Estimating the impact of an Early Childhood Parenting Programme on Childcare Decisions: Evidence from Colombia (preliminary draft-March 2016)*

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Abstract

Understanding how Early Childhood (EC) programmes can modify parental investments in their children is important for understanding how governments can support human capital accumulation and promote social mobility. New research shows that poor parents may underestimate the returns to early investments, but also, that successful EC interventions alter parental behaviour and improve child developmental outcomes. This paper examines the impact of an early childhood home visiting programme on different childcare arrangements in Colombia. Using OLS, matching, and difference-in-differences, I find that the EC programme has zero effect on most childcare measures. The only exception is informal childcare, where the intervention led to a 4.4 to 5.5 percentage points increase in use. Future research should focus on having a more comprehensive understanding of informal childcare services and its causal effect on later life outcomes. This is imperative for designing policies aiming to improve EC and subsidise childcare services for low-income families.

Keywords: early childhood, childcare, difference-in-differences, matching, evaluation, development, Colombia.

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1. Introduction

An increasing body of evidence suggests that attributes acquired before the age of 18 account for 50% of the variability in adult outcomes. Examples include earnings, educational attainment, and health status (Keane & Wolpin, 1997; Cunha, Heckman, & Navarro, 2005; Huggett, Ventura, & Yaron, 2011; Attanasio et al., 2013). This variability is intrinsically linked to differences in the environment that children experience in early years, hindering human capital accumulation (Cunha, 2014). Moreover, a vast amount of Early Childhood (EC) literature shows that boosting early investments in disadvantaged[3] children can extensively increase their performance in later life outcomes (Olds et al., 2002; Hoddinott, Maluccio, Behrman, Flores, & Martorell, 2008; Heckman, Moon, Pinto, Savelyev & Yavitz, 2010; Barnett, 2011; Campbell et al., 2012; Attanasio et al., 2013; Gertler et al., 2014, Cunha, 2014). Findings of EC interventions with positive outcomes on human capital accumulation show that these investments are delivered through goods or services directly to the child (Hoddinott et al., 2008; Heckman et al., 2010; Campbell et al., 2012), or indirectly, by improving parental knowledge so that the child is provided with an enriched environment (Olds et al., 2002; Attanasio et al., 2013; Gertler et al., 2014; Cunha, 2014).

Many EC home visiting programmes are designed to support child rearing, based on the premise that disadvantaged parents lack the information of "good" parenting practices (Garcia, 2015). Moreover, low-income households often do not have access to high-quality childcare (Blau, 2003; Elango, Garcia, Heckman, & Hofman, 2015). A major lesson from early intervention research is that successful EC programmes tend to support children and supplement parenting. This is the case for the EC home-parenting programme in Colombia. The

[3]In this paper the concept of "disadvantaged" refers to a/the low-income population.

psychosocial stimulation treatment[4] of this programme led to significant gains in cognitive and socio-emotional skills (Attanasio, Cattan, Fitzsimons, Meghir, & Rubio-Codina, 2015). The EC programme in Colombia provides a unique identification framework to analyse the relationship between a successful stimulation treatment and childcare decisions. The stimulation treatment provided weekly home visits to mothers, for a period of 18 months. The goal was to improve parenting practices in the early years and later (Attanasio, et al., 2015).

The EC programme in Colombia was a clustered randomised control trial (RCT) implemented in 2010. It had three treatment arms: stimulation alone, micronutrient supplementation alone, and both combined. The aim of each was to improve children's development, growth, and haemoglobin levels (Attanasio et al., 2014). I focus on examining the stimulation treatment only in childcare choices, as previous studies established that this was the one treatment arm with a positive impact on language and cognition development scores, compared to their peers in the control group (Attanasio et al., 2014). A later study demonstrated that these gains were due to increases in parental investments, improving the quality of the home environment[5] (Attanasio et al., 2015). Because the stimulation treatment raised parents' knowledge and awareness on how to better take care of their children (leading to improvements in child development measures and quality of the home environment indicators), I argue that it could also affects parents' childcare decisions. Research looking at childcare provision has increased given the growth in the labour force participation of women with children (Elango et al., 2015; Felfe & Lalive, 2012). However, there are considerable gaps in the literature on understanding parents' childcare choices. Some stem from the inherent difficulty in collecting

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[4]Stimulation treatment, hereafter

[5]Increases in varieties of play materials and play activities, measured by a family care indicator developed by UNICEF (Attanasio et al., 2013, 2014).

robust evidence on why parents made the choices they did (Bryson, Brewer, Sibieta, & Butt, 2012). Consequently, childcare researchers and policymakers continue to struggle with understanding the decision-making process parents go through when making childcare choices. Moreover, research on the joint impact of childcare and EC interventions in disadvantaged children is still scarce. A contribution of this paper is to shed light on childcare decisions among low-income parents.[6]

I divide the analysis of the stimulation effect in two different groups of childcare measures. In the first part, I looked into treatment effect between any childcare available against maternal care. In the second part, I broke down the any childcare category into public, private, and informal childcare compared to maternal care. To the best of my knowledge, this paper is the first to use the source of variation induced by the EC home-parenting programme to study childcare choices.

Despite the data comes from an RCT, the baseline analysis of childcare measures found significant differences in stimulation treatment and control groups. To tackle this issue, I used and compared childcare outcomes for three different strategies: linear probability model (OLS), difference-in-differences, and matching. The three estimates show consistently that the stimulation treatment had zero effect in most childcare measures. The only robust evidence of the stimulation impact was upon the informal childcare measure, where the intervention led to an increase of between 4.5 to 5.5 percentage points in use. Upcoming studies should focus on having an ample understanding of informal childcare services, particularly in disadvantaged populations, and include them in the discussion of public childcare. Learning about the

[6]Target population of the EC home-parenting programme in Colombia (Attanasio et al., 2014).

interactions among childcare providers and informal childcare is necessary for policies aiming to improve early childhood and subsidise childcare services for low-income populations.

The paper proceeds as follows. Section 2 describes the intervention and data. Section 3 reviews the literature on EC interventions and childcare and describes the conceptual framework. Section 4 outlines the methodology while Section 5 discusses the results. Finally, Section 7 lists some limitations and concludes.

2. Description of the intervention and data

The paper draws on baseline and follow-up data from an EC home-parenting programme conducted in Colombia between 2010 and 2011. The target population for this study was children aged 12-24 months at baseline data collection (n=1420).

The intervention was a cluster-RCT implemented in 96 municipalities (clusters) within Colombia using a 2x2 factorial design. In the initial trial, there was one control group and the following three treatment arms:

i. A psychosocial stimulation

ii. A micronutrient supplementation

iii. Both psychosocial stimulation and micronutrient supplementation

The focus of this paper is how parental childcare decisions differ after the stimulation treatment (i).[7] The stimulation intervention provided weekly home visits to mothers of the target children (aged 12-24 months) for a period of 18 months. The goal of these visits was to promote child development by supporting and strengthening mother-child interactions and by engaging families in play activities, centred around children's daily routines and using household

[7]The analytic sample of the paper is for the 636 children at follow-up from the stimulation treatment arm and the control group. More information on the sample size later on this section.

resources (Attanasio et al., 2015). The treatment included modelling (demonstrating to the mother, different play activities and interactions to undertake with the child), scaffolding (instructing the mother in providing tasks that were at the developmental level of the child so as to be challenging but not too difficult), practise (encouraging the mother to exercise activities), and conditional positive reinforcement for both mother and child (Attanasio et al., 2013). An important feature of the stimulation treatment was that the home visitors were drawn from a network of local women generated by the administrative set-up of the CCT programme Familias en Accion (*FeA*). This CCT programme is the largest national welfare system in the country; it began in 2002 and targeted the poorest 20% of households. Within *FeA*, every 50-60 beneficiaries periodically elect a representative who is in charge of organising social activities and who acts as a mediator between them and the programme administrators. These women, known as Madre Líderes (MLs), are beneficiaries of the programme themselves. They are typically more entrepreneurial and proactive than the average beneficiary and influential and well connected in their communities. These characteristics marked them out as potentially effective home visitors (Attanasio et al., 2013). In each municipality, three MLs were randomly selected and the children aged 12-24 months of the beneficiary households represented by each of these MLs, were recruited to the study.

To identify the sample for the EC home-parenting programme, eight departments were selected located in three geographical regions proximate to Bogotá: Cundinamarca, Boyacá, and Santander (oriental region); Antioquia, Risaralda, and Caldas (coffee zone region); and Huila and Tolima (central region). Within each of these three regions, they identified 32 municipalities (clusters) in which *FeA* had been in operation since its inception in 2002, and where the population ranged from 2,000 to 42,000 inhabitants. The municipalities were similar regarding their cultures and customs to design one curriculum—and associated materials such as pictures and books—identifiable to all.[8] The structure mirrored that of the Jamaica study[9] in that it included a psychosocial stimulation component and a micronutrient supplementation component.[10] It was not possible to blind study participants for their allocation to the stimulation treatment. However, testers and interviewers were blind to the treatment status of participants (Attanasio et al., 2014).

My exclusive focus upon the impact of the stimulation treatment arm is driven by both theoretical and empirical reasons. Attanasio et al. (2014) found it to be the only treatment arm to consistently have a positive impact upon children's cognitive development (effect size = 0.26) and language scores (effect size = 0.22). The other motivation for focusing upon the stimulation treatment is that it had an active component of parental education, teaching them how to engage in, and incentivising development for their children.[11] I examined the stimulation effect on available childcare arrangements in the community against the alternative of the mother providing care to the child. My hypothesis is that the stimulation component would affect childcare decisions, as parents' knowledge and awareness increases on how to better take care their children. Accordingly, the micronutrient supplementation arm would not have any hypothesized impact in childcare decisions, as it did not include any parental education component on child development and nurture, besides it only entailed on delivering sachets containing encapsulated micronutrients in powder form.

[8]The analytic sample of the paper is for the 636 children at follow-up from this treatment arm. More information on the sample size later on this section.

[9]See Grantham-McGregor, Powell, Walker, & Himes (1991) and Gertler et al. (2014), for an insightful overview of the Jamaica study.

[10]The Jamaican intervention has documented large impacts on cognitive development and earnings 20 years later (Grantham-McGregor, Powell, Walker, & Himes, 1991; Gardner et al., 2005; Walker, Chang, Vera-Hernandez, & Grantham-McGregor, 2011; Gertler et al., 2014).

[11]The stimulation with nutrition arm combined also included the parental education component. However, previous studies did not find any effect on any of the outcomes examined. Nevertheless, I conducted robustness tests comprising this treatment arm and the stimulation treatment arm only as the treatment group. Further details are included on the next page and in the Appendix.

