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Effects of Subsidized Childcare on Mothers' Labor Supply Under a Rationing Mechanism*

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Abstract

We estimate the marginal treatment effect of childcare use on mothers' labor market outcomes by using a staggered expansion of childcare services across regions in Japan. The estimates show that the treatment effect is negatively associated with propensity to use childcare, which implies that mothers who increase their labor supply more are less likely to use childcare. Negative selection into treatment arises, because the childcare rationing rule gives preferential treatment to mothers who work full-time before they apply for childcare. These mothers are strongly attached to the labor market and likely to work regardless of the availability of subsidized childcare.

1 Introduction

Many developed countries provide subsidized childcare to young families. One of the objectives of this policy is to increase mothers' labor supply by resolving the conflict between raising a family and pursuing a career. However, the existing evidence on the effectiveness of childcare reforms on mothers' labor supply is mixed across time and countries. Indeed, many papers find that the effect

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of childcare on maternal labor supply is small and/or statistically insignificant (see Lundin, Mörk, and Öckert (2008), Cascio (2009), Goux and Maurin (2010), Fitzpatrick (2010, 2012), Havnes and Mogstad (2011) and Asai, Kambayashi, and Yamaguchi (2015)).

One of the explanations for the insignificant effects of childcare reform is crowding out. Namely, subsidized formal childcare substitutes for informal childcare arrangements such as care by grandparents, and hence, mothers' labor supply does not increase. The availability and affordability of informal childcare arrangements vary across families, which means the treatment effect of childcare use is heterogeneous across families. When the supply of childcare is not large enough to take care of all children in the country, the rationing rule for childcare determines the subpopulation treated by a childcare reform. Some countries allocate childcare randomly by lottery, whereas other countries prioritize certain families by child's age, household income, parents' occupation, etc. Depending on the rationing rule, a childcare slot may not be given to mothers who would increase their labor supply. If this is the case, the average effect of a childcare reform may be small, even though there is a subpopulation that would be strongly affected by childcare availability. This may explain why many previous papers find no effect of childcare reforms.

The objective of this paper is to estimate the heterogeneous treatment effects of childcare on mothers' labor market outcomes including participation, hours of work, earnings, and job type. We allow treatment effects to vary by unobserved propensity for childcare use by applying the marginal treatment effect (MTE) framework developed by Björklund and Moffitt (1987) and Heckman and Vytlacil (2005). Unlike the standard instrumental variable (IV) regression adopted by previous papers in the literature, the MTE framework enables us to determine which mothers are likely to change their labor supply the most and how likely they are to use childcare services, which is useful for designing an effective childcare policy.

We identify the causal effects by analyzing the childcare reform that occurred in the early 2000s in Japan. The national government legislated policies to support young families, including the expansion of subsidized childcare, in order to increase female labor supply and the fertility rate. While the national government committed to increase the supply of childcare across the country, local governments are responsible for the implementation of the policy. Because local governments differ in their policy priorities, financial status, local institutions, etc., the timing of the program rollout varies by region, which is used for identification. Because our estimation method controls for time-constant differences across regions and nationwide changes in economic conditions and policies, this identification strategy is similar to the difference-in-differences approach.

Throughout the period of analysis (and to the present day), the demand for subsidized childcare is greater than the supply in most large cities. If excess demand exists, local governments assess each family's need for childcare. While single-parent families and families on welfare receive preferential treatment, most families are ranked according to parents' working hours at the time of childcare application. This rationing rule favors full-time workers over part-time workers and job seekers. The rationale is that parents working longer hours are more in need of childcare, but the rationing rule may undermine the efficacy of the childcare reform. This is because parents working full-time at the time of childcare application are likely to use informal childcare and to work even if a subsidized slot is not provided, which implies that the rationing rule is likely to cause crowding out.

Our estimates indicate that the MTEs of childcare use on market participation, hours of work, and earnings are positive for most mothers, but they are significantly heterogeneous across mothers. We find that the MTE is inversely related to the unobserved propensity for childcare use. That is, mothers with strong treatment effects are less likely to use childcare, while mothers with weak treatment effects are more likely to use childcare. Given the rationing rule that favors full-time workers, the unobserved propensity for childcare use is likely to represent an unobserved labor market attachment. We consider that mothers with a strong labor force attachment are willing to exert extra effort to find an informal childcare arrangement that allows them to work and raise children, even if a subsidized slot is not provided, which implies that their treatment effect is weak. By contrast, mothers with weak labor force attachment may be unable to work without a subsidized slot, which implies that their treatment effect is strong. We also find that this main result is robust to a number of issues including endogenous fertility, selective migration to the region in which childcare is more available, and functional form assumptions.

We then examine the consequences of the negative association between the treatment effect and the propensity for treatment in two ways. First, we calculate the average treatment effect on the treated (TT) and the average treatment effect on the untreated (TUT) by taking weighted averages of the MTE. The result indicates that TUT is greater than TT, which implies that the policy effects may improve by changing the rationing rule so that the government provides a childcare slot to mothers who do not have access to one currently. Second, we evaluate the effect of a further expansion in the childcare program by counterfactual simulations under the current rationing rule. The results indicate that the policy effects become increasingly stronger as the childcare program expansion occurs. This is because those with strong treatment effects use childcare at a later stage of the childcare expansion. Overall, our analysis suggests that the current rationing rule favors mothers with stronger labor market attachment, and hence, the policy effect is undermined by crowding out.

There are two more findings worth mentioning. First, the positive effects on participation, hours of work, and earnings are brought about mainly by increasing regular employment, while nonregular employment and self-employment are not affected significantly. This result implies that not only the amount of work but also the job quality is raised by childcare enrollment. Second, the treatment effect is strongest for mothers of an infant and decreases with the child's age. This seems reasonable because informal childcare arrangements and other options such as kindergarten are available for older children.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the institutional background. Section 4 discusses our identification strategy. Section 5 explains the MTE framework. Section 6 outlines the data structure and shows summary statistics. Section 7 presents our estimates of the treatment effects. Section 8 discusses the robustness of the results and shows counterfactual policy simulations. We conclude in Section 9.

2 Related Literature

Recent studies on childcare and maternal labor supply attempt to identify the causal effects using plausible exogenous variations. One of the first such papers is that by Gelbach (2002), who estimates the causal effects using the quarter of birth of five-year-old children as a source of exogenous variation. Using the 1980 US Census, Gelbach (2002) identifies the effects of the eligibility for kindergarten on maternal employment by comparing those who are barely eligible and those who are not because they were born shortly after the cutoff date to be eligible for kindergarten. He finds that the enrollment for kindergarten increased mothers' labor supply significantly. Fitzpatrick (2010) estimates the effect of childcare subsidies by applying regression discontinuity design techniques similar to those used in Gelbach (2002) to a newer cohort using the 2000 US Census and finds no subsidy effects except for single mothers. Fitzpatrick (2010, 2012) argues that childcare subsidies became less effective because the labor supply elasticity of US women has declined from 1980 to 2000.

The evidence is mixed not only across time but also across countries. Evidence from Argentina (Berlinski and Galiani (2007)), Quebec (Lefebvre and Merrigan (2008) and Haeck, Lefebvre, and Merrigan (2015)), Spain (Nollenberger and Rodriguez-Planas (2015)), and Germany (Bauernschuster and Schlotter (2015)) shows that childcare reforms increased maternal labor supply, while evidence from Sweden (Lundin et al. (2008)), France (Goux and Maurin (2010) and Givord and Marbot (2014)), Netherlands (Bettendorf, Jongen, and Muller (2015)), and Norway (Havnes and Mogstad (2011)) shows that the effect is negligibly small. Although the estimates are not directly comparable, the effect of childcare tends to be small in countries where female labor supply was already high prior to childcare reform. In those countries, the provision of formal childcare only crowds out informal childcare arrangements without affecting maternal labor supply. By contrast, in countries where the female labor force participation rate was low, a childcare reform tends to increase maternal labor supply. Cascio, Haider, and Nielsen (2015) point out that a variety of contextual factors are likely to be important moderators of policy effects. Availability of informal childcare arrangements, parental leave and other family-friendly policies, and labor market institutions may potentially strengthen or dampen the effectiveness of a childcare reform.

The effect of childcare also varies across demographic groups in a given country and period. Even in countries where the average policy effect was zero, childcare reform increased the labor supply of single mothers (see Cascio (2009), Fitzpatrick (2010), and Goux and Maurin (2010), for example). Andresen and Havnes (2016) find that Norwegian childcare reform in 2002 increased the labor supply of mothers of children aged 0–2 years, which is a younger age group than that studied in previous papers. Because many single mothers cannot afford to use other childcare arrangements and childcare for toddlers is less available than that for older children, the provision of subsidized childcare can increase the labor supply of single mothers and mothers of toddlers.

Using aggregate data at the province level in Japan from 1990 to 2010, Asai et al. (2015) estimate the intention-to-treat (ITT) effect on mothers' employment and find it to be insignificant. The current paper differs from this previous study in three important ways. First, the current paper estimates heterogeneous treatment effects using the MTE framework, while the previous paper estimates the average ITT effect only. Second, the current paper estimates the effect of childcare use by child's age, while the previous paper estimates the effect averaged over children aged 0–5 years. Given the findings by Andresen and Havnes (2016), a stronger effect is expected for younger children. Third, the current paper uses microdata after 2002, which is more recent data than that used in the previous paper. Three-generation households are common in Japan, and grandparents in the same household often take care of children while a young mother works. However, the share of three-generation households decreased from 29% in 1990 to 13% in 2010. This implies that informal childcare by grandparents has become less available, and hence, childcare is expected to have a stronger effect in more recent years.[1]

3 Institutional Background

3.1 Center-Based Childcare

Childcare centers generally accept children from age 0 to 6 years, but older children are often prioritized because the required child-teacher ratio is higher for older children. While childcare centers offer informal and play-based learning programs, their main objective is to provide safe and healthy environment for children while their parents work. Given this objective, most childcare programs are fulltime. Only 10% of enrolled children spend fewer than seven hours per day in

[1] Asai, Kambayashi, and Yamaguchi (2016) is a follow-up paper of the authors' 2015 paper and estimates the ITT effect on maternal employment for the periods of 1990-2000 and 2000-2010 separately. The authors find insignificant effects for the 1990-2000 period and a small, but positive significant effect for the 2000-2010 period. Very recently, Nishitateno and Shikata (2017) obtained a very similar estimate for the 2000-2010 period using municipality-level data, instead of province-level data.

childcare, and most spend seven to 10 hours. In addition, the vast majority attend childcare at least five days a week, with 18% attending as much as six days a week. Only 9% of children attend between one and four days a week.

Kindergartens provide similar programs for young children, but differ from childcare centers in a few important ways. First, kindergartens accept older children from age 3 to 6 years. Second, kindergartens typically offer a half-day program, which implies that mothers of children going to kindergarten can work at most parttime unless they also use another childcare mode. Parents usually use a childcare center if they want to work fulltime. Third, the supply of kindergartens is sufficient so that nearly all children who wish to go to kindergarten can do so, which is in contrast with the supply of childcare centers that falls short of the demand in major cities.

Childcare centers in Japan are strictly regulated for quality control and are heavily subsidized. According to the Comprehensive Survey of Living Conditions, 94% of childcare centers satisfy the national quality standard set by the Child Welfare Act and are accredited by the governor of the province. Accredited childcare centers are subsidized by municipal, provincial, and national governments so that average users pay about 40% of the cost.[2] The average monthly fee per child is low at about 28,408 yen ($\approx$ USD 284), although it depends on age, region, household income, and the number of siblings.[3]

The remaining 6% are nonaccredited childcare centers. Some of them are owned by large employers and/or are accredited by, and receive subsidies from, local governments but not from the national government.[4] Because the vast majority of childcare centers are accredited and our main data set LSN21 does not distinguish them, we sometimes refer to accredited childcare centers as "childcare centers" for shorthand in the following.

Because accredited childcare is heavily subsidized and of high quality, many parents would like to use it, which results in rationing. Rationing is severe for younger children aged 0-2 years, but not for children aged 3 years and older, because the required child-teacher ratio is high for older children and they can also go to kindergarten instead of a childcare center. By contrast, childcare centers are unable to accept many young children aged 0-2 years because of the low required child-teacher ratio and young children have no other formal childcare options. As of April 2011, 83% of waitlisted children were aged 0-2 years.

[2]Parents of children aged 0 pay 20% of the cost, parents of children aged 1 year pay 30%, and parents of older children pay 60%. See page 26 of Ministry of Health, Labour and Wealth (2008).

[3]See Table 7 of Ministry of Health, Labour and Wealth (2009).

[4]The fee for a child aged 0 is 46,330 JPY (about 460 USD), and that for child aged 5 years is 34,161 JPY (about USD 340). See Table 12 on page 14 of Ministry of Health, Labour and Wealth (2009).

3.2 Rationing Rule

To be eligible to use accredited childcare, parents and other extended family members under the age of 65 years and living in the same household must be unable to undertake childcare. The legitimate reasons for using an accredited childcare center include working during the day, childbearing, disability, caregiving for sick people or people with disabilities, schooling, and job search. In practice, 94.2% of parents using childcare centers satisfy the eligibility conditions because they work during the day.[5]

When there are more applications than available slots in a childcare center, the municipal government assesses the necessity of childcare use and ranks applications following the guidelines set by the Ministry of Health, Labour, and Welfare. Although details may vary across local governments, the rationing rule is largely uniform across the country.[6]

To be concrete, we describe the rationing rule for childcare using an example from the city of Yokohama. Yokohama is the largest city in Japan, with a population of 3.8 million. As is the case in major cities, there is excess demand for subsidized childcare in Yokohama. The municipality ranks applications for childcare from A (highest) to G (lowest) in the first round. Fathers and mothers are ranked individually, and the lower rank is ten applied to the family.

