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Childcare voucher and labour market behaviour: Experimental evidence from Finland.

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Abstract:

This paper provides experimental estimates of the impact of a voucher for private care within the Nordic system of universal provision of public care. The private childcare voucher acted as a significant boost for new childcare entrepreneurs to enter the market thus increasing the overall childcare provision in the municipalities participating in the experiment. In a market that was providing high-quality, low-cost public childcare, a voucher is nevertheless found to have a significant, positive effect for the use of private childcare with zero to negligible effects on the use of public care and labour force participation.

Keywords: Social experimentation, vouchers, childcare use, labour force participation

JEL Codes: H42, J2, J13

1. Introduction

Research on different ways of financing childcare is long overdue. Several European countries spend a large proportion of their GDP public childcare provision ranging from about 1 ½ per cent of GDP in Finland to 2 ¼ per cent of GDP in Denmark. However, the ageing population among other issues is putting a strain on the financing of all publicly subsidized welfare services. Bringing in elements of competition, for example, in the form of quasi-markets may increase the efficiency of the childcare market (Steuerle et al., 2000). This paper relies on an experimental setting to evaluate the impact of increased private provision due to a private childcare voucher on labour force participation and use of private and public childcare in a market that is already providing high-quality, low-cost public childcare.

Evidence points to the private childcare voucher resulting in an exogenous shift in the supply of private childcare places in the treated areas. The results indicate that the voucher for private care has a significant, positive effect (3-5 percentage points) for the use of private care, especially in areas that suffer from excess demand for childcare services (6-7 percentage points). Weak evidence points to increased labour force participation and use of public care, as well as increased private care use, within areas that initially reported excess demand for childcare.

The next section explains the voucher experiment in more detail while section 3 outlines the econometric method used in the analysis. Section 4 includes a description of the data. The results are presented in section 5 while section 6 concludes.

2. The Finnish voucher experiment

The childcare is provided by municipalities, which finance it through municipality taxes and contributions from the central government. However, the payment by the consumers of childcare only covers approximately 15% of the total cost of childcare[1]. The high level of public expenditure has led to pressures to enhance its effectiveness (Hemmings et al., 2003). The large public provision of childcare has led to an inefficient outcome where many municipalities suffer from excess demand while at the same time others experience excess supply according to the Finnish Ministry of Social Services and Health.

By the beginning of 1995, 33 municipalities, out of 450, reported wanting to take part in a voucher experiment for private childcare and all were accepted[2]. Out of the 33 participating municipalities, 13 were cities and half of the remaining participants were small municipalities of less than 10,000 inhabitants. Six municipalities are excluded from the analysis due to inconsistencies in their participation, for example, a few municipalities started the voucher experiment before others in 1994.

Each municipality pays a subsidy to the private childcare provider chosen by the family. The amount of the subsidy varies by municipality. The private childcare providers face the same laws regarding child-staff ratios and educational

[1] Users pay a means-tested fee, which is fixed by the municipality, of up to €168 per child (in 1998).

[2] 21 municipalities chose a means-tested voucher (€140-366/month/child for 0-2 year olds; €128-343/month/child for 3-6 year olds) while 12 municipalities gave out a lump-sum voucher (€304/month/child on average for 0-2 year olds; €263/month/child on average for 3-6 year olds).

requirements of the staff as publicly provided childcare and are regularly inspected by the municipality[3]. However, families choosing the voucher and using privately provided childcare, on average, and perhaps subjectively, valued the quality to be better than those using public care[4].

On average, the voucher cost €50 less per child per month than the publicly provided care. While the private care accounted for approximately 6% of all childcare provision, the average costs for the municipalities were only 1.5% of total childcare spending. The cost of private care provision is between 60% and 90% of the comparative public care.