Data

As discussed already, the analysis draws on cluster-RCT data from the EC home-parenting programme. A major benefit of randomisation is that, when properly designed and executed, it solves the problem of selection bias. RCTs can render treatment assignments statistically independent of unobserved characteristics that affect the choice of participation in a programme, and that might affect outcomes. Consequently, a well-implemented RCT enables analysts to evaluate mean treatment effects by using simple differences-in-means between treatment and control groups (Ludwig et al., 2011).

The evaluation sample at baseline was 1420 children in poor households, recipients of the CCT programme *FeA*, from 96 municipalities (clusters). The sample at follow-up across treatment arms went down to 1262 children (88 percent of the children initially recruited).[12] The difference in loss (attrition rate) between baseline and follow-up was not statistically significant.[13] Because I focused on the stimulation treatment arm that had positive effects, I retained for the analysis only the sample from this treatment arm (n=318, clusters=24) and the sample from the control group (n=318, clusters=24).[14] The analytic sample of this paper is for the 636 children who remained in the study at follow-up with complete information on the

[12]In Attanasio et.al. (2014), the Bayley scales were used to assess the EC programme impact in cognitive, language, and motor development. As stated previously, the EC intervention included three different treatment arms: stimulation, stimulation with nutrition, and nutrition. The overall attrition rate of the study across the three treatment arms for children with complete information on the Bayley scales was 10.7%. For the stimulation arm only, the attrition rate was 12.4 % (n=42). From the 42 children, 36 did not have information on the Bayley scales at follow-up, four children did not have information on Bayley scales at baseline, and two extra children who had extreme observations for Bayley scores were excluded from the analysis (see Figure 1).

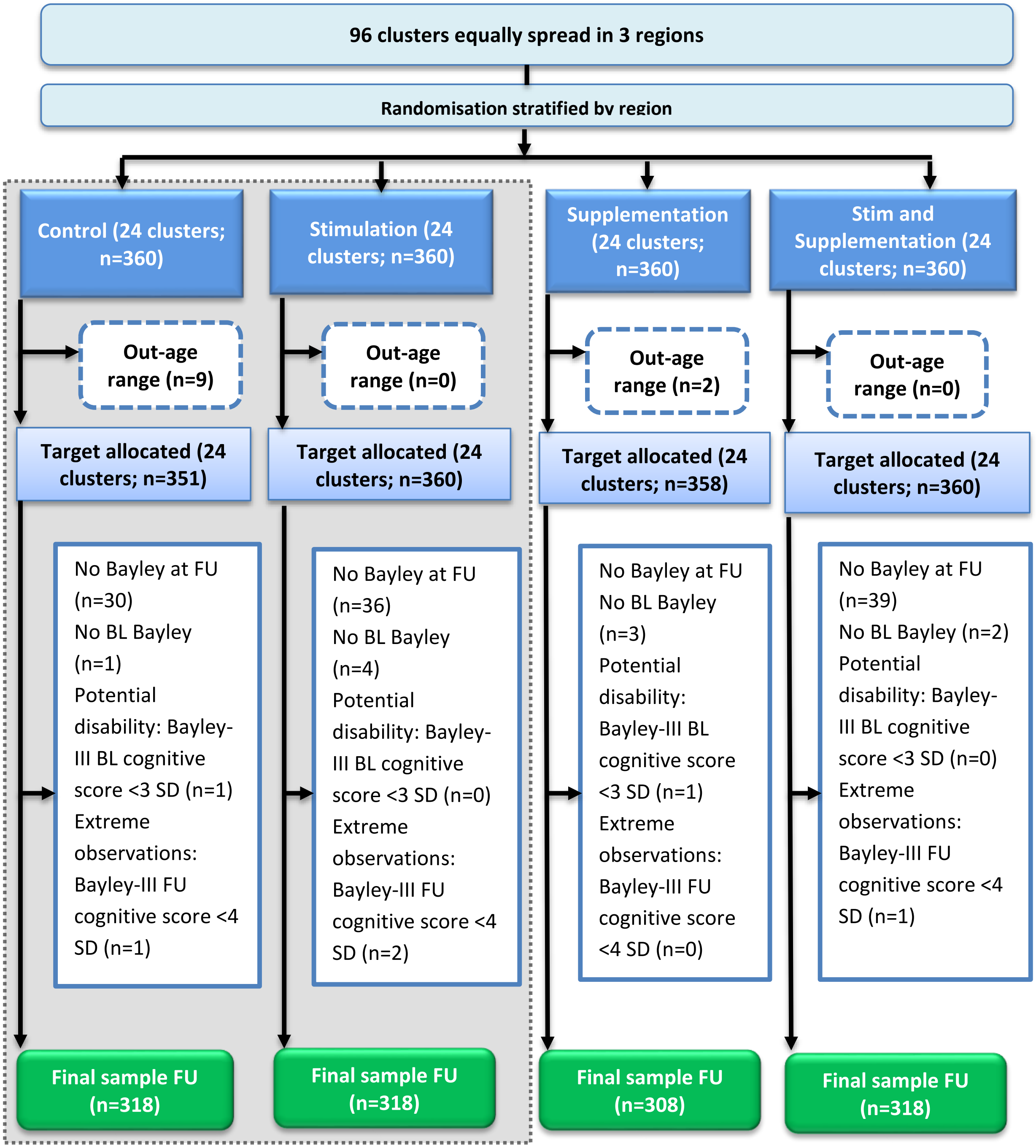
[13]I conducted baseline checks characteristics for the children who did not have complete information on the Bayley scales at baseline and follow-up, for the stimulation group (n=39) and control group (n=31). No differences were found among groups in predictors and childcare measures (see Appendix-Table 8).

[14]As stated previously, I also conducted robustness tests defining the treatment group as the group of children who received the home visits. Therefore, I combined the children who received only the home visits (stimulation only) and those who received both, the home visits and micronutrients (stimulation with nutrition arm), against the children from the control group. Results are similar from the ones presented in Section 5 and are included in the Appendix.

Bayley scales.[15] Figure 1 includes a flow of the participants through the study of the original design and highlights the analytic sample of the present study. The methodologies used to estimate the stimulation treatment effect (Section 4) account for the cluster sampling design.

[15]In the original design, power calculations were made to detect an effect size of a Bayley scale in the stimulation arm only and the micronutrient arm only (against the control group). The approach to "reduce" the overall sample is similar to subgroup analysis. Though smaller samples have reduced power to detect the overall treatment effect, I avoided the risk of a false-positive result (likely to incur by multiple hypothesis testing). The latter does not remove the chance of false-negative result of treatment effect (Brookes et al., 2001).

Figure 1. Flow of children participants through study



*BL=Baseline, FU=Follow-up. The gray-shaded area corresponds the analytic sample of this paper.
Original flow-chart in Attanasio et al. (2014). Using the infrastructure of a conditional cash transfer program to deliver a scalable integrated early child development program in Colombia: cluster randomized controlled trial. BMJ, 349:g5785.
See Bayley, N. (2006) for more information on the Bayley scales.

A summary of the characteristics of children, their mothers, and their households from the stimulation treatment and control groups is presented in Table 1.

Table 1. Baseline Characteristics of participant children, their mothers, and their households

Variable	*Control (n=318)*	*Stimulation (n=318)*	*P-value*
Children			
Mean (SD) age in months	18.27 (4.02)	18.05 (3.75)	>0.50
Proportion of Boys	0.50	0.47	0.21
Proportion of children that received any childcare before baseline	0.29	0.20	0.11
Mother			
Mean (SD) age (in years)	26.12 (6.97)	26.87 (6.93)	0.36
Proportion of depressed mothers[1]	0.46	0.39	>0.50
Proportion of single mothers	0.31	0.30	>0.50
Mean (SD) completed years of education	7.52 (3.66)	6.98 (3.59)	0.36
Employed mother	0.48	0.44	>0.50
Household			
Proportion of households with crowding[2]	0.21	0.27	0.39
Mean (SD) household wealth index[3]	0.206 (1.34)	-0.143 (1.98)	0.11
Mean (SD) Number of varieties of play materials[4]	4.29 (1.83)	4.26 (1.79)	0.18
Mean (SD) Number of varieties of play activities[5]	3.69 (1.76)	3.70 (1.72)	>0.50
Proportion of households with any grandparent living within the household	0.34	0.27	0.10

*Analytic sample. Values presented in percentages unless stated otherwise.
[1]Maternal depression was measured using the Spanish translation of the Centre for Epidemiologic Studies short depression scale (CES-D 10). Scores range from 1 to 30; with a score greater than 10 being considered depressed using the reference population norms (Attanasio et al., 2014).
[2]Binary index that denotes the presence of crowding in the household which takes the value of 1 if household has 3 or more people per room and 0 otherwise.
[3]First principal component of household asset and characteristics: dirt floor, solid walls, crowding index, home ownership, sewage, and ownership of car, computer, blender, fridge, washing machine, and cell phone.
[4]Number of varieties of play materials in the home that the child often played with over the three days before the interview. It includes toys that make or play music; toys or objects meant for stacking, constructing or building; things for drawing, writing, colouring, and painting; toys for moving around; toys to play pretend games; picture books and drawing books for children;

and toys for learning shapes and colours.
[5]Number of varieties of play activities the child engaged in with an adult over the three days before the interview. It includes reading books or looking at picture books; telling stories to child; singing songs with child; taking child outside home place or going for a walk; playing with child with toys; spending time with child scribbling, drawing, or colouring; and spending time with child naming things or counting.

Table 1 results indicate some concerns within the randomisation procedure. None of the variables revealed statistical differences of 5% level or below between stimulation treatment and control groups. However three of them: proportion of children that received any childcare before baseline, household wealth index, and proportion of households with any grandparent living within the household, showed statistical differences of 10% or slightly above 10%. The age of children in the control group was an average of 18.27 (SD 4.02) months. Around 29 percent of children in the control group have received some childcare [16] before baseline collection. The mean age of the mother was 26.12 (6.97) years and only 30% were single; 46 percent of mothers were classified as depressed.[17] The household wealth index (a measure of SES) mean in the control group was 0.206 (SD 1.34)

Childcare measures

To examine the stimulation effect on childcare choices, I constructed a series of childcare outcomes as binary indicators.

A baseline survey was collected before the programme began, including rich data on child development and family characteristics. Children were between 12 and 24 months old at baseline. The baseline survey also included a range of questions regarding the child's care arrangement. Parents were asked about the type of childcare used at the moment of the survey

[16]Children who before baseline collection reported to have received any type of formal childcare.
[17]Maternal depression was measured using the Spanish translation of the Centre for Epidemiologic Studies short depression scale (CES-D 10). Scores range from 1 to 30; with a score greater than 10 being considered depressed using the reference population norms (Attanasio et al., 2014).

and the type of childcare children received from Monday to Friday on a regular basis.[18] They were also asked if they had used any source of childcare before baseline collection (i.e., children younger than 12-24 months). A follow-up survey was conducted 18 months later after treatment implementation when children were between 30 and 42 months old. As discussed in the introduction, I performed two separate analyses to examine childcare participation. In the first part, I compared the stimulation effect in two mutually exclusive childcare choices: any childcare and maternal care. The *any childcare* outcome is a general category that comprises all the types of childcare surveyed at baseline excluding mother care. In the second part, I categorised children into four mutually exclusive childcare arrangements: *public*, *private, informal*, and *maternal* care. The reference category in both analyses is maternal care. The types of childcare measures proposed follow previous EC studies looking at the effects of diverse sources of childcare.[19]

Each childcare outcome listed in Table 2 represents a separate regression.