Table 1 summarizes how applications are ranked in the first round. Most parents use childcare because they usually work during the day. If a parent works outside of the home for 20 or more days per month and eight or more hours per day, he/she is ranked highest at A. The rank is lowered if a parent works less, and a rank of C is given if he/she works 16 or more days per month but works 4–7 hours per day. A parent who is currently not working but has a job offer is ranked lower than those currently working, and a rank of D is given if he/she works for 16 or more days per month and 7 hours per day. A parent working for fewer than 16 days per month or 4 hours per day is not considered to have a legitimate reason to use childcare. The days and hours of work are assessed 1 month prior to the childcare application and must be verified by a document signed by the employer. Those who are on parental leave can report their days and hours of work before they took leave.

Although a parent can use accredited childcare if he/she is searching for a job, he/she is given the lowest rank of G. This is problematic for some job seekers. Some employers may be unwilling to hire a young mother who does not find a childcare arrangement, because she may not be able to work without childcare. Employment is required for childcare use, but childcare use may also be essential for finding employment.

[5] See Table 3 of Ministry of Health, Labour and Wealth (2009).

[6] We confirm that the rationing rules are very similar among the largest cities, where rationing typically takes place. These cities include Yokohama, Osaka, Nagoya, Sapporo, Kobe, Kyoto, Fukuoka, Kawasaki, Saitama, Hiroshima, and Sendai.

Single parents and parents with disabilities are given the highest priority, and hence, a rank of A. The rank is raised by one unit if the family is on welfare, the main earner lost his/her job, etc.; however, household income has little influence on childcare allocation otherwise.

If many applications are ranked equally at the cutoff level, the municipal government further ranks these applications in the second and third rounds. For example, if older siblings are already enrolled in the same childcare center, extra points are given to the application in the second round.

Table 1: Necessity Assessment in the First Round (Yokohama, 2010)

Reason	Note	Rank
Work	$\geq$ 20 days/month and $\geq$ 8 hours/day	A
	$\geq$ 16 days/month and $\geq$ 7 hours/day	B
	$\geq$ 16 days/month and 4-7 hours/day	C
	$\geq$ 16 days/month and $\geq$ 7 hours/day (Job Offer)	D
	$\geq$ 16 days/month and 4-7 hours/day (Job Offer)	E
	(Rank is lowered by one unit if work at/from home.)	
Job Search	Up to 3 months	G
Single Parent	If engaged with work, training, or job search	A
Disability	Class 1 or 2	A
Childbearing	8 weeks before and after	D
School		D
⋮		⋮

Source: Page 12 of Aoba Ward, City of Yokohama (2009).
Note: If the family is on welfare, the rank is raised by one unit. If many households are in the same rank at the threshold level for childcare allocation, the application is further ranked for tie-break in the second and third rounds.

4 Identification Strategy

4.1 The Policy Reform

4.1.1 Background

The national government recognized the shortage of accredited childcare centers in the early 1990s. It launched the Angel Plan (1994–1998) and the New Angel Plan (1999–2003), which included an expansion of childcare capacity, extension of childcare service hours to include weekends and holidays, and subsidies to promote the take-up of parental leave and shorter working hours. Unfortunately, these two plans were too small and failed to increase the supply of accredited childcare. In 2003, the national government enacted the Basic Act for Measures to Cope with Society with Declining Birthrate and committed to taking legal and financial measures to increase the supply of childcare. This policy reform increased the number of accredited childcare slots by 12% from 2000 to 2010.

This policy reform affected younger children aged 1-2 years more strongly than children in other ages. First, children aged 3-5 years were given priority before the reform, because a childcare teacher can look after more children aged 3-5 years than children aged 0-2 years. Second, infants (children aged 0 years) were also not strongly affected, because many childcare centers did not accept infants because of the high cost of infant care. In addition, many mothers of infants do not want to use childcare, because maternal leave is available until the child reaches the age of 1 year.

Single parents and families on welfare were not strongly affected by the reform, because they were prioritized for childcare allocation before the reform. Mothers with strong labor market attachment were also not among the most strongly affected by the reform. Because of the rationing rule described in the previous section, they earn the highest rank. As the reform progressed, an increasing number of childcare slots were supplied over time, which allows mothers with weaker labor market attachment to use subsidized childcare.

4.1.2 Exogeneity of the Reform

While the national government covers half of the cost of the childcare reform, the provincial and municipal governments are responsible for its rollout. Depending on the financial status and policy priorities of the provincial and municipal governments, the pace of the program rollout varied by region. This variation in the pace of childcare expansion across regions is exploited for the identification of the causal effects. We examine the potential determinants of the growth of childcare availability. According to Cabinet Office (2010), there are three obstacles preventing childcare expansion. First, the regulations are strict and uniform across the country, even though some (e.g., area per child and requirement for a kitchen) are unnecessary or unrealistic for urban areas. Second, the local governments do not have a permanent budget for childcare operations, although the national government transfers some additional funds to the local governments temporarily. Third, some municipal governments cannot acquire land to build new childcare centers, because the rents and land prices are prohibitively high in urban areas.

We assess how these factors and other regional characteristics affect the pace of childcare expansion. Following the literature, childcare availability is measured by the coverage rate defined as childcare slots per child aged 0-5 years in a given region. Note that the number of childcare slot is different from the number of children enrolled in childcare. Unfortunately, the data on childcare slots are not available by age. We regress the change of the coverage rate from 2000 to 2010 on several prereform regional characteristics including the female labor force participation rate, the total fertility rate, the financial capability index of the local government, the land price, and the average female wage in 2000.

Table 2: Determinants of the Growth of Childcare Coverage Rate

	Model 1	Model 2
Female Labor Force Participation Rate	0.186	0.169
	(0.089)	(0.094)
Total Fertility Rate	−0.001	−0.001
	(0.050)	(0.050)
Financial Capability Index	−0.062	−0.063
	(0.035)	(0.035)
Log Land Price	0.009	0.009
	(0.015)	(0.015)
Log Average Female Wage	−0.060	−0.052
	(0.099)	(0.101)
Change in Unemployment Rate		0.484
		(0.813)
Num. obs.	80	80

Sources: All explanatory variables are measured in 2000. Labor force participation rate for women aged 20-64 is from the Census. The total fertility rate is from Vital Statistics. The financial capability index is from Table for Financial Capability Indices of Prefectures constructed by Ministry of Internal Affairs and Communications. The land price is the average land price per square meter in residential areas, which is taken from Survey on Land Price of Prefectures by Ministry of Land, Infrastructure, Transport and Tourism. The mean female wage is calculated by dividing scheduled cash earnings by scheduled hours of work, which are from Basic Survey of Wage Structure 2001. For data consistency, I omitted City of Yokosuka and non-major cities in Province of Kanagawa, although they are included in the main analysis.

The first column of Table 2 reports the regression results. The female labor force participation rate in the prereform period is positively and significantly correlated with the growth of the childcare coverage rate. The demand for childcare is high in regions where the female labor force participation rate is high. The estimates suggest that the supply of accredited childcare increased to meet the high demand in such regions. The total fertility rate in the prereform period has no effect on the growth of the coverage rate. Despite the argument by the Cabinet Office (2010), the financial status of the provincial government, the land price, and the female wage rate in the prereform period do not affect the growth of the coverage rate significantly. Additionally, we allow for the changes in the coverage rate to correlate with the changes in the local unemployment rate, but the coefficient is statistically insignificant and other coefficients are essentially unaffected.

The regression results indicate that the growth of the coverage rate is not completely random, and hence, accounting for potential policy endogeneity is necessary for unbiased estimates. To address this issue, we include interactions of the prereform regional characteristics and year dummies in our control variables, which allows for pre-treatment trends in mothers' labor supply to depend on the pre-reform characteristics.

To further address the issue of potential policy endogeneity, we allow for region-block-specific trends as a robustness check. Specifically, we group 47 provinces into seven region blocks based on the geographic location of provinces[7] and include interactions of region-block dummies and year dummies in our regressions as additional control variables.

4.2 Other Threats to Identification

Another threat to identification is reverse causality. Mothers' labor supply is affected not only by childcare use, but also by local labor market conditions. If the childcare coverage rate is correlated with local labor market conditions, our estimates will be biased. To avoid this endogeneity bias, we include the province-level unemployment rate for the population aged 15 years and older as a control variable in the main specification.

Selective migration also raises the possibility of endogeneity bias. A popular narrative says that obtaining a slot in an accredited childcare center is extremely difficult in Tokyo and that some people even move to other districts for childcare. Using the Employment Structure Survey[8] 2012, we take a sample of mothers of children under 6 years of age and examine their reasons for their most recent move and where they moved from. We find that "for childrearing and education," 9.5% moved within the same city, 4.6% moved from another city in the same province, and 1.4% moved from another province. Because a region in this study is defined by a combination of city

[7]The seven region blocks consist of Hokkaido-Tohoku, Kanto, Chubu, Kansai, Chugoku, Shikoku, and Kyushu-Okinawa.

[8]It is conducted by the Statistics Bureau every three years and covers about 1% of the population.

and province, at most 4.6% moved between regions for childcare. As we will show in Section 8.1, selective migration seems to have little effect on the estimates.

Although we are not aware of any major policy changes that may affect female labor supply at the regional level, there was a nationwide reform of the parental leave policy. In 2005, nonregular workers became eligible for 1-year paid parental leave. In addition, the replacement rate of cash benefits was raised gradually from 25% to 50% from 2000 to 2007.[9] As long as the effect of this policy reform is uniform across the country, it is accounted for by the year dummy; however, the effect of a parental leave reform may depend on childcare and other family policies at the region level. If the effects of a parental leave reform vary by region and are correlated with the changes of childcare availability, our estimates are biased. Although predicting the direction and degree of such biases is hard, we partially address this issue by allowing for flexible trends varying by region. Specifically, we include as control variables the interactions of pre-reform regional characteristics, region-block dummies, and time dummies.

Other issues that might affect our estimates include endogenous fertility, presence of siblings, and functional form assumptions. These issues are discussed extensively in Section 8.1, but our main results are largely unaffected.

5 Marginal Treatment Effect Framework

5.1 Setup

Using the MTE framework developed by Björklund and Moffitt (1987) and Heckman and Vytlacil (2005),[10] we estimate heterogeneous treatment effects varying by observed and unobserved characteristics of mothers.

Define $j \in \{0,1\}$ as an index for treatment status such that $j=1$ implies being treated and $j=0$ implies being untreated. A potential outcome Y_j for treatment status j is given by

$$Y_j = X\beta_j + U_j \tag{1}$$

$$E(U_j|X) = 0, \tag{2}$$

where X is a vector of control variables and U_j is a deviation of outcome from the conditional mean given X.

[9] See Asai (2015) and Yamaguchi (2016) for evaluation of these policy changes.

[10] Cornelissen, Dustmann, Raute, and Schönberg (2016) is an excellent introduction to the MTE framework for applied researchers.

Treatment status is determined by the following selection equation

$$D \;=\; 1\{X\gamma + \delta Z - V > 0\}, \tag{3}$$

where D is a dummy variable for treatment, $1\{\cdot\}$ is an indicator function that takes a value of one if the condition in the curly brackets is satisfied and zero otherwise, Z is a vector of instrumental variables excluded from the outcome equation (1), and V is a scalar of unobserved characteristics. Our instrument Z is the childcare coverage rate, which is defined as childcare slots per child in a given region. The validity of the instrument is discussed extensively in Section 4. We also include the interactions of the coverage rate and a subset of exogenous variables X in the instruments. Because a larger value of V keeps more mothers from treatment, we refer to it as a resistance to treatment.

The selection equation (3) can be rewritten as

$$\begin{aligned} D &= 1\{X\gamma + \delta Z > V\} && (4)\\ &= 1\{F_V(X\gamma + \delta Z) > F_V(V)\} && (5)\\ &= 1\{P(X\gamma + \delta Z) > U_D\}, && (6) \end{aligned}$$

where F_V is a cumulative distribution function for V, $P(\cdot)$ is a propensity score, and U_D is a quantile of the unobserved resistance V. We assume that (U_0, U_1, U_D) is conditionally independent of Z given X.

The MTE is defined as

$$MTE(X = x,\, U_D = u_D) \;=\; E(Y_1 - Y_0 | X = x,\, U_D = u_D). \tag{7}$$

It is interpreted as the gain from treatment for a mother whose observed characteristics are $X = x$ and the quantile of the unobserved resistance to treatment is $U_D = u$. Policy-relevant parameters such as the average treatment effect (ATE), the treatment effect on the treated (TT), the treatment effect on the untreated (TUT), and the local average treatment can be derived as weighted averages of the MTE.

We expect that the treatment effects vary by individual. Note that the treatment effect is the difference in mother's labor supply between the treated and untreated states. In the treated state, most mothers work because mothers' work is practically an eligibility condition to use childcare; however, in the untreated state, mothers may or may not work depending on the availability of an alternative childcare mode such as care provided by grandparents. This implies that the treatment effect varies by the availability of an alternative childcare mode.

To understand the economic interpretation of u_D in the context of this research, recall how the local governments select successful applications. The rationing rule sorts families by how much parents work. Because most fathers in the sample work fulltime, mothers' working hours are the key determinant of childcare use. The unobserved resistance u_D incorporates mothers' unobserved preference for work and their skills as well as the local governments' preference for mothers working fulltime. Hence, a low u_D implies strong labor market attachment, while a high u_D implies weak labor market attachment.

5.2 Local Instrumental Variable Estimator

Following Brinch, Mogstad, and Wiswall (forthcoming), we assume that an observed and an unobserved component are additively separable in the expected potential outcomes given $U_D = u_D$,

$$E(Y_j|X=x,\ U_D=u_D) \quad = \quad x\beta_j + E(U_j|U_D=u_D).$$

This linear separability assumption implies that the MTE is also additively separable into an observed and an unobserved component,

$$MTE(X=x,\ U_D=u_D) \quad = \quad x(\beta_1-\beta_0)+E(U_1-U_0|U_D=u_D). \tag{8}$$

Exploiting the linearity assumption leads to the following conditional mean outcome given the observed characteristics and the propensity score:

$$E(Y|X=x,\ P=p) \quad = \quad x\beta_0 + x(\beta_1-\beta_0)p + K(p), \tag{9}$$

where $K(p)$ is a nonlinear function of the propensity score. The MTE for the mother with $X = x$ and $U_D = p$ is given by the derivative of Equation (9) with respect to the propensity score,

$$\begin{aligned} MTE(X=x,\ U_D=p) \quad &= \quad \frac{\partial E(Y|X=x,\ P(X,Z)=p)}{\partial p} && (10)\\ &= \quad x(\beta_1-\beta_0)+\frac{\partial K(p)}{\partial p}. && (11) \end{aligned}$$

Note that the shape of the MTE curve is independent of X except for the intercept because of the linear separability assumption. If this assumption is not imposed, we would need a full common support of the propensity score for all unique combinations of the values of the X. The linear separability assumption allows identification of $K(p)$ across all values of the X, and hence, it only requires unconditional full common support.

