. χ^2-tests for joint significance of the presented coefficients are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

E Instrument Monotonicity

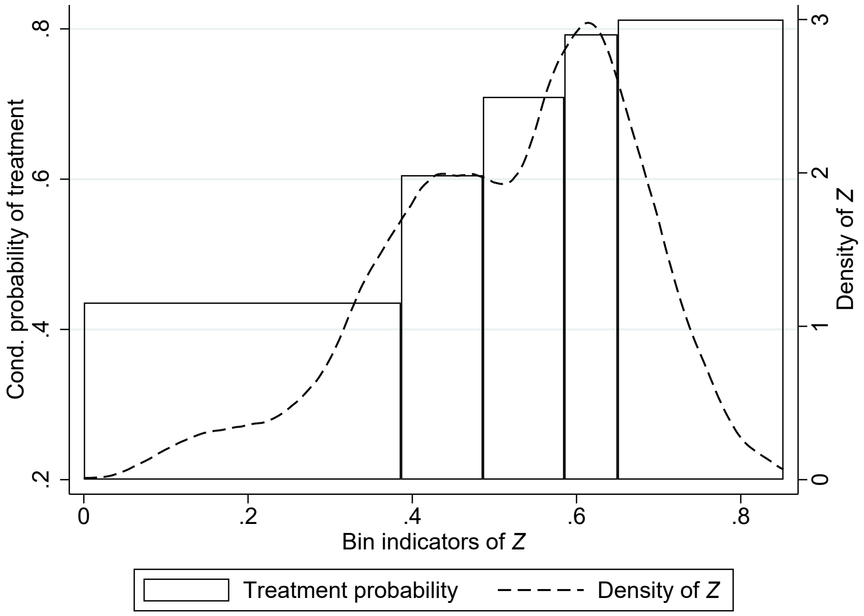


Figure E4
Probability of Enrollment in an Education-Oriented Preschool

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This graph shows the predicted probability of education-oriented preschool enrollment conditional on controlling for a set of control variables described in Section 3.2 for different partitions of the relative preschool availability. Partitions are based on the 20th, 40th, 60th, and 80th percentile. It also provides a kernel density estimate of the distribution of the relative preschool availability.

Table E4

First-Stage Estimates for Subsamples

	Educational vs. care orientation							
	Male (1)	Female (2)	1st quarter (3)	2nd–4th quarter (4)	Low income (5)	High income (6)	No college (7)	Some college (8)
Relative preschool enrollment	0.464**	0.915***	0.634**	0.635***	0.848***	0.677***	0.610***	0.810***
	(0.203)	(0.219)	(0.321)	(0.174)	(0.240)	(0.196)	(0.204)	(0.272)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture-pecific linear time trends	✓	✓	✓	✓	✓	✓	✓	✓
Observations	885	795	391	1289	867	813	915	755

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table shows results from first-stage regressions of enrollment in an education-oriented against a care-oriented preschool on the relative preschool availability and a set of control variables described in Section 3.2. Column (1) runs this regression only for males, Column (2) only for females, Column (3) only for children born in the first quarter, Column (4) only for children born in the second to fourth quarter, Column (5) only for children from low-income households, Column (6) only for children from high-income households, Column (7) only for children from parents without a college degree, and Column (8) only for children from parents with at least one college degree. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

F Full Estimation Results – First-Stage

Table F5

First-Stage Probit Regression – Full Estimation Results

	Educational vs. care orientation		
	(1)	(2)	(3)
Relative preschool enrollment	0.923***	0.842***	0.632***
	(0.088)	(0.108)	(0.138)
= 1 if female		−0.030	−0.028
		(0.020)	(0.019)
= 1 if born in first quarter		−0.008	−0.017
		(0.027)	(0.026)
# siblings		0.049**	0.048***
		(0.020)	(0.018)
Mother age at birth		−0.000	0.000
		(0.003)	(0.003)
= 1 if mother has college		−0.009	0.020
		(0.036)	(0.034)
= 1 if father has college		0.119***	0.103***
		(0.032)	(0.030)
= 1 if HH in 2nd income quartile		0.103***	0.092**
		(0.038)	(0.037)
= 1 if HH in 3rd income quartile		0.121***	0.105***
		(0.042)	(0.040)
= 1 if HH in 4th income quartile		0.008	−0.012
		(0.049)	(0.046)
= 1 if grandfather has college		0.023	0.021
		(0.035)	(0.034)
# children per kindergarten		−0.000	−0.000
		(0.000)	(0.000)
# children per nursery school		−0.000	−0.001
		(0.001)	(0.001)
Inhabitants per ha		0.000	0.000
		(0.000)	(0.000)
Female empl. rate		−5.338	−4.283
		(3.824)	(5.207)
Unemployment rate		−4.700	−8.417*
		(3.179)	(4.387)
Per capita income in 1,000 Yen		−0.000	−0.000
		(0.000)	(0.000)
Prefecture fixed effects			✓
Cohort fixed effects			✓
Prefecture-pecific linear time trends			✓
χ^2-stat	83.696	52.605	20.107
p-value	0.000	0.000	0.000
Observations	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents average partial effects from first-stage Probit regressions of enrollment in an education-oriented against a care-oriented preschool on the relative preschool availability and a set of control variables described in Section 3.2. χ^2-tests of significance of the coefficient on the instrument are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