Table 2. Childcare measures

Childcare outcomes	*Definition (types of childcare included)**
(I)	
Any childcare	If the child is in any of the following categories for current and main childcare response: public day care centre, private day care centre, public pre-school, private pre-school, community house/FAMI, paid caregiver, non-paid caregiver. This category integrates formal and informal sources of care.
(II)	

[18]The childcare options included in the questionnaire were specified as binary variables and mutually exclusive categories. For results in Section 6, I matched childcare arrangements responses for current childcare and main childcare. The definition of main childcare in the study relates to the main childcare provision that the child is receiving from Monday to Friday. The concept of current childcare was specified as the type of childcare that the child was receiving at the moment of the questionnaire.

[19]Researchers have compared various child-care arrangements, including centres, preschools, licensed homes, or individual caregivers, to determine which might hold the most promise for improving cognitive and social-behavioural outcomes (Blau & Currie, 2006; Loeb, Bridges, Bassok, Fuller, & Rumberger, 2007; Drange & Havnes, 2015).

Childcare outcomes	*Definition (types of childcare included)**
Public childcare	If child is in any of the following categories for current and main childcare response: public day care centre, public pre-school or community house/FAMI. This outcome includes institutional types of childcare and licensed homes (i.e., community house/FAMI), all provided/subsidised by the government.
Private childcare	If child is in any of the following categories for current and main childcare response: private day care centre, private pre-school or paid caregiver. This category includes childcare arrangements that families pay a fee for it. It can be institutional or individual caregivers.
Informal childcare[1]	If child is in any of the following categories for current and main childcare response: non-paid. This outcome denotes individual caregivers (such as a family member, friend, neighbour, or other person within or outside the household) that take care of the child without receiving any payment.
Reference category	
Maternal care	If the child for current and main childcare response is taken care of by the mother.

*Childcare arrangements included in original questionnaire of the study, matching current childcare and main childcare responses. The category of reference in both analyses (I) and (II) is maternal care. The grouping follows previous EC analyses examining different types of childcare (Blau & Currie, 2006; Drange & Havnes, 2015).
[1]In earlier studies looking at "informal childcare", there are some groups of people who are usually included in this category: grandparents, other family members and friends or neighbours. However, at its broadest, informal childcare is simply the converse of "formal childcare", then it is defined as "unregulated childcare" (Bryson, Brewer, Sibieta, & Butt, 2012. For the analysis, I narrowed down this definition, which includes family members, friends, neighbours, or other person within, or outside the household, that does not involve payment.

In Tables 3.1 and 3.2, I examined randomisation conditions for the childcare outcomes and estimated the programme effect using simple differences-in-proportions[20] between treatment and control (considering data came from a clustered-RCT). All standard errors have been clustered at the municipality level.

[20]As each childcare measure (dependent variable) is defined as a binary variable.

Table 3.1 Proportion of children participating in childcare (outcomes) at baseline and end of intervention

Childcare outcomes	*Baseline*				*Follow-up*				*Change (BL/FU)*
	Stim	*Control*	*Diff*	*p-value*	*Stim*	*Control*	*Diff*	*p-value*	
(I)									
Any childcare	0.151 (0.035)	0.204 (0.033)	-0.053	>0.5	0.390 (0.043)	0.462 (0.037)	-0.072	0.19	-0.019
Maternal care	0.846 (0.036)	0.792 (0.034)	0.054	>0.5	0.601 (0.044)	0.535 (0.036)	0.066	0.28	0.012

*p<0.05, **p<0.01, ***p<0.001 for difference with respect to control group. P values for difference in proportions adjusted for clustering standard errors at municipality level. Standard errors in parentheses.

In the first set of childcare measures, randomisation bias is not a concern. Results with simple difference-in-proportions show that the stimulation treatment does not have any impact among childcare arrangements.

Table 3.2 Proportion of children participating in childcare categories (outcomes) at baseline and end of intervention

Childcare outcomes	*Baseline*				*Follow-up*				*Change (BL/FU)*
	Stim	*Control*	*Diff*	*p-value*	*Stim*	*Control*	*Diff*	*p-value*	
(II)									
Public childcare	0.072 (0.031)	0.075 (0.024)	-0.003	>0.5	0.305 (0.046)	0.381 (0.040)	-0.076	0.33	-0.073
Private childcare	0.041 (0.018)	0.050 (0.025)	-0.009	>0.5	0.016 (0.008)	0.035 (0.011)	-0.019	0.35	-0.010
Informal childcare (non-paid)	**0.038*** (0.009)	0.079 (0.015)	**-0.041***	0.03	**0.075*** (0.017)	0.047 (0.010)	**0.028***	0.03	**0.069***
Maternal care	0.846 (0.036)	0.792 (0.034)	0.054	>0.5	0.601 (0.044)	0.535 (0.036)	0.066	0.28	0.012

*p<0.05, **p<0.01, ***p<0.001 for difference with respect to control group. P values for difference in means adjusted for clustering standard errors at municipality level. Standard errors in parentheses.

Regarding the second set of childcare measures, the Table 3.2 results show that the treatment and control group in the *informal childcare* outcome at baseline are statistically different (p-value<0.05). If randomisation had worked, there should not be statistical differences among groups in any of the childcare measures. Hence, the estimates of the programme effect (in column *Change (BL/FU)*) by simple difference-in-proportions are likely upward biased. The use of quasi-experimental methods is required to check the robustness of results and guarantee to reach balance between the treatment and control group. Section 4 describes the methods employed to overcome this challenge.

3. Early Childhood: literature review and conceptual framework

Importance of EC

The policy attention pointing to public investment in EC is fuelled by results from a large body of research highlighting the importance of EC years (Heckman, 2008; Currie & Almond, 2011). Several EC interventions targeted at vulnerable children based on stimulation treatments (and, at times, nutrition) have obtained sustainable improvements in developmental outcomes (Grantham-McGregor, Fernald, Kagawa, & Walker, 2014).

Research suggests that for disadvantaged children, each $1 devoted to effective EC programmes in developing countries, leads to $2–$23 in future savings to investing localities and states (Bialik, 2012; Heckman, 2011). EC interventions in developing countries are likely to be more effective if they are comprehensive (i.e., they include health, nutrition, and stimulation), run for longer, have greater intensity (i.e., higher frequency and longer duration of contacts), use a structured curriculum, and enable parents and children to participate together to practise stimulation activities and receive feedback (Engle et al., 2011, 2007; Yousafzai et al., 2014). Moreover, some of these EC interventions have been implemented using networks of existing social welfare schemes of large-scale programmes or health services already rolling, generating substantial economies of scale and exploiting the experience of local human capital.

This might be a promising approach to scaling up EC programmes in developing countries and one of the characteristics of our intervention of interest[21] (Attanasio et al., 2014).

For instance, a study conducted in three countries from the Caribbean (Jamaica, Antigua and St Lucia) analysed the results of a parenting training programme integrated into primary health centre visits. The intervention had a significant benefit to children's cognitive development, with a treatment effect of 3.09 points (e.s. =0.3 SDs). Moreover, mothers in the intervention group improved significantly more in parenting scores than the control group (Chang et al., 2015).

Regarding EC long-term benefits, a recent study from Jamaica reports substantial effects on the earnings of participants in a randomised intervention conducted in 1986–1987 that gave psychosocial stimulation to growth-stunted Jamaican toddlers.[22] The authors reinterviewed 81 percent of study participants 20 years later and found that the intervention increased earnings by 25 percent, enough for them to catch up to the earnings of a non-stunted comparison group identified at baseline (Gertler et al., 2014). These findings add to the efficacy and effectiveness of community-based approaches to promote EC development in the first two years of life.

Childcare findings

Research looking at childcare provision has increased given the growth in the labour force participation of women with children (Elango et al., 2015). A research field in childcare focuses on examining differential effects according to the type and quality of childcare attended. There is growing consensus that the quality of EC services matters critically. Van Huizen and

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[21]Using the infrastructure of the CCT programme *FeA* and tapping on the newtork of local women (*Madres Lideres*), as described in Section 2.

[22]The intervention consisted of weekly visits from community health workers over a 2-year period that taught parenting skills and encouraged mothers and children to interact in ways that develop cognitive and socioemotional skills.

Plantenga (2015) conducted a meta-analysis from natural experiments studies examining the effects of EC education and care arrangements, focusing on non-parental childcare arrangements (formal and centre-based) before the child enters school/kindergarten. Across many different specifications and measuring childcare quality in various ways, high-quality EC care arrangements consistently produced more favourable outcomes. The issue of quality is relevant in the case of universal childcare arrangements, as this type of childcare may be mainly targeted towards stimulating parental employment, and have less emphasis on child development. Furthermore, universal childcare is also available to parents with higher income/socio-economic status: if the quality provided by daycare centres is weak, it is likely that the alternative type of care (parental care) may be of higher quality (van Huizen & Plantenga, 2015). For example, concerned about childcare quality, some parents might have a preference against it (Ham & Buchel, 2004; Parera-Nicolau & Mumford, 2005) and might not use non-relative care even if it was free (Ermisch, 2002).

In studies examining how childcare affects child development, it is important to consider the alternative type of care that children would have been exposed to if they did not attend childcare. Usually, researchers consider three alternatives: parental childcare, formal childcare and other, more informal sources of care (Blau & Currie, 2006; Drange & Havnes, 2015). Any empirical analysis looking at the effects of childcare arrangements is complex due to endogeneity issues. We cannot exclude the possibility that there are unobserved preferences related both to childcare and labour market decisions (Arpino, Pronzato, & Tavares, 2012). Controlling for selection into childcare is relevant, particularly in natural experiments and observational studies. Estimations that consider these selection issues may produce opposite results compared to estimates that do not (Loeb et al., 2004; Herbst, 2013; van Huizen & Plantenga, 2015).

Another field of childcare research focuses on looking at the effect of external childcare arrangements on maternal labour supply. In the traditional female labour supply model, formal childcare (non-maternal) is assumed to be provided by the market and considered a perfect substitute. However, in countries where childcare services are scarce or prices of private childcare are very high, families tend to rely on informal childcare provided by relatives (Arpino, Pronzato, & Tavares, 2010). Previous studies have shown that the use of informal childcare, particularly grandparents, significantly increases mothers' labour participation, with stronger effects in disadvantaged families (Arpino et al., 2012; Posadas & Vidal-Fernández, 2012).