How does the local IV estimator identify the MTE defined by unobserved characteristics u_D? We ignore the observed characteristics X to simplify the argument for the moment. The selection equation (6) implies those with the unobserved characteristics $u_D < p$ are selected into treatment and that those with $u_D = p$ are indifferent. If we increase the propensity score by a small amount, those with $u_D = p$ are newly induced into the treatment. Note that the average outcome as expressed in Equation (9) changes in response to the change in the propensity score p. The MTE is given by the change in the average outcome divided by the fraction of individuals newly selected into treatment.

5.3 Empirical Implementation

We implement the local IV estimator as follows. In the first step, we estimate the propensity score using a flexible probit model. The covariates include the coverage rate up to the third-order term, parents' age and education, the province-level unemployment rate, and year and region dummies. To allow for heterogeneous responses to the coverage rate, we interact the coverage rate and parents' characteristics. In addition, we include the interactions of year dummies and prereform regional characteristics to address policy endogeneity.

In the second step, we estimate the outcomes equation (9) using a linear regression with the assumption that $K(p)$ is a quadratic function. We allow for higher-order terms of the propensity score in the robustness checks. To allow for heterogeneous treatment effects by parents' age and education, we interact them with the propensity score. Standard errors are bootstrapped with 100 replications and clustered at the regional level. Note that one replication in our bootstrap procedure includes both the first and second steps so that uncertainty in the estimates in the first step is taken into account.

6 Data

6.1 Data Sources

Our main data source is LSN21, which is a census of children who were born January 10–17, 2001, July 10–17, 2001, and May 10–24, 2010. The first survey is conducted when the child is 6 months old. Subsequent questionnaires are completed every year about 6 months after their birthdays. The response rates are high at 93.5 and 88.1% in the first survey years for cohorts born in 2001 and 2010, respectively. About 83% of respondents in the first survey participate in the survey 3 years later at 3.5 years old. These response rates for the LSN21 are higher than those for the National Longitudinal Survey of Children and Youth,[11] which provides Canadian longitudinal data used by

[11] In the National Longitudinal Survey of Children and Youth in Canada, the response rate in the first cycle conducted in 1994/1995 was 86.5%, and 67.8% of the children in the original cohort responded in cycle 3 conducted in 1998/1999.

Baker, Gruber, and Milligan (2008), among others.

We draw data on accredited childcare centers from the annual Report on Social Welfare Administration and Services, which covers all provinces and major cities with a population of over 200,000. We define region by a combination of city and province: a region is a major city or a set of all municipalities in a province except for the major cities. We include 82 regions that are included in the data in both 2002 and 2011, which consist of 45 provinces and 37 major cities. The provinces of Fukushima and Miyagi were omitted because of missing data, as they were severely affected by the Great East Japan Earthquakes and Tsunami in 2011.

Child population is taken from the quinquennial census. For the years when the census was not conducted, we estimate child population by linear interpolation. Other regional characteristics in 2000 are drawn from various sources. See the note on Table 2 for details.

6.2 Descriptive Statistics

Table 3 shows the summary statistics of the sample. The childcare enrollment rate is low at 3.6% when the child is 0.5 years old, but it increases to 23.4% 1 year later. As children grow older, the enrollment rate increases to 36.8% when the child is 3.5 years old.

The coverage rate, defined as the number of slots per child, is about 0.3 and increases gradually with the child's age, which reflects the progress of the childcare reform. The average coverage rate is higher for the treated than for the untreated, implying that the coverage rate is positively associated with the childcare enrollment rate.

Parents' ages are evaluated when the child is 0.5 years old. The average age of mothers is 30.405, and fathers are about 2 years older on average than mothers. Parents' education is measured when the child is 1.5 years old. About 5% of parents are less-than-high-school educated and about one-third of parents are high school educated. Two-year college is the most common education level for mothers, and about 20% of mothers went to university. In contrast, 4-year university is the most common education level for fathers, and about 17% of fathers went to 2-year college. We do not find large systematic differences in mothers' characteristics between the treated and untreated when other characteristics are not controlled for. In contrast, fathers' characteristics are substantially different between the treated and untreated. The treated fathers are younger and less educated than the untreated fathers.

The fraction of working mothers is 13.3% when the child is 0.5 years old. Note that many mothers are entitled to 1 year of paid maternity leave until their child reaches the age of 1 year. Many mothers return to the labor market after their paid leave period, and 33.7% of mothers are working when their child is 1.5 years old. The fraction of working mothers increases with child's age, and 42.8% of mothers are working when their child is 3.5 years old. There is a strong as-

Table 3: Summary Statistics

	All			Comparison by Treatment		
	Nobs.	Mean	S.D.	Treated	Untreated	p-value for Difference
Childcare Enrollment						
Age 0.5	72475	0.036	0.188	1.000	0.000	
Age 1.5	72477	0.234	0.423	1.000	0.000	
Age 2.5	67929	0.314	0.464	1.000	0.000	
Age 3.5	65242	0.368	0.482	1.000	0.000	
Coverage Rate						
Age 0.5	72475	0.305	0.111	0.328	0.304	0.000
Age 1.5	72477	0.313	0.113	0.336	0.306	0.000
Age 2.5	67929	0.321	0.116	0.348	0.309	0.000
Age 3.5	65242	0.331	0.118	0.360	0.313	0.000
Mother's Characteristics						
Age	72475	30.405	4.516	30.663	30.395	0.003
Less Than High School	72475	0.046	0.210	0.057	0.046	0.012
High School	72475	0.334	0.472	0.343	0.334	0.314
2-Yr College	72475	0.419	0.493	0.431	0.419	0.233
4-Yr University or Higher	72475	0.200	0.400	0.169	0.201	0.000
Father's Characteristics						
Age	72475	32.402	5.524	32.565	32.396	0.146
Less Than High School	72475	0.073	0.261	0.109	0.072	0.000
High School	72475	0.354	0.478	0.439	0.350	0.000
2-Yr College	72475	0.169	0.375	0.176	0.168	0.307
4-Yr University or Higher	72475	0.404	0.491	0.276	0.409	0.000
Market Work						
Age 0.5	71817	0.133	0.339	0.878	0.104	0.000
Age 1.5	72046	0.337	0.473	0.912	0.161	0.000
Age 2.5	67338	0.374	0.484	0.873	0.146	0.000
Age 3.5	64215	0.428	0.495	0.828	0.195	0.000
Hours Per Week Worked						
Age 0.5	71957	3.255	10.717	30.921	2.215	0.000
Age 2.5	67338	12.503	18.704	31.317	3.900	0.000
Age 3.5	64010	13.587	18.742	28.884	4.761	0.000
Earnings (mil. JPY)						
Age 0.5	70552	0.741	1.557	2.135	0.691	0.000
Age 1.5	67555	0.451	1.098	1.458	0.183	0.000
Age 3.5	61746	0.797	1.561	1.802	0.245	0.000
Regular Work						
Age 0.5	71817	0.041	0.199	0.493	0.024	0.000
Age 1.5	72046	0.168	0.374	0.541	0.054	0.000
Non-Regular Work						
Age 0.5	71817	0.039	0.193	0.303	0.029	0.000
Age 1.5	72046	0.113	0.316	0.305	0.054	0.000
Self-Employed						
Age 0.5	71817	0.040	0.195	0.069	0.039	0.000
Age 1.5	72046	0.042	0.200	0.058	0.037	0.000

Source: LSN21.

Note: The sample includes two-parent families. Parents' ages and education are measured when child is 0.5 and 1.5 year old, respectively. Not all labor market outcomes are available at all ages. One million yen is about USD 10,000.

sociation between the use of center-based childcare and mothers' labor market participation. The labor market participation rate of childcare users is high at 83–91%, but that of nonusers is only 10–20%.

Note that the fraction of working mothers is higher than the enrollment rate at the same age, implying that many mothers work without using formal childcare. The labor market participation rate among mothers not using childcare increases with child's age, suggesting greater availability of informal childcare for older children.

The mean number of working hours increases with child's age, although they are not observed at 1.5 years of age. The mean number of working hours among childcare users is stable at about 30 hours per week, while that among nonusers is about 2–5 hours per week. Mean earnings are not monotonically increasing with child's age. The mean earnings of childcare users are higher than those of nonusers. Earnings are not observed at 2.5 years of age.

Market work is categorized into either regular work, nonregular work, or self-employment. Regular employment is typically under a permanent contract and a full-time job, while nonregular employment is typically under a limited-term contract and a part-time job. Jobs also differ in hourly wages, nonwage benefits, employer-sponsored training, and eligibility for the mandated PL (see Kambayashi and Kato (2013)). Information on employment type is available when the child is aged 0.5 and 1.5 years old. The fraction of regular workers is slightly higher than that of nonregular workers, and only 4% of mothers are self-employed.

Table 4: Shares of Childcare Mode for Working Mothers

Care Mode	Childcare Center	Grandparents	Sitter/ Nannies	Parents Only
Age 0.5	0.241	0.334	0.062	0.362
Age 1.5	0.633	0.198	0.031	0.138
Age 2.5	0.733	0.150	0.020	0.098
Age 3.5	0.712	0.101	0.070	0.117

Source: LSN21
Note: Childcare mode is mutually exclusive and collectively exhaustive as defined by the following rule. If enrollment for a childcare center is reported, this is considered as the primary mode, because most enrolled children attend fulltime. If a child is cared by grandparents only, the primary caregiver is grandparents. If any caregiver other than a childcare center and grandparents is reported, the primary caregiver is a child sitter. If no caregiver except is reported, parents are the primary caregiver.

Many working mothers use informal childcare arrangements, and their choice of childcare mode changes with child's age. Table 4 shows the shares of childcare mode for working mothers. When the child is 0.5 years old, only 24.1% of working mothers use a childcare center. Most children at age 0.5 years are cared for by their parents or grandparents. The use of babysitters and nannies is rare, at 6.2%.

While most working mothers of infants do not use formal childcare, it is the most common childcare mode for working mothers of older children aged 1.5–3.5 years. At age 1.5 years, 63.3% of working mothers use childcare, and more than 70% of working mothers use childcare when the child is 2.5–3.5 years old. The use of informal care by grandparents becomes less common as the child grows older. The use of babysitters or nannies is rare regardless of the child's age. About 10% of the children of working mothers are cared for by parents only.[12]

7 Results

We show our main results in three steps, over which the econometric model becomes increasingly complex. First, in Section 7.1, we show the estimates for the first-stage and reduced-form regressions. Our estimates indicate that the childcare coverage rate indeed increases childcare enrollment and maternal employment rates, which implies that our instrument, the childcare coverage rate, is not weak. Second, in Section 7.2, assuming a homogeneous treatment effect for tractability, we show the estimates of the treatment effect of childcare enrollment by conventional IV regression and bivariate probit model. We hope that the analysis here is useful for readers, because these econometric methods are used routinely. In addition, the estimates can be compared with those from previous studies that use IV regressions. Third and finally, we allow for heterogeneity in the treatment effect in Section 7.3. There, we show estimates of the marginal treatment effects that vary by unobserved propensity for childcare enrollment.

7.1 Effects of Childcare Coverage Rate on Enrollment and Maternal Employment

We begin our analysis by presenting region-level evidence. The panels in the left column of Figure 1 present the relationship between the region-level coverage rate and childcare enrollment rate by child's age, after removing the effects of prereform regional characteristics, parental characteristics, and region and year fixed effects (see the note on Figure 1 for details). The panels in the right column show the relationship between the coverage rate and mothers' employment rate at the regional level.

In all graphs, the slope is positive and statistically significant at the 10% level for all ages from 0.5 to 3.5 years. Note that the results do not seem to be driven by an outlier. The graphs provide

[12] We are not entirely sure who is actually taking care of children when mothers work and only parents are reported as caregivers. As mentioned by Baker et al. (2008), these responses may be misreported and parents may actually use some form of informal childcare. We are unable to confirm if this hypothesis is true.

