Does Subsidized Childcare Matter for Maternal Labor Supply? A Policy-Relevant Cutoff-Based Estimate

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Abstract: We estimate the effect of subsidized childcare availability on Hungarian mothers' labor supply based on a discontinuity in kindergarten eligibility rules. The effect is identified at a child age when the mothers' participation rate is still lower compared to mothers with older children, thus lack of childcare is potentially a binding constraint and policy intervention may be effective. Our sampling methodology ensures that similar individuals are compared, and seasonal effects are corrected for using a combination of instrumental variables and difference in differences. The results show that, despite an otherwise unsupportive institutional setting, access to subsidized childcare increases maternal labor market participation by 18 percent compared to the 51.5% baseline rate. A comprehensive policy approach could therefore achieve even greater results.

Keywords: Subsidized Childcare, Maternal Labor Supply, Discontinuity, Cutoff, Instrumental Variables

JEL codes: H24, J13, J22

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I. Introduction

Encouraging the higher labor market participation of women, especially mothers of young children, is an important policy goal in most countries.[1] The possible range of policy tools is varied, but the recent consensus among policymakers is that the expansion of subsidized childcare is an important component.[2] To find the most effective mix of policies and forecast the benefits of investment in childcare expansion, it is important to estimate the impact of childcare on mothers' labor supply precisely. Previous empirical results of the relevant literature are ambiguous, with some pointing to a significant positive impact, and others finding no evidence of an effect. We add to this literature by applying one of the most credible empirical methodologies seen in recent studies in a setting that differs in some key aspects, highlighting the main reasons for these mixed results. We find evidence of a significant impact of childcare expansion on maternal labor supply (a) if the expansion pertains to children at a young enough age where maternal participation is still low relative to that of mothers with older children, and (b) despite other possibly constraining institutional factors, such as the low availability of flexible work forms or traditional cultural views of mothers' roles.

We utilize a discontinuity in the eligibility rules for subsidized kindergarten in Hungary to identify the effect of childcare on maternal labor supply. The eligibility of 3-year-olds depends on whether the child was born before or after the eligibility cutoff point, January 1st. We compare the labor market participation of mothers on the two sides of the cutoff point, using standard instrumental variables estimation (IV), where birthdate serves as an instrument for childcare availability. Due to data constraints, the windows defined around the cutoff are rather wide. The two groups may therefore differ not only in

[1] It is key to sustainable growth, lowering budget deficits, and gender equality (Bloom et al. 2009), demographic policy (Apps and Rees 2001), and satisfying increased skill demand (Krusell et al. 2000).
[2] In the US and Canada, universal subsidized pre-kindergarten was introduced in several places (Fitzpatrick 2010, Lefebvre and Merrigan 2008), and the EU set targets for increasing childcare availability (EU 2002).

childcare access, but also other child age-related aspects, mainly parental leave entitlement and separation preferences. By selecting our sample so that we compare mothers when their children are the same age, we disentangle the effect of childcare from these other factors that are related to child age, but do not vary by birthdate.

The wide windows also raise concerns of seasonality bias, as noted by Bound and Jaeger (1994).[3] To address this problem, a difference-in-differences (DID) model is estimated, based on comparison groups of mothers of 4-5-year-olds who are subject to the same seasonal effects, but no childcare effect. The results are robust in all specifications and suggest a significant positive impact: we find that if the fraction of children covered by subsidized childcare increased from 0 to 100% - i.e. if subsidized childcare became available to mothers who did not previously have access at all - their participation rate would increase by 9.5 percentage points, or 18 percent compared to the 51.5% baseline rate. Our study provides an intent-to-treat analysis, as it is the effect of an increase in childcare availability and not enrollment itself that is of first order relevance to policymaking.

The results of the numerous previous estimates available from various countries are mixed for two main reasons. First, they are sensitive to the estimation methods used; and second, the magnitude of the effect is highly dependent on the point of estimation in terms of the maternal labor market return process as a function of child age. Of the three main empirical approaches used in the literature, studies based on structural models have the advantage of being able to control for fertility and other types of selection biases. However, they usually utilize regional or time variation in childcare availability for identification, which makes them likely to be affected by omitted variable bias, and they are based on strict behavioral and distributional assumptions. Several of these studies support the existence of a negative effect of childcare costs on participation or employment (Lokshin, 2004; Borra, 2010; Kimmel, 1992; Connelly,

[3] In our case, the sampling design used means that the groups differ not only in season of birth of their children, but we also observe them in different seasons, leading to further seasonal differences that need to be controlled for.

1992; Haan and Wrohlich, 2011; Del Boca, 2002), while others find little or no significant effect (Chevalier and Viitanen, 2002; Chone, Le Blanc, and Robert-Bobee, 2003; Ribar, 1995).[4]

Studies using policy changes for identification require fewer assumptions and may eliminate the omitted variables bias, however, they are based on the crucial assumption that the policy change is exogenous, which is often a questionable. Some policy change-based studies find a significant positive impact (Baker, Gruber, and Milligan, 2008; Lefebvre and Merrigan, 2008; Hardoy and Schone, 2013), while others find none (Cascio, 2009; Lundin et al., 2008; Havnes and Mogstad, 2011). Baker et al. (2008) note that the estimated elasticities from policy change based studies (Berger and Black, 1992; Gelbach, 2002; Herbst, 2008; Cascio, 2009) are at the lower end of the range of estimates based on structural models.

Cutoff-based estimates (Gelbach 2002, Fitzpatrick 2010, Bauernschuster and Schlotter 2015) are relatively rare in the literature, nevertheless, they have the potential to measure the effect based on a truly exogenous variation in the availability of childcare. Cutoff-based methods need no stringent assumptions on exogeneity, only the existence of such a cutoff and data that allows for relatively small windows around the cutoff with a sufficient number of observations. The internal validity of these estimates is high; however, this comes at the cost of limited external validity, since they measure a local treatment effect. The local nature of the estimates may explain why the results of these studies is mixed: no effect was found when the effect is estimated at a child age when most mothers have already returned to work (Fitzpatrick 2010),[5] while the single recent cutoff-based analysis carried at a child age when mothers' participation rate is still low found a significant positive effect (Bauernschuster and Schlotter 2015).

[4] In line with our reasoning, previous surveys of this evidence note that the evidence from these studies varies because of differences in methodology and data, and also in the age of the children analyzed and cross-country differences in institutional and hard-to-observe preferential factors (Blau, 2003).

[5] Gelbach (2002) finds a significant impact at age 5, however, this result is likely biased by age-related effects as noted by Fitzpatrick (2010).

Our study fits into this narrow strand of cutoff-based estimations. We identify the effect of childcare availability at age 3 of children, when the participation of mothers in Hungary is still low: at our point of estimation, the participation rate is around 47%, as opposed to the 67% rate of mothers with older children.[6] Ideally, we would carry out a standard regression discontinuity (RD) analysis in the same fashion as is done in Fitzpatrick (2010), however, due to data limitations we have to tackle some issues in the analysis. Our results indicate that the estimates are robust to these issues, and in line with our expectation of a significant effect at an earlier point in the mothers' labor market return process.

Additionally, our analysis bears further policy relevance, as it is the first to measure the effect of subsidized childcare in an institutional framework that is relatively unsupportive of the reconciliation of family and work obligations. One of the most essential elements is that the attitude of the Hungarian population towards working mothers is rather traditional: the majority opposes the labor market participation of mothers with a young child.[7] Another vital institutional element, the availability of flexibility work forms, is also relatively low.[8] We find that childcare expansion can have a significant impact even under relatively unsupportive institutional conditions, however, our results also highlight that

[6] The studies using US data identify the effect at age 4-5 of the child, where the relevant employment percentages are 70 and 72%, respectively (Fitzpatrick 2010 and Bureau of labor Statistics).