The evidence on the effects of EC childcare in the context of developing countries is scarce. One study from Chile, using regional variation in the availability of childcare, found short-run gains from childcare targeted to children aged 5-14 months, particularly in motor and cognitive skills. They also document potential adverse effects in the areas of child-adult interactions, reasoning, and memory, raising awareness of the importance of securing quality when increasing childcare coverage (Noboa Hidalgo & Urzua, 2012).

Conceptual framework

Findings in the economics of human development stress the pattern of high returns to early investments versus low returns to late ones in human capital accumulation (Cunha, Heckman, Lochner, & Masterov, 2006; Cunha & Heckman, 2008; Cunha, Heckman, & Schennach, 2010). The primary objective of this paper is to understand how childcare participation changes for children after parents received the stimulation intervention. Previous findings of this treatment have shown gains in cognitive and receptive language and increases in parental investments (Attanasio et al., 2014, 2015). As mentioned in the introduction and previous section, this result and the characteristics of having an active component of parental education is part of the motivation to examine the effect of the stimulation treatment only in childcare choices. My hypothesis is that this component would also affect childcare decisions, as parents' knowledge and awareness increases regarding how to engage and incentivise development for their children (anticipation of the change denoted in Tables 3.1 and Table 3.2).

Two possibilities might arise on how the stimulation treatment affects childcare decisions, or in other words, alter parental behaviour. First, the intervention increases the child's skills and this, in turn, induces a change in parental behaviour. The latter case is consistent with the complementarity central to the dynamic model of skill formation presented in Cunha and Heckman (2008). In most of the EC literature, parental investments (including childcare) are assumed to be made under perfect knowledge of the child's current skills as well as the technology that determines their law of motion. In reality, parent-child interactions are a developing system shaped by mutual interactions and learning (Gottlieb, 1999; Sroufe, Egeland, Carlson, & Collins, 2005; Cunha et al., 2010). The Cunha-Heckman model captures this evolving system. It provides a framework for understanding the effectiveness of early interventions for disadvantaged children. The central component of this model is the technology of skill formation. In this technology, skills produced at one stage increase the skills attained at late stages. It embraces the idea that skills acquired in one period persist into future years (skills self-produce skills and are self-reinforcing). Another characteristic of skill formation is complementarity. Skills produced at one stage raise the productivity of investment at subsequent stages. In a multistage technology, complementarity also implies that levels of skill investments at different ages boost each other (synergistic). Complementarity also indicates that early investments have to be followed up by later investments in order for the early investments to be productive. Together, complementarity and self-productivity create multiplier effects which explain how skills produce skills and abilities build abilities (Cunha et al., 2006).

Second, the EC intervention may deliver information to the parents about their child's skills, and on successful investment strategies and their returns, thereby increasing parental knowledge (Cunha, 2014). As the stimulation treatment increased parents' knowledge on how to better take care of their kids, parents reduce reliance on childcare. However, better knowledge of the importance of early stimulation and development reveals the potential long-term benefits of selecting "good" quality childcare. Therefore, parents could increase the demand for childcare, moving the child from informal childcare centres to more institutional childcare arrangements. The childcare decisions might be influenced by other variables such as mother labour participation or if within the household, another family member has the knowledge to take proper care of the child. The model of skill formation (Cunha & Heckman, 2008; Cunha et al., 2010) also establishes the importance of accounting for: (1) multiple periods in the life cycle of childhood and adulthood and the existence of critical and sensitive periods of childhood in the formation of skills, (2) multiple skills for both parents and children which extend traditional notions about the skills required for success in life, and (3) multiple forms of investment (Cunha & Heckman, 2008; Cunha et al., 2010; Elango et al., 2015). The next section describes the methodology used to measure the stimulation effect on childcare outcomes.

4. Methodology

There are two challenges to identify and measure the stimulation treatment effect in childcare participation. The first is related to the randomisation issues with one of the childcare measures (*informal childcare*), as reported in Section 2. The second is related to the fact that parents choose selection into childcare (somewhat related to the fact that randomisation did not work for childcare outcomes). Earlier studies indicate that parental preferences when selecting childcare vary by certain child characteristics, including child's age, temperament, and social skills (Forry, Tout, Rothenberg, Sandstrom, & Vesely, 2013).

In such a context, childcare decisions in any period will depend on initial conditions, on the childcare options available in the community, and on other observed and unobserved factors (i.e., mother labour status). Any proposed method to estimate the treatment effect should adjust for these differences to improve the precision of the estimates and reduce the error term (Wooldridge, 2010; Bloom, Richburg-Hayes, & Rebeck, 2007; Gelman & Hill, 2007). Hence, I used and compared three methods to control for prior differences: (1) linear probability model (OLS), (2) difference-in-differences (DiD), and (3) propensity score matching (PSM). The three methods are widely used in the evaluation policy field. I estimated two models for each of the childcare measures (any childcare against maternal care, and public, private, and informal childcare, against maternal care) using the three methods. In the first model, I conditioned on the baseline childcare measures reported by the mother. In the second model, I added to the baseline childcare measures a range of key predictors of household level demand for childcare: mother employment, if the mother is single, mother years of education, and if any of the grandparents live in the same household.[23] I also controlled for child's age, gender, and a household wealth index. The complete list of predictors fixed to their baseline values is shown in Table 4.

[23] Posadas and Vidal-Fernández (2012) found that grandparents' childcare increases mother labour force participation by around 15 percentage points. Most of the effect is driven by families from socio-economically disadvantaged backgrounds.

Table 4. Complete list of predictors for estimation models

Variable	*Unit of observation*	*Type*
Age of target child in months	child	continuous
Second order polynomial in age of target child	child	continuous
If target child is a boy	child	binary
If target child received any childcare before baseline[1]	child	binary
If mother of target child is single	mother	binary
Completed years of education from the mother	mother	continuous
If mother is employed	mother	binary
If any of the grandparents of the target child lives in the same household	household	binary
HH wealth index[2]	household	continuous

[1]If before baseline collection children has received any type of childcare.
[2]First principal component of household asset and characteristics: dirt floor, solid walls, crowding index, home ownership, sewage, and ownership of car, computer, blender, fridge, washing machine, and mobile phone.

For the child unit variables (age, gender, and baseline childcare measures) and household unit variables (grandparents living in the household and household wealth index), information is complete for the analytic sample. For the mother type variables, there are 28 missing observations.[24] I handle potential bias by including in the full model a dummy indicator for the missing variable.

Linear Probability Model (OLS-LPM)

In OLS-LPM, the coefficients describe the effect of the explanatory variables on the probability that the childcare outcome (i) equals 1. The standard errors in all regressions are robust and adjusted for clustering at the municipality level. I also conducted additional checks, computing estimates with bootstrapped standard errors by cluster. These results are reported in the Appendix and are similar to the ones presented in Section 5. Equation 1 summarises the

[24]I test for differences in the 28 children with missing information on treatment status. The result was significant at the 5 percent level.

approach for the complete model. Each type of childcare represents a separate regression:[25]

$$Y_{(y=1|x),1} = \beta_0 + \beta_1 T_{ni} + \beta_2 y_{i,0} + \beta_n X_i + \mu_i \qquad (1)$$

Where:

$Y_{i,1}$ = binary outcome variable which takes the value of 1 if the child is enrolled in one of the types of childcare and 0 if otherwise at follow-up.

T_n = binary variable indicating treatment status set to 1 if target child$_i$ is in in the stimulation treatment group, and 0 if target child$_i$ is in the control group.

$y_{i,0}$ = series of dummy variables for childcare measures reported at baseline. It takes the value of 1 if the child is enrolled in one of the types of childcare and 0 if otherwise

$X_{i,}$ = vector of full list of predictors listed in Table 4.

μ_i = error term.

There are some problems with this approach. An obvious flaw of the method is that probabilities of Y will not necessarily be in the [0,1] interval. Another issue is that the error μ cannot be independent of any regressors, even exogenous regressors unless X_i consists of a single binary regressor. This arises because, for any given X_i, μ must equal either 1-Xβ or – Xβ, which are functions of all elements of X_i. As a result, the errors can never be normally distributed, causing problems for hypothesis testing (Baum, Dong, Lewbel, & Yang, 2012). Another issue is that the OLS-LPM is necessarily heteroskedastic, in other words, the variance of y depends on the values of X and β and is, therefore, heteroskedastic by construction. One

[25]I estimate two regressions for the first set (I) of childcare measures: *any childcare* versus *mother care*; and four regressions for the second set (II) of childcare categories: *public*, *private*, *informal*, and *maternal care*.

more limitation is the functional form. Given the nature of probabilities, we would expect that the marginal impact of an independent variable would exhibit diminishing returns; that is, as the value of the independent variable increases, its effect on *y* should decrease. The OLS-LPM does not allow for this possibility (Baum, Dong, Lewbel, & Yang, 2012; Cameron & Trivedi, 2009).

However, none of these complications causes a problem with the point estimates. Moreover, the interpretation of programme impacts is straightforward. The coefficients indicate how a one-unit change in X affects Pr(y = 1), making the interpretation of the coefficients easier. For a robustness check, I used a *dprobit* model to estimate marginal effects to compare the magnitudes with OLS-LPM outcomes. The results only vary by 0.001-0.002 percentage points (see Appendix-Table 13 and Table 14).

Difference-in-Differences (DiD)

The use of quasi-experimental methods is required, given the issues regarding randomisation and endogeneity in parents' childcare selection, discussed earlier in this section. One suitable approach is DiD, since I estimate the impact of an intervention which occurred at a particular moment in time (2010) and that affected a particular group (stimulation treatment group). This method is also useful to account for some of the unobservable differences in both groups. For the DiD model, I defined my dependent variable as change in childcare between baseline and follow-up. Like the previous method, each change in childcare outcome is a separate regression. The complete fitted model is described in Equation 2:

$$\Delta(Y_{(y=1|x),1} - Y_{(y=1|x)})_{,} = \beta_0 + \beta_1 T_{ni} + \beta_2 y_{i,0} + \beta_n X_i + \mu_i \quad (2)$$

Where:

$\Delta(Y_{(y=1|x),1} - Y_{(y=1|x)})$ = denotes the difference/change in childcare between the binary indicators of childcare in follow-up and baseline.

T_n = binary variable indicating treatment status set to 1 if target child$_i$ is in in the stimulation treatment group, and 0 if target child$_i$ is in the control group.

$y_{i,0}$ = binary variable indicating treatment status set to 1 if target child$_i$ is in the stimulation treatment group, and 0 if target child$_i$ is in the control group.

$X_{i,}$ = vector of full list of predictors listed in Table 4.

μ_i = error term.

Within this framework, childcare measures are observed for two groups (stimulation and control) for two periods (baseline or time=0 and follow-up or time=1). The stimulation group is exposed to the treatment in the second term but not in the first period. The control group is not exposed to the treatment in either period. As we observed the same units (children) within a group in each period, the average gain in the control group is subtracted from the average gain of treatment group. [26] This subtraction removes biases in second-period comparisons between the treatment and control group that could result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends (Wooldridge, 2012).