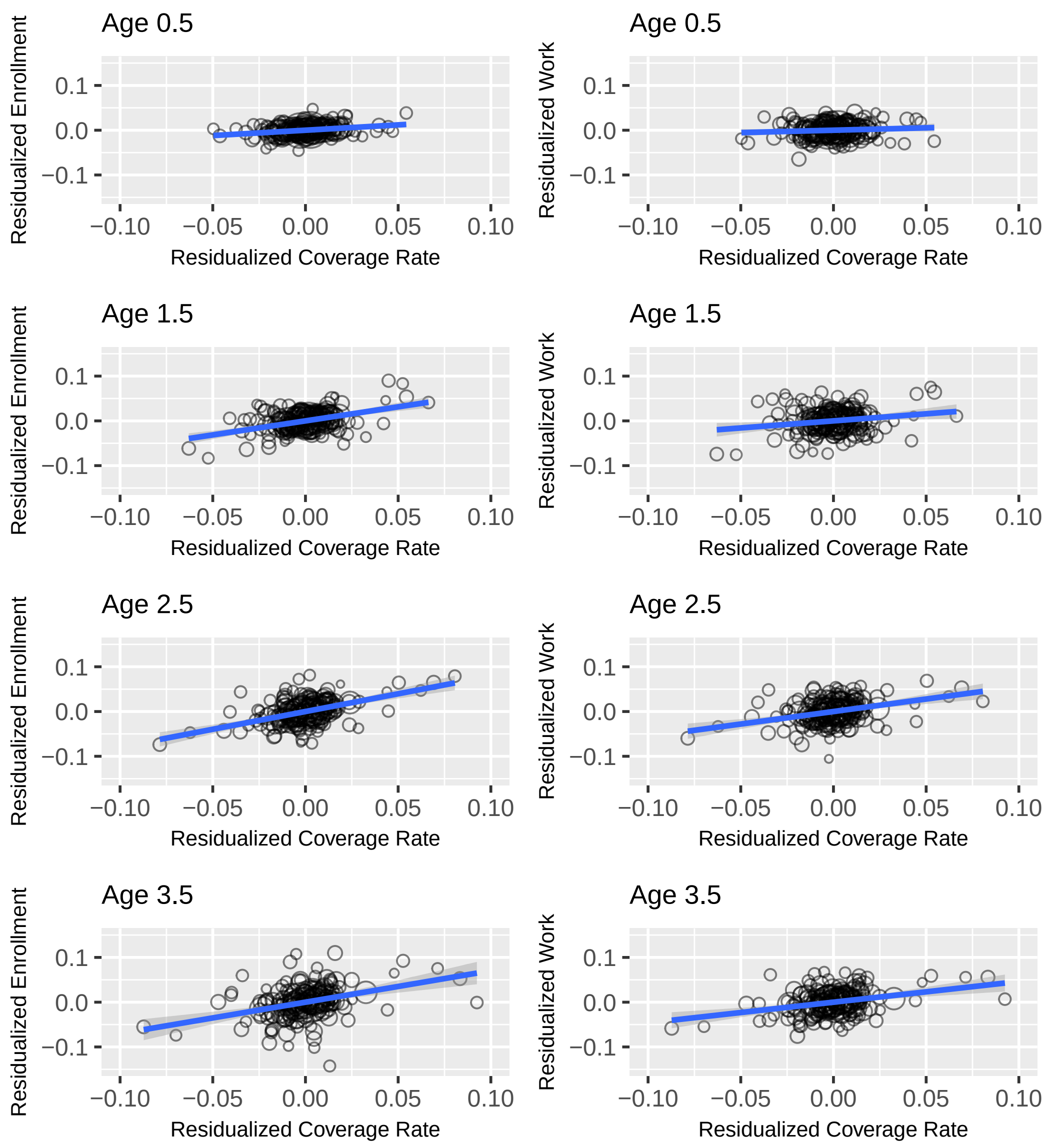

Figure 1: Coverage Rate and Childcare Enrollment by Region

Source: Authors' calculation based on LSN21.

Note: Residualized coverage, childcare enrollment, and maternal employment rates are calculated as follows. We regress each of the variables on parents' age and education, province-level unemployment rate, regional characteristics at the 2000, and year and region dummies, and then, take averages of the residuals by region. The size of the bubbles indicates the number of observations in the region. The fitted line is estimated by the weighted least squares and shown with the 90% confidence interval.

prima facie evidence that the expansion of childcare slots increases the enrollment of children and the employment of their mothers.

These graphs make our identification strategy transparent; however, the residual plot can only help us visualize the linear relationship. The marginal effect of the coverage rate on the enrollment rate may vary by the coverage rate, but that is masked in these graphs. To examine potential nonlinearity between the coverage rate and outcomes, we estimate a flexible probit model that includes up to third-order polynomials of the coverage rate and parents' and regional characteristics.

The top-left panel of Figure 2 shows the effects of the coverage rate on childcare enrollment by child's age. The enrollment rate increases with the coverage rate for all age groups, which confirms the results from the region-level analysis. In addition, the graph indicates that the enrollment rate changes with the coverage rate. The graph for children aged 3.5 years shows a concave profile, implying that their enrollment rate does not increase much at a higher coverage rate. This is presumably because many parents of 3.5-year-old children choose to enroll them in kindergarten instead of childcare, even if childcare is available. By contrast, the graph for younger children aged 0.5-2.5 years show a convex profile. At a low coverage rate, older children are likely to be prioritized because the required child-teacher ratio is higher, which is consistent with the fact that 83% of waitlisted children are 0-2 years old. At a high coverage rate, more and more children aged 0-2 years are allowed to enroll in childcare.

The top-right panel of Figure 2 shows the effects of the coverage rate on the fraction of working mothers. It increases with the coverage rate and the child's age. Note that the fractions of working mothers and childcare users do not generally coincide for two reasons. First, some working mothers use informal childcare arrangements. Second, the municipal governments accept applications from mothers who do not work but are unable to care for their children because of sickness, disability, schooling, job seeking, etc. These eligible but nonworking mothers are given low priority, but they are able to use childcare when the coverage rate is high.

To see whether an expansion of childcare crowds out informal childcare arrangements for working mothers, we estimate probit models for the joint choice of mothers' work and childcare mode. The bottom-left panel shows how the coverage rate affects the fraction of mothers who work and use a childcare center. The fraction increases with the coverage rate and the child's age. The graph is concave for 3.5-year-old children, because they are eligible to use kindergarten as well as childcare. By contrast, the profile is convex for younger children, because older children are prioritized and younger children are not given a slot unless the coverage rate is high. The bottom-right panel shows how the coverage rate affects the fraction of mothers who work and use an informal childcare arrangement. It decreases with the coverage rate, but no clear pattern can be seen by the child's age.

Many working mothers rely on informal childcare arrangements when the coverage rate is low,

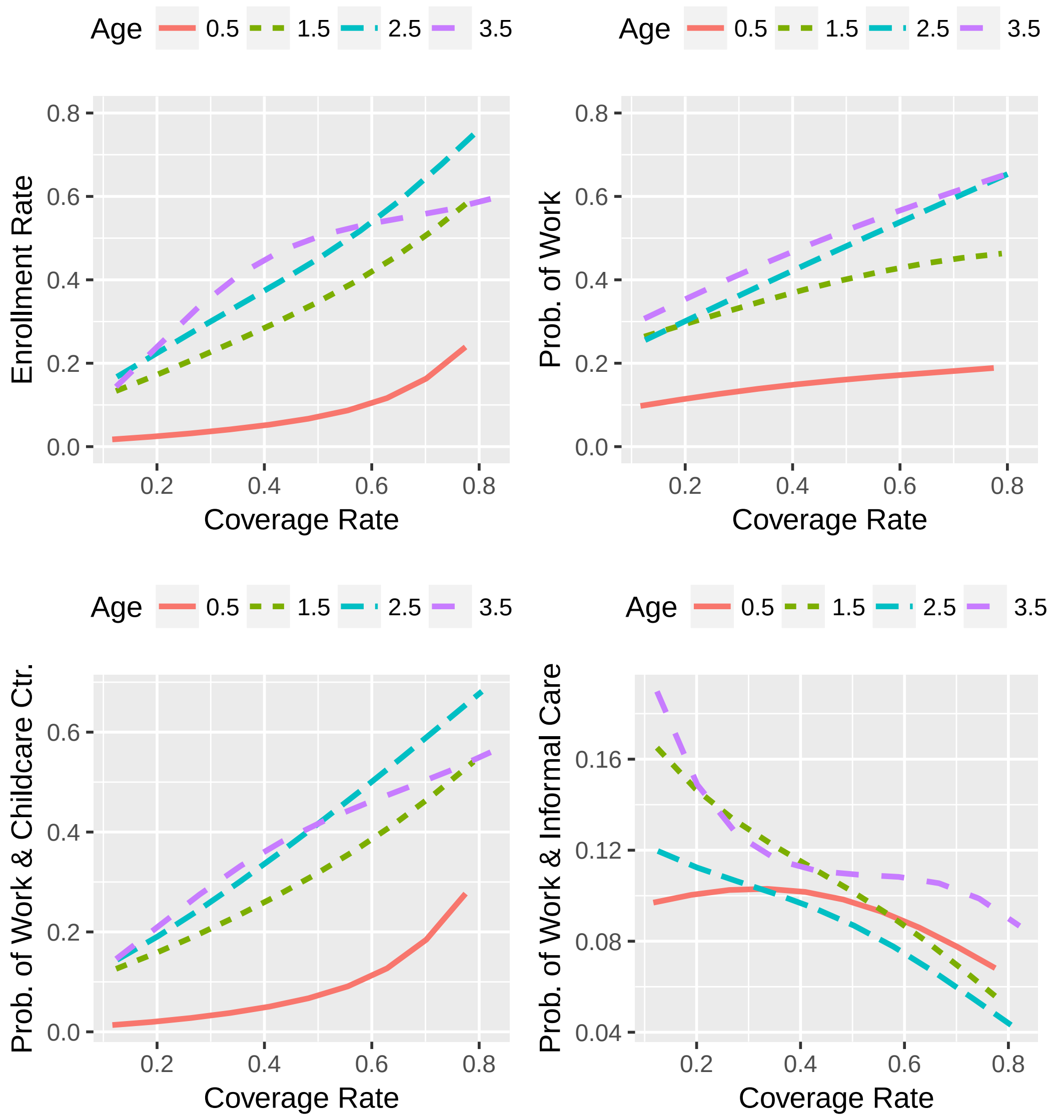

Figure 2: Coverage Rate, Childcare Enrollment, and Mother's Work

Note: Estimates are based on the probit model in which the explanatory variables include the coverage rate up to the third-order polynomial, parents' age and education, province-level unemployment rate, regional characteristics in 2000, and region and year fixed effects. The polynomials of the coverage rate are interacted with parents' characteristics.

but informal childcare is increasingly substituted with formal childcare centers as the coverage rate increases. This result implies that the expansion of childcare supply crowds out informal childcare among working mothers. Even though parents' work is effectively a prerequisite for the use of a childcare center, providing a new childcare slot does not necessarily add a mother to the labor market, because some of them simply substitute informal childcare arrangements and continue to work.

Childcare enrollment and mothers' work are also affected by parents' age and education. Table 5 shows the average marginal effects of the coverage rate and parental characteristics based on the probit model (see Equation 3). The coverage rate has positive effects on the enrollment rate and the effect increases with child's age. Mothers' education is positively correlated with the enrollment rate. Note that the reference group is mothers with 4-year university education. Remember that parents' work is virtually required for childcare use. Skilled mothers are more likely to work and to use childcare, because their opportunity cost of staying at home is high. In addition, the rationing rule gives a higher priority to mothers with stronger labor market attachment, which is positively correlated with education.

Fathers' age and education are negatively correlated. If a wife takes her husband's earnings as given, her labor supply and childcare use are negatively correlated with her husband's earnings because of the income effect, which accounts for why childcare use is negatively correlated with fathers' age and education.

We show that the childcare coverage rate increases the mothers' employment rate in Table 5 (also see Equation 3), but the interpretation of the result is not necessarily straightforward. This is because the effect of the coverage rate on mothers' employment is the product of the effect on childcare enrollment and the treatment effect of childcare enrollment. In the following subsections, we show estimates of the treatment effect of childcare enrollment.

7.2 Estimating Treatment Effects by IV Regression and Bivariate Probit

In this subsection, we present estimates of treatment effects on mothers' labor market outcomes using a conventional IV regression and bivariate probit model, assuming that treatment effects are homogeneous. Because these methods are well known and commonly used, our estimates can be compared with those in the previous studies.

We use the propensity score as an instrument rather than the coverage rate itself. The propensity score is a function of the coverage rate and other exogenous variables, but the use of the propensity score as an instrument has advantages over the use of the coverage rate in our context. First, it is required by the local IV estimator for the MTE. By using the same instrument across different

Table 5: The Average Marginal Effects of Coverage Rate on Childcare Enrollment

	Age 0.5	Age 1.5	Age 2.5	Age 3.5
Childcare Enrollment				
Mother's Age	0.001	0.002	0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Less Than HS (Mother)	-0.001	-0.095	-0.098	-0.075
	(0.004)	(0.008)	(0.010)	(0.010)
HS (Mother)	-0.007	-0.099	-0.104	-0.079
	(0.002)	(0.005)	(0.006)	(0.006)
2-Yr College (Mother)	-0.001	-0.055	-0.071	-0.058
	(0.002)	(0.005)	(0.005)	(0.005)
Father's Age	-0.000	-0.002	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Less Than HS (Father)	0.034	0.111	0.148	0.185
	(0.004)	(0.007)	(0.008)	(0.008)
HS (Father)	0.020	0.056	0.078	0.101
	(0.002)	(0.004)	(0.004)	(0.005)
2-Yr College (Father)	0.013	0.055	0.072	0.091
	(0.002)	(0.005)	(0.005)	(0.005)
Coverage Rate	0.133	0.571	0.770	0.955
	(0.062)	(0.130)	(0.137)	(0.135)
Mother's Work				
Mother's Age	0.003	0.004	0.004	0.005
	(0.000)	(0.001)	(0.001)	(0.001)
Less Than HS (Mother)	0.011	-0.144	-0.124	-0.072
	(0.007)	(0.009)	(0.010)	(0.011)
HS (Mother)	-0.014	-0.136	-0.119	-0.078
	(0.004)	(0.006)	(0.006)	(0.006)
2-Yr College (Mother)	-0.008	-0.083	-0.072	-0.054
	(0.004)	(0.005)	(0.005)	(0.005)
Father's Age	0.002	-0.001	-0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Less Than HS (Father)	0.111	0.160	0.183	0.222
	(0.006)	(0.008)	(0.008)	(0.008)
HS (Father)	0.059	0.093	0.111	0.127
	(0.003)	(0.004)	(0.005)	(0.005)
2-Yr College (Father)	0.059	0.091	0.098	0.115
	(0.004)	(0.005)	(0.005)	(0.006)
Coverage Rate	0.146	0.358	0.595	0.546
	(0.120)	(0.149)	(0.147)	(0.143)

Note: Standard errors are in parenthesis. Estimates are based on the probit model in which the explanatory variables include the coverage rate up to the third-order polynomial, parents' age and education, province-level unemployment rate, interactions of time dummies and pre-reform regional characteristics, and region and year dummies. The pre-reform regional characteristics include female labor force participation rate, total fertility rate, financial capability index, log land price, and log average female wage in 2000. The polynomials of the coverage rate are interacted with parents' age (linear) and education dummies. The reference group for education is those with 4-year university education or higher.

models (IV, probit, and local IV models), the estimates become comparable. In particular, an IV estimate can be interpreted as a weighted average of the MTE (see Heckman and Vytlacil (2005)). Second, the propensity score provides the efficient IV if it is correctly specified (see Wooldridge (2010)). Note that this method produces a consistent IV estimate even if the propensity score is not modeled correctly.