[7] Blaskó (2011) found that the majority of Hungarians (56%) believe that it is wrong for a mothers to return to work prior to age 3 of the child, and 20% believe it is wrong prior to age 6. The International Social Survey Programme questionnaire in 2002 showed that 66.1% of Hungarian respondents felt that a preschool child is likely to suffer if his or her mother works, which is 15 percentage points above the average, the 6th highest among the 35 participating countries. Countries from Southern America (Brazil, Chile, Mexico), and Southern and Eastern Europe (Portugal, Bulgaria) belonged to the most traditional countries in this survey.

[8] 21.4% of Hungarians stated in the European Survey on Working Conditions in 2010 that the working hours do not fit well in with the family or social commitments outside work, Hungary ranked the 24th among the 35 participating European countries. EU Labour Force Survey data for 2010 shows that in Hungary, part-time jobs make up only 4.7% of all jobs.

interdependencies between childcare and these factors play a key role. Consequently, this study is informative to policymakers who need to take such non-supportive institutional factors into account.[9]

II. Institutional Framework

Figure 1 presents the participation rate of Hungarian mothers by the age of their youngest child. It shows a low rate prior to age 3, when kindergarten enrollment begins, followed by a sharp increase and levelling off around age 4. This steep rise in participation is also due to some other factors that change simultaneously with childcare availability around age 3 of the child: parental leave ends, and preferences regarding the separation of mothers from their children change.

[Figure 1 here]

State subsidized childcare availability improves significantly at age 3 of children. In general, nursery schools accept children between the ages of 5 months and 3 years, while kindergartens accept children from the age of 3 to 6.[10] Up to the age of 5, it is not compulsory for institutions to accept children or for parents to enroll them. Acceptance following age 3 is mainly determined by local availability. The rate of children covered by kindergartens is significantly higher (74.2% on average) than that covered by nursery schools (10.2% on average), with significant regional variation, as can be seen in Figure 2.

[Figure 2 here]

The kindergarten school year officially begins in September. The enrollment cutoff rule for subsidized kindergartens is the following: children who turn 3 before December 31 are able to enroll soon after their

[9] For instance, this is important in the EU, when considering how childcare targets (e.g. Barcelona target) will affect maternal labor supply in relatively traditional Eastern and Southern European countries, or in the US, when thinking about the effect of childcare availability on immigrants.

[10] This was the case during the period analyzed up to 2010. Eligibility rules have changed since then to allow younger children to enroll as well.

birthday, while those born after December 31 can only enroll in the following September.[11] Compliance with this rule is high, as is seen based on EU-SILC data on actual childcare usage and birthdates in Figure A1 of the Appendix. Mothers of children born prior to the cutoff wait a significantly shorter time on average to enroll their children in kindergarten than those of children born after January 1st.

Besides childcare availability, there are two further factors that change suddenly around age 3, and are therefore important to consider. The first is the flat-rate parental leave that can be received between the ages of 2 and 3 of children, the period of interest in our analysis.[12] One parent in every family is entitled to it, but the overwhelming majority (98.1%) is received by mothers. The amount of the parental leave subsidy is low (23.4% of the average female wage in 2008); nevertheless, it may still have an impact on the labor supply decision of mothers, especially for those with low expected wage. Furthermore, the end date of parental leave itself may be taken as an institutional signal by mothers regarding the appropriate time for returning to work. Second, preferences regarding separation from children change as they age, and, in the case of Hungary, a survey by Blaskó (2011) suggests that they change sharply at age 3.[13] Haskova et al. (2012) discuss the strong relationship between preferences and institutions, but for our purposes, the important aspect is that these are also child age-dependent factors that change suddenly around the analyzed age of 3, so mothers may differ significantly if their child is a few months older in terms of these labor supply determinants as well.

[11] Of the children of mothers in our treatment group (born before January 1st), those born prior to September 1st may enroll when the school year begins, while those born between September 1 and December 31 may enroll in September prior to their third birthday, or in a second enrollment wave in January. Control group mothers' children have to wait until September, when the next school year begins.

[12] Flat-rate parental leave is universal: it can be received by anyone, with high or low previous income, whether they were insured previously or not. The sum of this benefit equals the old-age pension minimum. Parental leave also provides basic health insurance and social security payments.

[13] The survey results show that the ratio of those believing that the child is old enough for the mother to return to work increases from 19.6% to 76% at the age of 3.

III. Data

The primary source of the data used in the analysis is the Hungarian Labor Force Survey (H-LFS). It is a rotating panel dataset, which consists of individual-level data on all members of the household, which is the unit of observation. Approximately 17% of the households are rotated in each quarter; the maximum length of observation time is 1.5 years. The sample is representative of Hungary; sample weights based on the data of the Hungarian Central Statistical Office (CSO) are used. Our estimation sample includes mothers with or without a partner, for the years 1998-2011. Throughout the analysis we refer to the age of the youngest child in the family as child age,[14] and include mothers with 1 or more children in our sample.

The dataset includes detailed demographic and labor market data about each individual. Our labor supply measure is the binary variable of labor market participation, which is based on the ILO definition of participation. Participation is a more direct measure of labor supply than employment, which is often used in other studies but is determined by labor demand as well, so we focus on the former. However, results using employment are presented as a robustness check. We include individual (age, schooling, occupation), family (number of children, husband's labor market status), and regional (settlement type, region, local unemployment) characteristics linked from the T-STAR regional dataset of the Hungarian Central Statistical Office as control variables (see Table A1 for the full list of variables).

[14] It is important to emphasize that we always examine the youngest child, as only mothers who do not have an even younger child are likely to be affected by subsidized childcare availability for their 3-year-old. It may occur that expectant mothers are also included in the sample, if the birth occurred after the last observation in our LFS data. These mothers most probably do not plan to return to the labor market, irrespective of childcare availability. However, this does not bias our results, as the probability of their inclusion is likely to be the same in the treatment and the control group.

Finally, the database has two drawbacks that need to be highlighted. First, the exact date of child birth is not available, we only know the quarter of birth.[15] As a result, relatively wide windows – of at least 3 months – must be defined around the cutoff for the estimation. As noted earlier, this leads to other child age-related differences among mothers in our groups that need to be addressed. Second, there is no data on actual enrollment to kindergarten, only coverage data at the local level. Since our main analysis focuses on the intent-to-treat effects of kindergarten availability, we use local coverage rates to help interpret the magnitude of the effect. For coverage rates, we rely on administrative data aggregated to small regional units.[16] We check the reliability of the administrative data with additional analysis based on data from the 2011 Hungarian census: the administrative childcare coverage data is indeed representative of the enrollment rates around the cutoff point.[17]

IV. Empirical methodology and results

IV.1. Sampling design and instrumental variables estimation

The basic idea of the cutoff-based methodology, inspired by Angrist and Krueger (1991), is to use the birthdate of the child to sort mothers into treatment and control groups. We compare mothers on the two sides of the cutoff when their children are around age 3, when 74.2% of those born before the cutoff date are covered by subsidized childcare (treatment), but this rate is only 10.2% for those on the other side of the cutoff (control). The treatment variable is defined as follows:

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[15] We know the quarter of birth, but use 5 month windows in our main analysis due to the low number of observations. The results are robust to this as shown later.

[16] Nursery (kindergarten) coverage rates are defined as the number of slots available in nursery (kindergarten) in each township, divided by the number of children of age 0-2.99 (3-5.99) in each township. Townships are merged based on data on commuting to childcare facilities (based on Kertesi et al. 2012), there are 530 of these.

[17] Using census data, we confirm that the local nursery and kindergarten enrollment rates (using the five month window around age 3) are comparable in magnitude to those used in our analysis.

$$T_i = \begin{cases} 1 \quad \text{if} \qquad 1^{\text{st}}\text{August} \leq \text{b}_\text{i} \leq 31^{\text{st}} \text{ December} \\ 0 \quad \text{if} \qquad 1^{\text{st}} \text{ January} \leq \text{b}_\text{i} \leq 31^{\text{st}}\text{May} \end{cases} \tag{1}$$

where b_i is the date of the third birthday of the youngest child, and January 1 is the cutoff date. In order for the estimated treatment effect to be unbiased, we need sorting into treatment to be random so that the groups differ inly in terms of treatment status.