Propensity Score Matching (PSM)

PSM is a useful method when only observed characteristics are believed to affect

[26] One important condition that must be satisfied is that the treatment and control groups display common trends before the treatment (Dearden, Fitzsimons, & Wyness, 2014). However, this is not possible to prove with cross-sectional data. As the original data comes from a randomisation procedure and that we are controlling for observable differences in initial characteristics, we assume that the "common trends" condition is satisfied.

programme participation (Khandker, Koolwal, & Samad, 2010). The first step of this approach allows me to estimate the probabilities or likelihood (propensity score) of all the observations in our sample to be assigned to the stimulation treatment based on differences in baseline childcare measures or mother characteristics. The propensity score is estimated by the following *dprobit* model (Equation 3), with *D* as the binary dependent variable taking values of 0 and 1, indicating treatment status, and X as the vector of independent variables. I estimate two set of *dprobit* models, the first one considering the baseline childcare measures and the second one taking into account the complete list of predictors (listed in Table 4):

$$p(x)=prob\ (D=1|x) = E(D|x) \qquad (3)$$

After estimating the propensity scores, the next step consists in matching treatment and control students, according to the scores estimated. I use the nearest neighbour matching technique to match children that have the closest propensity scores within a specified distance that did not receive the treatment. Results of the three methods are reported in the following section.

5. Main Findings

Childcare measures: Any childcare against maternal care

In the following section, I report results of the stimulation treatment effect of *any childcare* against *maternal care* for the three methods. For coefficients of the full set of predictors, see Appendix-Table 11.

a) Linear Probability Model Results

For the first method, I fitted equation (1) for each childcare outcome. All statistical inference adjusts standard errors for clustering at the municipality level.[27] Estimates are reported in Table 5.1 for the comparison *any childcare* versus *no childcare*, adjusting only for baseline childcare measures (I) and for the complete list of predictors (II).

Table 5.1 Effect of Stimulation treatment on childcare participation at follow-up, including baseline childcare regressors (I) and complete (II) model

	Stimulation treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Any childcare	-0.049 (0.052)	[-0.153 to 0.055]	0.346	-0.020 (0.051)	[-0.122 to 0.082]	0.696
Maternal care	0.042 (0.051)	[-0.061 to 0.145]	0.417	0.013 (0.050)	[-0.087 to 0.114]	0.795
N	636			620		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available in Appendix-Table 11. Using Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.025. The probability of observing at least one signicant result when using this correction is 0.049. In this table, two hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

Estimates in Table 5.1, show that controlling only for baseline childcare measures, the stimulation treatment effect reduces *any childcare* participation by 4.9 percentage points. For the complete model (II), the effect is smaller, reducing reliance in *any childcare* by 2 percentage points. However, the impact on both models is not statistically significant.[28]

[27]Level of randomisation.
[28]The results of other characteristics that are significant are: pre-baseline childcare and baseline childcare predictors, which explain around 23 to 77 percentage points of any childcare participation; and being a working mother increases the probability of using any childcare by 8.8 percentage points (see Appendix-Table 11).

b) Difference-in-Differences Results

In the second method, I fitted equation (2) to estimate the difference in childcare choices. Each regression adjusts standard errors for clustering at the municipality level (clusters (n)=48). Table 5.2 includes results for the differences in *any childcare* versus *no childcare.* Column (I) estimates adjust for baseline childcare measures only, and column (II) controls for the complete list of predictors (II).

Table 5.2 Difference-in-differences estimators of Stimulation treatment on childcare participation, baseline childcare regressors (I) and complete (II) model

	Stimulation treatment					
Childcare measures	(I)			(II)		
	β *(Std. Error)*	*CI*	*P-value*	*β* *(Std. Error)*	*CI*	*P-value*
Any childcare	-0.049 (0.052)	[-0.153 to 0.055]	0.348	-0.020 (0.051)	[-0.122 to 0.083]	0.696
Maternal care	0.041 (0.051)	[-0.061 to 0.145]	0.420	0.013 (0.050)	[-0.088 to 0.114]	0.796
N	636			620		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available in Appendix-Table 11. Using Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.025. The probability of observing at least one signicant result when using this correction is 0.049. In this table, two hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

The DiD results in Table 5.2 are very similar to the LPM ones shown in Table 5.1. The difference for *any childcare* indicates that the stimulation treatment reduces the probability of enrolment in *any childcare* by 4.9 percentage points for the baseline childcare model (I), and by 2 percentage points in the complete model (II). The result is not statistically significant.[29]

[29] Regarding significant predictors, pre-baseline and baseline childcare account for an increase of 23 to 76 percentage points in *any childcare* use. Working and single mothers increase the difference of *any childcare* enrolment by 8.9 to 10 percentage points, respectively (see Appendix-Table 11).

c) Propensity Score Matching Results

For the third method, I estimated the propensity score with equation (3), matching on baseline childcare measures (I), and the full list of predictors (II). Each propensity score prediction adjusts for standard errors at the municipality level.

Table 5.3 Propensity Score Matching estimates, baseline childcare regressors (I) and complete (II) model

Childcare measures	***Stimulation treatment***							
	(I)				(II)			
	ATT sample (M=3)				ATT sample (M=3)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Any childcare	0.390	0.438	-0.048 (0.039)	-1.22	0.388	0.408	-0.019 (0.046)	-0.42
Maternal care	0.601	0.559	0.041 (0.040)	1.06	0.602	0.590	0.012 (0.046)	0.26
N	318	318	-	-	309	306	-	-

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate dprobit and psmatch estimation. Standard errors in parentheses are adjusted for clustering at municipality level. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).

Table 5.3 displays the results for the matching estimator (nearest-neighbour caliper matching with replacement).[30] For the PSM estimates, the difference of being in *any childcare* for the children in the treatment group is 4.8 percentages points less in the baseline childcare model, and 1.9 percentage points less in the complete model, compared to the children in the control group. Only a 0.1 decimal difference from the LPM and DiD results. As in the previous methods, the treatment effect is not statistically significant. In the Appendix, I included a set of checks to assess the achieved quality of the matching estimator. Overall, the support of the estimated propensity score is large for both treated and control children (see Appendix-Graph 1) and the probabilities used for matching also balances our regressors (see Appendix-Table 9).

Childcare measures: public, private, informal, and maternal

Results of the stimulation treatment influence for the *public*, *private*, and *informal* childcare measures against *maternal* care, are reported in the next section. For coefficients of the full set of predictors, see Appendix-Table 12.

a) Linear Probability Model Results

Table 6.1 reports estimates for the four-way split childcare measures controlling only for baseline childcare measures (I) and for the complete list of predictors (II). Each regression adjusts standard errors for clustering at the municipality level.

[30]Using three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches). For robustness test, I conducted a PSM with different specifications (see Appendix-Table 17).

Table 6.1 Effect of Stimulation treatment on childcare participation at follow-up (LPM), including baseline childcare regressors (I) and complete (II) model

	Stimulation treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Public childcare	-0.065 (0.056)	[-0.179 to 0.048]	0.252	-0.031 (0.052)	[-0.135 to 0.074]	0.560
Private childcare	-0.017 (0.014)	[-0.046 to 0.011]	0.239	-0.019 (0.012)	[-0.044 to 0.005]	0.118
Informal childcare	0.042* (0.019)	[0.005 to 0.080]	0.028	0.044* (0.018)	[0.008 to 0.081]	0.019
Maternal care	0.040 (0.052)	[-0.064 to 0.144]	0.443	0.006 (0.051)	[-0.096 to 0.107]	0.910
N	636			620		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls in Appendix-Table 12. Using the Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.0125. The probability of observing at least one signicant result when using this correction is 0.049. In this scenario, the stimulation treatment effect would be insignificant (though the p-value for the complete model is close to the Bonferroni value). In this table, four hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

When decomposing the types of childcare available, results indicate interesting differences across childcare participation. Results in Table 6.1 suggest that the stimulation intervention increases *informal childcare* participation by 4.2 to 4.4 percentage points, in the baseline childcare model and the complete model, respectively. The treatment effect is positive and statistically significant (p-value<0.05). No evidence of impact treatment was found in the other childcare measures.[31]

[31]The coefficients of other characteristics vary depending on the childcare measure. For *public childcare*, pre-baseline childcare and baseline childcare regressors increase *public care* use by 31 to 72 percentage points (*informal childcare* with the largest coefficient). Working mothers increase it by 6.8 percentage points. Regarding *private childcare*, the only significant predictor was the mother's years of education, but the influence was less than 1 percentage point. For *informal childcare*, besides the stimulation effect, only baseline *maternal care* and baseline *informal childcare* are significant, and augment *informal childcare* use by 5.8 to 24 percentage points respectively (see Appendix-Table 12).

b) Difference-in-Differences Results

Table 6.2 presents results for the differences in *public*, *private*, *informal*, and *maternal* childcare choices. Each regression adjusts standard errors for clustering at the municipality level (clusters (n)=48). Column (I) results adjust for baseline childcare measures only and column (II) controls for the complete list of predictors (II).

Table 6.2 Difference-in-differences estimators of Stimulation treatment on childcare participation, baseline childcare regressors model (I) and complete (II) model

	Stimulation treatment					
Childcare measures	(I)			(II)		
	β *(Std. Error)*	*CI*	*P-value*	*β* *(Std. Error)*	*CI*	*P-value*
Public childcare	-0.065 (0.056)	[-0.179 to 0.048]	0.252	-0.031 (0.052)	[-0.136 to 0.074]	0.554
Private childcare	-0.016 (0.014)	[-0.046 to 0.013]	0.273	-0.020 (0.013)	[-0.046 to 0.006]	0.123
Informal childcare	0.044* (0.019)	[0.005 to 0.082]	0.026	0.046* (0.019)	[0.008 to 0.084]	0.018
Maternal care	0.040 (0.052)	[-0.064 to 0.145]	0.445	0.006 (0.051)	[-0.096 to 0.107]	0.908
N	636			620		

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available in Appendix-Table 12. Using the Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.0125. The probability of observing at least one signicant result when using this correction is 0.049. In this scenario, the stimulation treatment effect would be insignificant (though the p-value for the complete model is close to the Bonferroni value). In this table, four hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

DiD results in Table 6.2 are consistent with the LPM ones. The stimulation treatment has a significant effect on increasing *informal childcare* between 4.4 to 4.6 percentage points, for the baseline childcare and complete model respectively. Coefficients are more precisely estimated with this method, with a 0.2-percentage point difference from the estimates in Table 6.1).

c) Propensity Score Matching Results

Results for the PSM model[32] are listed in Table 6.3. Column (I) includes estimates for the baseline childcare model, while column (II) includes estimates for the complete model

[32]Using three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches). For robustness test, I conducted a PSM with different specifications (see Appendix-Table 18).