The first column of Table 6 shows the effects of childcare use on mothers' work estimated by OLS. The estimates range from 0.619 to 0.754, and the treatment effects decrease with age. Of course, they cannot be interpreted as causal because of possible endogenous selection into treatment.

Table 6: Treatment Effects on Mother's Market Work

	Linear Models			**Nonlinear Models**	
	OLS	IV	F-stat for Weak IV	Probit	Bivariate Probit
Age 0.5	0.754	1.137	208.484	0.752	0.731
	(0.008)	(0.155)		(0.007)	(0.064)
Age 1.5	0.744	0.685	147.590	0.744	0.690
	(0.010)	(0.086)		(0.003)	(0.040)
Age 2.5	0.723	0.662	95.601	0.723	0.498
	(0.012)	(0.089)		(0.003)	(0.068)
Age 3.5	0.619	0.434	118.849	0.618	0.160
	(0.015)	(0.098)		(0.003)	(0.069)

Note: Standard errors are in parenthesis and those for OLS and IV are clustered at the region level. The dependent variable is a dummy for mother's market work. The endogenous variable is a dummy for the use of a childcare center. The IV is the propensity score estimated by the flexible probit (see Section 7.1). The propensity score is interacted with parents' age (linear) and education dummies. Other exogenous variables include parents' age and education, province-level unemployment rate, interactions of time dummies and pre-reform regional characteristics, and region and year dummies. The pre-reform regional characteristics include female labor force participation rate, total fertility rate, financial capability index, log land price, and log average female wage in 2000.

The estimates from the IV regression are reported in the second column. The estimated effect on mothers of children aged 0.5 years is incredibly large. Given that only about 13% of them work and only about 3% of them use a childcare center (see Table 3), this implausible estimate is caused by poor approximation by the linear probability model. For this age group, accounting for nonlinearity by the probit model seems to be important. The IV estimates for other age groups range from 0.434 to 0.685. The treatment effects decrease with child's age. Note that we soundly reject the null hypothesis that our instrument is weak, as shown in the third column.

To account for nonlinearity, we estimate the treatment effects using probit models. The fourth column shows the estimates of a univariate probit model, which does not address possible endogeneity biases. They are very similar to the estimates by OLS. The fifth and last column shows estimates of a bivariate probit model that accounts for endogenous selection into childcare enrollment. The bivariate probit estimates are smaller than those from a univariate probit for all age groups. Moreover, the difference between univariate and bivariate probit estimates increases with child's age, suggesting that endogeneity bias is more severe for older children.

Although estimates vary between the IV regression and the bivariate probit, they share some important features: the estimated treatment effect is positive and significant, and decreases with child's age. The treatment effect is smaller for older children, because informal childcare is more readily available. In particular, children aged 3.5 years are eligible to enroll in kindergarten. Providing a childcare slot to an older child does not change his/her mother's work hours, because it only crowds out the existing informal childcare. Our estimates from the IV and bivariate probit models help to interpret the ITT effects in the bottom half of Table 5. The ITT effects are small for mothers of children aged 0.5 years, because they are less likely to use a childcare center, even though their treatment effects are greater than those of the mothers of older children.

The estimates for LATE from the IV regression range from 0.434 to 0.685 for children aged 1.5-3.5 years. While many previous papers find no effects of childcare use on maternal labor supply because of crowding out, our estimates are largely comparable with the estimate reported by Baker et al. (2008). The sample used by Baker et al. (2008) include children aged 0-4 years in Quebec, and the estimated treatment effect on the treated is 0.51.[13] Our estimates are large, but not implausible relative to the estimates in the literature.

7.3 Estimating Marginal Treatment Effect by Local IV Regression

7.3.1 Estimates

We estimate the MTE using the local IV estimator outlined in Section 5.2. Compared with the IV regression and bivariate probit models, the local IV regression is more flexible in that it allows for heterogeneous treatment effects varying by unobserved characteristics. In the following, we discuss the results for mothers of children aged 1.5–3.5 years. The estimator does not provide reasonable estimates for mothers of children aged 0.5 years, because both the enrollment rate and the fraction of working mothers are very low, and the linear probability model in the second-stage regression provides a poor approximation.

Table 7 presents the support of the propensity score for treated and untreated individuals. Following the literature, we discard observations if their propensity scores are outside the common support. The common support is reasonably broad except for children aged 0.5 years. As a robust-

[13] This is obtained by dividing the ITT effect on mothers' work (0.077) by the ITT effect on institutional childcare (0.152). The estimates are reported in Table 2.

ness check, we also use a thicker support that takes the 99th percentile of the treated as the upper bound, but the results remain the same (see Section 8.1).[14]

Table 7: Support of the Propensity Score for Treated and Untreated Individuals

Age	**Control**		**Treated**		
	Min	Max	Min	99th Percentile	Max
Age 0.5	0.001	0.398	0.003	0.148	0.338
Age 1.5	0.034	0.727	0.048	0.516	0.757
Age 2.5	0.049	0.865	0.062	0.627	0.866
Age 3.5	0.054	0.861	0.058	0.680	0.889

Figure 3 shows how the MTE on various labor market outcomes changes with the quantile of the unobserved resistance to treatment u_D. The MTE is averaged over observed characteristics and shown with a 90% confidence interval. The three panels in the top row show the MTE curves for mothers' market work by child's age. They are all significantly above zero and increase with the resistance to treatment, which implies a reverse selection on the treatment effect. Remember that those with a lower value of resistance to treatment are more likely to be enrolled in childcare. The upward-sloping MTE curves imply a negative relationship between the treatment effect and the propensity for childcare use; that is, those with weak treatment effects are more likely to be given a childcare slot, while those with stronger treatment effects are less likely to be given a childcare slot.

The panels in the second row show the MTE on weekly hours of work. Work hours are not included in the data when the child is aged 1.5 years. Again, the MTE is positive and significant and increases with the unobserved resistance. The panels in the third row show the MTE on annual earnings in million yen ($\approx$ USD 10,000). The MTE on earnings is positive and significant except for very low values of u_D and increases with the unobserved resistance.

Figure 4 shows the MTE on the choice of employment types that are unavailable when the child is 2.5 and 3.5 years old. Market work is categorized into either regular work, nonregular work, or self-employment. A typical regular worker is a full-time worker, better paid, with more fringe benefits, and under a permanent contract, while a typical nonregular worker is not. The MTE on regular work is positive and significant for a broad range of the resistance to treatment, while the MTE on nonregular work is positive and marginally insignificant. We find no effects on

[14]We also examine if the common support is significantly broadened by the interaction terms of the coverage rate (IV) and other covariates. Table 13 reports the support of the propensity score for treated and untreated individuals using a model without the interaction terms. The support and the 99th percentile for treated individuals remain the same regardless of whether the interaction terms are included or not.

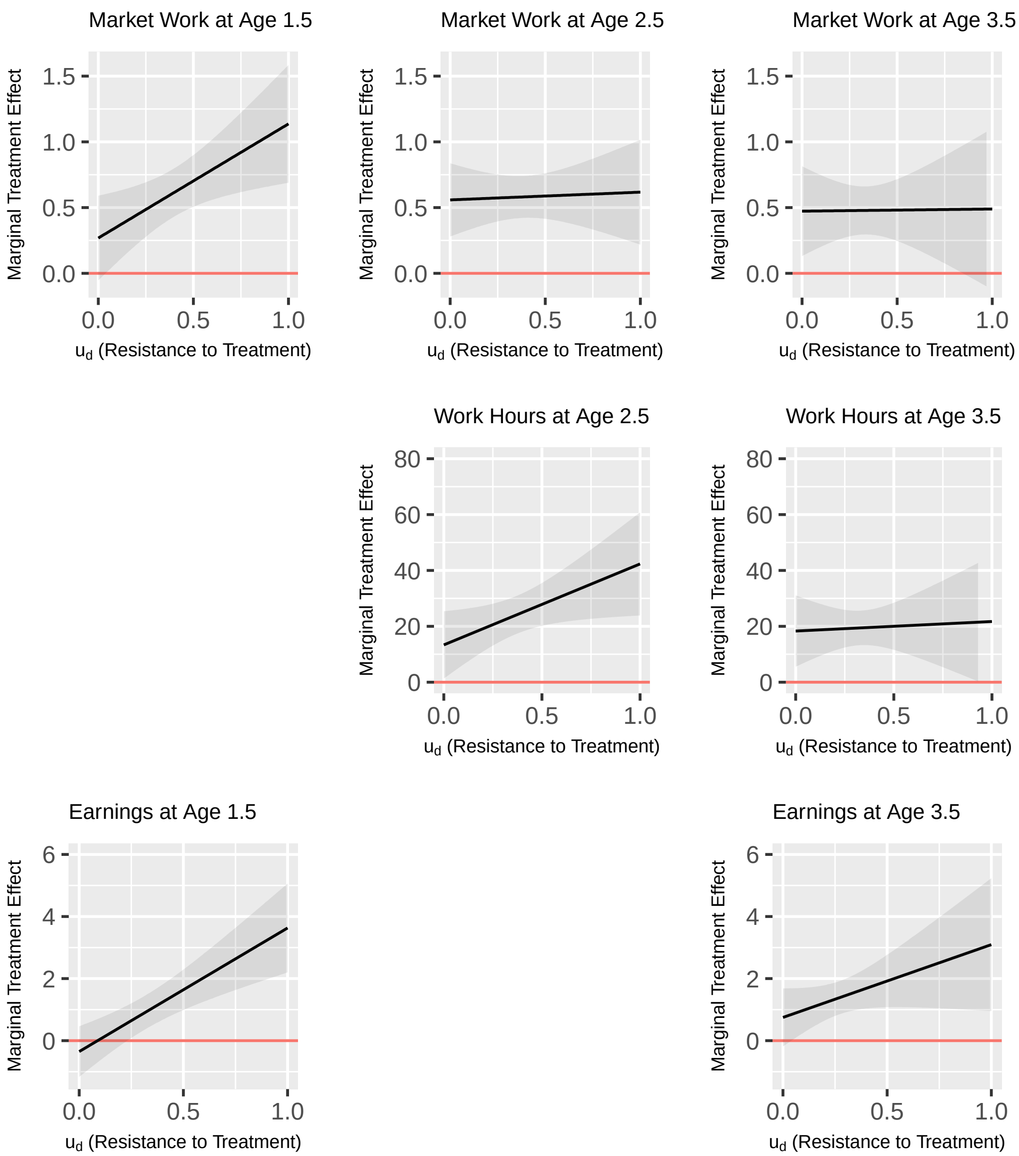

Figure 3: Marginal Treatment Effect Curve

Note: The MTE is averaged over observed characteristics and shown with the 90% confidence interval. Standard errors are clustered at the region level and estimated by a bootstrap with 100 replications. The dependent variables are employment (0 or 1), weekly hours of work, and annual earnings in million yen (≈ USD 10,000). The explanatory variables used in the local IV estimator include the propensity score up to the second-order term, parents' age and education, province-level unemployment rate, regional characteristics in 2000 interacted with year dummies, and sets of year and region dummies. To allow for heterogeneous treatment effects by observed characteristics, we interact the propensity score with parents' characteristics.

self-employment. These graphs indicate that childcare use increases mothers' market work largely through regular work instead of nonregular work or self-employment.

Figure 4: Marginal Treatment Effect Curve on Employment Type

Note: The MTE is averaged over observed characteristics and shown with the 90% confidence interval. See the note for Figure 3 for details.

The selected parameter estimates from the local IV regression model (i.e. Equation 9) are shown in Table 8. The coefficients for the quadratic term of the propensity score are slopes of the marginal treatment curves in Figures 3 and 4. Under the parametric assumption, we can test if MTE is heterogeneous by testing the significance of the coefficient for the quadratic term of the propensity score.

The MTE varies also by observed characteristics. The treatment effect increases with mothers' age for most outcomes. The effects on work and work hours are smaller for mothers with low (less-than-high-school) or high (4-year university or above) education than a mother with medium education (high school or 2-year college education). A possible explanation is that many low- and high-education mothers have alternative informal childcare options. In LSN21, 25% of low-education mothers live with their parents or in-laws, while 20% of medium-education mothers do so. This implies that informal childcare by grandparents is more readily available for low-education mothers than for medium-education mothers. Fewer high-education mothers live with their parents or in-laws, but they may have a greater willingness to pay for informal childcare services or to seek help from their parents. For both low- and high-education mothers, the provision of childcare is more likely to cause crowding out of their informal care arrangement than it is for medium-education mothers.

While the MTE on participation and hours is nonmonotonic in mothers' education, the MTE on earnings increases largely with mothers' education. This is because the hourly wage increases with mothers' education, which dominates the effects on participation and hours. A similar difference by mothers' education is also seen for employment type. The MTE on regular work increases with education, while that on nonregular work decreases with education.

The MTEs tend to decrease with fathers' age and education, although some estimates are noisy. Because the primary earner is typically the father in Japan, mothers' labor supply decreases with fathers' earnings. When fathers' earnings are low, the mother tries hard to find informal childcare and to work to raise her family. Providing a childcare slot to this mother is likely to crowd out her informal childcare without affecting her labor market outcomes.

7.3.2 Interpretation

Our analysis indicates that mothers with weaker treatment effects are more likely to be treated, while mothers with stronger treatment effects are less likely to be treated. To understand why selection is negatively associated with the treatment effect, consider how childcare enrollment is determined. Families decide on whether they apply for a childcare center given the pecuniary and nonpecuniary benefits of the childcare use relative to nonuse. If there are more applications than available slots, the local governments rank their applications by how many hours the parents work when they use a childcare center. Because we do not observe a mother's work at the time of childcare application, the unobserved resistance to treatment u_D should be interpreted as (the negative of) the unobserved component of her labor market attachment.

