MPRA
Munich Personal RePEc Archive

Cognitive and Non-Cognitive Effects of Nursery Care in the Medium Run under Unobserved Heterogeneity

Contreras, David and Sanchez, Rafael

Universidad Adolfo Ibáñez

16 April 2018

Online at https://mpra.ub.uni-muenchen.de/86289/
MPRA Paper No. 86289, posted 24 Apr 2018 08:35 UTC

Cognitive and Non-Cognitive Effects of Nursery Care in the Medium Run under Unobserved Heterogeneity

David Contreras*
University of Nottingham

Rafael Sánchez†
Universidad Adólfo Ibáñez

April 16^{th}, 2018

Abstract

Unlike the previous literature which focuses on the short run cognitive effects of attending childcare (3-5 years old), we estimate the medium run cognitive and non-cognitive effects of nursery care (0-2 years old) considering not only observed but also unobserved heterogeneity. We constructed a panel dataset with national coverage from different administrative sources. Our results suggest positive selection for Language, Mathematics, Motivation and Self-Esteem, implying that babies and toddlers who are more likely (for unobserved reasons) to attend nursery care have a higher treatment effect. We also find heterogeneous effects in a way that further expansions of public nursery care centers that successfully attract babies and toddlers with high resistance and not currently enrolled in nursery care may yield low returns. This calls into question childcare policies at very early stages especially when there is poor quality involved.

Keywords: Marginal Treatment Effects, Cognitive skills, Non Cognitive skills, Unoberved Heterogeneity
JEL Classification: I26, I28, J08, J13

*School of Economics. Sir Clive Granger Building, University of Nottingham. University Park, Nottingham, United Kingdom.

†Business School, Universidad Adolfo Ibáñez and Ministry of Finance, Santiago, Chile. email: rsanchez@hacienda.cl. Phone: (+56) 2-28282162

1 Introduction

In the last decade and a half, a growing literature has focused on studying the effects of childcare on several future outcomes of the child (see **Almond et al. (2018)** for a recent survey). This interest in childcare can be explained by of the higher returns to this kind of investment relative to those that occur later in life (e.g. those to higher education and job training, among others). High childcare returns come from the fact that 1) the neurons as well as the synapses, which connect the neurons, develop rapidly and are shaped by the stimulation from the environment in the early years and 2) skills have two crucial characteristics: dynamic complementarities and self-productivity. The former means that previously acquired capabilities may make current investments more productive, while the latter means that a given dimension of capacity may also affect the accumulation of another distinct dimension (i.e. cognitive capacity might promote health or vice versa) (**Heckman 2008**). Additionaly, in recent years there has been a significant increase in monoparental families which has motivated an interest in the study of early childcare as a booster for labor market participation (**Elango et al. 2015**).

Despite the enormous significance of this topic, and as suggested by **Cornelissen et al. (2018),** robust evidence for the effectiveness of childcare is scarce, far from unified, and is highly concentrated in children in developed countries older than three years. For example, on the one hand, the litarature has found large gains for participants in targeted programs such as Head Start or the Perry Preschool Project in the U.S.. But on the other hand, evidence for the effectiveness of universal childcare programs targeted to all children is mixed, with effects ranging from positive to negative. One of the possible reasons given in the literature (**Elango et al, 2015, Cornelissen et al. 2018**) to explain the difference in returns is treatment effect heterogeneity.

Treatment effect heterogeneity may come from observed and unobserved dimensions. Regarding the former, the quality of the care available at home in comparison to the quality of the care provided by the center shapes the benefits of early care attendance. Regarding unobserved dimensions, parents may prefer child care to home care because child care benefits their child's development. If this is the case, the effects of child care will be strong for children whose parents have a strong preference for child care. If preferences are unrelated to the effects of early care, expansions of early care will generate average benefits. But, if children whose parents value early care most have the highest benefits, low levels of early care generate the largest impact, and expanding care generates small benefits for the children attending early care (**Felfe and Lalive 2015**).