Table 6.3 Propensity Score Matching estimates, baseline childcare regressors (I) and complete (II) model

	Stimulation treatment							
Childcare measures	(I)				(II)			
	ATT sample (M=3)				ATT sample (M=3)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Public childcare	0.305	0.368	-0.063 (0.038)	-1.66	0.313	0.337	-0.024 (0.044)	-0.55
Private childcare	0.016	0.033	-0.017 (0.013)	-1.33	0.013	0.026	-0.013 (0.014)	-0.91
Informal childcare	0.075	0.036	0.040* (0.019)	2.06	0.071	0.016	0.055 (0.018)	3.03*
Maternal care	0.601	0.560	0.041 (0.040)	1.02	0.60	0.620	-0.020 (0.046)	-0.44
N	318	318	-	-	314	306	-	-

*p<0.05, **p<0.01, ***p<0.001. Each row represents a separate dprobit and psmatch estimation. Standard errors in parentheses are adjusted for clustering at municipality level. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).

With the PSM method, the treatment effect in *informal childcare* is slightly higher than the other estimates, with a 4 to 5.5 percentage point increase in this childcare outcome, for the baseline childcare and complete model respectively. Robustness tests to assess the quality of the matching estimator for the full model indicate that there is a large support of the estimated propensity score for treated and control children (see Appendix-Graph 2). Moreover, the probabilities used for matching also balances our regressors (see Appendix-Table 10).[33]

Summary of results

The following table summarises the stimulation treatment impact, in each childcare measure and across the three methods.

Table 7. Estimates for the three methods, including baseline childcare regressors (I) and complete (II) model

	Stimulation treatment					
Childcare measures	(I)			(II)		
	LPM	*DiD*	*PSM*	*LPM*	*DiD*	*PSM*
Any childcare	-0.049	-0.049	-0.048	-0.020	-0.020	-0.019
Maternal care	0.042	0.041	0.041	0.013	0.013	0.012
Public childcare	-0.065	-0.065	-0.063	-0.031	-0.031	-0.024
Private childcare	-0.017	-0.016	-0.017	-0.019	-0.020	-0.013
Informal childcare	**0.042***	**0.044***	**0.040***	**0.044***	**0.046***	**0.055***
Maternal care	0.040	0.040	0.041	0.006	0.006	-0.020
N	636			620		

*p<0.05, **p<0.01, ***p<0.001 Standard errors (not included) are adjusted for clustering at municipality level.

[33]Due to lack of satisfactory match, four observations of the treated group were dropped (as were in the off-support region).

Table 7 results show that the stimulation treatment only affected childcare decisions for the *informal childcare* outcome and in a marginally small percentage. The final section includes some possible explanations and limitations of these findings.

6. Discussion and Conclusion

Previous results showed that an EC intervention with a parenting programme component had zero effect on different childcare outcomes, and only relatively small positive impact on informal childcare participation (4.4 to 5.5 percentage point increase). The impact of informal childcare is in line with the hypothesis outlined in Section 3 and partially explained by the dynamic model of skill formation (Cunha & Heckman, 2008; Cunha et al., 2010).

Several explanations help to understand parental childcare choices induced by "successful" EC programmes. First, intervention increases the child's skills and this, in turn, produces a change in parental behaviour. The effect in informal childcare might be that parents perceived that the stimulation treatment increased the child's skills and would not benefit from being in a more formal childcare setting. This is consistent with the complementarity central to the model presented in Cunha and Heckman (2008). Second, the stimulation intervention delivered information to the parents about their child's skills, increasing parental confidence and their knowledge in child nurture, hence supplementing the need for formal childcare and using informal care arrangements instead to save costs. In this scenario, the stimulation treatment might be acting simultaneously as a substitute of childcare and complement of parents' knowledge. Third, the result might be a reflection of parental preferences for "internal" childcare arrangements. Mothers may be less willing to entrust their children to institutions and may prefer either to care for the children themselves or having them in the custody of relatives, especially when they are very young (Arpino et al., 2010). Interestingly, no significant association was found related to the age of the child predictor (somewhat similar to previous EC findings looking at starting age of childcare, with inconclusive results).[34] Moreover, many parents might use a combination of informal and formal childcare (including early years education) and, so, a rise in the use in one will not necessarily lead to a fall in use of the other (Bryson et al., 2012)). However, I delimit the present analysis for mutually exclusive childcare arrangements.

There are several caveats to the present analysis. The main one relies on the ineffectiveness of the randomisation process in the childcare outcomes. The use of quasi-experimental techniques was required to have an unbiased estimate of the treatment effect and correct for endogeneity in childcare selection. Another limitation relies on focusing the analysis on only one treatment arm. Both limitations have direct implications for the external validity of the conclusions.

Furthermore, providing evidence that the stimulation treatment affected informal childcare participation, and previously improved cognitive and language outcomes (Attanasio et al., 2014, 2015), is not enough to establish the causal impact of childcare (outside the scope of the present analysis). However, the results provide evidence that the EC programme could be used as an instrument to explore the causal impact of informal childcare in later life outcomes from the child or maternal labour participation for mothers in the stimulation treatment.

Overall, more studies on the effectiveness of EC programmes that complement rather than substitute for family care are needed. Previous EC evidence shows that successful interventions alter parental behaviour. Understanding why this happens, how parenting can be incentivised, and through which channels parenting influences child development are crucial tasks for

[34]Coefficients of the predictors included in Appendix-Table 11 & Table 12.

upcoming studies (Heckman, 2014; Heckman & Mosso, 2014). Likewise, it is essential to have a more comprehensive understanding of informal childcare services, particularly for the disadvantaged population. This type of care should be included in the discussion of public childcare, as is usually overlooked because it has been seen purely as a “family matter”, and hence not of interest to public policy (Bryson et al., 2012). Still, earlier findings have shown that the use of informal childcare, particularly grandparents, significantly increases mothers’ labour participation, with stronger effects in disadvantaged families (Arpino et al., 2012; Posadas & Vidal-Fernández, 2012). Future analyses should focus on identifying profiles and characteristics of informal childcare providers to understand potential factors that drive this impact and enhance the effectiveness of EC interventions in other outcomes of interest.

Lastly, resources to support childcare decision-making should acknowledge the multiple interconnected factors that shape how decisions are made and the fact that preferences for different features of child care arrangements may vary by the characteristics of the families (Weber, 2011; Forry et al., 2013).

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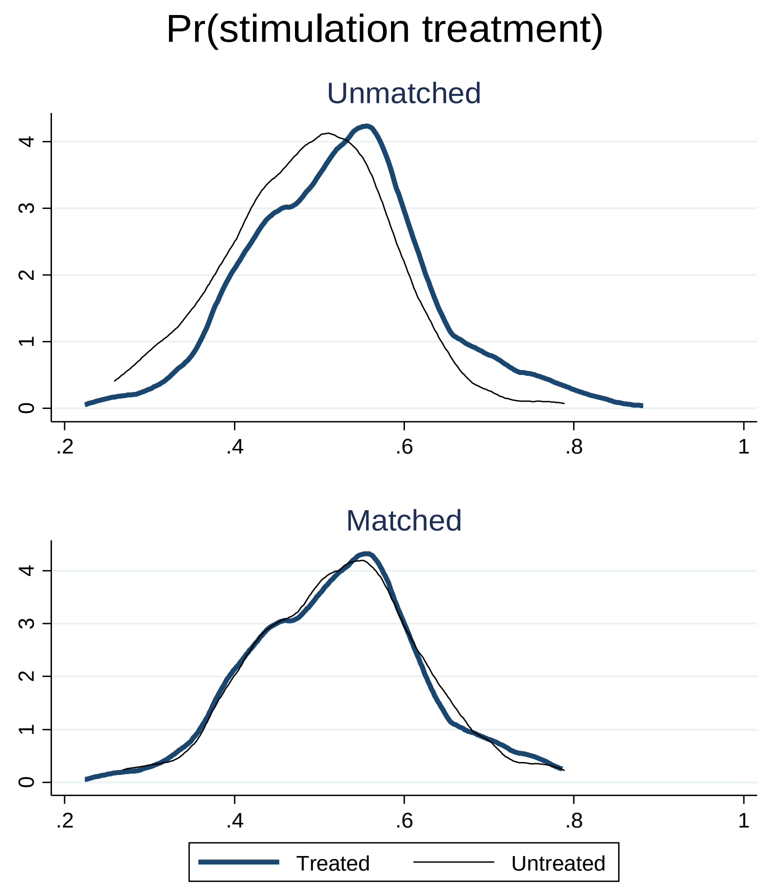
Appendix

Table 8. Baseline characteristics of the children who were not in the follow-up sample

Variable	*Control (n=31)*	*Stimulation (n=39)*	*P-value*
Children			
Mean (SE) age in months	18.39 (0.60)	17.54 (0.53)	>0.50
Proportion of Boys	0.42	0.44	>0.50
Household			
Proportion of households with crowding[2]	0.32	0.33	0.49
Mean (SE) household wealth index[3]	-0.007 (0.40)	-0.203 (0.33)	>0.50
Mean (SE) Number of varieties of play materials[4]	4.39 (0.31)	4.18 (0.30)	0.12
Mean (SE) Number of varieties of play activities[5]	3.84 (0.30)	3.77 (0.24)	0.48
Childcare measures			
Any childcare	0.161	0.103	0.41
Public childcare	0.065	0.077	>0.50
Private childcare	0.032	0.00	0.23
Informal childcare	0.065	0.026	0.33
Maternal care	0.839	0.897	0.41

*Children that did not have complete information on the Bayley scales.

Graph 1. Quality check for the propensity score matching for *any childcare* against *maternal* care: propensity score overlap (complete model)



*This graph plots the probability density function of the estimated propensity scores, separately for children in the stimulation and control group, based on the complete list of predictors, before matching and after matching. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).