G Full Estimation Results – OLS and 2SLS

Table G6

OLS and 2SLS Regressions – Full Estimation Results

	Math		Japanese		SDQ		QOL	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
Educational vs. care orientation	0.187***	0.324	0.193***	0.871**	0.102	0.608	−0.005	0.747
	(0.055)	(0.344)	(0.056)	(0.386)	(0.067)	(0.404)	(0.065)	(0.514)
= 1 if female	−0.066	−0.062	0.126***	0.146***	0.261***	0.273***	0.043	0.060
	(0.045)	(0.044)	(0.042)	(0.045)	(0.050)	(0.049)	(0.055)	(0.055)
= 1 if born in first quarter	−0.142**	−0.140**	−0.122**	−0.112**	−0.080	−0.067	−0.086	−0.052
	(0.059)	(0.058)	(0.051)	(0.053)	(0.058)	(0.058)	(0.065)	(0.070)
# siblings	−0.124***	−0.131***	−0.157***	−0.190***	0.047	0.024	−0.082**	−0.117**
	(0.035)	(0.036)	(0.034)	(0.038)	(0.045)	(0.044)	(0.036)	(0.048)
Mother age at birth	0.018***	0.018***	0.021***	0.021***	0.016**	0.018***	−0.001	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
= 1 if mother has college	0.246***	0.242***	0.240***	0.217***	0.068	0.045	−0.011	−0.059
	(0.062)	(0.062)	(0.071)	(0.074)	(0.080)	(0.081)	(0.077)	(0.087)
= 1 if father has college	0.250***	0.236***	0.213***	0.147**	0.046	0.001	0.074	0.006
	(0.054)	(0.063)	(0.060)	(0.073)	(0.072)	(0.076)	(0.063)	(0.083)
= 1 if HH in 2nd income quartile	0.175**	0.162**	0.080	0.014	0.236***	0.188**	0.033	−0.014
	(0.071)	(0.075)	(0.077)	(0.091)	(0.085)	(0.091)	(0.079)	(0.083)
= 1 if HH in 3rd income quartile	0.180**	0.163*	0.018	−0.064	0.160*	0.099	0.080	−0.005
	(0.080)	(0.087)	(0.081)	(0.095)	(0.092)	(0.101)	(0.081)	(0.098)
= 1 if HH in 4th income quartile	0.400***	0.402***	0.250***	0.257***	0.373***	0.380***	0.228**	0.250**
	(0.085)	(0.083)	(0.096)	(0.099)	(0.108)	(0.108)	(0.095)	(0.105)
= 1 if grandfather has college	0.014	0.011	0.037	0.023	−0.076	−0.087	0.020	0.000
	(0.059)	(0.058)	(0.067)	(0.070)	(0.068)	(0.070)	(0.088)	(0.091)
# children per kindergarten	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children per nursery school	0.001	0.001	0.002	0.003	0.006***	0.007***	−0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Inhabitants per ha	0.000	−0.000	0.001	0.001	−0.001	−0.001	−0.002	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female empl. rate	1.208	2.200	−2.770	2.164	13.438	18.926	−19.079**	−12.105
	(9.572)	(9.241)	(10.438)	(11.345)	(10.882)	(11.801)	(9.577)	(10.487)
Unemployment rate	1.223	2.687	−0.603	6.687	10.727	17.234	−12.232	−3.648
	(7.836)	(7.962)	(8.259)	(9.642)	(9.035)	(10.532)	(7.839)	(10.193)
Per capita income in 1,000 Yen	−0.000	−0.000	−0.000	−0.000	0.000	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−1.995	−3.060	1.961	−3.335	−15.288	−21.336*	18.720*	11.245
	(9.553)	(9.255)	(10.425)	(11.381)	(10.931)	(12.003)	(9.577)	(10.709)
Prefecture fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture-specific linear time trends	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1680	1680	1680	1680	1514	1514	1341	1341

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from OLS and 2SLS regressions of the cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

H Robustness Check – 2SLS

Table H7

2SLS Estimates with and without Ability Proxies

	Math		Japanese		SDQ		QOL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Educational vs. care orientation	0.325	0.324	0.797**	0.871**	0.560	0.608	0.699	0.747
	(0.338)	(0.344)	(0.379)	(0.386)	(0.401)	(0.404)	(0.490)	(0.514)
= 1 if female	−0.065	−0.062	0.143***	0.146***	0.267***	0.273***	0.062	0.060
	(0.046)	(0.044)	(0.047)	(0.045)	(0.050)	(0.049)	(0.055)	(0.055)
= 1 if born in first quarter	−0.135**	−0.140**	−0.103**	−0.112**	−0.066	−0.067	−0.057	−0.052
	(0.060)	(0.058)	(0.052)	(0.053)	(0.059)	(0.058)	(0.071)	(0.070)
# siblings	−0.146***	−0.131***	−0.196***	−0.190***	0.020	0.024	−0.117**	−0.117**
	(0.038)	(0.036)	(0.038)	(0.038)	(0.044)	(0.044)	(0.046)	(0.048)
Mother age at birth	0.028***	0.018***	0.028***	0.021***	0.021***	0.018***	0.004	0.000
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
= 1 if mother has college		0.242***		0.217***		0.045		−0.059
		(0.062)		(0.074)		(0.081)		(0.087)
= 1 if father has college		0.236***		0.147**		0.001		0.006
		(0.063)		(0.073)		(0.076)		(0.083)
= 1 if HH in 2nd income quartile		0.162**		0.014		0.188**		−0.014
		(0.075)		(0.091)		(0.091)		(0.083)
= 1 if HH in 3rd income quartile		0.163*		−0.064		0.099		−0.005
		(0.087)		(0.095)		(0.101)		(0.098)
= 1 if HH in 4th income quartile		0.402***		0.257***		0.380***		0.250**
		(0.083)		(0.099)		(0.108)		(0.105)
= 1 if grandfather has college		0.011		0.023		−0.087		0.000
		(0.058)		(0.070)		(0.070)		(0.091)
# children per kindergarten	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children per nursery school	0.001	0.001	0.003	0.003	0.007***	0.007***	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Inhabitants per ha	0.000	−0.000	0.001	0.001	−0.001	−0.001	−0.002*	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female empl. rate	−0.868	2.200	−0.676	2.164	16.659	18.926	−13.849	−12.105
	(9.184)	(9.241)	(11.510)	(11.345)	(12.338)	(11.801)	(10.341)	(10.487)
Unemployment rate	−2.231	2.687	2.575	6.687	13.665	17.234	−6.302	−3.648
	(7.856)	(7.962)	(9.848)	(9.642)	(10.810)	(10.532)	(9.955)	(10.193)
Per capita income in 1,000 Yen	−0.000	−0.000	−0.000	−0.000	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.070	−3.060	−0.508	−3.335	−18.855	−21.336*	13.001	11.245
	(9.211)	(9.255)	(11.569)	(11.381)	(12.547)	(12.003)	(10.559)	(10.709)
Prefecture fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture-specific linear time trends	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1680	1680	1680	1680	1514	1514	1341	1341

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Columns (1), (3), (5), and (7) exclude household characteristics that are most likely to capture ability of the children. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