The sparce research on heterogeneity in returns to childcare typically focuses on treatment heterogeneity in observed characteristics (e.g. **Behrman et al. 2004, Berlinski et al. 2006, Berlinski et al. 2008, Bernal et al. 2009, Bernal and Kane 2010**). The very few studies which focuses on unobserved heterogeneity all analyze the short run effects (typically childcare effects at school entrance or in the first few years in school) of attending childcare and most of them concentrate on children of 3-5 years old and usually only on cognitive skills (**Noboa-Hidalgo and Urzúa 2012, Bucarey et al. 2014, Rojas et al. 2014, Felfe and Lalive 2015, Cornelissen et al. 2018, Kline and Walters 2016**). This is significant, as usually 3-5 year old education tends to be more formative, whereas from 0-2 years old tends to be more about care.[1] Aditionally, despite the significance of cognitive skills, the recent literature has also highlighted the importance of non-cognitive skills. For example, **Cunha and Heckman (2007)** find that non-cognitive skills promote the formation of cognitive skills (but not vice versa). Furthermore, not only are early non-cognitive skills important prerequisites for learning, for performance on test scores and for schooling, they are also found to have long term consequences (**Cunha et al. 2006**).

We contribute by filling a gap that exists in the literature. In particular, and to the best of our knowledge, we are the first to analyze the medium run (14 year olds) cognitive and non-cognitive effects of nursery care (0-2 years old) considering observed and unobserved heterogeneity. Furthermore, unlike most of previous literature, we have constructed a panel dataset with national coverage from different administrative datasets instead of surveys. Finally, it is important to point out that we use the Marginal Treatment Effect framework, which enables us to discuss the full range of heterogeneity in the effects of nursery care exposure on child cognitive and non-cognitive skills.

This study is organized as follows. Section 2 presents a summary of the related literature. Section 3 explains the institutional background of the Chilean childcare system. Section 4 describes the administrative data sources, the final dataset used, and some summary statistics. Section 5 presents the empirical framework, the identification strategy, and its potential problems. Section 6 present the results and Section 7 concludes.

2 Literature Review

The literature and practice distinguish between nursery care 0–2 (for toddlers) and childcare 3–5 (e.g., playgroup/kindergarten programs for preschoolers) due to their different roles in children's development.[2]

[1] See for example: https://www.parentfurther.com/content/ages-0-2-developmental-overview and https://www.parentfurther.com/content/ages-3-5-developmental-overview

[2] See for example: https://www.healthychildren.org/English/ages-stages/Pages/default.aspx or https://extension.illinois.edu/babysitting/age-toddler.cfm.

For this reason and for the sake of data availability, the latter group has been extensively investigated (e.g. **Berlinski et al 2009; Bernal and Keane 2010; Havnes and Mogstad 2011; Cascio and Schanzenbach 2013; Heckman et al 2013; Cornelissen et al. 2018 among many others)** finding mostly neutral or positive effects. On the other hand, much less is known about the effects of nursery care targeting toddlers in the very first years of their life (0-2 years old). As this study aims at filling this gap, we focus the literature review on the very few studies analyzing the effects of nursery care in that age range.

Of the studies which analyze children's early years most of them consider an age range that mixes toddlers and preschool age children. For example, **Behrman et al (2004)** study the effects of the Bolivian preschool program (Proyecto Integral de Desarrollo Infantil, PIDI) on cognitive, psycho-social and anthropometric outcomes. This program is targeted at children between 0-6 years who live in poor urban areas. They find positive effects of the program on cognitive and psycho-social outcomes for children who participate for at least seven months. In the same line, **Loeb et al. (2007)** use data from the Early Childhood Longitudinal Study (ECLS-K) in the U.S. to study whether there are optimal levels of duration and intensity of center care. They find that on average attending center care (0-4 years) is associated with positive gains in pre-reading and math skills, but negative social behavior in kindergarten. Similarly, **Bernal et al (2009)** study the effect of the HCB program (Hogares Comunitarios de Bienestar) in Colombia for children between 0-6 years old who live in poor areas or who have economic, social, cultural, nutritional, or psychoafective vulnerability. They find that childcare negatively affected cognitive skills although the results are more positive for children with at least 16 months of exposure.