Table 9. Quality check for the propensity score matching for *any childcare* against *maternal* care: effectiveness of reducing bias (complete model)

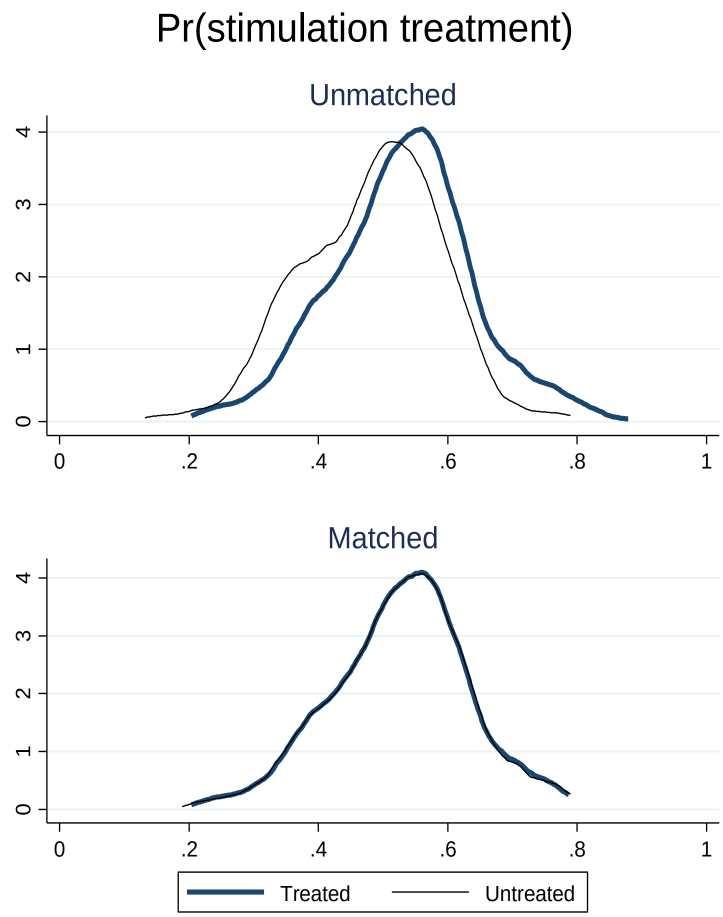
Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
Any Childcare BL	U	0.140	0.173	-9.1	51.1	-1.13	0.258
	M	0.142	0.159	-4.4		-0.56	0.574
Maternal care BL	U	0.857	0.824	9.0	51.2	1.13	0.261
	M	0.854	0.838	4.4		0.56	0.578
If child is a boy	U	0.475	0.490	-3.1	86.2	-0.39	0.697
	M	0.469	0.467	0.4		0.05	0.957
Age of target child at BL	U	18.051	18.173	-3.2	80.6	-0.39	0.694
	M	18.049	18.072	-0.6		-0.08	0.937
Squared term of Age of target child at BL	U	339.82	346.01	-4.4	83.1	-0.55	0.584
	M	339.7	340.74	-0.7		-0.10	0.924
Mother years of education at BL	U	6.98	7.520	-14.9	98.6	-1.86	0.063
	M	7.016	7.023	-0.2		-0.03	0.979
Occupied mother at BL	U	0.439	0.477	-7.5	45.5	-0.94	0.348
	M	0.443	0.423	4.1		0.51	0.608
Single mother dummy at BL	U	0.296	0.314	-3.8	100.0	-0.47	0.636
	M	0.301	0.301	0.0		-0.00	1.000
Any institutional care before baseline	U	0.201	0.294	-21.8	80.4	-2.71	0.007
	M	0.201	0.219	-4.3		-0.56	0.576
Any grandparent living in household at BL	U	0.277	0.356	-17.0	94.5	-2.12	0.034
	M	0.278	0.283	-0.9		-0.12	0.905
Household wealth index	U	-0.157	0.228	-22.7	78.8	-2.82	0.005
	M	-0.051	-0.132	4.8		0.59	0.555
Missing dummy variable	U	0	0	.	.	.	.
	M	0	0	.		.	.

* if variance ratio outside [0.80; 1.25] for U and [0.80; 1.25] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.030	25.92	0.007	10.6	9.0	41.1*	1.28	25
Matched	0.002	1.33	1.000	2.3	0.9	9.3	1.10	0

*if B>25%, R outside [0.5; 2]

Graph 2. Quality check for the propensity score matching for *public, private,* and *informal* against *maternal* care: propensity score overlap (complete model)



*This graph plots the probability density function of the estimated propensity scores, separately for children in the stimulation and control group, based on the complete list of predictors, before matching and after matching. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).

Table 10. Quality check for the propensity score matching for *any childcare* against *maternal* care: effectiveness of reducing bias (complete model)

Variable	Unmatched Matched	Mean		%bias	%reduct	t-test	
		Treated	Control		|bias|	t	p>|t|
Public Childcare BL	U	0.073	0.078	-2.0	58.5	-0.24	0.808
	M	0.074	0.076	-0.8		-0.10	0.919
Private Childcare BL	U	0.041	0.042	-0.5	-98.7	-0.07	0.947
	M	0.042	0.040	1.1		0.14	0.893
Informal Childcare BL	U	0.025	0.052	-13.9	100.0	-1.73	0.084
	M	0.026	0.026	0.0		-0.00	1.000
Maternal care BL	U	0.857	0.824	9.0	96.8	1.13	0.261
	M	0.855	0.856	-0.3		-0.04	0.970
If child is a boy	U	0.475	0.490	-3.1	21.1	-0.39	0.697
	M	0.471	0.483	-2.5		-0.31	0.758
Age of target child at BL	U	18.051	18.173	-3.2	63.9	-0.39	0.694
	M	18.035	17.991	1.1		0.15	0.883
Squared term of Age of target child at BL	U	339.82	346.01	-4.4	74.8	-0.55	0.584
	M	339.24	337.68	1.1		0.14	0.886
Mother years of education at BL	U	6.978	7.520	-14.9	71.7	-1.86	0.063
	M	7.029	6.876	4.2		0.53	0.598
Occupied mother at BL	U	0.439	0.477	-7.5	72.9	-0.94	0.348
	M	0.445	0.435	2.0		0.26	0.798
Single mother dummy at BL	U	0.296	0.314	-3.8	-68.5	-0.47	0.636
	M	0.3	0.270	6.4		0.81	0.416
Any institutional care before baseline	U	0.201	0.294	-21.8	77.0	-2.71	0.007
	M	0.203	0.225	-5.0		-0.65	0.515
Any grandparent living in household at BL	U	0.277	0.356	-17.0	71.5	-2.12	0.034
	M	0.281	0.258	4.9		0.63	0.527
Household wealth index	U	-0.157	0.228	-22.7	78.4	-2.82	0.005
	M	-0.047	-0.130	4.9		0.59	0.555
Missing dummy variable	U	0	0	.	.	.	.
	M	0	0	.		.	.

* if variance ratio outside [0.80; 1.25] for U and [0.80; 1.25] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.036	30.58	0.004	9.5	7.5	44.7*	1.12	25
Matched	0.003	2.17	1.000	2.6	2.0	11.8	0.93	0

*if B>25%, R outside [0.5; 2]

Table 11. Coefficients for the complet model, *any childcare* against *maternal care* for OLS-LPM and DiD

	Types of childcare			
	Any childcare	*Maternal care*	*Any childcare*	*Maternal care*
	OLS-LPM		DiD	
Maternal care at BL	0.534** (0.187)	-0.537*** (0.190)	0.764*** (0.064)	-
Any childcare at BL	0. 766*** (0.171)	-0.783** (0.175)	-	0.740*** (0.064)
Boys (=1 if male)[1]	-0.045 (0.038)	0.044 (0.038)	-0.045 (0.038)	0.044 (0.039)
Children age (months) at BL	-0.046 (0.048)	0.053 (0.046)	-0.046 (0.048)	0.050 (0.049)
Children age (months) at BL (polynomial second order)	0.001 (0.001)	-0.002 (0.001)	0.001 (0.001)	-0.002 (0.001)
Mother total years of education at BL	0.007 (0.006)	-0.008 (0.006)	0.007 (0.006)	-0.008 (0.006)
Employed mother at BL	0.088* (0.037)	-0.093* (0.038)	0.089* (0.037)	-0.083* (0.039)
Single mother at BL	0.100 (0.053)	-0.104 (0.054)	0.101 (0.053)	-0.094 (0.055)
Any type of childcare before BL	0.233*** (0.047)	-0.239*** (0.047)	0.231*** (0.048)	-0.236*** (0.047)
Any grandparent lives in HH at BL	0.001 (0.052)	0.003 (0.051)	-0.001 (0.051)	-0.006 (0.053)
HH wealth index[2]	-0.013 (0.009)	0.016 (0.012)	-0.013 (0.011)	0.017 (0.012)
_constant	0.027 (0.554)	0.907 (0.539)	-0.199 (0.440)	-0.612 (0.439)
N	620	620	620	620

*p<0.05, **p<0.01, ***p<0.001
Standard errors in parentheses are adjusted for clustering at municipality level.

Table 12. Coefficients for the complet model, *public*, *private* and *informal* against *maternal care* for OLS-LPM and DiD

	Types of childcare							
	Public	*Private*	*Informal*	*Maternal care*	*Public*	*Private*	*Informal*	*Maternal care*
	OLS-LPM				DiD			
Public childcare at BL	0.633**	0.044	0.014	-0.680**	-	0.941***	0.705***	0.850***
	(0.207)	(0.031)	(0.020)	(0.214)		(0.013)	(0.093)	(0.109)
Private childcare at BL	0. 657***	0.035	0.090	-0.777***	1.007***	-	0.784***	0.759***
	(0.162)	(0.044)	(0.057)	(0.164)	(0.121)		(0.102)	(0.088)
Informal childcare at BL	0.718**	0.013	0. 242*	-0.969***	1.066***	0.908***	-	0.571***
	(0.234)	(0.042)	(0.092)	(0.206)	(0.153)	(0.067)		(0.074)
Maternal care at BL	0.482*	0.008	0.058*	-0.549**	0.830***	0.905***	0.755***	-
	(0.194)	(0.016)	(0.023)	(0.203)	(0.112)	(0.054)	(0.089)	
Boys (=1 if male)[1]	-0.031	-0.005	-0.001	0.044	-0.031	-0.003	0.000	0.044
	(0.034)	(0.015)	(0.017)	(0.038)	(0.034)	(0.015)	(0.017)	(0.039)
Children age (months) at BL	-0.060	0.006	0.003	0.059	-0.060	0.005	0.000	0.056
	(0.046)	(0.011)	(0.020)	(0.047)	(0.045)	(0.011)	(0.020)	(0.050)
Children age (months) at BL (polynomial second order)	0.002	-0.000	-0.000	-0.002	0.002	-0.000	0.000	-0.002
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Mother total years of education at BL	0.004	0.004**	-0.001	-0.008	0.004	0.004**	-0.001	-0.008*
	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)
Employed mother at BL	0.069	0.006	0.011	-0.086**	0.071	0.011	0.012	-0.076*
	(0.036)	(0.012)	(0.021)	(0.038)	(0.036)	(0.012)	(0.021)	(0.039)
Single mother at BL	0.043	0.013	0.039	-0.097*	0.044	0.017	0.027	-0.088*
	(0.051)	(0.018)	(0.027)	(0.053)	(0.051)	(0.019)	(0.018)	(0.054)
Any childcare before BL	0.312***	-0.021*	-0.019	-0.282***	0.306***	-0.026	0.039	-0.276***
	(0.054)	(0.011)	(0.014)	(0.053)	(0.056)	(0.013)	(0.026)	(0.055)
Any grandparent lives in HH at BL	-0.040	0.007	0.022	0.008	-0.042	0.001	0.015	-0.001
	(0.047)	(0.012)	(0.023)	(0.050)	(0.047)	(0.013)	(0.024)	(0.053)
HH wealth index[3]	-0.007	-0.001	-0.005	0.017	-0.007	-0.002	-0.004	0.017
	(0.010)	(0.002)	(0.006)	(0.012)	(0.010)	(0.002)	(0.006)	(0.012)
_constant	0.193	-0.060	-0.098	0.882	-0.152	-0.951***	-0.776***	-0.649
	(0.494)	(0.101)	(0.177)	(0.556)	(0.404)	(0.117)	(0.219)	(0.448)
N	620	620	620	620	620	620	620	620

*p<0.05, **p<0.01, ***p<0.001
Standard errors in parentheses are adjusted for clustering at municipality level.