Vouchers in general increase consumer choice, and hence increased consumer satisfaction, and may therefore lead to increased competition between providers (Steuerle et al., 2000)[5]. In fact, the private childcare voucher had a major boost on the supply of care; 22% of the private childcare entrepreneurs who were in operation in 1998 started operating at the start of the voucher experiment. Of the entrepreneurs that started their business during the experiment, 59% reported that the reason for starting was the private childcare voucher according to the Finnish Ministry of Social Services and Health. The experiment ended in 1997 and private childcare subsidy

[3] Average child/staff ratio is 4.2 in childcare centres and 2.8 in childminder care.

[4] The subjective quality is reported to be better in the private sector in terms of co-operation between the family and the childcare centre. Public care was considered especially good in terms of food, rest and safety.

[5] However, Besharov and Samari (2000) note the importance of calibrating the childcare voucher payments to the local market conditions to prevent subsidies meant for low-income families to benefit more affluent families or increasing profits for providers.

was adopted nationally. By 2002, a fifth of all childcare centres (approximately 3,000 in total) in Finland were private enterprises accounting for about 6% of all childcare places[6].

Overall, the universal public provision led to excess supply of childcare at the national level. Thus, our estimates provide a lower bound estimate for most countries where excess demand is experienced nationally. However, many municipalities in the experiment (including three in the capital region) experienced excess demand. Hence using this information we can also evaluate the impact of the voucher under the conditions of demand outstripping the supply of childcare services.

3. Econometric method

Exogenous variation induced by, for example, a policy change in the main explanatory variables is especially useful in situations in which the estimates are ordinarily biased by omitted variables or selection bias (Meyer, 1995). Studies based on experiments also avoid any strict behavioural assumptions.

To estimate the effect of the voucher on the use of childcare and labour force participation of mothers, I rely on propensity score matching, pairing mothers with similar observed characteristics in the treated and non-treated areas. Propensity score matching highlights the support problem in a way that is often overlooked in a regression analysis. The lack of common support may lead to biased estimates of the

[6] The Finnish Ministry of Social Services and Health interviewed municipality representatives after the experiment finished in 1997 and found that private childcare is available in 85% of the bigger municipalities (over 10,000 inhabitants) and 53% of the smaller municipalities (less than 10,000 inhabitants).

effect of the treatment on the treated (see Heckman et al., 1997 for details). Hence, it is crucial that the common support is as large as possible otherwise the matching is done on the tails of the two distributions i.e. matching individuals that are quite different than the rest of the population.

A primary assumption underlying matching is the conditional independence assumption (CIA), which states that the treatment status is random conditional on a set of observable characteristics *X*. The CIA will be satisfied if *X* includes all of the variables that affect both participation and outcomes (see, for example, Rosenbaum and Rubin, 1983). Rather than matching on *X* it is equivalent to match on *P(X)*, thus avoiding the problem of dimensionality.

All matching estimators can be written as follows:

$$\hat{E}(Y_0 \mid \hat{P}(X_i)) = \sum_{j=1}^{J} w(\hat{P}(X_i), \hat{P}(X_j))Y_{0j} \tag{1}$$

,where subscript *i* denotes treated individuals and *j* indexes the untreated comparison group observations. The matching estimator constructs an estimate of the unobserved counterfactual for each treated observation by taking a weighted average of the outcomes of the untreated observations. The difference between the various matching estimators lies in the type of weighting placed on the *j*th observation in constructing a counterfactual for the *i*th treated observation.

This paper uses two alternative matching estimators: the nearest neighbour estimator and the Epanechnikov kernel matching estimator. The nearest neighbour matching estimator assigns the weight of 1 to the comparison observation with the closest propensity score to each treated observation and 0 to all other observations[7]. The nearest neighbour estimator does not impose a support condition but instead constructs a counterfactual for every treated observation no matter how large the distance is to the propensity score of the nearest comparison group observation. Hence, to overcome this potential problem, the nearest neighbour estimator is combined with a caliper. A caliper defines an interval around each treated unit within which the propensity score of a control individual should lie for it to be included in the estimation. The nearest neighbour matching in this paper is done with replacement[8].