Similarly but with more negative results **Baker et al. (2008)** study a reform in a region of Canada. In 1997, the government of Quebec introduced a universal policy for families with children of ages 0 to 4. Regulated, center-based childcare was subsidized to have an effective price of at most 5.00 Canadian dollars a day. **Baker et al. (2008)** evaluate the effects of the policy, exploiting cross-regional variation around the years of its implementation, comparing the pre- and post-policy outcomes of families in Quebec with the outcomes of families in the rest of Canada. They find that the effects of these reforms on child behavior and parent-child interactions are negative. The policy caused a sizable increase in the maternal labor supply, with its effect mainly being experienced by high-income families, for which the program dramatically changed the cost of childcare. As a result, it crowded out parental care, which may be of a higher quality than center-based arrangements for some high-income families. Offsetting these negative findings, in later work, **Baker et al. (2015)** find that the policy had small, but beneficial effects for disadvantaged children. These include reduced hyperactivity, anxiety, and aggression at ages 2-3.

Because all this evidence mixes toddlers and preschool age children, **Fort et al. (2016)** proposed to concentrate on the former. In this way they study the causal effects of time spent at ages 0–2 in the high-quality public nursery care system offered by the city of Bologna, Italy, on cognitive and non-cognitive outcomes at ages 8–14. Specifically, they focus on IQ and conscientiousness. They find that an additional month in nursery care at ages 0–2 reduces IQ, on average, by about 0.5%. This effect corresponds to 0.6 IQ points and to 4.5% of the standard deviation of IQs. The effect on conscientiousness is very small and imprecisely estimated. Furthermore, they find difference by gender with a more negative effect on girls than on boys.

As one can see, most of the literature on early childhood mixes toddlers and preschool age children, confounding years where it is more care that is needed (0-2) with those which are more educative (3-5). Furthermore, most of these studies focus in narrowly defined programs, in particular cities/regions and only analyze short run effects, usually at kindergarten (**Loeb et al. 2007**) or in the initial years of school (**Behrman et al 2004, Bernal et al 2009**). Only **Fort et al. (2016)** concentrates on toddlers and extends the analysis to the medium run (up to the age of 14), although they analyze the case of a particular city in Italy. Furthermore, none of these previous studies consider unobserved heterogeneity, which may be important for identifying the effects of nursery care, as they are very heterogeneous with respect to unobserved preferences even within narrowly defined groups of children (**Felfe and Lalive 2015)**. One of the first studies that analyzed 0-2 years olds considering unobserved heterogeneity is **Noboa-Hidalgo and Urzua (2012)** who, with a very small sample (482 individuals), estimate the effects on cognitive and socioemotional development from participation in public child care centers targeting low-income populations in Chile. They find significant positive incremental effects in the area of emotional regulation but potentially severely negative incremental effects on child-adult interactions.

Noboa-Hidalgo and Urzua (2012) only analyze the very short run effects of early nursery care (i.e. the effect after six months). In order to go further, and also for Chile, **Bucarey et al (2014)** and **Rojas et al. (2014)** also analyzed nursery care (0-2) effects on cognitive skills but extended the analysis up to fourth grade in school. Both studies use the marginal treatment effect approach (MTE), which considers the effects of observed and unobserved heterogeneity. The former study finds negative effects of 0-2 nursery care on test scores in the fourth grade (i.e. when the children are nine years old), while the latter find a nonsignificant effect on the average population and negative effects on those treated. None of these studies analyze the effect on non-cognitive skills.