By the standard argument of the regression-discontinuity design, the selection of mothers into the groups can be regarded random if the window around the cutoff is narrow enough: mothers of children born on December 31 can be assumed to be very similar to mothers of children born on January 1. Due to small sample sizes and imprecise data on birthdates, we define the groups as those with children born 5 months before and after the cutoff date. The wider windows around the cutoff mean that we need to consider certain possible sources of bias more carefully. As shown in the background section, not only does childcare availability increase suddenly around age 3, parental leave also ends, and the willingness to separate from the child appears to change sharply as well. These age-related changes can lead to significant differences between the groups, because the average age of children in the two groups differs significantly.[18]

In order to separate these other effects from the childcare effect, we define the estimation sample so that we include mothers in the treatment and control groups when their children are the same age, rather than observing them in a single cross-section of the data. We select mothers whose children were born between 1st August and 31st December into the treatment group, and observe them in the quarter after their children turn 3 (between the 1st of January and the 31st of March). We construct the control group similarly: with child birthdates between January 1st and May 31st, and observation dates the quarter after they turn 3 (1st of

[18] With 5- month windows, child age differs by an average of 5 months between the two groups at any single point in time, so the effects of these differences may be significant. For example, by the 1st of June, parental leave had ended an average of 7.5 months ago for treatment group mothers, and only 2.5 months ago for control group mothers. Preferences regarding separation from the child are also likely to change significantly during these 5 months around age 3 (Blaskó 2011).

June to the 31st of August). This sampling design ensures that child and therefore the effect of parental leave and separation preferences will be the same on average in the two groups.

[Table 1 here]

Descriptive statistics of key characteristics for the treatment and the control group are presented in Table 1 (the full set of variables can be seen in Appendix Table A1). We can see that the control characteristics do not differ significantly between the two groups. On the other hand, they do differ significantly in terms of the participation rate and the rate of children covered by subsidized childcare. The similarity of the other characteristics supports the assumption that selection into the groups based on the date of birth is indeed random. Figure 3 provides some preliminary evidence in the form of a graphical illustration of the treatment effect. It shows that the participation rates of the treatment and control mothers move together as their children grow older, except for a period following age 3, when the treated mothers' participation rate is higher for a while. This corresponds exactly to the period when they become eligible to subsidized kindergarten while the control group does not, suggesting that childcare availability positively impacts mothers' labor supply.

[Figure 3 here]

Table 1 and Figure 3 show the raw differences between the two groups. To confirm causality and estimate the effect more precisely, we turn to IV estimation where T is an instrument for childcare availability and also control for differences in various characteristics between the groups. We first estimate the reduced form regressions of the following form:

$$L_{yri} = \beta T_i + \alpha_y + \gamma_r + X'_{yri}\pi_1 + S'_{yr}\pi_2 + \xi_{yri} \qquad (2)$$

where subscripts indicate yearly (y), regional (r), and individual (i) variation, and L_{yri} is the participation dummy for individual i. The equation adjusts for a set of individual (X_{yri}) and regional covariates (S_{yr}), α_y represents year fixed effects, and γ_r region fixed effects.

The parameter β captures the effect of belonging to the treatment group on the probability of labor market participation. It can be interpreted as representing how much more active mothers are if they are eligible for kindergarten rather than nursery school, which has significantly lower coverage. Panel (a) of Table 2 shows the results. The estimates are significant at the 1% level in all three specifications. Year and regional fixed effects are controlled for in each specification, while demographic and regional control variables are added gradually. The estimate does not change significantly as controls are added, which again suggests that the control and treatment groups do not differ significantly in terms of their characteristics. Belonging to the treatment group – and therefore becoming eligible for kindergarten - increases the probability of labor market participation by 7.8-8.5 percentage points (around 16% compared to the 51.5% baseline rate) after the third birthday. Taking the national average childcare coverage rates and the participation rates for the treated and the control group into account, we can calculate the Wald estimator:

$$W = \frac{(L^S|T=1)-(L^S|T=0)}{(C|T=1)-(C|T=0)} \tag{3}$$

where C is childcare coverage. This gives $W = 0.128$, which means that, based on the reduced form estimates, increasing childcare coverage by 100 percentage points would cause a roughly 12.8 percentage point increase in female participation rate.

To refine this result, we apply a strategy similar to Angrist (1990) and supplement the database with administrative data on childcare coverage rates. We estimate the corresponding two-stage least squares (2SLS) regressions that take regional differences of coverage and participation rates into account. The first stage is:

$$C_{yri} = \beta_1 T_{yri} + \alpha_y + \gamma_r + X'_{yri}\pi_{11} + S'_{yr}\pi_{12} + \xi_{1yri} \tag{4}$$

where

$$C_{yri} \equiv p^n_{yr}(1 - T_{yri}) + p^k_{yr}T_{yri} \tag{5}$$

and p_{yr}^{n} is nursery school coverage and p_{yr}^{k} is kindergarten coverage in township r and year y. C_{yri} is the regionally aggregated childcare coverage in township r and year y for the relevant treatment group. Equation (5) shows that each individual is assigned the relevant regional nursery school coverage if the individual belongs to the control group and the relevant regional kindergarten coverage if the individual belongs to the treatment group. Equation (4) also includes a set of individual ($\mathrm{X_i}$) and regional covariates ($\mathrm{S_{yr}}$), α_y represents year fixed effects, and γ_r region fixed effects.

The second stage regression is then given by:

$$L_{yri} = \beta_2 \widehat{C_{yri}} m_{yri} + \alpha_y + \gamma_r + X'_{yri}\pi_{21} + S'_{yr}\pi_{22} + \pi_{23}\widehat{C_{yri}} + \pi_{24} m_{yri} + \xi_{2yri} \quad (6)$$

where $\widehat{\mathrm{C_{yri}}}$ represent the fitted values of $\mathrm{C_{yri}}$ from the first stage regression. In this setup, the parameter β_1 in the first-stage reflects how much group membership determines childcare availability. The parameter β_2 in the second stage is the main parameter of interest: it shows the estimated effect of childcare availability on labor supply. The 2SLS results presented in Table 2 panel (b)[19] indicate a similar significant positive effect as calculated using the Wald estimator: in the third specification, with all controls included, the coefficient estimate is 0.135, suggesting that the effect of increasing childcare coverage by 100 percentage points is a 13.5 percentage point increase in maternal participation.

[Table 2 here]

IV.2. Seasonality bias and difference-in-differences

In the setup presented in the previous section, the treatment and the control groups differ notably in terms of both their dates of birth and of observation, which may introduce seasonal bias of various forms. First,

[19] The first stage results (Eq. (4)) are reported in Table A2.

Bound and Jaeger (1996) argue that quarter of birth may be associated with various individual characteristics. They cite Kestenbaum (1987), who find that parents with higher incomes tend to have spring babies. Second, child development may differ by season of birth, which may influence the mother's willingness to separate from the child. For instance, Currie and Schwandt (2013) show that even after controlling for maternal characteristics, health status and weight at birth depend on the season of birth. The third possible bias is related to the different dates of observation in our sampling design: labor demand varies seasonally as well, which affects the actual and expected probability of employment, and thereby, the labor supply of mothers.

In order to ensure that we measure the effect of childcare availability but not that of these seasonal factors, we expand the sample with reasonably close labor market substitutes: mothers of children aged 4-5 years (separated into two groups based on the same cutoff date), and run a difference in differences (DID) regression. 4-5 year old children already have access to kindergarten, irrespective of their birth date, so these comparison groups should be affected by the same seasonal effects, but not the treatment effect, allowing us to separate out seasonal factors.[20] Any difference between the two groups of mothers with 4-5 year olds should be the result of the seasonal factors mentioned above. We construct a variable indicating the original and the comparison sample:

$$m_{yri} = \begin{cases} 1 & if\ 3 \leq a_{yri} < 4 \\ 0 & if\ 4 \leq a_{yri} < 6 \end{cases} \tag{7}$$

where a_{yri} indicates the age of the youngest child.