Rather than relying on a single control, it is possible to construct a synthetic individual based on a group of control individuals. The weight attached to each control is given by a kernel. The kernel matching potentially assigns a non-zero weight to several observations in the comparison group in constructing the counterfactual for each treated observation[9].

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[7] The weighting for the nearest neighbour matching estimator takes the following form:

$$w(\hat{P}(X_i), \hat{P}(X_j)) = \begin{cases} 1 & if \quad j = \arg\min_{k \in \{D=0\}} \{|P(X_i) - P(X_k)|\} \\ 0 & otherwise \end{cases} \qquad (2)$$

[8] Matching without replacement keeps variance low at the cost of potential bias while matching with replacement keeps bias low at the cost of larger variance.

[9] The standard form for the weighting function is given by:

$$w(\hat{P}(X_i), \hat{P}(X_j)) = \frac{K\left[\dfrac{\hat{P}(X_i) - \hat{P}(X_k)}{a_n}\right]}{\sum_{k \in \{D=0\}} K\left[\dfrac{\hat{P}(X_i) - \hat{P}(X_k)}{a_n}\right]} \qquad (3)$$

where *K(.)* is a kernel function and a_n is a bandwidth. This paper uses the Epanechnikov kernel which takes the following form:

Asymptotically, all the matching estimators produce the same estimate because they all end up comparing only exact matches. However, in finite samples, different matching estimators produce different results because of the variation in the weighting (see Dehejia and Wahba, 2002 for details)[10].

A further threat to the validity of the estimates results from the fact that the experiment determines partial equilibrium effects. In other words, the impact of the treatment is estimated when only a proportion of the population is treated. The following estimation assumes no general equilibrium effects i.e. that the persons outside the experimental treatment area are not affected by the treatment. In the statistics literature this assumption is called the stable unit treatment value assumption (SUTVA). The results may be different when the full population is treated, however, this issue is not dealt with in this paper.

4. Data description

The estimation uses data from the Income Distribution Survey[11] (referred to as IDS from hereon) from 1994 until 1997. The IDS is a rotating panel survey interviewing 10,000 households per year. Each household is interviewed for two consecutive years. The interview data is linked with data from administrative

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$$K(\psi) = \begin{cases} \frac{3}{4}(1-\psi^2) & if \quad |\psi| < 1 \\ 0 & otherwise \end{cases} \tag{4}$$

[10] The choice of the matching estimator depends on the data. For many and evenly distributed comparison observations, the multiple nearest neighbour provides the best estimates while for many and asymmetrically distributed comparison observations kernel matching may be the best choice. Local linear matching should be used when there are many observations with the propensity score near zero or one.

[11] Tulonjakotilasto in Finnish.

registers, for example, on income and subsidies. All the data are provided on an annual basis, for example, employment participation is reported as months per year.

The information on the municipality of residence is not released in the IDS due to confidentiality reasons. Instead Statistics Finland has, on request, created dummies to identify the experimental regions including any variation in the type of voucher.

The childcare voucher experiment was administered between 1.3.1995 and 31.7.1997. Hence the pre-treatment period is 1994. The experiment began on 1.3.1995 hence the first two months of the year are not affected by the experiment. Similarly, in 1997 the last five months of the year are not affected by the experiment. However, this should not affect the estimation results and any bias resulting from the time frame should reduce the coefficient estimates.

[TABLE 1 ABOUT HERE]

The estimating sample includes all the mothers with pre-school age children (aged 0-6) who are married or cohabiting and whose partner works[12] (see Table 1 for details). Some regions were dropped from the sample because they do not represent either the control or the treatment region, for example, in some cases the private childcare voucher was used prior to the start of the experiment. Single mothers are not used in the analysis because of the small sample sizes, especially for the treatment region. The unit of observation is a pre-school age child, hence each mother observation is weighted by the number of pre-school age children. The standard errors are corrected to account for clustering at individual level The sample size for 1994-97, inclusive, is 6,651, of which 2,618 are mothers of 0-2 year old

[12] Non-employed fathers are dropped from the analysis because of the requirement to work in one type of voucher.

children and 4,033 are mothers of 3-6 year old children. The sample used in the analysis further drops 1,525 observations from the pre-experiment period (1994).