Lastly, **Felfe and Lalive (2015)** study whether attending child care before age three affects children's development around age six, when children in Germany, enter the regular school system. They use pediatrician's assessments of a child's language skills, motor skills, socio-economic development, and school readiness. They exploit variation in early care attendance in these districts across three birth cohorts. They also adopt the MTE approach, which allows them to document elements that usually were not present before, such as unobserved heterogeneity. They find that early child care benefits children whose parents have a preference for child care, substantially improving immigrant children's language development. Early care also benefits those native children's motor and socio-emotional development whose mother has not completed college, but does not affect native children whose mother has completed college.

Therefore, as can be seen from the very scarce evidence on 0-2 years old nursery care, most of them do not consider unobserved heterogeneity and non-cognitive skills and of those studies who actually do consider unobserved heterogeneity and non-cognitive skills, all of them analyze only the short run effects (i.e. when children are entering school at around ages 6-7). We propose to extend the analysis to the study of cognitive and non-cognitive skills in the medium run, up to the end of primary school in Chile (i.e. 14 years old) considering observed and unobserved heterogeneity.

3 Institutional Background: The Chilean Childcare System

3.1 General Structure

Preschool education is considered as the first level of Chile's educational system, which includes both boys and girls from three months[3] of age until they start primary school (six years old). Children who attend preschool institutions are divided into several levels according to their age: the first level, between three months and two years old ("Nursery" or *Sala Cuna* in Spanish); the second level, between three and four years old (Medium Level-Playgroup, *Niveles Medios* in Spanish); and the third level, which includes children from four to six years old (transition level or *Niveles de Transición* in Spanish). This last is further subdivided into two sublevels of transitional levels, the first is for those between 4-5 years old and the second, for 5-6 years old. Preschool education in Chile is not mandatory except for those who are in the second transitional level (five to six years old), as this has been a requisite for entry into primary school since the reform of 2013.

There are several institutions which provide nursery care in Chile. They are: i) private childcare centers, ii) public childcare centers provided directly by JUNJI ("Junta Nacional de Jardines Infantiles"), iii)

[3] Changed in 2012 to six months.

public childcare centers managed by the municipal government under agreement with JUNJI (known as Vía Transferencia de Fondos) (VTF) and iv) those provided by the INTEGRA Foundation. Overall, there are around 3,500 public childcare centers in Chile, around 2,600 belong to JUNJI (of which 1,670 are VTF) and 960 to INTEGRA. Also, there is an estimatimate from the Ministry of Education (MINEDUC) that there are around 700 private childcare centers in the country.

JUNJI was founded in 1970 with the purpose of providing free educational services, food, and assistance, to children over the whole country, with an emphasis on the most vulnerable ones (i.e. 60% of the most vulnerable households). The INTEGRA Foundation was created in 1990 from the centers of the National Foundation of Community Aid (FUNACO). Nowadays, INTEGRA also offers free nursery care for vulnerable families for the 0-2 years old range (it also emphasizes the 60% most vulnerable households). The rest of the institutions are composed of autonomous organizations, whether VTF or private institutions. VTF institutions are those that operate via funds transferred from the JUNJI (they are also free). Meanwhile, private childcare centers must have certifications from the Ministry of Education plus permissions from the municipal government of the city in which they are to operate. Unlike the other centers, the certification of private centers is not mandatory.

3.2 Coverage

In Chile, babies and toddlers may attend public or private nursery care centers that provide educational and care services. The nursery care system is peculiar, as some segments of the population lack coverage while others have double coverage. For example, there is the program "Chile Crece Contigo" (ChCC) that provides free public nursery care centers for preschool children who come from economically low-income households (the poorest 60% of the population regardless of whether they are working or not). This service is provided via JUNJI, VTF, or INTEGRA centers. Also, there is the Article 203 in the labor code, which mandates that all firms with 20 or more female workers provide nursery care services within the firm or outside the firm but paid for by the firm.[4] There are also private nurseries paid for by the parents, which cost around one-half of the minimum wage on average. The ChCC program and the labor regulations that mandate childcare provision by firms have generated and increase in the number of nursery care centers (see **Figure 1**). However, there is still an important fraction of the population that is not covered by nursery care centers.