Table H8

2SLS Estimates for the Math Score

	Main specification			Stricter treatment definition			Facilities as instrument		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Educational vs. care orientation	0.241	0.328	0.324	0.205	0.279	0.297	0.178	0.308	0.411
	(0.176)	(0.216)	(0.344)	(0.175)	(0.211)	(0.330)	(0.216)	(0.222)	(0.403)
= 1 if female		−0.065	−0.062		−0.094**	−0.095**		−0.066	−0.060
		(0.044)	(0.044)		(0.045)	(0.046)		(0.044)	(0.044)
= 1 if born in first quarter		−0.146***	−0.140**		−0.152***	−0.145**		−0.147***	−0.138**
		(0.056)	(0.058)		(0.057)	(0.058)		(0.056)	(0.058)
# siblings		−0.123***	−0.131***		−0.128***	−0.136***		−0.122***	−0.135***
		(0.036)	(0.036)		(0.037)	(0.036)		(0.035)	(0.037)
Mother age at birth		0.017***	0.018***		0.015**	0.014**		0.017***	0.019***
		(0.006)	(0.006)		(0.006)	(0.006)		(0.006)	(0.006)
= 1 if mother has college		0.241***	0.242***		0.234***	0.230***		0.241***	0.239***
		(0.056)	(0.062)		(0.057)	(0.062)		(0.056)	(0.063)
= 1 if father has college		0.219***	0.236***		0.236***	0.250***		0.221***	0.228***
		(0.059)	(0.063)		(0.059)	(0.061)		(0.059)	(0.067)
= 1 if HH in 2nd income quartile		0.156**	0.162**		0.141*	0.170**		0.159**	0.153*
		(0.076)	(0.075)		(0.079)	(0.079)		(0.077)	(0.079)
= 1 if HH in 3rd income quartile		0.150*	0.163*		0.126	0.155*		0.153*	0.152*
		(0.082)	(0.087)		(0.084)	(0.091)		(0.084)	(0.091)
= 1 if HH in 4th income quartile		0.388***	0.402***		0.348***	0.383***		0.388***	0.403***
		(0.085)	(0.083)		(0.086)	(0.083)		(0.085)	(0.083)
= 1 if grandfather has college		0.016	0.011		0.014	−0.003		0.016	0.009
		(0.053)	(0.058)		(0.054)	(0.059)		(0.053)	(0.058)
# children per kindergarten		0.000	0.000		−0.000	−0.000		0.000	−0.000
		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)	(0.001)
# children per nursery school		0.000	0.001		0.001	0.002		0.000	0.001
		(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.002)
Inhabitants per ha		−0.000	−0.000		−0.000	−0.000		−0.000	−0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Female empl. rate		−1.808	2.200		−3.972	−1.057		−2.072	2.833
		(6.341)	(9.241)		(6.767)	(9.444)		(6.345)	(9.359)
Unemployment rate		−4.424	2.687		−5.981	−0.162		−4.611	3.624
		(5.152)	(7.962)		(5.386)	(8.100)		(5.159)	(8.177)
Per capita income in 1,000 Yen		−0.000**	−0.000		−0.000**	−0.000		−0.000**	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Constant	−0.187	1.596	−3.060	−0.156	3.868	0.353	−0.145	1.864	−3.740
	(0.120)	(6.366)	(9.255)	(0.120)	(6.781)	(9.461)	(0.144)	(6.368)	(9.389)
Prefecture fixed effects			✓			✓			✓
Cohort fixed effects			✓			✓			✓
Prefecture-specific linear time trends			✓			✓			✓
Observations	1680	1680	1680	1573	1573	1573	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the math score on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Columns (1) to (3) correspond to our main specification. Columns (4) to (6) use a stricter treatment definition to assign children as having attended a kindergarten or a nursery school (i.e., children who attended both preschools for a short period of time are excluded). Columns (7) to (9) use the relative availability of preschool facilities as instrument in the first stage. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

Table H9

2SLS Estimates for the Japanese Score

	Main specification			Stricter treatment definition			Facilities as instrument		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Educational vs. care orientation	0.161	0.328	0.871**	0.100	0.264	0.801**	0.223	0.298	0.966**
	(0.183)	(0.233)	(0.386)	(0.177)	(0.228)	(0.371)	(0.225)	(0.242)	(0.454)
= 1 if female		0.127***	0.146***		0.105**	0.124***		0.126***	0.148***
		(0.041)	(0.045)		(0.042)	(0.045)		(0.041)	(0.047)
= 1 if born in first quarter		−0.153***	−0.112**		−0.147***	−0.115**		−0.153***	−0.110**
		(0.050)	(0.053)		(0.053)	(0.055)		(0.050)	(0.054)
# siblings		−0.169***	−0.190***		−0.171***	−0.197***		−0.168***	−0.194***
		(0.037)	(0.038)		(0.039)	(0.039)		(0.037)	(0.041)
Mother age at birth		0.020***	0.021***		0.020***	0.021***		0.020***	0.021***
		(0.005)	(0.006)		(0.006)	(0.006)		(0.005)	(0.006)
= 1 if mother has college		0.217***	0.217***		0.239***	0.243***		0.217***	0.214***
		(0.066)	(0.074)		(0.067)	(0.076)		(0.066)	(0.076)
= 1 if father has college		0.177***	0.147**		0.189***	0.173**		0.181***	0.137*
		(0.061)	(0.073)		(0.060)	(0.072)		(0.061)	(0.077)
= 1 if HH in 2nd income quartile		0.049	0.014		0.040	0.016		0.053	0.004
		(0.081)	(0.091)		(0.084)	(0.093)		(0.082)	(0.095)
= 1 if HH in 3rd income quartile		−0.019	−0.064		−0.014	−0.064		−0.015	−0.076
		(0.085)	(0.095)		(0.090)	(0.098)		(0.087)	(0.100)
= 1 if HH in 4th income quartile		0.254***	0.257***		0.222**	0.219**		0.254***	0.258**
		(0.091)	(0.099)		(0.093)	(0.098)		(0.091)	(0.101)
= 1 if grandfather has college		0.010	0.023		0.013	0.019		0.011	0.021
		(0.063)	(0.070)		(0.065)	(0.074)		(0.063)	(0.072)
# children per kindergarten		−0.001	−0.000		−0.001	−0.001		−0.001	−0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
# children per nursery school		0.002	0.003		0.002	0.003		0.001	0.003
		(0.001)	(0.002)		(0.002)	(0.002)		(0.001)	(0.002)
Inhabitants per ha		0.001	0.001		0.001	0.001		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Female empl. rate		−5.775	2.164		−6.210	1.683		−6.177	2.854
		(7.831)	(11.345)		(8.146)	(11.773)		(7.794)	(11.806)
Unemployment rate		−7.148	6.687		−7.744	4.761		−7.432	7.705
		(6.190)	(9.642)		(6.454)	(9.761)		(6.165)	(10.340)
Per capita income in 1,000 Yen		−0.000**	−0.000		−0.000**	−0.000		−0.000**	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Constant	−0.146	5.585	−3.335	−0.102	6.108	−2.532	−0.188	5.994	−4.076
	(0.128)	(7.850)	(11.381)	(0.124)	(8.162)	(11.802)	(0.154)	(7.811)	(11.870)
Prefecture fixed effects			✓			✓			✓
Cohort fixed effects			✓			✓			✓
Prefecture-specific linear time trends			✓			✓			✓
Observations	1680	1680	1680	1573	1573	1573	1680	1680	1680