[TABLE 2 ABOUT HERE]

Table 2 reports the summary statistics separately for the control region *G=0* and the treatment region *G=1* prior to the start of the experiment (1994). Column 3 of Table 2 reports the results of a test for differences in the means between the control and the treatment region. There are no significant differences in the working status of the control and treatment region, however, the use of private and public childcare are 7 percentage points lower in the control region compared to the treated region before the start of the experiment. Another significant difference between the control and the treatment region is the level of unemployment, which is almost 6 percentage points higher in the control region[13]. Significant difference exists also for the size of the household.

There are significant differences in the level of education between the control and the treated region for both mothers and fathers of the pre-school age children. Mothers are more likely to have finished their schooling at the baccalaureate level in the control region whereas, in the treated population, significantly more women have acquired at least a Masters degree. A similar trend is observed for fathers' level of education. Therefore on average the treated region is more educated. These differences are partly due to the fact that the capital region accounts for about 50% of

[13] Unemployment figures are included in the analysis since VATT estimates that 1% decrease in average unemployment rate increases the demand for childcare by 2,500 places.

the treated areas and that there is over 30 percentage point difference in the proportion of rural municipalities between the two groups.

Throughout the analysis, the main variables of interest are labour force participation, use of public care and use of private care (referred to as *LFP*, *PUB* and *PRIV*, respectively, from hereafter). Employment participation in the IDS is provided only as months worked per year. Similarly, the use of childcare is reported as months per year for each type of care. *LFP* takes the value 1 if the individual has worked at least one month a year either full-time, part-time or as an entrepreneur[14]. Similarly, the binary variables for *PUB* and *PRIV* take the value 1 for those who have used any public or private childcare services, respectively. Sensitivity analysis is conducted using six months and twelve months as the cut-off points, however, this has no significant impact on the results[15].

The family benefits and maternal and paternal leave are more generous for parents with children below three years old than for parents with older pre-school age children. Hence the consequent kink in the budget constraint motivates the examination separately for 0-2 and 3-6 year olds.

To account for the possible bias due to self-selection of municipalities into the treatment discussed in Section 3, we estimate the voucher effect with propensity score matching. The propensity score matching estimation uses information from the period of experimentation (1995-1997).

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[14] The share of part-time employees is only slightly higher than 10% among female employees and hence no difference between full-time and part-time employment is taken into account in the estimation.

[15] The results are available from the author upon request.

The matching methods include the nearest neighbour and the Epanechnikov kernel estimation with caliper/bandwidth values of 0.1, 0.01, and 0.005. The common support is examined both graphically and with appropriate test statistics.

The propensity score is estimated with a probit where the covariates are mother's and father's age and their level of education, interaction of mother's and father's age, the household size, age of the youngest child, number and age of pre-school children, age of the pre-school age child interacted with father's and mother's age, interaction between the number of pre-school age children and the age of the youngest child, father's earnings, father's earnings interacted with the size of household, father's trade union status and year dummies.

Finally, it is possible to identify three municipalities within the experiment region that suffer from excess demand for childcare[16]. Unfortunately, it is not possible to identify similar excess demand regions within the control area due to data confidentiality reasons.

5. Empirical results

The results for the whole country are reported in section 6.1 while section 6.2 presents the analysis for parts of the country that experienced excess demand for childcare prior to the start of the experiment.

[16] These municipalities are identified as suffering from excess demand for childcare by the Ministry for Social Affairs and Health in Finland in their publication "Lasten päivähoitoselvitys – syyskuu 1997".

5.1 Whole country

The propensity score matching estimates for the impact of the private childcare voucher experiment are presented in Table 3. The distribution of propensity scores is reported in Figure 1. The top histogram corresponds to the treated (*G=1*) group, while the bottom histogram corresponds to the control (*G=0*) group. In these histograms, each bin has a width of 0.05. Figure 1 shows that there is thick support providing strong identification throughout the distribution of propensity scores.