Why is the MTE negatively associated with the unobserved preference for work? The treatment effect is the difference in an outcome (e.g., labor market participation) between the treated and untreated states. In the treated state in which families use childcare, most mothers work because it is effectively a prerequisite for childcare use. However, in the nontreated state, the probability of labor market participation may vary considerably by individual depending on the availability and affordability of alternative childcare arrangements.

Mothers with a strong preference for work (or low u_D) are likely to exert extra effort to find an informal childcare arrangement. For example, young families may choose to live close to their parents or in-laws so that grandparents can take care of the children (see Compton and Pollak (2014)). Seeking help from in-laws may not be painless depending on the relationship, given that old Japanese people tend to have the traditional family value that the mother is expected to stay at home to raise her children. However, a mother with a stronger attachment to the labor market may not hesitate to ask in-laws to take care of her children, because she is desperate for childcare. This mother is likely to work even in the untreated state in which she is not given a childcare slot. This implies that the treatment effect is small for those with low u_D.

In contrast, mothers with a weak labor market attachment are unlikely to exert much effort to find an informal childcare arrangement in the untreated state. They are willing to work only if they are given a slot in a childcare center. This implies that the treatment effect is large for those with high u_D.

Table 8: Treatment Effect Heterogeneity by Observed Characteristics

	Market Work			**Work Hours**		**Earnings**		**Reg. Work**	**Non-Reg. Work**	**Self-Empl.**
	Age 1.5	Age 2.5	Age 3.5	Age 2.5	Age 3.5	Age 1.5	Age 3.5	Age 1.5	Age 1.5	Age 1.5
PS	0.114	0.229	0.346	4.057	10.128	-1.536	0.754	-0.107	0.154	0.038
	(0.236)	(0.212)	(0.251)	(8.061)	(9.251)	(0.691)	(0.753)	(0.243)	(0.155)	(0.109)
PS^2	0.434	0.029	0.008	14.495	1.706	1.991	1.173	0.417	0.143	-0.142
	(0.205)	(0.181)	(0.266)	(8.249)	(10.297)	(0.587)	(0.864)	(0.222)	(0.151)	(0.122)
PS×Age (Mother)	0.009	0.012	0.007	0.503	0.528	0.045	0.038	0.013	-0.007	0.002
	(0.005)	(0.004)	(0.004)	(0.161)	(0.176)	(0.015)	(0.013)	(0.004)	(0.003)	(0.002)
PS×Less Than HS (Mother)	0.018	-0.044	-0.083	-3.105	-8.292	-0.194	-0.699	-0.146	0.187	-0.003
	(0.109)	(0.079)	(0.078)	(3.570)	(2.738)	(0.166)	(0.218)	(0.063)	(0.068)	(0.054)
PS×HS (Mother)	0.160	0.134	0.129	2.618	-0.271	-0.195	-0.601	-0.138	0.261	0.038
	(0.065)	(0.060)	(0.057)	(2.261)	(2.150)	(0.168)	(0.202)	(0.059)	(0.060)	(0.024)
PS×2-Yr College (Mother)	0.149	0.167	0.198	5.653	3.622	0.008	-0.125	0.014	0.136	0.019
	(0.071)	(0.047)	(0.051)	(1.832)	(1.888)	(0.171)	(0.195)	(0.062)	(0.050)	(0.022)
PS×Age (Father)	-0.007	-0.005	-0.005	-0.297	-0.302	0.001	-0.017	-0.005	-0.002	0.001
	(0.004)	(0.003)	(0.002)	(0.156)	(0.118)	(0.013)	(0.012)	(0.004)	(0.003)	(0.002)
PS×Less Than HS (Father)	-0.100	-0.042	-0.210	-3.705	-2.905	-0.464	-0.947	-0.039	-0.029	0.029
	(0.080)	(0.086)	(0.123)	(3.280)	(4.170)	(0.180)	(0.356)	(0.064)	(0.066)	(0.038)
PS×HS (Father)	-0.057	0.005	-0.084	-0.107	-0.570	-0.353	-0.759	-0.029	0.024	-0.002
	(0.049)	(0.055)	(0.081)	(2.444)	(2.720)	(0.146)	(0.252)	(0.048)	(0.040)	(0.020)
PS×2-Yr College (Father)	0.086	0.017	-0.013	2.218	2.980	-0.208	-0.388	0.100	0.032	-0.014
	(0.060)	(0.050)	(0.083)	(2.024)	(3.024)	(0.196)	(0.284)	(0.066)	(0.038)	(0.028)

Note: PS stands for propensity score. Standard errors are in parenthesis. They are clustered at the region level and estimated by a bootstrap with 100 replications. The dependent variables are employment (0 or 1), weekly hours of work, and annual earnings in million yen (≈ USD 10,000). The explanatory variables used in the local IV estimator include the propensity score up to the second-order term, parents' age and education, province-level unemployment rate, regional characteristics in 2000 interacted with year dummies, and sets of year and region dummies. To allow for heterogeneous treatment effects by observed characteristics, we interact the propensity score with parents' characteristics.

7.3.3 Aggregate Treatment Effect Parameters

Aggregate treatment effect parameters including the ATE, TT, and TUT can be calculated by taking a weighted average of the MTE. The weights for the aggregate treatment effect parameters are graphically presented in Figure 5 when the child is aged 1.5 years (see Appendix A for details). For the TT, greater weight is given to those with lower values of resistance to treatment. In contrast, for the TUT, greater weight is given to those with higher values of resistance to treatment. The weights are similar for other age groups.

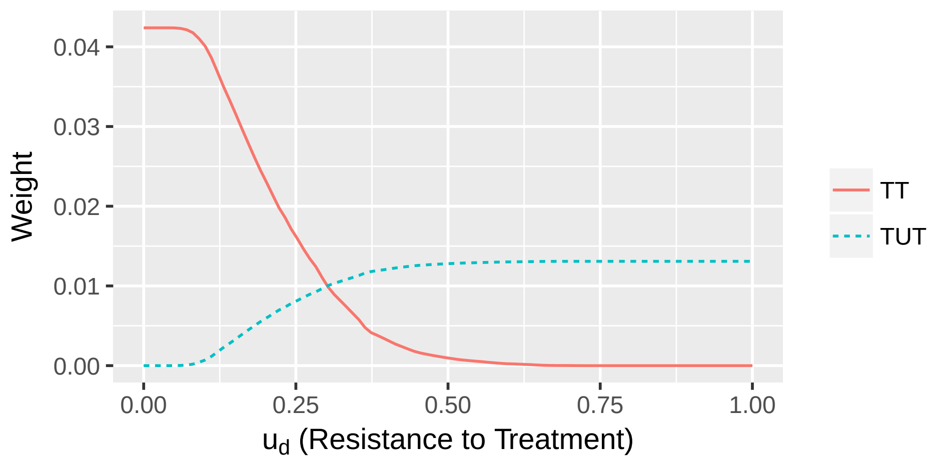

Figure 5: Weights for Treatment Effects on the Treated and Untreated

Note: Weights for TT and TUT for mothers of children age 1.5 are presented. The details for weights are given in Appendix A.

Table 9 presents estimates for the aggregate treatment effect parameters. The ATE on mothers' work ranges from 0.481 to 0.703 and decreases with child's age. For all age groups, the TT on mothers' work is smaller than the TUT, which implies negative selection into treatment. This result is consistent with the upward-sloping MTE curves seen in Figure 3. The analysis here takes into account not only unobserved but also observed heterogeneity and hence gives a more complete picture of the relationship between the treatment effect and selection pattern.

The ATE on weekly hours of work is positive and significant and decreases with child's age, while the ATE on annual earnings is positive and significant, and increases with child's age. For all of these outcomes, the TT is smaller than the TUT, and the differences are statistically significant except for work hours when the child is at aged 3.5 years.

ATE on regular work is about three times greater than ATE on nonregular work, while they are both positive and significant. The TT is smaller than the TUT for both types of work. We find no effect on self-employment.

Table 9: Aggregate Treatment Effects

	Market Work			**Work Hours**		**Earnings**		**Reg. Work**	**Non-Reg. Work**	**Self-Empl.**
	Age 1.5	Age 2.5	Age 3.5	Age 2.5	Age 3.5	Age 1.5	Age 3.5	Age 1.5	Age 1.5	Age 1.5
ATE	0.703	0.588	0.481	27.842	20.014	1.640	1.921	0.503	0.163	-0.002
	(0.120)	(0.105)	(0.143)	(4.668)	(5.129)	(0.396)	(0.513)	(0.115)	(0.091)	(0.057)
TT	0.388	0.569	0.476	18.558	19.002	0.189	1.222	0.201	0.060	0.101
	(0.153)	(0.122)	(0.130)	(5.123)	(4.542)	(0.389)	(0.343)	(0.148)	(0.107)	(0.077)
TUT	0.800	0.597	0.484	32.139	20.606	2.077	2.325	0.596	0.195	-0.034
	(0.143)	(0.136)	(0.213)	(6.220)	(8.000)	(0.483)	(0.766)	(0.146)	(0.110)	(0.075)
TT - TUT	-0.411	-0.028	-0.008	-13.581	-1.605	-1.888	-1.103	-0.395	-0.136	0.135
	(0.193)	(0.169)	(0.250)	(7.682)	(9.658)	(0.560)	(0.815)	(0.210)	(0.143)	(0.116)

Note: Standard errors are in parenthesis and clustered at the region level. The ATE is the average treatment effect, TT is the treatment effect on the treated, and TUT is the treatment effect on the untreated.

8 Discussion

8.1 Robustness Checks

We examine the robustness of our main results from different perspectives. The first issue is policy endogeneity. Because our identification strategy is basically the difference-in-differences approach, the common trend assumption is the crucial identifying assumption. If the growth of the coverage rate is correlated with the region-specific trend in female labor force participation, our estimates are biased. The main specification tries to avoid this endogeneity bias by including the interactions of pre-reform region characteristics and year dummies, but unobserved region characteristics may still be correlated with the trend. We address this issue by allowing for a region-block-specific trend. Cities and provinces are grouped into one of seven region blocks based on their geographic locations. In a robustness check, we include the interactions of region-block dummies and year dummies as additional control variables. Under this specification, the identifying variation is a variation of the growth of the coverage rate within a region block.

The second issue is endogenous fertility. Our instrument is the coverage rate, which is a proxy for childcare availability. Childcare availability may affect fertility, and hence, the number of children, which is used to define the coverage rate. To avoid this concern about endogenous fertility, we use an alternative instrument given by the number of childcare slot per woman aged 20–44 years. Arguably, this instrument is more likely to be exogenous than the coverage rate.

The third issue is selective migration. If mothers with stronger labor market attachment move to a region where childcare is more readily available, our estimates are upwardly biased. To assess the extent of biases from selective migration, we estimate the model using the coverage rate and other regional characteristics at the province level, which is a more aggregated level than the preferred specification. Evidence from the Employment Structure Survey 2012 shows that 9.5% of mothers of children under 6 years old moved within the same city for childrearing and education in their last move, but only 1.4% moved from other provinces. Hence, we have much less concern about biases from selective migration in this alternative specification.

The fourth issue is the role of siblings. We do not include the number of siblings in the preferred specification, because fertility may be affected by the availability of childcare. However, if it is exogenous and relevant for childcare enrollment and/or mothers' labor supply, controlling for the number of siblings can reduce the size of the standard errors. Indeed, municipal governments prefer an application from a family in which an older sibling has already attended childcare. We estimate the propensity score and the outcome equations using a model that includes the numbers of younger and older siblings.

The fifth issue is concerned with the model for childcare enrollment. In our preferred specification, we use the coverage rate in the current year only, but childcare enrollment may also be affected by the coverage rates in previous years. This is because some children started childcare at an earlier age, and they can remain enrolled if they wish. The enrollment status of these children is not affected by the current coverage rate but by the coverage rates in previous years. Although leaving out the coverage rates in previous years does not bias our estimates, the estimates may become more precise by using these additional variables. We estimate the propensity score using a probit model augmented by the second-order polynomials of the coverage rates from age 0.5 years to the current age.

The sixth issue is the common support condition. In the preferred specification, observations are omitted if their propensity scores are outside the common support for both treated and untreated individuals, but we may have very few observations near the right tail, which may result in unstable estimates. For a robustness check, we omit observations with propensity scores that are above the 99th percentile of treated individuals.

The seventh and last issue is model specification. While we assume that the MTE changes linearly with the unobserved resistance to treatment u_D, this assumption may be restrictive. We allow for nonlinearity of the MTE curve by including polynomial terms up to the fourth order in the outcome equations.

We assess the sensitivity of our main results by comparing the estimates of the aggregate treatment effect parameters in the benchmark model with those of the alternative models. Table 10 reports the estimates for selected outcomes. Although statistical significance changes across specifications, our estimates are largely robust to the issues raised above with two exceptions. First, there is no difference between TT and TUT in specification (3) that accounts for inter-city migration. However, the standard error is very large so that we cannot exclude the possibility that TUT is greater than TT. Second, estimates are implausible and standard errors are large when the higher order terms of the propensity score are included in the local IV regression. The corresponding MTE curves are shown in Figures 8 and 9 in the appendix. Overall, our main results seem to be robust to policy endogeneity, the endogenous fertility, selective migration, and other model specification issues.[15]

8.2 Policy Simulations

Using the estimated model, we simulate childcare reforms that increase the coverage rate. These reforms do not change the distribution of the treatment effects, but their policy effects vary because different policies induce different individuals into treatment.

In the first simulation, we evaluate a policy that changes the coverage rate from 0.28 to 0.35, which corresponds to the change from 2002 to 2011. This simulation is useful for understanding

[15]The number of older siblings has a positive effect on childcare enrollment for children aged 1.5 years, but no effects for older children. The number of younger siblings has a negative effect for children of all ages.