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the Japanese score on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Columns (1) to (3) correspond to our main specification. Columns (4) to (6) use a stricter treatment definition to assign children as having attended an education-oriented or a care-oriented preschool (i.e., children who attended both preschools for a short period of time are excluded). Columns (7) to (9) use the relative availability of preschool facilities as instrument in the first stage. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

Table H10
2SLS Estimates for the SDQ Score

	Main specification			Stricter treatment definition			Facilities as instrument		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Educational vs. care orientation	0.235	0.433*	0.608	0.272	0.457*	0.603	0.562**	0.481*	0.779
	(0.200)	(0.255)	(0.404)	(0.195)	(0.249)	(0.379)	(0.240)	(0.271)	(0.489)
= 1 if female		0.246***	0.273***		0.220***	0.234***		0.247***	0.277***
		(0.048)	(0.049)		(0.048)	(0.050)		(0.048)	(0.050)
= 1 if born in first quarter		−0.079	−0.067		−0.114*	−0.108*		−0.078	−0.062
		(0.057)	(0.058)		(0.059)	(0.059)		(0.057)	(0.060)
# siblings		0.018	0.024		−0.006	−0.002		0.015	0.016
		(0.042)	(0.044)		(0.042)	(0.045)		(0.043)	(0.047)
Mother age at birth		0.017***	0.018***		0.017***	0.017***		0.017***	0.018***
		(0.006)	(0.006)		(0.006)	(0.007)		(0.006)	(0.007)
= 1 if mother has college		0.044	0.045		0.070	0.072		0.044	0.038
		(0.076)	(0.081)		(0.074)	(0.080)		(0.076)	(0.084)
= 1 if father has college		0.013	0.001		0.002	−0.011		0.008	−0.015
		(0.072)	(0.076)		(0.071)	(0.077)		(0.073)	(0.081)
= 1 if HH in 2nd income quartile		0.120	0.188**		0.101	0.163*		0.115	0.172*
		(0.083)	(0.091)		(0.087)	(0.097)		(0.083)	(0.095)
= 1 if HH in 3rd income quartile		0.062	0.099		0.068	0.089		0.056	0.078
		(0.089)	(0.101)		(0.095)	(0.107)		(0.090)	(0.106)
= 1 if HH in 4th income quartile		0.282***	0.380***		0.267***	0.344***		0.283***	0.383***
		(0.099)	(0.108)		(0.099)	(0.109)		(0.100)	(0.112)
= 1 if grandfather has college		−0.061	−0.087		−0.058	−0.100		−0.062	−0.091
		(0.070)	(0.070)		(0.072)	(0.075)		(0.070)	(0.073)
# children per kindergarten		−0.001*	−0.000		−0.001*	−0.000		−0.001*	−0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
# children per nursery school		0.005***	0.007***		0.005***	0.008***		0.005***	0.008***
		(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.002)
Inhabitants per ha		−0.001	−0.001		−0.001	−0.001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Female empl. rate		4.346	18.926		4.137	20.733		5.116	20.778*
		(8.318)	(11.801)		(8.634)	(12.611)		(8.458)	(12.546)
Unemployment rate		0.830	17.234		−1.445	17.515		1.367	19.428*
		(6.671)	(10.532)		(6.681)	(10.790)		(6.762)	(11.453)
Per capita income in 1,000 Yen		0.000	0.000		0.000	0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Constant	−0.203	−5.631	−21.336*	−0.216*	−5.221	−22.971*	−0.424***	−6.415	−23.352*
	(0.134)	(8.398)	(12.003)	(0.131)	(8.678)	(12.797)	(0.164)	(8.542)	(12.826)
Prefecture fixed effects			✓			✓			✓
Cohort fixed effects			✓			✓			✓
Prefecture-specific linear time trends			✓			✓			✓
Observations	1514	1514	1514	1414	1414	1414	1514	1514	1514

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the SDQ score on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Columns (1) to (3) correspond to our main specification. Columns (4) to (6) use a stricter treatment definition to assign children as having attended an education-oriented or a care-oriented preschool (i.e., children who attended both preschools for a short period of time are excluded). Columns (7) to (9) use the relative availability of preschool facilities as instrument in the first stage. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