[FIGURE 1 ABOUT HERE]

Table 3 reports propensity score matching estimates of the impact of the private childcare voucher for the whole country. Nearest neighbour matches are reported with a caliper of 0.1, 0.01 and 0.005. Similarly, kernel estimates use a bandwidth of 0.1, 0.01 and 0.005. As indicators of match quality, the table reports the proportion of matched treated observations and, as an indicator of the thickness of the common support, the number of control observations accounting for 50% of the matches[17]. When a few controls are used several times, the precision of the estimates suffers (Abadie and Imbens, 2002). Standard errors are obtained by bootstrap with 100 replications.

[TABLE 3 ABOUT HERE]

None of the estimates for the younger age group are significant. On the other hand, for the older age group the use of private childcare has increased significantly as a result of the experiment. The nearest neighbour kernel gives a 3-4 percentage

[17] These statistics are reported for the nearest neighbour estimates only but they are the same for the Epanechnikov kernel estimates.

point increase for the use of private childcare, while using the Epanechnikov kernel the impact increases to up to 5 percentage points. Even the nearest neighbour estimates with a caliper of 0.005 results in over 95% of common support with 176 observations accounting for 50% of the matches.

The estimates for *LFP* and *PUB* are not significantly different from zero, hence the new entrants to private care were previously using informal childcare while being employed.

5.2 Areas of excess demand

Municipalities that experience excess demand for childcare are expected to exhibit a zero or a positive impact of the voucher on the labour force participation. The former result would occur if new users had moved from informal care use to private care customers whereas in the latter case the private childcare voucher would release previously non-employed mothers to work. In the data it is possible to identify three municipalities within the experiment region that experienced excess demand for childcare prior to the voucher experiment. The following analysis includes these three municipalities as the treated while the non-experimental municipalities provide a control group.

[FIGURE 2 ABOUT HERE]

The results in Table 4 give the impact of the private childcare voucher on *LFP*, *PUB* and *PRIV* of the treated group in the areas that experienced excess demand for childcare. The results are reported separately for the mothers of children aged between 0-2 and 3-6. The distributions of propensity scores are reported in Figure 2 and show somewhat less support at the right-hand tail of the distribution that the estimates for the whole country.

[TABLE 4 ABOUT HERE]

Similarly to the results for the whole country, the results for the 0-2 year olds are insignificant with respect to *LFP* or the use of either type of care. The impact on *PRIV* is substantial for the older age group with a significant increase in use of between 6-7 percentage points. The matching is not as good as for the whole country; the percentage matched drops to between 90-96% matched. However, as a proportion of the treated observations the support is thicker than previously although sample sizes go down considerably. A weak positive impact on *LFP* is also found with both sets of estimates ranging from 5-7 percentage points.

The estimates for the areas of excess demand also show the differences between the matching methods. With the Epanechinov kernel (*EK*), there is a trade-off between bias and precision and, as shown with the *EK* estimates, the variance overall is lower than for nearest neighbour.

Interestingly, *EK* provides significant positive estimates for the use of public care as a result of the private care voucher (8-10 percentage points). This finding supports Epple and Romano (1996), whose theoretical framework predicts that the combined public and private use of a good, such as childcare, will be higher under a “dual-provision regime” such as analyzed here, than under either alternative. However, the results for the whole country reported in Section 6.1 reject their prediction.

As an overall conclusion, the impact of the private care voucher is positive for the use of private childcare. The results regarding labour force participation and use of public care are more open to interpretation , however, weighing the pros and cons leads to less weak support for any impact on labour force participation and use of public care.

6. Conclusion

This paper provides experimental estimates on labour participation as well as public and private childcare use of a switch from a predominantly public childcare system to a quasi-market with a voucher for private childcare.