Table 10: Robustness of The Main Results

	Baseline	(1) Region-Block Trends	(2) Endogenous Fertility	(3) Migration	(4) Siblings	(5) Lagged Cov. Rate	(6) Thick Common Support	(7) 3rd-Order	(8) 4th-Order
Market Work at Age 1.5									
ATE	0.703	0.749	0.678	0.692	0.606	0.691	0.796	1.568	0.720
	(0.120)	(0.182)	(0.123)	(0.184)	(0.107)	(0.107)	(0.160)	(0.485)	(1.563)
TT	0.388	0.414	0.463	0.697	0.259	0.375	0.437	0.258	0.378
	(0.153)	(0.150)	(0.169)	(0.290)	(0.146)	(0.160)	(0.169)	(0.224)	(0.321)
TUT	0.800	0.853	0.744	0.691	0.714	0.788	0.906	1.972	0.822
	(0.143)	(0.230)	(0.149)	(0.223)	(0.130)	(0.141)	(0.209)	(0.582)	(2.097)
TT-TUT	-0.411	-0.439	-0.281	0.006	-0.455	-0.413	-0.469	-1.714	-0.444
	(0.193)	(0.255)	(0.218)	(0.362)	(0.188)	(0.232)	(0.286)	(0.445)	(2.293)
Work Hours at Age 2.5									
ATE	27.842	27.597	22.518	37.625	41.949	27.322	33.359	27.717	25.462
	(4.668)	(4.222)	(4.010)	(5.081)	(3.360)	(4.436)	(5.310)	(6.472)	(10.417)
TT	18.558	17.745	13.158	34.908	22.396	16.720	23.667	29.148	20.556
	(5.123)	(5.778)	(5.244)	(4.750)	(5.097)	(5.733)	(6.686)	(6.941)	(10.493)
TUT	32.139	32.157	26.850	38.882	51.004	32.230	37.845	27.054	27.642
	(6.220)	(5.803)	(5.136)	(6.690)	(3.770)	(5.835)	(7.545)	(7.006)	(16.786)
TT-TUT	-13.581	-14.412	-13.692	-3.974	-28.608	-15.510	-14.178	2.094	-7.086
	(7.682)	(8.396)	(6.980)	(7.339)	(5.681)	(7.877)	(10.810)	(5.767)	(23.510)
Earnings at Age 1.5									
ATE	1.640	1.774	1.677	1.655	1.471	1.626	1.055	2.873	1.889
	(0.396)	(0.461)	(0.384)	(0.421)	(0.308)	(0.380)	(0.503)	(0.947)	(3.878)
TT	0.189	0.232	0.528	0.609	-0.061	0.154	-0.116	-0.536	0.015
	(0.389)	(0.441)	(0.446)	(0.497)	(0.331)	(0.387)	(0.432)	(0.556)	(0.755)
TUT	2.077	2.239	2.023	1.970	1.932	2.070	1.408	3.901	2.435
	(0.483)	(0.540)	(0.426)	(0.489)	(0.379)	(0.455)	(0.650)	(1.102)	(5.194)
TT-TUT	-1.888	-2.007	-1.495	-1.362	-1.993	-1.916	-1.524	-4.437	-2.420
	(0.560)	(0.552)	(0.460)	(0.592)	(0.481)	(0.523)	(0.812)	(0.796)	(5.725)

Note: Standard errors are in parenthesis and clustered at the region level. The ATE is the average treatment effect, TT is the treatment effect on the treated, and TUT is the treatment effect on the untreated. We show estimates of the preferred specification for convenience. In model (1), the interactions of region-block dummies and year dummies are included as additional control variables. See footnote 7 for names of region blocks. In model (2), the instrument is the number of childcare slots per women aged 20-44. In model (3), regional variables are aggregated to the province level. In model (4), the numbers of younger and older siblings are included. In model (5), the coverage rates in previous years since age 0.5 are also included in the set of instruments. In model (6), observations are omitted if their propensity scores are greater than the 99th percentile of the treated individuals. In models (7) and (8), up to the third and fourth order polynomials of the propensity score are included, respectively.

the effects of childcare expansion during this period. In the second simulation, the coverage rate is raised from the 2011 level (= 0.35) to 0.42. The size of the change in the coverage rate is the same as that in the first simulation. In the third simulation, the coverage rate is further increased from 0.42 to 0.82, which is the highest coverage rate in the sample.

Policies are evaluated by aggregating the MTE to the policy-relevant treatment effect (see Heckman and Vytlacil (2005)). Suppose that a new policy changes the propensity score for an individual i from p_i to p_i'. Let $\bar{p}$ and $\bar{p}'$ be the sample means of the propensity score in the baseline policy and a new policy, respectively. The policy-relevant treatment effect $PRTE$ is given by

$$PRTE = \frac{1}{N}\sum_{i}^{N}\frac{p_i' - p_i}{\bar{p}' - \bar{p}} MTE_i,$$

where N is the number of individuals in the sample, and MTE_i is the MTE for individual i. Details are provided in Appendix A.

The weights for the policy-relevant treatment effects are graphically presented in Figure 6. As the coverage rate increases from one policy to another, greater weight is given to individuals with a higher unobserved resistance to treatment u_D. This implies that individuals with a higher resistance to treatment are induced gradually into treatment, as childcare reforms progress.

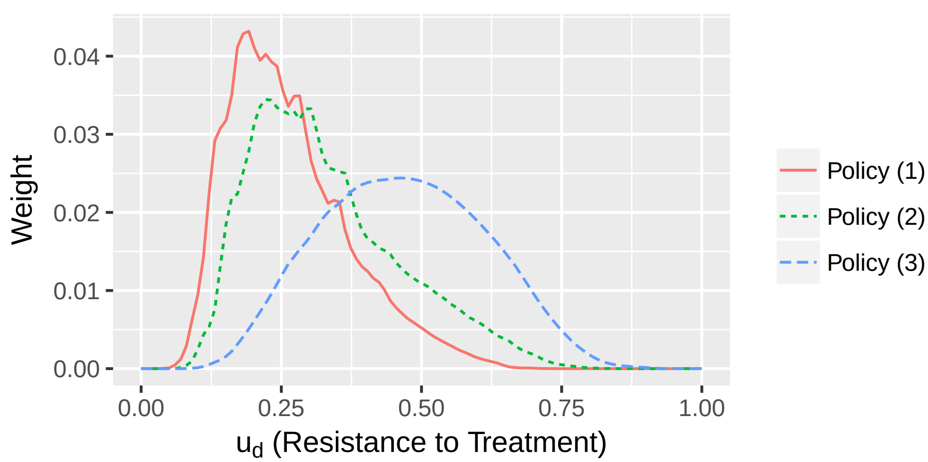

Figure 6: Weights for Policy-Relevant Treatment Effects
Note: In policy (1), the coverage rate is increased from 0.28 to 0.35. In policy (2), the coverage rate is increased from 0.35 to 0.42. In policy (3), the coverage rate is increased from 0.42 to 0.82.

Table 11 summarizes the results. The childcare expansion during 2002–2011 increased the coverage rate from 0.28 to 0.35, which eventually changed the childcare enrollment or propensity score from 0.214 to 0.257 for children aged 1.5 years. The corresponding policy-relevant treatment effects on mothers' work and earnings are 0.498 and 0.675, respectively. If the coverage rate continues to increase to the same extent from 0.35 to 0.42, the enrollment rate increases from

0.257 to 0.306. While the change in the enrollment rate is similar to that in the first simulation, the policy-relevant treatment effects on work and earnings are 0.554 and 0.959, respectively, which are greater than those in the first simulation.

A further childcare expansion has even stronger effects. Raising the coverage rate from 0.42 to 0.82 increases the enrollment rate to 0.633 for children aged 1.5 years, which is close to the enrollment rate for children aged 0–2 years in formal childcare in Denmark, where the participation rate is highest among the OECD countries (see NOSOSCO (2015)). The policy-relevant treatment effects of the third simulation are 0.675 for work and 1.514 for earnings, which are greater than those of the first two simulations.

The simulation results for children aged 2.5 and 3.5 years are also reported in Table 11. For both age groups, the simulated policies increase childcare enrollment, mothers' work, hours of work, and earnings. The policy-relevant treatment effects become stronger as the coverage rate increases.

Table 11: Counterfactual Simulations of Policies to Increase the Coverage Rate

	Propensity Score		**Policy-Relevant Treatment Effect**		
	Baseline	New Policy	Work	Hours	Earnings
Age 1.5					
(1) Raise Coverage Rate from 0.28 to 0.35	0.214	0.257	0.498		0.700
	(0.009)	(0.011)	(0.130)		(0.305)
(2) Raise Coverage Rate from 0.35 to 0.42	0.257	0.306	0.554		0.959
	(0.011)	(0.022)	(0.124)		(0.323)
(3) Raise Coverage Rate from 0.42 to 0.82	0.306	0.633	0.675		1.514
	(0.022)	(0.120)	(0.145)		(0.465)
Age 2.5					
(1) Raise Coverage Rate from 0.28 to 0.35	0.282	0.340	0.578	23.093	
	(0.013)	(0.015)	(0.081)	(4.010)	
(2) Raise Coverage Rate from 0.35 to 0.42	0.340	0.401	0.583	25.384	
	(0.015)	(0.021)	(0.078)	(4.042)	
(3) Raise Coverage Rate from 0.42 to 0.82	0.401	0.786	0.592	30.070	
	(0.021)	(0.061)	(0.108)	(5.665)	
Age 3.5					
(1) Raise Coverage Rate from 0.28 to 0.35	0.322	0.391	0.479	19.491	1.562
	(0.013)	(0.014)	(0.117)	(4.284)	(0.421)
(2) Raise Coverage Rate from 0.35 to 0.42	0.391	0.445	0.479	19.697	1.703
	(0.014)	(0.025)	(0.124)	(4.624)	(0.468)
(3) Raise Coverage Rate from 0.42 to 0.82	0.445	0.594	0.481	20.030	1.932
	(0.025)	(0.124)	(0.146)	(5.768)	(0.597)

Note: Standard errors are in parenthesis. They are calculated by bootstrap with 100 replications and clustered at the region level.

Overall, our simulations indicate that the policy-relevant treatment effects become stronger as childcare reforms progress. Mothers with weak labor market attachment would be strongly affected by the treatment, but they are unlikely to use a childcare center, because the rationing rule gives them a lower rank. As the coverage rate increases, mothers with weak labor force attachment gradually start to use a childcare center, which explains why the treatment effects become increasingly stronger. Our analysis suggests that the current rationing rule causes inefficient allocation of mothers' labor supply. Even if the government is unable to use a price mechanism because of political ideologies, not ranking applications by how much parents work may improve the efficacy of a childcare reform.

9 Conclusion

We estimate the MTE of childcare enrollment on mothers' labor market outcomes by exploiting regional variations in the growth of the childcare coverage rate. The demand for subsidized childcare exceeds the supply in many regions, and the local governments rank childcare applications by how much parents work in order to assign a childcare slot to families in need. Mothers' labor force attachment is a key determinant for a successful application, but it is not observed in the data. The MTE framework enables us to estimate variation in the treatment effects by unobserved propensity for treatment.

Our estimates indicate that mothers with stronger MTE are less likely to use childcare, whereas mothers with weaker MTE are more likely to find a childcare slot. The rationing rule prioritizes mothers with stronger labor market attachment, but they are likely to exert extra effort to find an alternative informal childcare arrangement if they are not given a childcare slot. Because these mothers are likely to work regardless of the availability of subsidized childcare, the treatment effects on these mothers are small. Mothers with weak labor market attachment are unlikely to work without subsidized childcare, which implies that the treatment effects on these mothers are strong. Regarding mothers' labor market outcomes, our analysis suggests that the current rationing rule may be inefficient.

We also find significant treatment effect heterogeneity by the child's age. The estimates show that the treatment effect on mothers' labor market outcomes decreases with the child's age, which is robust to alternative modeling assumptions. However, note that this result does not necessarily imply that a childcare slot should be assigned to mothers of infants, because infant care is particularly expensive.

The main limitation of this paper is that we have not identified an optimal rationing rule and only suggested a potential problem with the current rationing rule. An optimal rationing rule should take into account not only the mothers' labor market outcomes but also child development[16] and

[16] See Yamaguchi, Asai, and Kambayashi (2017).

other dimensions of family welfare in the long run. We leave this important research agenda for future work.

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A Treatment Parameters

We calculate treatment parameters following the method outlined by Cornelissen et al. (2016). Let x_i and p_i be a vector of control variables and the propensity score for family i. The unobserved component of the MTE is denoted by $K^{'}(u_D)$. The sample mean of the propensity score is $\bar{p} = 1/N\sum_{i=1}^{N} p_i$. The ATE, TT, and TUT are given by

$$
\begin{aligned}
\text{ATE} &= \frac{1}{N}\sum_{i=1}^{N} x_i(\beta_1 - \beta_0) + \int_0^1 K^{'}(u)du \\
\text{TT} &= \frac{1}{N}\sum_{i=1}^{N} \frac{p_i}{\bar{p}} x_i(\beta_1 - \beta_0) + \int_0^1 K^{'}(u) \cdot \frac{1/N\sum_{i=1}^{N} I(p_i > u)}{\bar{p}} du \\
\text{TUT} &= \frac{1}{N}\sum_{i=1}^{N} \frac{1-p_i}{1-\bar{p}} x_i(\beta_1 - \beta_0) + \int_0^1 K^{'}(u) \cdot \frac{1/N\sum_{i=1}^{N} I(p_i \leq u)}{1-\bar{p}} du.
\end{aligned}
$$

The integral can be easily calculated by discretizing the grid for u_D.