We then run the following reduced form regression:

$$L_{yri} = \beta^s T_{yri} m_{yri} + \alpha_y + \gamma_r + X'_{yri}\pi_1 + S'_{yr}\pi_2 + \pi_3 T_{yri} + \pi_4 m_{yri} + \xi_{yri} \tag{8}$$

[20] Alternatively, we also used mothers of 2 year olds as the comparison group, with similar results. According to our calculations (regressions with season dummies), the seasonal effects suffered by the different age groups are similar. The regarding tests are available upon request.

where the estimated effect of treatment, corrected for seasonality, is given by β^s, the coefficient of the interaction term. The corresponding 2SLS equations are the following:

$$C_{yri} = \beta_1 T_{yri} m_{yri} + \alpha_y + \gamma_r + X'_{yri}\pi_{11} + S'_{yr}\pi_{12} + \pi_{13} T_{yri} + \pi_{14} m_{yri} + \xi_{1yri} \quad (9)$$

where equation (5) also applies, and the second stage is:

$$L_{yri} = \beta_2 \widehat{C_{yri}} m_{yri} + \alpha_y + \gamma_r + X'_{yri}\pi_{21} + S'_{yr}\pi_{22} + \pi_{23}\widehat{C_{yri}} + \pi_{24} m_{yri} + \xi_{2yri} \quad (10)$$

The seasonality corrected results are reported in Table 3. The estimates decrease by 2.2 percentage points to around 0.06 in the reduced form (panel (a)), and by 4 percentage points to 0.095 in the 2SLS specification (panel (b)) after correcting for seasonality bias compared to the baseline estimates reported in Table 2. This suggests that some seasonal bias is indeed be present, as the magnitude of the effect is somewhat affected by the correction. The estimate is still significant and positive, and highly robust to the inclusion of control variables. Our preferred estimate therefore suggests that a 100 percentage point increase in childcare availability leads to a 9.5 percentage point, or 18% increase in maternal participation.

[Table 3 here]

IV.3. Robustness and long-term effects

We now turn to various tests to evaluate the robustness of the results and the length of the effect on maternal labor supply. A key assumption for DID estimation is that the participation probability in treatment and control group would follow the same time trend in the absence of the treatment. This parallel trends assumption can be tested by running regressions with various placebo cutoffs before January 1st, the actual cutoff date. We use 1st November and 1st September as placebo cutoffs, and find that the estimated effect is insignificant, thus the assumption is likely to hold. The reduced form results without seasonal correction are reported in Table A3.

As a check that the results are robust and meaningful and to evaluate long-term effects, we carry out the reduced form estimation at each child age from 1 to 7 years using the January 1st cutoff. Table 4 summarizes the results. They indicate the significant effect estimated so far at age 3, but no significant effects at any other age. These findings are in line with what we observe in Figure 3: there is no significant difference between the groups – i.e. no birthdate-related effects – apart from what we measured at age 3 due to the difference in kindergarten eligibility. The effect of treatment is not long-term, as by age 4 there is no significant difference between the groups. However, the difference in access to childcare availability is also relatively brief, only 5.5 months on average, since even control group mothers are able to apply for kindergarten in September. The results therefore suggest that the short-run constraint that lack of childcare poses does not lead to further disadvantages beyond the direct effect on labor supply.

[Table 4 here]

Next, we narrow the birthdate windows around the cutoff from 5 to 4 months[21] and 3 months.[22] The results are shown in Table A4. The estimates are of similar pattern and magnitude as those presented with 5 month windows; however, as the sample size decreases, their significance decreases gradually. Estimates of the childcare effect based on 4-month windows have a p-value of around 0.1, near the border of significance, while those of the estimates based on 3-month windows are around 0.11 and just below significance.

Finally, we test whether the childcare effect is still significant if we use employment as the dependent variable instead of participation. Many previous studies measure the effect on employment, however, since our aim is to measure labor supply cleared from the effect of labor demand, our preferred dependent

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[21] Treatment mothers: child born between September and December, control mothers: child born between January and April.

[22] Treatment mothers: child born between October and December, control mothers: child born between January and March.

variable is labor market participation. We run the same specifications based on the employment measure as well, with the results shown in Table A5. The results also show a significant positive impact that is robust to the specification of controls: the coefficient estimate of C*m (childcare coverage) is around 0.08 when the seasonality correction is included. This suggests that the impact on employment is very similar to what we measure using participation, allowing our results can be directly compared to previous studies that used employment as the labor supply measure.

V. Conclusion

In this study, we provide a causal estimate of the effect of subsidized childcare availability on maternal labor supply. We analyze the case of mothers of 3-year-olds in Hungary, who are much more likely to be able to enroll their children in subsidized childcare if they turn 3 before the 1st of January. The applied estimation technique overcomes some estimation issues (endogeneity of childcare availability, data issues that affect the windows around the cutoff, and concurrent child age-related changes), and provides evidence that the findings of a significant positive impact are robust to corrections for these.

Our results suggest that if childcare opportunities are expanded at a child age when mothers' labor market participation is still relatively low compared to that of mothers with older children such a policy intervention can have a significant positive effect. The results show that a 100 percentage point increase in availability can increase maternal participation by 9.5 percentage points, or 18% compared to the 51.5% baseline. Our analysis focuses on intent-to-treat analysis, which allows us to make relevant predictions regarding the expected impact of investments in the expansion of subsidized childcare: we study the effect of childcare availability, not that of usage. The evidence suggests that subsidized childcare availability impacts maternal labor supply, though to a lesser extent compared to countries with institutions that better facilitate the reconciliation of family and work obligations. The estimates of Bauernschuster and Schlotter (2015) – using a very similar methodology on German data - suggest that a more supportive environment[23] results in significantly larger labor supply effects: they find that access to subsidized childcare increases the maternal labor supply by 35 percentage points.

The effectiveness of childcare expansion may be limited by several factors, such as the characteristics of maternity and parental benefits, the lack of flexible work forms, traditional societal views, or the inflexibility of childcare hours.[24] Our analysis also shows that these have a large impact. When children are around age 3, the sharp increase in mothers' participation rate is around 31 percentage points, of which, according to our estimates, increased childcare availability explains 9.5 percentage points, roughly one third. Determining the effect of other factors and their interdependencies is outside the scope of this study, however, the end of parental leave is unlikely to explain the rest, since the monetary amount received in the last year before the child turns 3 is relatively small. Changes in preferences regarding separation also play a key role, the timing of which suggests that they are highly related to the institutional framework. Studies based on both cross-country analysis of these characteristics using uniform methodology and harmonized data may in the future shed more light on the best comprehensive policy approach under various institutional conditions.

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[23] The ratio of female part-time workers relative to all employed females was as high as 45.5% in 2010, according to the Eurostat data, whereas it was 8.1% in Hungary for the same year.
[24] In Hungary, state-owned institutions provide childcare from 6 a.m. to 4 p.m. The ratio of part-time jobs is low, about 4.4% of overall employment (H-LFS). Del Boca (2002) also points out that policies need to combine the aims of more flexible work schedule choices and greater childcare availability.