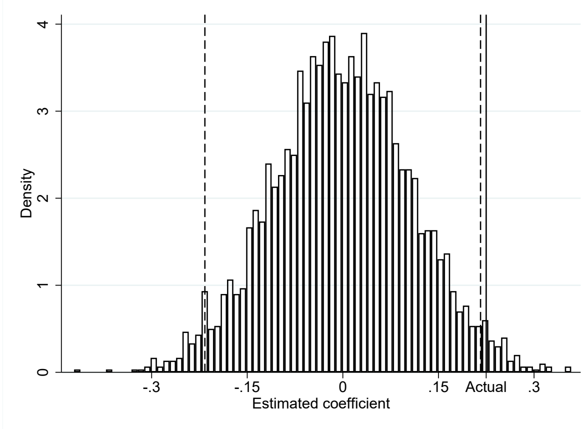
Table H11

2SLS Estimates for the QOL Score

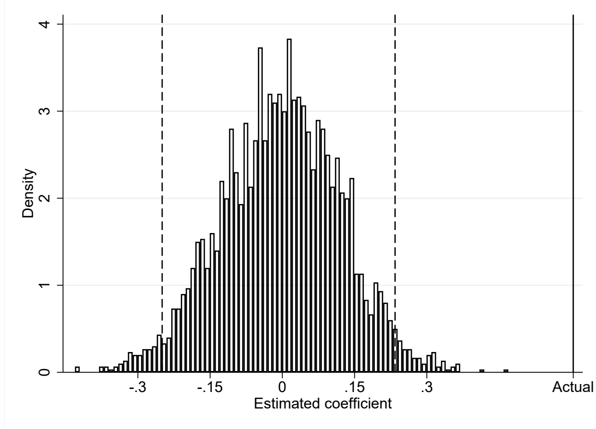
	Main specification			Stricter treatment definition			Facilities as instrument		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Educational vs. care orientation	0.308	0.505*	0.747	0.298	0.397	0.738	0.432*	0.494*	0.790
	(0.204)	(0.276)	(0.514)	(0.192)	(0.255)	(0.468)	(0.255)	(0.297)	(0.613)
= 1 if female		0.038	0.060		0.012	0.040		0.037	0.061
		(0.053)	(0.055)		(0.054)	(0.056)		(0.053)	(0.056)
= 1 if born in first quarter		−0.094	−0.052		−0.098	−0.049		−0.095	−0.050
		(0.066)	(0.070)		(0.066)	(0.070)		(0.066)	(0.072)
# siblings		−0.122***	−0.117**		−0.124***	−0.122**		−0.121***	−0.119**
		(0.040)	(0.048)		(0.040)	(0.048)		(0.040)	(0.051)
Mother age at birth		0.004	0.000		0.003	−0.001		0.004	0.000
		(0.006)	(0.006)		(0.006)	(0.007)		(0.006)	(0.006)
= 1 if mother has college		0.005	−0.059		0.028	−0.052		0.006	−0.062
		(0.074)	(0.087)		(0.078)	(0.088)		(0.074)	(0.091)
= 1 if father has college		0.011	0.006		0.009	0.000		0.012	0.002
		(0.071)	(0.083)		(0.071)	(0.082)		(0.072)	(0.088)
= 1 if HH in 2nd income quartile		0.018	−0.014		0.015	−0.013		0.019	−0.017
		(0.083)	(0.083)		(0.085)	(0.085)		(0.082)	(0.086)
= 1 if HH in 3rd income quartile		−0.004	−0.005		0.010	0.008		−0.002	−0.010
		(0.094)	(0.098)		(0.097)	(0.098)		(0.095)	(0.107)
= 1 if HH in 4th income quartile		0.211**	0.250**		0.215**	0.273***		0.211**	0.252**
		(0.098)	(0.105)		(0.098)	(0.105)		(0.098)	(0.106)
= 1 if grandfather has college		−0.026	0.000		−0.034	−0.022		−0.025	−0.001
		(0.085)	(0.091)		(0.088)	(0.095)		(0.086)	(0.092)
# children per kindergarten		−0.000	−0.001		−0.000	−0.001		−0.000	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
# children per nursery school		0.002	0.001		0.002	0.002		0.002	0.001
		(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.002)
Inhabitants per ha		−0.000	−0.002*		−0.000	−0.002*		−0.000	−0.002*
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Female empl. rate		0.926	−12.105		−0.306	−11.534		0.765	−11.703
		(7.581)	(10.487)		(7.830)	(10.929)		(7.645)	(10.961)
Unemployment rate		1.858	−3.648		1.382	−1.682		1.752	−3.154
		(6.329)	(10.193)		(6.486)	(10.230)		(6.352)	(10.917)
Per capita income in 1,000 Yen		−0.000	−0.000		−0.000	0.000		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Constant	−0.237	−1.198	11.245	−0.232*	0.024	10.497	−0.322*	−1.035	10.801
	(0.145)	(7.632)	(10.709)	(0.139)	(7.872)	(11.123)	(0.180)	(7.704)	(11.272)
Prefecture fixed effects			✓			✓			✓
Cohort fixed effects			✓			✓			✓
Prefecture-specific linear time trends			✓			✓			✓
Observations	1341	1341	1341	1256	1256	1256	1341	1341	1341

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the QOL score on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Columns (1) to (3) correspond to our main specification. Columns (4) to (6) use a stricter treatment definition to assign children as having attended an education-oriented or a care-oriented preschool (i.e., children who attended both preschools for a short period of time are excluded). Columns (7) to (9) use the relative availability of preschool facilities as instrument in the first stage. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

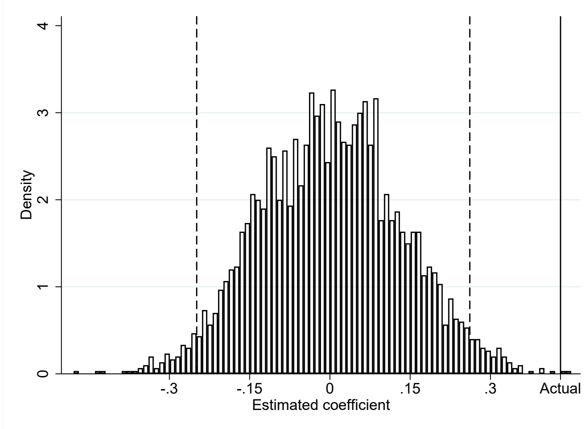
I Permutation Test of Inference – Reduced-Form Estimates