The main finding is that consumers reacted positively to the introduction of a private childcare voucher, moving from informal care use to customers of private childcare. The use of private care increased by 3 to 5 percentage points for older pre-school age children. None of the estimates are significant for the 0-2 age group. However, since the use of public childcare did not decrease concomitantly, this raises some doubts regarding the ability of the private provision to decrease the dead-weight losses associated with public care provision, at least in the short-run.

Most likely the increased use of private childcare relieved some previously unmet demand for childcare that the public sector could not provide, for example, increased flexibility. This conclusion is supported by findings for areas of the country that suffered from excess demand for childcare. In excess demand areas, the labour force participation increased by over 5 percentage points, while public and private childcare use increased by 5-9 percentage points each.

Interestingly, the combined public and private use of childcare is found to be higher under a "dual-provision regime" than under either alternative in areas with excess demand for childcare, but not in the whole country.

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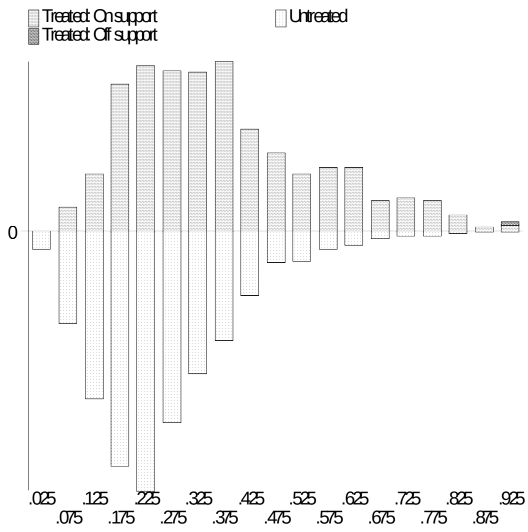
Figure 1: Distribution of propensity scores in whole country

0-2 year olds



3-6 year olds

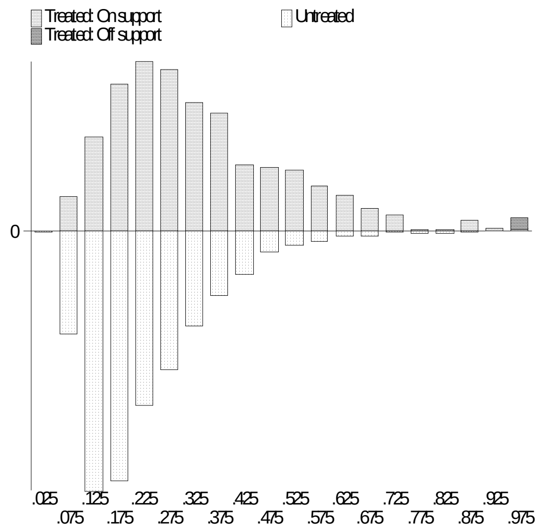
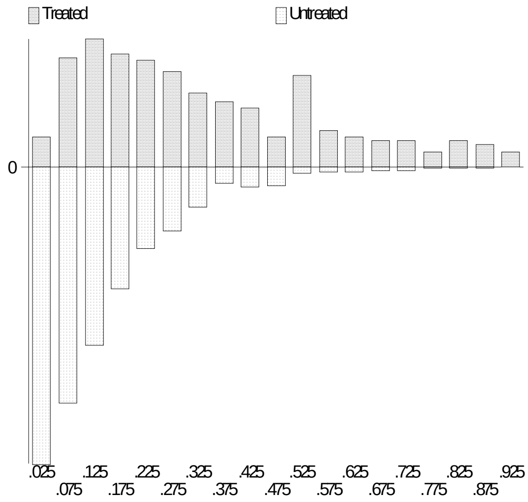