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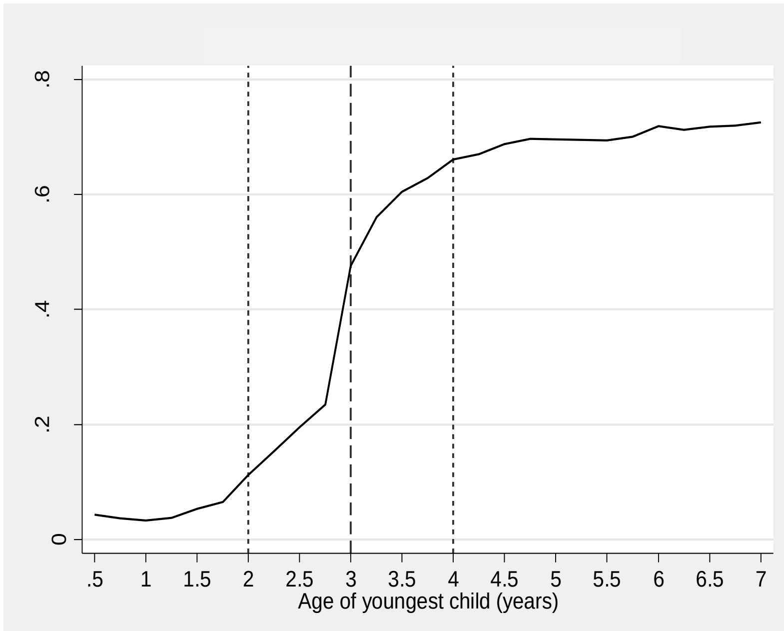
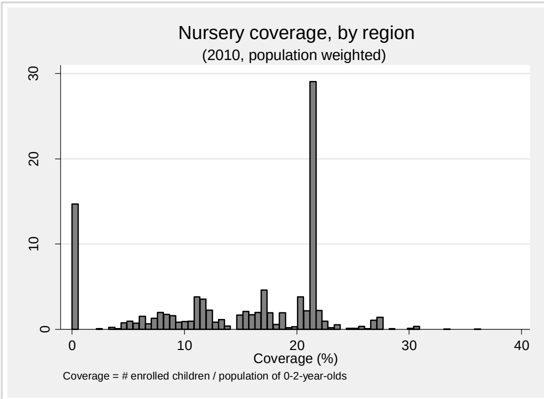
Figures and Tables

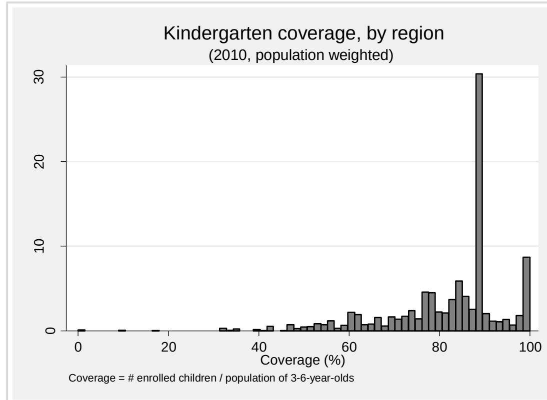
Figure 1: The participation rate of mothers in Hungary by the age of their youngest child



Source: Authors' calculations based on the Hungarian Labour Force Survey, 1998-2011.

Figure 2: Distribution of nursery and kindergarten coverage rates by region

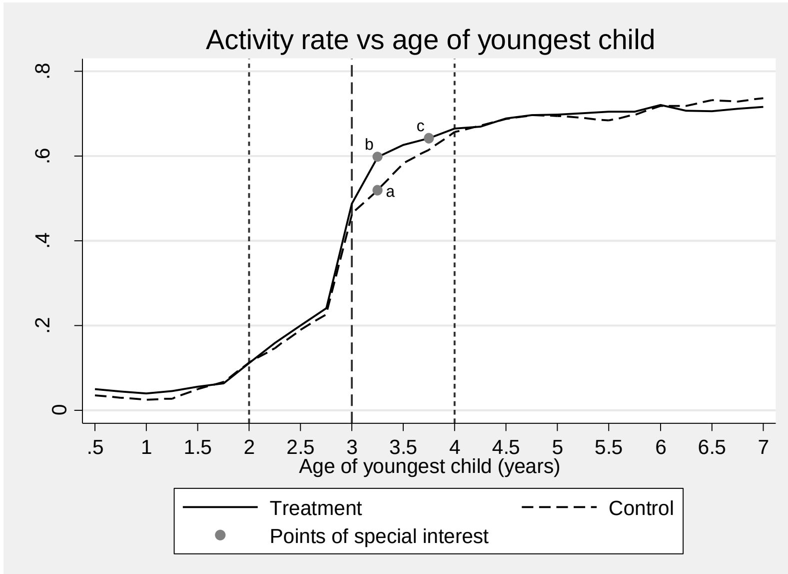




Source: T-STAR Hungarian regional data, 2010.

Notes: Coverage rate refers to the number children enrolled within each region, divided by the number of children of relevant age (0-2 for nursery, 3-6 for kindergarten) in each region. Region refers to townships merged based on kindergarten commuting data, there are 530 regions in the sample.

Figure 3: The participation rate of mothers in Hungary, by the age of their youngest child and by treatment status



Source: Authors' calculations based on the Hungarian Labour Force Survey, 1998-2011.
Note: Treatment group refers to mothers of children born between the 1st of August and the 31st of December. Control group refers to mothers of children born between the 1st of January and the 31st of May.

Table 1: Summary statistics of the estimation sample by group, select variables

	Child of age 3 (m=1)			Child of age 4-5 (m=0)		
	Treatment[(a)]	Control[(b)]	Diff/SD	Treatment[(a)]	Control[(b)]	Diff/SD
Mother						
Participation rate (1997-2011) (%)	59.60	51.50	0.161	68.32	68.15	0.004
Childcare coverage (%)	74.2	10.2	-	74.2	74.2	-
Number of children	1.3	1.3	-0.022	1.1	1.1	-0.04
Age of youngest child	3.3	3.3	-0.03	4.8	4.8	-0.043
Age (years)	31.1	31.1	0.001	32.4	32.5	-0.004
Education (%):						
Primary	23.60	22.10	0.037	23.20	23.10	0
Vocational school	26.90	27.20	-0.006	28.00	25.30	0.063
High school	31.90	33.30	-0.03	34.40	35.00	-0.013
University	17.60	17.50	0.004	14.50	16.60	-0.057
Husband or partner						
Age (years)	30	29.8	0.017	30.8	30.8	-0.002
Employment status (%):						
No partner	13.30	13.20	0.004	14.10	12.70	0.042
Partner without job	13.30	13.20	0.004	14.10	12.70	0.042
Partner with job	76.00	75.60	0.007	73.20	75.00	-0.042
Environment						
Type of settlement (%):						
Village	27.50	28.60	-0.025	28.80	26.80	0.045
Town	35.70	40.70	-0.103	39.50	42.60	-0.063
City	21.00	17.10	0.104	19.10	17.60	0.039
Unemployment rate (%)	4.40	4.40	0.006	4.60	4.60	-0.017
Number of obs.	1,732	1,577		2,975	2,868	

Source: Hungarian Labour Force Survey, 1998-2011.
Note: (a) Children born between August 1 – December 31. Mothers observed through January 1 – March 31
(b) Children born between January 1 – May 31. Mothers observed through June 1 – August 31