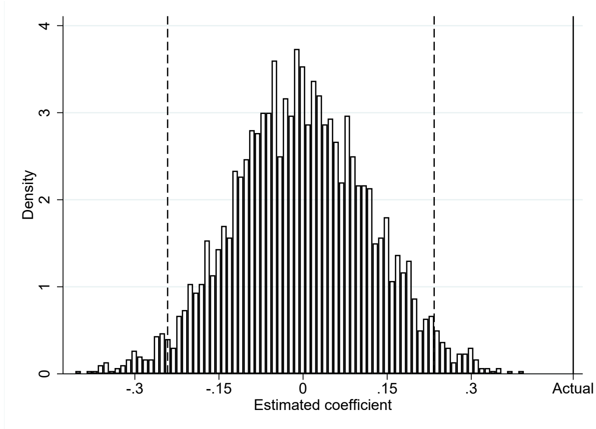
(a) Math



(b) Japanese



(c) SDQ



(d) QOL

Figure I5
Placebo Distributions of Reduced-Form Estimates

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: These graphs show the distributions of placebo reduced-form regressions and the actual reduced-form estimates as solid vertical line. First, birth years are randomly assigned to children. Second, municipalities are randomly assigned to children living in the same municipality (without replacement). Given this random assignment, we run the reduced form of the outcome variables on the relative preschool availability and a set of control variables described in Section 3.2. This procedure is repeated 3000 times. This approach is based on Bertrand et al. (2004). Dashed lines indicate 95% confidence intervals.

J Effect on the Subscales of the SDQ and QOL scores

Table J12
Effect on Subscales of the SDQ Score (2SLS)

	Socioemotional outcomes – SDQ				
	Conduct problems (1)	Emotional symptoms (2)	Hyperactivity (3)	Peer relationships (4)	Prosociality (5)
Educational vs. care orientation	0.158	0.425	−0.003	1.084**	−0.114
	(0.388)	(0.369)	(0.375)	(0.440)	(0.478)
Control variables	✓	✓	✓	✓	✓
Prefecture fixed effects	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓
Prefecture-pecific linear time trends	✓	✓	✓	✓	✓
Observations	1514	1514	1514	1514	1514

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the subscales of the SDQ score and prosociality on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. All subscales are rescaled such that higher values imply a better socioemotional development. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

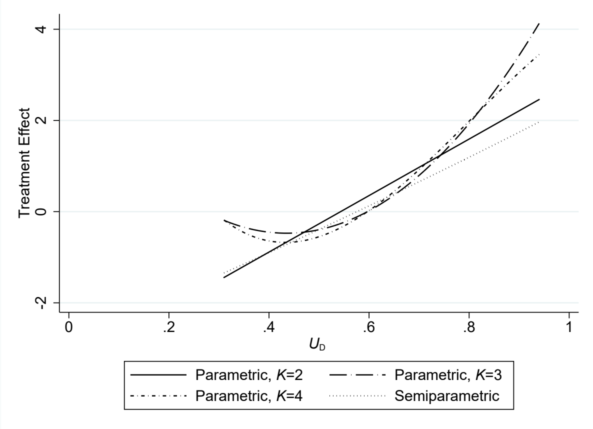
Table J13

Effect on Subscales of the QOL Score (2SLS)

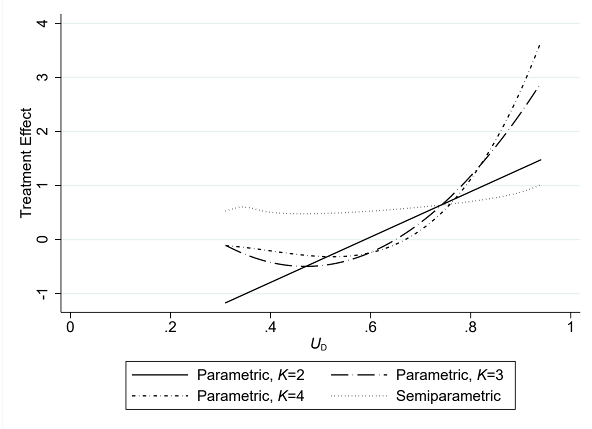
	Socioemotional outcomes – QOL					
	Physical health (1)	Emotional well-being (2)	Self-esteem (3)	Family (4)	Friends (5)	School (6)
Educational vs. care orientation	−0.324	−0.157	0.371	0.231	0.417	0.205
	(0.380)	(0.425)	(0.399)	(0.384)	(0.353)	(0.391)
Control variables	✓	✓	✓	✓	✓	✓
Prefecture fixed effects	✓	✓	✓	✓	✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓
Prefecture-pecific linear time trends	✓	✓	✓	✓	✓	✓
Observations	1289	1289	1289	1289	1289	1289

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents results from 2SLS regressions of the subscales of the QOL score on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