Denote the propensity score under the baseline policy by p_i and the propensity score under the alternative policy by $p_i^{'}$. The sample means of the propensity scores under these two policies are denoted by $\bar{p}$ and $\bar{p}^{'}$. The PRTE is given by

$$
\text{PRTE} = \frac{1}{N}\sum_{i=1}^{N} \frac{p_i^{'} - p_i}{\bar{p}' - \bar{p}} x_i(\beta_1 - \beta_0) + \int_0^1 K^{'}(u) \cdot \frac{1/N\sum_{i=1}^{N} I(p_i^{'} > u) - 1/N\sum_{i=1}^{N} I(p_i > u)}{\bar{p}' - \bar{p}} du.
$$

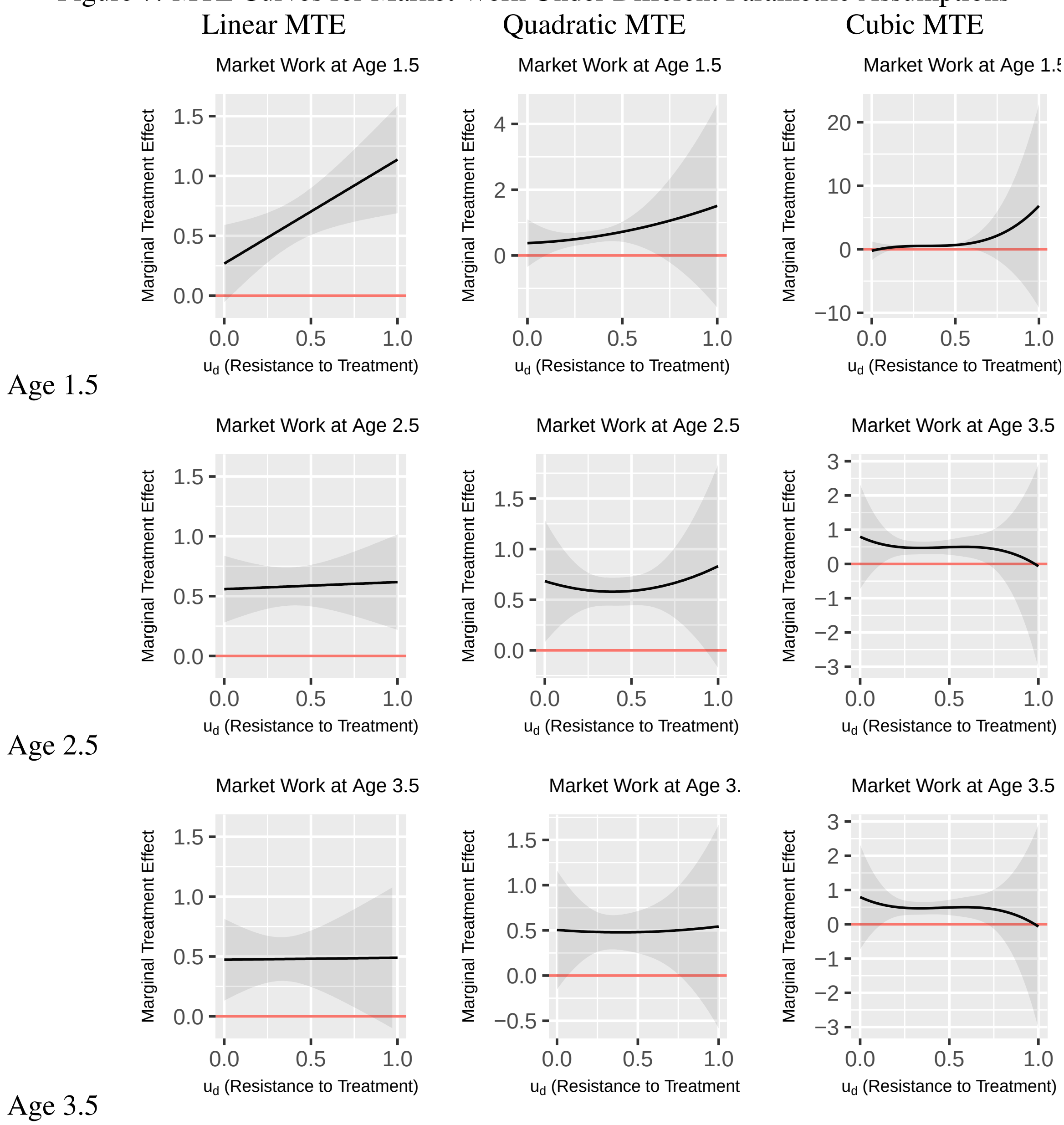
B Additional Tables and Figures

Table 12: The Average Marginal Effects of Coverage Rate on Childcare Enrollment

	Age 0.5	Age 1.5	Age 2.5	Age 3.5
Childcare Enrollment				
Mother's Age	0.001	0.002	0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Less Than HS (Mother)	-0.002	-0.096	-0.099	-0.075
	(0.004)	(0.008)	(0.010)	(0.010)
HS (Mother)	-0.007	-0.099	-0.105	-0.079
	(0.002)	(0.005)	(0.006)	(0.006)
2-Yr College (Mother)	-0.002	-0.056	-0.071	-0.058
	(0.002)	(0.005)	(0.005)	(0.005)
Father's Age	-0.000	-0.002	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Less Than HS (Father)	0.034	0.109	0.147	0.184
	(0.004)	(0.007)	(0.008)	(0.008)
HS (Father)	0.020	0.056	0.078	0.101
	(0.002)	(0.004)	(0.004)	(0.005)
2-Yr College (Father)	0.013	0.055	0.072	0.091
	(0.002)	(0.005)	(0.005)	(0.005)
Coverage Rate	0.138	0.595	0.795	0.973
	(0.062)	(0.130)	(0.137)	(0.135)
Mother's Work				
Mother's Age	0.003	0.004	0.004	0.005
	(0.000)	(0.001)	(0.001)	(0.001)
Less Than HS (Mother)	0.011	-0.143	-0.123	-0.070
	(0.007)	(0.009)	(0.010)	(0.011)
HS (Mother)	-0.014	-0.136	-0.119	-0.078
	(0.004)	(0.006)	(0.006)	(0.006)
2-Yr College (Mother)	-0.009	-0.083	-0.072	-0.054
	(0.004)	(0.005)	(0.005)	(0.005)
Father's Age	0.002	-0.001	-0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Less Than HS (Father)	0.111	0.160	0.183	0.223
	(0.006)	(0.008)	(0.008)	(0.008)
HS (Father)	0.059	0.093	0.111	0.127
	(0.003)	(0.004)	(0.005)	(0.005)
2-Yr College (Father)	0.059	0.092	0.099	0.116
	(0.004)	(0.005)	(0.005)	(0.006)
Coverage Rate	0.148	0.368	0.603	0.557
	(0.120)	(0.149)	(0.147)	(0.143)

Note: Unlike the preferred specification, the coverage rate (IV) is not interacted with other covariates in the first stage regression to estimate the propensity score. Standard errors are in parenthesis. Also see note for Table 5.

Figure 7: MTE Curves for Market Work Under Different Parametric Assumptions



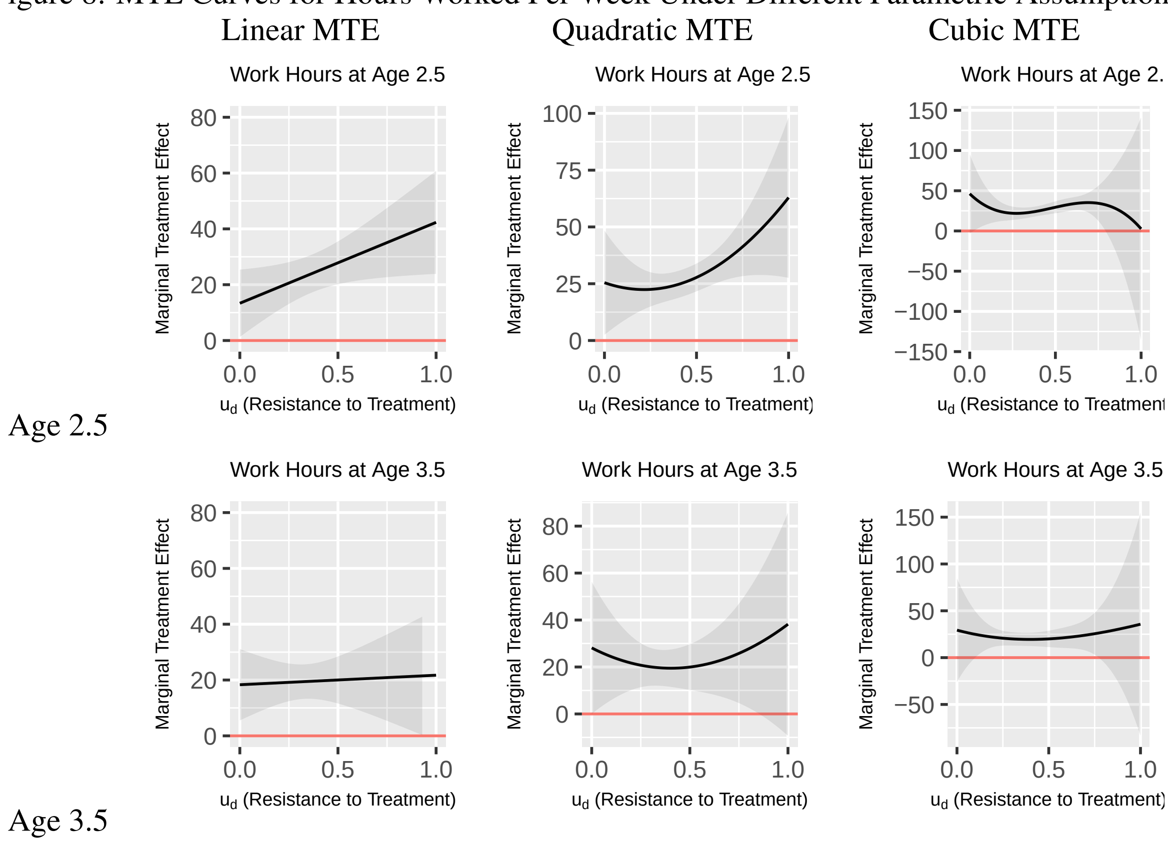
Note: The graphs show the MTE curves for mother's market work. The graphs in the first columns are estimated under the assumption that the MTE curves are linear. The graphs in the second and third columns are based on the assumption that the MTE curves are quadratic and cubic, respectively. The first row shows the results for mothers of children age 1.5. The second and third rows show results for mothers of children age 2.5 and 3.5, respectively.

Table 13: Support of The Propensity Score When The Instrument Is Not Interacted With Other Covariates

Age	**Control**		**Treated**		
	Min	Max	Min	99th Percentile	Max
Age 0.5	0.001	0.350	0.005	0.144	0.329
Age 1.5	0.036	0.723	0.049	0.522	0.762
Age 2.5	0.052	0.863	0.061	0.636	0.869
Age 3.5	0.057	0.858	0.059	0.679	0.889

Note: Unlike the preferred specification, the coverage rate (IV) is not interacted with other covariates in the first stage regression to estimate the propensity score.

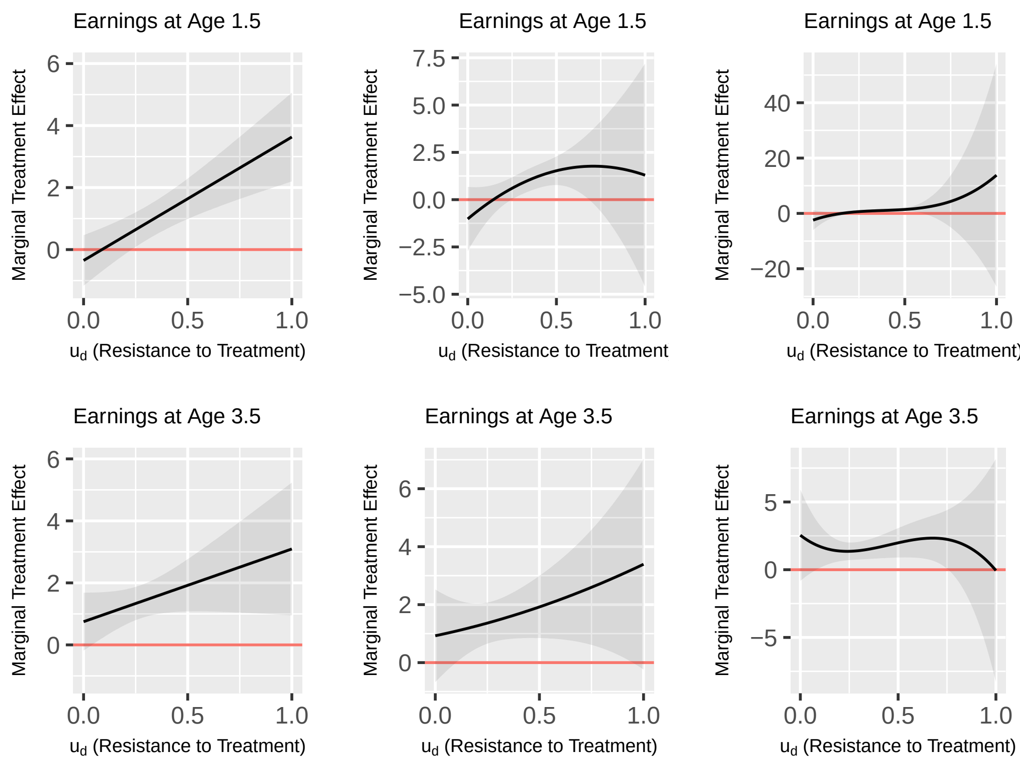
Figure 8: MTE Curves for Hours Worked Per Week Under Different Parametric Assumptions



Note: The graphs show the MTE curves for hours worked per week. The graphs in the first columns are estimated under the assumption that the MTE curves are linear. The graphs in the second and third columns are based on the assumption that the MTE curves are quadratic and cubic, respectively. The first and second row show the results for mothers of children age 2.5 and 3.5, respectively.

Figure 9: MTE Curves for Annual Earnings Under Different Parametric Assumptions

Linear MTE   Quadratic MTE   Cubic MTE



Age 1.5

Age 3.5

Note: The graphs show the MTE curves for hours worked per week. The graphs in the first columns are estimated under the assumption that the MTE curves are linear. The graphs in the second and third columns are based on the assumption that the MTE curves are quadratic and cubic, respectively. The first and second row show the results for mothers of children age 2.5 and 3.5, respectively.