Table 2: Reduced form and 2SLS results without seasonality correction

	(a) Reduced form ($\vartheta = T$) Eq. (1)			(b) 2SLS ($\vartheta = \hat{C}$) Eq. (2-4)		
Specifications	1	2	3	1	2	3
ϑ	0.078**	0.085**	0.082**	0.129**	0.141**	0.135**
(Clustered, robust SE)	(0.022)	(0.023)	(0.022)	(0.032)	(0.034)	(0.034)
# of children		-0.117**	-0.117**		-0.118**	-0.118**
		(0.021)	(0.022)		(0.019)	(0.019)
Partner w/o job		0.003	0.007		0.004	0.008
		(0.063)	(0.062)		(0.056)	(0.056)
Partner w/ job		0.032	0.032		0.033	0.034
		(0.062)	(0.062)		(0.056)	(0.055)
Vocational school		0.191**	0.186**		0.191**	0.187**
		(0.035)	(0.035)		(0.031)	(0.031)
High school		0.250**	0.245**		0.251**	0.246**
		(0.035)	(0.035)		(0.031)	(0.031)
University		0.374**	0.367**		0.374**	0.367**
		(0.051)	(0.050)		(0.045)	(0.045)
Age		0.018	0.020		0.018	0.020
		(0.021)	(0.021)		(0.018)	(0.019)
Age squared		-0.000	-0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Partner: University		0.089*	0.083		0.087*	0.081*
		(0.044)	(0.044)		(0.039)	(0.039)
Partner: High sc.		0.074	0.071		0.075	0.072
		(0.060)	(0.060)		(0.052)	(0.053)
Partner: Vocational		0.063	0.060		0.063*	0.061
		(0.036)	(0.036)		(0.032)	(0.032)
Partner's age		-0.004*	-0.004*		-0.004**	-0.004**
		(0.002)	(0.002)		(0.002)	(0.002)
Unemployment level			-2.006**			-2.027**
			(0.765)			(0.681)
Village			0.218**			0.219**
			(0.064)			(0.057)
City			0.243**			0.241**
			(0.058)			(0.051)
Large city			0.250**			0.250**

			(0.072)			(0.064)
Constant	0.480**	0.168	0.074			
	(0.099)	(0.384)	(0.374)	0.023	0.114	0.117
R^2	0.245	0.316	0.318	3676.866	3404.436	3401.121
AIC	3789.217	3494.741	3491.096	3018.000	3018.000	3018.000
N	3244.000	3244.000	3244.000	0.129**	0.141**	0.135**
Year dummies	x	x	x	x	x	x
Individual controls		x	x		x	x
Regional controls			x			x

Source: H-LFS and T-STAR datasets, years 1998-2011.
Note: The dependent variable is the participation dummy. Year and region dummies are included in all regressions. Clustered, robust standard errors are given in parentheses. Stars indicate significance as: * p<0.05; ** p<0.01.

Table 3: Reduced form and 2SLS results with seasonality correction

	(a) Reduced form ($\vartheta = T$) Eq.(8)			(b) 2SLS ($\vartheta = \hat{C}$) Eq.(9-10)		
	1	2	3	1	2	3
$\vartheta * m$	0.061*	0.060*	0.060*	0.096**	0.095*	0.095*
	(0.024)	(0.027)	(0.026)	(0.037)	(0.041)	(0.041)
ϑ	0.007	0.014	0.012	0.014	0.025	0.021
	(0.018)	(0.016)	(0.016)	(0.027)	(0.024)	(0.024)
m	-0.169**	-0.156**	-0.156**	-0.179**	-0.166**	-0.166**
	(0.024)	(0.023)	(0.023)	(0.027)	(0.027)	(0.027)
# of children		-0.123**	-0.122**		-0.125**	-0.124**
		(0.015)	(0.015)		(0.014)	(0.014)
Partner w/o job		-0.004	0.000		-0.006	-0.002
		(0.043)	(0.043)		(0.042)	(0.041)
Partner w/ job		0.038	0.039		0.037	0.039
		(0.043)	(0.043)		(0.042)	(0.041)
Vocational school		0.177**	0.175**		0.178**	0.176**
		(0.020)	(0.020)		(0.019)	(0.019)
High school		0.289**	0.287**		0.289**	0.286**
		(0.019)	(0.019)		(0.018)	(0.018)
University		0.415**	0.412**		0.414**	0.410**
		(0.037)	(0.037)		(0.035)	(0.035)
Age		-0.004	-0.004		-0.004	-0.004
		(0.012)	(0.012)		(0.012)	(0.012)
Age squared		0.000	0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Partner: University		0.058*	0.055*		0.058*	0.054*
		(0.025)	(0.024)		(0.024)	(0.023)
Partner: High sc.		0.087*	0.085*		0.088*	0.085*
		(0.037)	(0.037)		(0.036)	(0.036)
Partner: Vocational		0.075**	0.073**		0.074**	0.072**
		(0.023)	(0.023)		(0.022)	(0.022)
Partner's age		-0.005**	-0.005**		-0.005**	-0.005**
		(0.001)	(0.001)		(0.001)	(0.001)
Unemployment level			-1.218**			-1.251**
			(0.470)			(0.450)
Village			0.100**			0.100**
			(0.031)			(0.030)
City			0.102**			0.104**
			(0.020)			(0.019)
Large city			0.118**			0.119**
			(0.045)			(0.043)
Constant	0.627**	0.700**	0.690**			
	(0.052)	(0.217)	(0.218)			
R^2	0.179	0.272	0.273	0.025	0.135	0.136
AIC	10632.499	9578.493	9572.289	10482.230	9449.600	9442.833
N	8980	8980	8980	8809.000	8809.000	8809.000
Year dummies	x	x	x	x	x	x
Individual controls		x	x		x	x
Regional controls			x			x

Source: H-LFS and T-STAR datasets, years 1998-2011.

Note: The dependent variable is the participation dummy. The table gives coefficient estimates of township-level childcare coverage relevant to the given group (kindergarten if treated, nursery if not), the dummy indicating seasonality comparison group membership (m=0 if the child is 4-5), and their interaction. Year and region dummies are included. Standard errors are given in parentheses. Stars indicate significance as: * $p<0.05$; ** $p<0.01$.

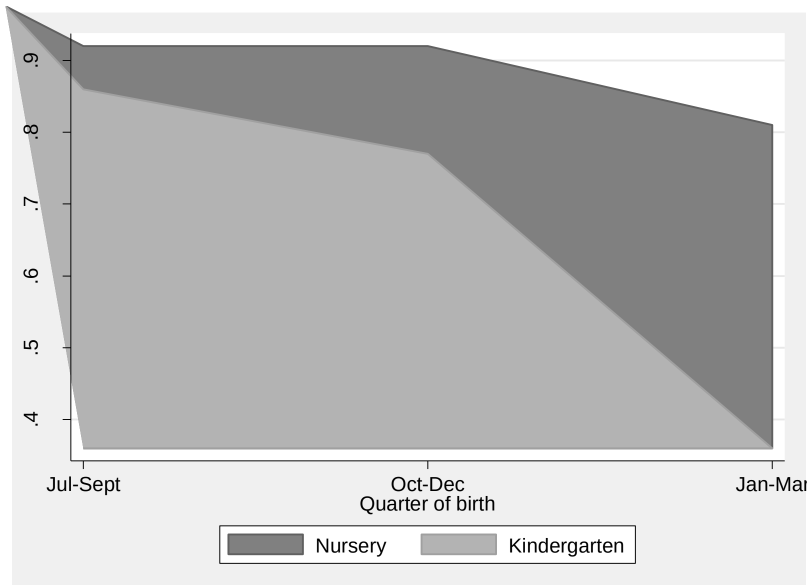
Table 4: Reduced form results at each child age