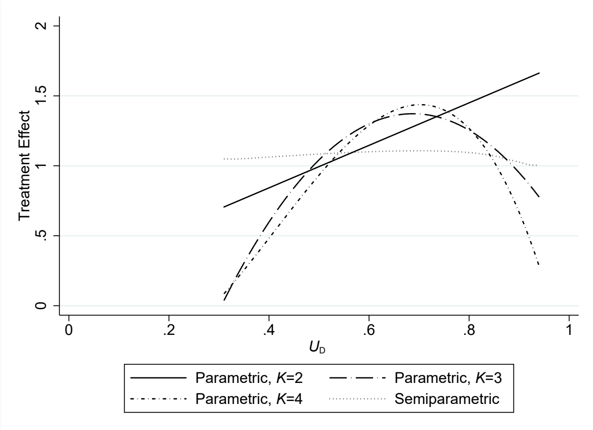
K Robustness Check – MTE



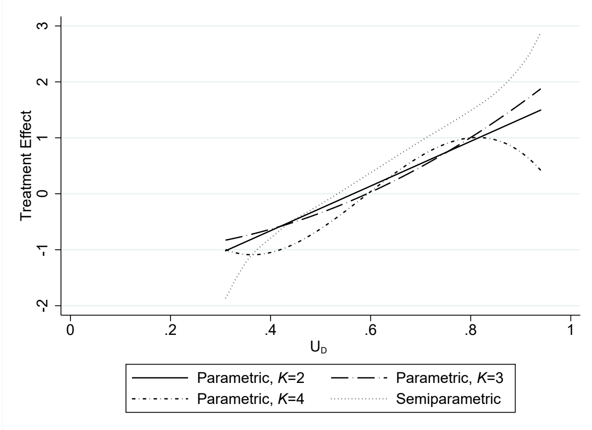
(a) Math



(b) Japanese



(c) SDQ



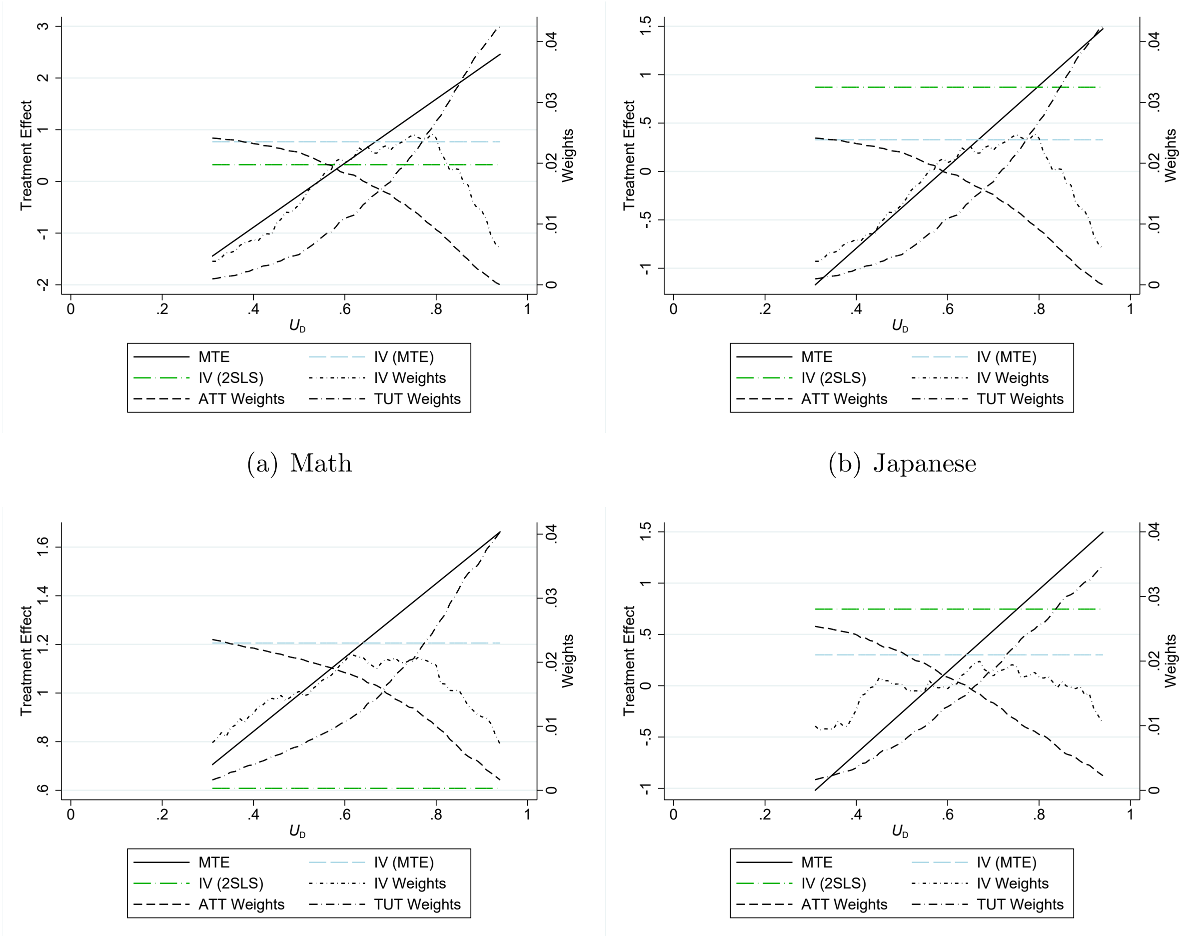
(d) QOL

Figure K6

MTE Curves for Different Functional Form Assumptions

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: These graphs show MTE curves from parametric MTE specifications with $K = 2$, $K = 3$, and $K = 4$, as well as from a semiparametric MTE specification. Covariates are held constant at their means.

L MTE Weights



(a) Math (b) Japanese

(c) SDQ (d) QOL

Figure L7
MTE Weights

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: These graphs show the weights put on the propensity score to calculate the 2SLS results in Table 3 and the ATT and ATU in Table 4, together with 2SLS estimates as horizontal lines. MTE curves from a parametric MTE specification with $K = 2$ are also added.

More formally, the parameters are defined as

$$\begin{aligned}
\text{ATT}(x) &= \text{E}(Y \mid X = x, D = 1) \\
&= \int_0^1 \text{MTE}(x, u_D)\omega_{ATT}(x, u_D)du_D, \\
\text{ATE}(x) &= \text{E}(Y \mid X = x) \\
&= \int_0^1 \text{MTE}(x, u_D)\omega_{ATE}(x, u_D)du_D, \\
\text{TUT}(x) &= \text{E}(Y \mid X = x, D = 0)
\end{aligned}$$

$$= \int_0^1 \mathrm{MTE}(x, u_D)\omega_{TUT}(x, u_D) du_D,$$

with the weights taken from Heckman et al. (2006) and Carneiro et al. (2011) as

$$\omega_{ATT}(x, u_D) = \left[\int_{u_D}^1 f(p \mid X = x) dp\right] \frac{1}{\mathrm{E}(P \mid X = x)},$$

$$\omega_{ATE}(x, u_D) = 1,$$

$$\omega_{TUT}(x, u_D) = \left[\int_0^{u_D} f(p \mid X = x) dp\right] \frac{1}{\mathrm{E}((1 - P) \mid X = x)}.$$

M Effect of Preschool Types Over Time – Estimation Results

Table M14

Effect of Preschool Types Over Time

	Math			Japanese			SDQ			QOL		
	LES	HES	LSS	LES	HES	LSS	LES	HES	LSS	LES	HES	LSS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Educational vs. care orientation	−0.17	0.23	1.11**	−0.25	0.97	1.06**	0.42	1.09*	0.90		1.17*	0.66
	(0.42)	(0.58)	(0.53)	(0.51)	(0.64)	(0.44)	(0.48)	(0.56)	(0.61)		(0.63)	(0.60)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Prefecture fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Cohort fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Prefecture-specific linear time trends	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
F-stat	15.14	11.43	14.18	15.14	11.43	14.18	10.47	11.51	9.65		9.86	8.93
Observations	846	943	913	846	943	913	743	847	812		826	807