Figure 2: Distribution of propensity scores in areas of excess demand

0-2 year olds



3-6 year olds

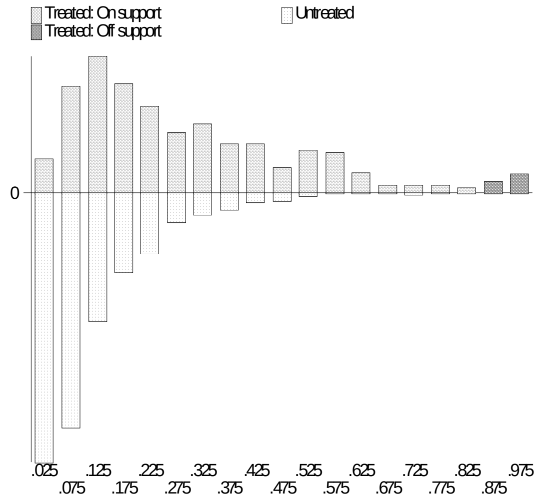


Table 1: Sample derivation (1994-97)

	Number of observations
Original 1994-97 data	29,083
Drop voucher problem regions	27,676
Drop households without 0-6 year olds	20,427
Drop men and children	5,904
Drop single parents	4,511
Drop if father not employed	4,355
Drop 1994	1,525
Expand data by child aged 0-6	5,126

Table 2: Pre-experiment summary statistics (1994)

	Control G=0		*Treated G=1*	*Difference*
LFP	0.692	(0.462)	0.665 (0.473)	
PUB	0.347	(0.476)	0.417 (0.494)	**
PRIV	0.038	(0.191)	0.115 (0.320)	***
Age	32.605	(4.874)	32.977 (4.563)	**
Dad's age	35.622	(5.476)	34.900 (5.118)	
No. of children <7	1.838	(0.870)	1.772 (0.673)	
Age of youngest child	2.200	(1.867)	2.223 (1.789)	
Size of household	4.613	(1.375)	4.297 (1.017)	***
Mother's schooling				
Compulsory school	0.106	(0.308)	0.102 (0.303)	
Baccalaureate	0.450	(0.465)	0.366 (0.482)	**
Baccalaureate plus vocational	0.316	(0.465)	0.309 (0.463)	
Bachelors	0.048	(0.213)	0.046 (0.210)	
Masters and above	0.081	(0.270)	0.177 (0.375)	***
Father's schooling				
Compulsory school	0.181	(0.385)	0.118 (0.323)	***
Baccalaureate	0.485	(0.500)	0.348 (0.476)	***
Baccalaureate plus vocational	0.165	(0.371)	0.156 (0.378)	
Bachelors	0.065	(0.247)	0.100 (0.310)	**
Masters and above	0.104	(0.303)	0.279 (0.415)	***
Capital region	0.001	(0.030)	0.499 (0.501)	***
Cities	0.373	(0.484)	0.274 (0.446)	***
Densely populated municipalities	0.194	(0.396)	0.120 (0.326)	***
Rural municipalities	0.432	(0.496)	0.107 (0.310)	***
Unemployment rate	0.213	(0.047)	0.158 (0.050)	***
Number of observations	1,134		391	

Note: Standard deviations in parenthesis. *** denotes significance at 1% level, ** at 5% level and * at 10% level of significance.

Table 3: Propensity score matching estimates for whole country (1995-97)