	Child age						
	Year1	Year2	Year3	Year4	Year5	Year6	Year7
T	0.021	0.009	0.082**	-0.01	0.009	-0.009	0.008
	-0.012	-0.015	-0.022	-0.028	-0.021	-0.024	-0.02
# of children	-0.021**	-0.048**	-0.117**	-0.120**	-0.171**	-0.210*	
	-0.008	-0.01	-0.022	-0.028	-0.047	-0.096	
Partner w/o job	-0.02	-0.068	0.007	0.032	-0.044	-0.212**	-0.166
	-0.022	-0.058	-0.062	-0.121	-0.079	-0.082	-0.127
Partner w/ job	-0.03	-0.081	0.032	0.077	-0.018	-0.129	-0.107
	-0.022	-0.061	-0.062	-0.107	-0.074	-0.068	-0.127
Vocational school	-0.009	0.003	0.186**	0.133**	0.203**	0.187**	0.200**
	-0.009	-0.021	-0.035	-0.034	-0.038	-0.04	-0.04
High school	0.01	0.075*	0.245**	0.298**	0.322**	0.287**	0.278**
	-0.009	-0.029	-0.035	-0.036	-0.029	-0.039	-0.042
University	0.035*	0.148**	0.367**	0.430**	0.440**	0.394**	0.371**
	-0.015	-0.045	-0.05	-0.045	-0.045	-0.048	-0.05
Age	0.009	0.024	0.02	-0.005	-0.039	-0.017	-0.013
	-0.009	-0.016	-0.021	-0.024	-0.024	-0.028	-0.035
Partner: University	0.027	0.021	0.083	0.03	0.074	0.009	0.077
	-0.021	-0.042	-0.044	-0.045	-0.038	-0.05	-0.046
Partner: High sc.	0.02	0.034	0.071	0.121	0.104**	0.046	0.113**
	-0.011	-0.027	-0.06	-0.062	-0.036	-0.04	-0.041
Partner: Vocational	0.009	0.028	0.06	0.093*	0.094**	0.063	0.086*
	-0.007	-0.019	-0.036	-0.042	-0.035	-0.038	-0.038
Partner's age	0	0.002	-0.004*	-0.006*	-0.003	0.002	0
	-0.001	-0.002	-0.002	-0.003	-0.002	-0.002	-0.003
Unemployment level	0.341	0.207	-2.006**	-0.092	-2.795**	-1.679*	-1.04
	-0.21	-0.538	-0.765	-1.032	-0.808	-0.84	-1.185
Village	-0.092**	-0.001	0.218**	0.226**	0.008	-0.258**	0.146
	-0.018	-0.049	-0.064	-0.066	-0.057	-0.095	-0.084
City	-0.073**	-0.036	0.243**	0.197**	0.041	-0.249**	0.132*
	-0.011	-0.031	-0.058	-0.051	-0.035	-0.086	-0.066
Large city	-0.118**	0.025	0.250**	0.237**	0.021	-0.202*	0.207**
	-0.024	-0.043	-0.072	-0.076	-0.062	-0.089	-0.076
Constant	-0.132	-0.231	0.074	0.574	1.452**	1.457**	0.972
	-0.142	-0.26	-0.374	-0.383	-0.404	-0.481	-0.656
R^2	0.177	0.213	0.318	0.369	0.403	0.366	0.406
AIC	-2579	2055.402	3491.096	2579.223	2258.491	2197.612	1831.307
N	3796	3688	3244	2883	2853	2666	2603
Year dummies	x	x	x	x	x	x	x
Individual controls	x	x	x	x	x	x	x
Regional controls	x	x	x	x	x	x	x

Source: H-LFS and T-STAR datasets, 1998-2011.
Note: The table shows the coefficient estimates of reduced-form regressions with control and treatment groups based on a January 1 cutoff: T=1 if birthdate is August-December, T=0 if it is January-May. The dependent variable is the participation dummy. Year dummies are included in all regressions. Standard errors are given in parentheses. Stars indicate significance as: * p<0.05; ** p<0.01.

Appendix

Figure A1: Enrollment rate of 3 year old children born in a given quarter



Source: Authors' calculations based on EU-SILC, 2006-2012
Note: Childcare enrollment status is observed in May.

Table A1: Summary statistics of the estimation sample by group

	Child of age 3 (m=1)			Child of age 4-5 (m=0)		
	Treatment[(a)]	Control[(b)]	Diff/SD	Treatment[(a)]	Control[(b)]	Diff/SD
Mother						
Participation rate (1997-2011) (%)	59.60	51.50	0.161	68.32	68.15	0.004
Childcare coverage (%)	74.2	10.2	-	74.2	74.2	-
Number of children	1.3	1.3	-0.022	1.1	1.1	-0.04
Age of youngest child	3.3	3.3	-0.03	4.8	4.8	-0.043
Age (years)	31.1	31.1	0.001	32.4	32.5	-0.004
Education (%):						
Primary	23.60	22.10	0.037	23.20	23.10	0
Vocational school	26.90	27.20	-0.006	28.00	25.30	0.063
High school	31.90	33.30	-0.03	34.40	35.00	-0.013
University	17.60	17.50	0.004	14.50	16.60	-0.057
Occupation (%):						
Leader, executive	19.90	20.60	-0.016	20.20	18.20	0.053
Higher educ. requiring	1.80	1.90	-0.006	2.10	2.60	-0.031
GED requiring	11.40	12.10	-0.022	10.00	12.00	-0.061
Clerical, customer service	15.40	14.70	0.02	15.20	14.40	0.022
Service, commerce	9.50	9.30	0.005	9.70	10.70	-0.033
Agricultural	17.00	20.10	-0.077	18.50	18.20	0.008
Construction, industry	1.20	0.80	0.05	2.00	1.70	0.019
Operation, assembly	8.80	7.30	0.056	7.60	6.90	0.028
Unskilled	8.20	8.10	0.004	7.80	7.40	0.012
Armed forces	6.70	5.00	0.077	7.00	7.80	-0.033
Husband or partner						
Age (years)	30	29.8	0.017	30.8	30.8	-0.002
Employment status (%):						
No partner	13.30	13.20	0.004	14.10	12.70	0.042
Partner without job	13.30	13.20	0.004	14.10	12.70	0.042
Partner with job	76.00	75.60	0.007	73.20	75.00	-0.042
Education (%):						
Primary	16.60	16.00	0.017	15.80	16.80	-0.025
Vocational school	38.20	38.20	0	38.50	37.90	0.012
High school	20.70	21.40	-0.017	21.80	22.30	-0.012
University	13.40	13.00	0.012	11.00	10.50	0.014
Occupation (%):						
Leader, exec.	17.80	17.80	0.002	20.60	17.70	0.076

Higher educ. requiring	6.30	5.90	0.015	5.60	5.60	-0.001
GED requiring	7.60	7.70	-0.006	5.80	5.60	0.007
Clerical, customer serv.	7.20	7.10	0.003	6.60	7.10	-0.019
Service, commerce	0.30	0.70	-0.052	0.60	0.50	0.021
Agricultural	11.00	12.00	-0.032	11.00	10.40	0.02
Construction, industry	3.50	3.80	-0.017	4.40	4.00	0.021
Operation, assembly	25.00	24.70	0.005	25.50	27.20	-0.038
Unskilled	14.90	13.70	0.032	14.30	14.30	0
Armed forces	6.60	6.40	0.004	5.50	7.50	-0.075
Environment						
Type of settlement (%):						
Village	27.50	28.60	-0.025	28.80	26.80	0.045
Town	35.70	40.70	-0.103	39.50	42.60	-0.063
City	21.00	17.10	0.104	19.10	17.60	0.039
Region (%):						
Central Hungary	28.10	28.30	-0.005	26.40	25.50	0.022
Central Transdanubia	10.60	10.70	-0.003	10.90	11.10	-0.008
Western Transdanubia	9.30	9.40	-0.003	9.30	9.60	-0.007
Southern Transdanubia	9.70	9.40	0.008	10.20	10.60	-0.013
Northern Hungary	14.10	11.20	0.092	12.90	12.80	0.003
Northern Plains	15.00	16.80	-0.049	16.80	16.60	0.006
Southern Plains	13.20	14.20	-0.027	13.50	13.90	-0.012
Unemployment rate (%)	4.40	4.40	0.006	4.60	4.60	-0.017
Nursery coverage (%)	11.20	10.20	0.106	10.50	10.00	0.053
Kindergarten coverage (%)	105.10	105.00	0.005	103.50	102.80	0.022
Average population	310147	260321	0.085	248879	252224	-0.006
Number of obs.	1,732	1,577		2,975	2,868	

Source: Hungarian Labour Force Survey and T-STAR datasets, 1998-2011.
Note: (a) Children born between August 1 – December 31. Mothers observed through January 1 – March 31
(b) Children born between January 1 – May 31. Mothers observed through June 1 – August 31

Table A2: First stage results of the 2SLS regression without seasonality correction

	Eq.(4)	
	Coef.	Robust SE
C	0.135	0.034
# of children	-0.118	0.019
Partner w/o job	0.008	0.056
Partner w/ job	0.034	0.055
Vocational school	0.187	0.031
High school	0.246	0.031
University	0.367	0.045
Age	0.020	0.019
Age squared	0.000	0.000
Partner: University	0.081	0.039
Partner: High school	0.072	0.053
Partner: Vocational	0.061	0.032
Partner's age	-0.004	0.002
Unemployment level	-20.027	0.681
Village	0.219	0.057
City	0.241	0.051
Large city	0.250	0.064
R^2	0.1172	
N	3018	

Source: H-LFS and T-STAR datasets, years 1998-2011.
Note: The dependent variable is the participation dummy.