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020).
Note: This table presents results from 2SLS regressions of the cognitive and socioemotional ability measures on a dummy for attendance at an education-oriented against a care-oriented preschool and a set of control variables described in Section 3.2, while instrumenting the preschool decision with our measure of the relative preschool availability for children in lower elementary school (LES), higher elementary school (HES), and lower secondary school (LSS), respectively. There are not enough observations for the QOL score at lower elementary school. F-tests of weak instruments in the first stage are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

N Test for Selective Panel Attrition

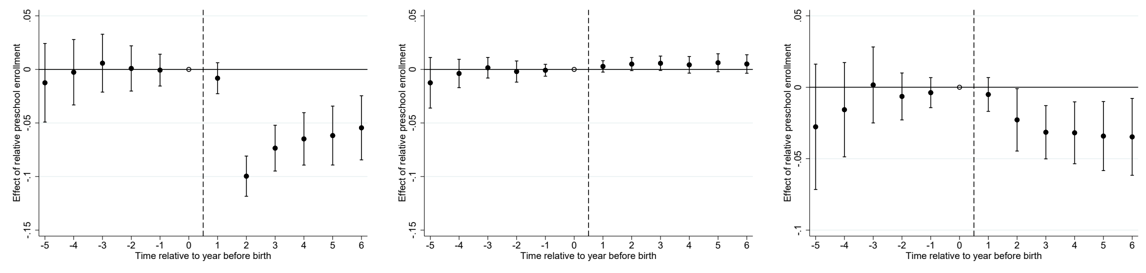
Table N15

Probit Regressions of Panel Dropout after One or Two Observations

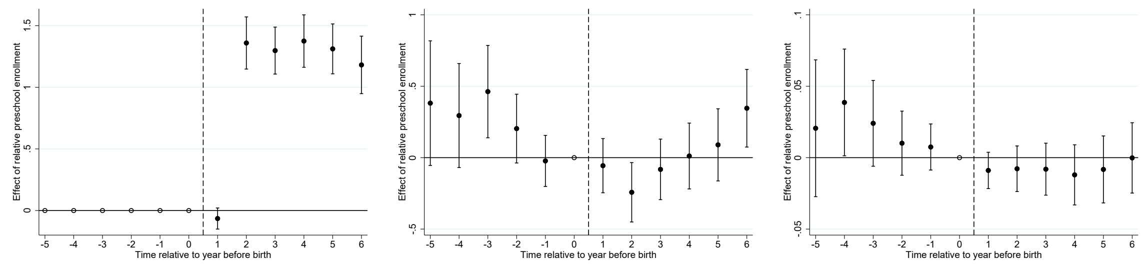
	Care-oriented preschool sample				Education-oriented preschool sample			
	One panel obs.		Two panel obs.		One panel obs.		Two panel obs.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math score	−0.024	−0.041*	−0.016	−0.025	−0.017	−0.023	−0.010	−0.027
	(0.024)	(0.023)	(0.027)	(0.027)	(0.015)	(0.015)	(0.026)	(0.024)
Japanese score	0.005	−0.008	0.004	0.020	−0.006	0.009	−0.035	0.001
	(0.023)	(0.018)	(0.025)	(0.024)	(0.016)	(0.018)	(0.024)	(0.027)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture fixed effects		✓		✓		✓		✓
Cohort fixed effects		✓		✓		✓		✓
Prefecture-specific linear time trends		✓		✓		✓		✓
χ^2-stat of test of joint significance	1.071	4.081	0.350	1.293	2.134	2.274	2.945	1.398
p-value of test of joint significance	0.585	0.130	0.840	0.524	0.344	0.321	0.229	0.497
Observations	342	300	394	265	612	545	685	504

Source: Authors' calculations using data from JCPS, KHPS/JHPS, and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: This table presents average partial effects from Probit regressions of dummy variables indicating panel dropout after one observation in Columns (1), (2), (5) and (6), or after two observations in Columns (3), (4), (7), and (8) on the math and Japanese score and a set of control variables described in Section 3.2. Regressions were run separately for the nursery school sample in Columns (1) to (4) and the kindergarten sample in Columns (5) to (8). χ^2-tests for joint significance of the presented coefficients are conducted and the results are presented at the end of the table. Robust standard errors clustered at the municipality level are given in parentheses. *, **, and *** denote significance at the 10%-, 5%-, and 1%-level, respectively.

O Effect of Relative Preschool Enrollment on Household Characteristics



(a) Full-time empl., mother (b) Full-time empl., father (c) Household income



(d) Child care time at home (e) Education expenditures (f) Total expenditures

Figure O8

Effect of Relative Preschool Enrollment on Household Characteristics

Source: Authors' calculations using data from KHPS/JHPS and Statistics Bureau, Ministry of Internal Affairs and Communications (2020). *Note*: These graphs show the effect of relative preschool enrollment on household characteristics based on the difference-in-differences model $Y_{it} = \alpha + \sum_p \beta_p Z_{cp} \times \mathbb{1}(m = p) + X'_{it}\xi + \gamma_c + \delta_t + \phi_k + \epsilon_{it}$, where Y_{it} is (a) a dummy indicating whether the mother is full-time employed ($N = 5336$), (b) a dummy indicating whether the father is full-time employed ($N = 5336$), (c) the log household income ($N = 4492$), (d) the weekly hours spent doing child care at home ($N = 4864$), (e) log education expenditures ($N = 5336$), and (f) log total expenditures ($N = 5324$). X_{it} corresponds to household characteristics (i.e., mother's age at birth of the child, dummies for each parent having graduated from a college, and a dummy for the grandfather's college education), γ_c are municipality fixed effects, δ_t are year fixed effects, ϕ_k are fixed effects for the year of child birth, and ϵ_{it} is an error term. β_p is the year-specific effect of the relative preschool enrollment on Y_{it} relative to the year before child birth (i.e., $\beta_0 = 0$) presented in the graphs together with 95% confidence intervals based on robust standard errors clustered at the municipality level. Effects correspond to responses in Y to a 10 percentage points increase in the relative preschool enrollment (i.e., more children in education-oriented preschools) in the year relative to a child's birth. The sample is restricted to households with children, and the effects are for the first-born child.