	LFP		*PUB*		*PRIV*		
	Age 0-2	*Age 3-6*	*Age 0-2*	*Age 3-6*	*Age 0-2*	*Age3-6*	
NN 0.1	-0.012	-0.006	0.028	0.003	0.019	0.043	**
	(0.036)	(0.026)	(0.035)	(0.036)	(0.015)	(0.019)	
	[99.83]	[99.24]	[99.83]	[99.24]	[99.83]	[99.24]	
	{104}	{164}	{104}	{164}	{104}	{164}	
NN 0.01	-0.012	-0.006	0.021	0.009	0.018	0.039	**
	(0.038)	(0.026)	(0.034)	(0.035)	(0.015)	(0.018)	
	[97.24]	[97.72]	[97.24]	[97.72]	[97.24]	[97.72]	
	{108}	{170}	{108}	{170}	{108}	{170}	
NN 0.005	-0.011	-0.011	0.018	0.013	0.018	0.030	*
	(0.039)	(0.026)	(0.033)	(0.034)	(0.015)	(0.018)	
	[95.17]	[95.82]	[95.17]	[95.82]	[95.17]	[95.82]	
	{108}	{176}	{108}	{176}	{108}	{176}	
EK 0.1	-0.009	-0.009	0.004	0.010	0.014	0.051	***
	(0.023)	(0.018)	(0.024)	(0.021)	(0.011)	(0.013)	
EK 0.01	-0.014	-0.008	0.005	0.003	0.005	0.050	***
	(0.025)	(0.020)	(0.025)	(0.021)	(0.012)	(0.015)	
EK 0.005	-0.012	-0.005	0.012	0.011	0.004	0.038	**
	(0.027)	(0.020)	(0.025)	(0.022)	(0.013)	(0.015)	
N	2,006	3,120	2,006	3,120	2,006	3,120	
T	580	790	580	790	580	790	

Note: LFP: labour force participation. PUB: use of public childcare. PRIV: use of private childcare. NN: nearest neighbour. EK: Epanechnikov kernel. N: number of observations. T: number of treated observations. Standard errors reported in parentheses. Standard errors obtained by bootstrapping (100 replications). *** denotes significance at 1% level, ** at 5% level and * at 10% level of significance. Percentage of treated observations matched to a control observation in square brackets. Number of control observations responsible for 50% of matches in curly brackets.

Table 4: Propensity score matching estimates for areas of excess demand (1995-97)

	LFP			*PUB*			*PRIV*		
	Age 0-2	*Age 3-6*		*Age 0-2*	*Age 3-6*		*Age 0-2*	*Age3-6*	
NN	-0.033	0.065	*	-0.030	0.063		0.000	0.073	***
0.1	(0.042)	(0.037)		(0.050)	(0.053)		(0.020)	(0.026)	
	[100.00]	[96.72]		[100.00]	[96.72]		[100.00]	[96.72]	
	{48}	{77}		{48}	{77}		{48}	{77}	
NN	-0.018	0.068	*	-0.011	0.070		-0.004	0.065	***
0.01	(0.045)	(0.038)		(0.043)	(0.051)		(0.022)	(0.025)	
	[93.65]	[93.18]		[93.65]	[93.18]		[93.65]	[93.18]	
	{57}	{83}		{57}	{83}		{57}	{83}	
NN	-0.035	0.056		-0.019	0.073		-0.012	0.062	**
0.005	(0.048)	(0.039)		(0.040)	(0.051)		(0.024)	(0.026)	
	[86.29]	[89.39]		[86.29]	[89.39]		[86.29]	[89.39]	
	{64}	{89}		{64}	{89}		{64}	{89}	
EK	0.018	0.052	**	0.016	0.095	***	0.018	0.063	***
0.1	(0.027)	(0.025)		(0.039)	(0.030)		(0.014)	(0.021)	
EK	0.036	0.052	*	0.030	0.080	**	0.020	0.061	***
0.01	(0.032)	(0.029)		(0.038)	(0.032)		(0.015)	(0.019)	
EK	0.029	0.038		0.028	0.085	***	0.010	0.059	***
0.005	(0.035)	(0.027)		(0.036)	(0.030)		(0.017)	(0.020)	
N	1,721	2,718		1,721	2,718		1,721	2,718	
T	299	396		299	396		299	396	

Note: LFP: labour force participation. PUB: use of public childcare. PRIV: use of private childcare. NN: nearest neighbour. EK: Epanechnikov kernel. N: number of observations. T: number of treated observations. Standard errors reported in parentheses. Standard errors obtained by bootstrapping (100 replications). *** denotes significance at 1% level, ** at 5% level and * at 10% level of significance. Percentage of treated observations matched to a control observation in square brackets. Number of control observations responsible for 50% of matches in curly brackets.