Table A3: Reduced form results for placebo cutoffs

	Cutoff date: November 1 Specifications			Cutoff date: September 1 Specifications		
	1	2	3	1	2	3
T	0.026	0.030	0.029	-0.019	-0.021	-0.021
	(0.019)	(0.020)	(0.020)	(0.025)	(0.025)	(0.025)
# of children		-0.134**	-0.131**		-0.118**	-0.116**
		(0.020)	(0.020)		(0.019)	(0.019)
Partner w/o job		-0.029	-0.023		-0.003	-0.006
		(0.061)	(0.060)		(0.088)	(0.088)
Partner w/ job		0.021	0.025		0.035	0.028
		(0.054)	(0.054)		(0.081)	(0.081)
Vocational school		0.206**	0.203**		0.145**	0.141**
		(0.036)	(0.036)		(0.035)	(0.035)
High school		0.273**	0.269**		0.219**	0.214**
		(0.032)	(0.031)		(0.046)	(0.046)
University		0.426**	0.417**		0.400**	0.393**
		(0.041)	(0.040)		(0.046)	(0.046)
Age		0.026	0.027		0.027	0.027
		(0.022)	(0.022)		(0.020)	(0.020)
Age squared		-0.000	-0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Partner: University		0.051	0.043		0.011	0.010
		(0.048)	(0.047)		(0.048)	(0.048)
Partner: High sc.		0.067	0.059		0.073	0.072
		(0.051)	(0.051)		(0.069)	(0.069)
Partner: Vocationa..		0.062	0.058		0.071	0.070
		(0.032)	(0.032)		(0.040)	(0.041)
Partner's age		-0.003*	-0.003*		-0.005*	-0.004
		(0.001)	(0.001)		(0.002)	(0.002)
Unemployment level			-0.436			-1.762*
			(0.891)			(0.735)
Village			-0.037			-0.016
			(0.050)			(0.071)
City			-0.128**			0.004
			(0.031)			(0.053)
Large city			-0.032			0.028
			(0.065)			(0.064)
Constant	0.720**	0.252	0.333	0.581**	0.144	0.257
	(0.119)	(0.344)	(0.365)	(0.070)	(0.293)	(0.285)
r2	0.236	0.32	0.323	0.247	0.32	0.322
aic	3963.927	3594.151	3588.504	3742.727	3438.164	3435.935
N	3373	3373	3373	3229	3229	3229

Source: H-LFS and T-STAR datasets, years 1998-2011.
Note: The dependent variable is the participation dummy.

Table A4: 2SLS results with 3 and 4 month windows around the cutoff

	Window: 4 months		Window: 3 months	
	2SLS w/o seasonal correction Eq. (2-4)	2SLS w/ seasonal correction Eq. (9-10)	2SLS w/o seasonal correction Eq. (2-4)	2SLS w/ seasonal correction Eq. (9-10)
C	0.149**	0.006	0.147*	-0.021
	(0.042)	(0.033)	(0.058)	(0.046)
C*m		0.106		0.110
		(0.054)		(0.078)
m		-0.174**		-0.174**
		(0.026)		(0.040)
# of children	-0.101**	-0.119**	-0.042	-0.099**
	(0.023)	(0.017)	(0.038)	(0.026)
Partner w/o job	0.037	-0.005	0.299*	0.018
	(0.085)	(0.060)	(0.139)	(0.071)
Partner w/ job	0.032	0.051	0.271*	0.061
	(0.080)	(0.056)	(0.134)	(0.073)
Vocational school	0.149**	0.151**	0.151*	0.167**
	(0.042)	(0.027)	(0.063)	(0.036)
High school	0.198**	0.273**	0.131	0.239**
	(0.057)	(0.027)	(0.085)	(0.046)
University	0.314**	0.383**	0.187	0.312**
	(0.084)	(0.050)	(0.122)	(0.067)
Age	0.031	0.005	0.048	0.015
	(0.023)	(0.015)	(0.042)	(0.021)
Age squared	-0.000	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Partner: University	0.142*	0.059	0.247*	0.087
	(0.066)	(0.031)	(0.122)	(0.050)
Partner: High sc.	0.136	0.095	0.165	0.084
	(0.090)	(0.052)	(0.131)	(0.059)
Partner: Vocational	0.116*	0.083**	0.152	0.108*
	(0.046)	(0.030)	(0.084)	(0.046)
Partner's age	-0.006**	-0.005**	-0.010**	-0.004
	(0.002)	(0.001)	(0.004)	(0.002)
Unemployment level	-1.832	-1.180*	-1.467	-1.492
	(1.132)	(0.579)	(1.914)	(0.859)
Village	-0.169	0.134**	0.018	-0.173
	(0.127)	(0.042)	(0.110)	(0.105)
City	-0.136	0.151**	0.055	-0.148
	(0.138)	(0.031)	(0.095)	(0.103)
Large city	-0.134	0.146**		-0.156
	(0.150)	(0.056)		(0.116)
R^2	0.115	0.142	0.117	0.121
AIC	2,085.522	5,950.73	838.14	2,639.585
N	1,871	5,696	782	2,660
Year dummies	x	x	x	x
Individual controls	x	x	x	x
Regional controls	x	x	x	x

Source: H-LFS and T-STAR datasets, years 1998-2011.
Note: The dependent variable is the participation dummy. All controls included as in Specification (3) of the main results.

Table A5: 2SLS results with employment as the dependent variable

	2SLS w/o seasonal correction Eq. (2-4)	2SLS w/ seasonal correction Eq. (9-10)
C	0.124**	0.021
	(0.036)	(0.023)
C*m		0.077*
		(0.039)
m		-0.170**
		(0.023)
# of children	-0.114**	-0.114**
	(0.017)	(0.013)
Partner w/o job	-0.015	-0.023
	(0.059)	(0.044)
Partner w/ job	0.056	0.049
	(0.060)	(0.044)
Vocational school	0.143**	0.177**
	(0.029)	(0.018)
High school	0.245**	0.293**
	(0.032)	(0.018)
University	0.413**	0.465**
	(0.041)	(0.030)
Age	0.011	0.003
	(0.022)	(0.012)
Age squared	-0.000	-0.000
	(0.000)	(0.000)
Partner: University	0.055	0.046
	(0.038)	(0.025)
Partner: High sc.	0.057	0.075**
	(0.043)	(0.027)
Partner: Vocational	0.043	0.062**
	(0.030)	(0.020)
Partner's age	-0.004*	-0.003**
	(0.002)	(0.001)
Unemployment level	-1.508**	-1.169**
	(0.580)	(0.382)
Village	0.277**	0.141**
	(0.050)	(0.029)
City	0.267**	0.143**
	(0.042)	(0.019)
Large city	0.236**	0.157**
	(0.059)	(0.042)
R^2	0.126	0.146
AIC	3418.963	9957.799
N	3018	8809
Year dummies	x	x
Individual controls	x	x
Regional controls	x	x

Source: H-LFS and T-STAR datasets, years 1998-2011.
Note: The dependent variable is the employment dummy.