Table 13. Robustness test: Dprobit Model outcomes for each type of childcare

	Stimulation treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Any childcare	-0.054 (0.057)	[-0.165 to 0.057]	0.342	-0.023 (0.058)	[-0.137 to 0.091]	0.694
Maternal care	0.046 (0.057)	[-0.066 to 0.158]	0.420	0.015 (0.058)	[-0.099 to 0.129]	0.799
N	636			620		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available upon request.

Table 14. Robustness test: Dprobit model Effect of Stimulation treatment on childcare participation at follow-up (LPM), including baseline childcare regressors (II) and complete (III) model

	Stimulation treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Public childcare	-0.068 (0.060)	[-0.185 to 0.049]	0.255	-0.036 (0.059)	[-0.151 to 0.079]	0.545
Private childcare	-0.016 (0.013)	[-0.042 to 0.009]	0.208	-0.012 (0.009)	[-0.029 to 0.005]	0.110
Informal childcare	0.044* (0.019)	[0.006 to 0.082]	0.014	0.043** (0.018)	[0.008 to 0.078]	0.007
Maternal care	0.044 (0.057)	[-0.068 to 0.156]	0.444	0.009 (0.058)	[-0.105 to 0.123]	0.874
N	636			620		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available upon request.

Table 15. Robustness test: Difference-in-difference estimators with bootstrapped standard errors for stimulation treatment on childcare participation, baseline childcare regressors (I) and complete (II) model

	Stimulation treatment					
Childcare measures	(I)			(II)		
	β *(Std. Error)*	*CI*	*P-value*	*β* *(Std. Error)*	*CI*	*P-value*
Any childcare	-0.049 (0.052)	[-0.152 to 0.054]	0.350	-0.020 (0.052)	[-0.122 to 0.082]	0.701
Maternal care	0.042 (0.052)	[-0.059 to 0.143]	0.417	0.013 (0.050)	[-0.086 to 0.112]	0.796
N	636			620		

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate regression. Standard errors in parentheses are computed by bootstrap methods (5000 replications) and adjusted for clustering at municipality level.

Table 16. Robustness test: Difference-in-difference estimators with bootstrapped standard errors for stimulation treatment on childcare participation, baseline childcare regressors model (I) and complete (II) model

	Stimulation treatment					
Childcare measures	(I)			(II)		
	β *(Std. Error)*	*CI*	*P-value*	*β* *(Std. Error)*	*CI*	*P-value*
Public childcare	-0.065 (0.055)	[-0.174 to 0.043]	0.236	-0.031 (0.053)	[-0.136 to 0.073]	0.560
Private childcare	-0.016 (0.015)	[-0.046 to 0.013]	0.271	-0.020 (0.013)	[-0.046 to 0.005]	0.121
Informal childcare	0.044* (0.019)	[0.007 to 0.081]	0.021	0.046* (0.019)	[0.010 to 0.083]	0.013
Maternal care	0.040 (0.053)	[-0.063 to 0.143]	0.446	0.006 (0.051)	[-0.093 to 0.105]	0.908
N	636			620		

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate regression. Standard errors in parentheses are computed by bootstrap methods (5000 replications) and adjusted for clustering at municipality level.

Table 17. Robustness test: PSM with n(10) and without ties

Childcare measures	*Stimulation treatment*							
	(I)				(II)			
	ATT sample (M=10)				ATT sample (M=10)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Any childcare	0.390	0.643	-0.253	-1.97	0.388	0.411	-0.021	-0.53
Maternal care	0.601	0.357	0.244	1.90	0.602	0.587	0.015	0.34
N	318	318	-	-	309	306	-	-

*p<0.05, **p<0.01, ***p<0.001. Each row represents a separate dprobit and psmatch estimation. Standard errors (not included) for the dprobit model are adjusted for clustering at municipality level. The psmatch specifications used were 10 neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and no ties.

Table 18. Robustness test: PSM with n(10) and without ties

Childcare measures	*Stimulation treatment*							
	(I)				(II)			
	ATT sample (M=10)				ATT sample (M=10)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Public childcare	0.305	0.347	-0.042	-0.30	0.313	0.373	-0.060	-1.46
Private childcare	0.016	0.096	-0.081	-1.09	0.013	0.022	-0.009	-0.66
Informal childcare	0.075	0.184	-0.109	-1.21	0.071	0.020	0.051	2.76
Maternal care	0.601	0.372	0.228	1.86	0.60	0.584	0.016	0.38
N	318	318	-	-	310	306	-	-

*p<0.05, **p<0.01, ***p<0.001. Each row represents a separate dprobit and psmatch estimation. Standard errors (not included) for the dprobit model are adjusted for clustering at municipality level. The psmatch specifications used were 10 neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and no ties.

Table 19. Robustness test: Effect of treatment (stimulation and stimulation with nutrition) on childcare participation at follow-up (LPM), including baseline childcare regressors (I) and complete (II) model

	Home visits treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Any childcare	-0.009 (0.044)	[-0.098 to 0.079]	0.832	0.019 (0.044)	[-0.068 to 0.106]	0.670
Maternal care	0.007 (0.044)	[-0.080 to 0.095]	0.866	-0.020 (0.043)	[-0.106 to 0.066]	0.643
N	954			932		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available upon request.

Table 20. Robustness test: Effect of treatment (stimulation and stimulation with nutrition) on childcare participation at follow-up (LPM), including baseline childcare regressors (I) and complete (II) model

	Home visits treatment					
	(I)			(II)		
Childcare measures	*β (Std. Error)*	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Public childcare	-0.029 (0.047)	[-0.123 to 0.064]	0.536	-0.005 (0.044)	[-0.094 to 0.084]	0.915
Private childcare	-0.015 (0.012)	[-0.040 to 0.009]	0.218	-0.015 (0.012)	[-0.039 to 0.009]	0.218
Informal childcare	0.041** (0.014)	[0.012 to 0.069]	0.006	0.045** (0.014)	[0.017 to 0.072]	0.002
Maternal care	0.006 (0.044)	[-0.083 to 0.094]	0.901	-0.023 (0.043)	[-0.109 to 0.063]	0.595
N	954			932		

*p<0.05, **p<0.01, ***p<0.001
Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Coefficients on the full set of controls available upon request. Using the Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.0125. The probability of observing at least one signicant result when using this correction is 0.049. In this scenario, the stimulation treatment effect is still significant for both models. In this table, four hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

Table 21. Robustness test: Difference-in-difference estimators (stimulation and stimulation with nutrition) on childcare participation, baseline childcare regressors (I) and complete (II) model

	Home visits treatment					
Childcare measures	(I)			(II)		
	β (Std. Error)	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Any childcare	-0.010 (0.044)	[-0.098 to 0.079]	0.828	-0.020 (0.052)	[-0.122 to 0.082]	0.701
Maternal care	0.005 (0.044)	[-0.083 to 0.093]	0.907	0.013 (0.050)	[-0.086 to 0.112]	0.796
N	954			932		

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate regression. Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level.

Table 22. Robustness test: Difference-in-difference estimators (stimulation and stimulation with nutrition) on childcare participation, baseline childcare regressors (I) and complete (II) model

	Home visits treatment					
Childcare measures	(I)			(II)		
	β (Std. Error)	*CI*	*P-value*	*β (Std. Error)*	*CI*	*P-value*
Public childcare	-0.029 (0.047)	[-0.123 to 0.064]	0.531	-0.005 (0.045)	[-0.094 to 0.083]	0.903
Private childcare	-0.017 (0.013)	[-0.042 to 0.009]	0.201	-0.017 (0.013)	[-0.042 to 0.008]	0.175
Informal childcare	0.040** (0.019)	[0.012 to 0.069]	0.007	0.044** (0.014)	[0.016 to 0.072]	0.003
Maternal care	0.003 (0.044)	[-0.085 to 0.092]	0.942	-0.025 (0.043)	[-0.112 to 0.061]	0.559
N	954			932		

*p<0.05, **p<0.01, ***p<0.001

Each row represents a separate regression. Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level. Using the Bonferroni correction for multiple hypothesis testing, adjusted p-value would be 0.0125. The probability of observing at least one signicant result when using this correction is 0.049. In this scenario, the stimulation treatment effect is still significant for both models. In this table, four hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008). In this table, four hypotheses are considered, corresponding to each row. The Bonferroni correction tend to be extremely conservative, leading to a high rate of false negatives (Goldman, 2008).

Table 23. Robustness test: PSM (stimulation and stimulation with nutrition) with n(3)

Childcare measures	***Home visits treatment***							
	(I)				(II)			
	ATT sample (M=3)				ATT sample (M=3)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Any childcare	0.437	0.444	-0.007 (0.034)	-0.20	0.430	0.435	-0.005 (0.039)	-0.12
Maternal care	0.558	0.553	0.006 (0.035)	0.16	0.565	0.563	0.002 (0.039)	0.05
N	636	318	-	-	616	306	-	-

*p<0.05, **p<0.01, ***p<0.001. Each row represents a separate dprobit and psmatch estimation. Standard errors in parentheses are adjusted for clustering at municipality level. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).

Table 24. Robustness test: PSM (stimulation and stimulation with nutrition) with n(3)

Childcare measures	***Home visits treatment***							
	(I)				(II)			
	ATT sample (M=3)				ATT sample (M=3)			
	Treated	*Controls*	*Difference*	*T-stat*	*Treated*	*Controls*	*Difference*	*T-stat*
Public childcare	0.344	0.370	-0.026 (0.034)	-0.77	0.349	0.335	0.014 (0.040)	0.34
Private childcare	0.019	0.033	-0.014 (0.012)	-1.17	0.018	0.026	-0.008 (0.014)	-0.57
Informal childcare	0.077	0.039	0.038 (0.016)	2.38	0.067	0.027	0.040 (0.016)	2.48
Maternal care	0.558	0.372	0.228 (0.035)	1.86	0.565	0.608	-0.043 (0.041)	-1.03
N	636	318	-	-	616	306	-	-

*p<0.05, **p<0.01, ***p<0.001. Each row represents a separate dprobit and psmatch estimation. Standard errors in parentheses are adjusted for clustering at municipality level. The psmatch specifications used were three neighbours, setting a caliper of ¼ of standard deviation of the *pscore*, and allowing matching with those with identical *pscores* (i.e., multiple matches).