The coverage of preschool education has been constantly increasing since 2000. We can see this in **Figure 2**. In particular, it shows the attendance of children from 0 to 6 years of age in preschool institutions. It

[4] Women who work in firms with 20 or more female workers and who belong to the 60% most vulnerable households can choose to send their child to the public system or to the one provided by the firm.

is particularly interesting to compare the data from two different surveys. On the one hand, we have the National Socioeconomic Characterization survey ("Encuesta CASEN") and on the other hand, the Longitudinal Survey of Early Childhood (ELPI). The data available for the ELPI in 2012 suggests that the attendance rate in preschool institutions is near 53%. This is consistent with the data extracted from the CASEN survey for 2011 and 2013, for which we have between 52% (2011) and 57% (2013) attendance.

If we further break down the coverage rate, for example by income, the attendance has been increasing for all income quintiles since 2000, according to the CASEN survey (**Figure 3**). The amount of this increase differs by groups, e.g., between 200 and 2015 it was, for the first quintile, 31 percentage points, while for the fifth quintile it was 23 percentage points. In fact, the difference between groups when looking at the attendance in preschool education has been decreasing, e.g., the difference in attendance in 2000 between the fifth quintile and the first quintile was 19 percentage points, while the difference for the next years (the final ones in the sample) converged to 10-11 percentage points.

If we break down the preschool education attendance rate (around 53%) by its varous levels, we find that the attendance rates to nursery (*sala cuna*) are around 30% while attendance at the upper levels of preschool education reaches rates of around 50% for the medium level (i.e. Playgroup) and 90% for the transition level (i.e. at ages four to six). The overall attendance rate in childcare is one of the lowest among the OECD countries and even lower than some countries in the region, such as Argentina (72%) and Brazil (65%).

When children leave preschool education, their parents can choose to enroll them in three different types of schools: i) public (under municipal administration) ii) private-voucher (funded by a voucher system and administered by the private sector) or iii) private-non voucher schools (private fee-paying establishments funded and administered by the private sector). Regarding the distribution of students, around 40% of the students are in public schools, 8% in private non-voucher (i.e. fee-paying) schools, and 52% in private voucher schools. Unlike voucher schemes implemented in other countries, private voucher and non-voucher schools in Chile can choose their students. However, public schools are prohibited from choosing, except in cases where the demand for places exceeds the availability. This scheme where private schools can select students generates a positive sorting of students from high and middle income families into private schools and the most vulnerable students into public schools (as found by **Contreras et al. 2010**). One of the reasons for this is that private voucher schools in Chile are allowed to operate for profit and may, therefore, select students who are less expensive to educate. This has resulted in high segregation between private and public schools in Chile (**Valenzuela et al. 2013**).

3.3 Quality

Chile is one of the countries of the OECD with the highest expenditure in preschool education (0.6% and 0.1% of GDP in public and in private childcare respectively).[5] Only a few spend more on nursery care as % of GDP (e.g. Iceland and Sweden are those with the highest expenditures reaching 1.8% and 1.6% of GDP respectively).

Despite its budgetary efforts, the quality of the childcare in Chile is not particularly high. One of the reasons is that high school students who want to become preschool teachers usually do not score very well in the PSU test (the test required to applying to Chilean universities).[6] See, for example, column 1 of **Table 1** where we present the average score of the lowest score student accepted at the Pontificia Universidad Católica de Chile and the Universidad de Chile for 2013-2017. These are the two Chilean universities with the highest PSU scores and usually the best performers in international ranking comparisons.We observe that, even in the best two universities, a score of 602.6 is enough to enter to be a preschool educator, which is less than one standard deviation from the average of the test. In contrast, the lowest score of the accepted student into medicine obtained almost 788 points, which is equivalent to 2.6 standard deviations above the mean. The same happens with Civil Engineering, with more than 2 standard deviations above the mean, Business and Economics, with 2 standard deviations above the mean, and so on with several other degree programs. This pattern is repeated in the rest of the Chilean universities with preschool teaching scoring much lower than the rest of the professional programs. Furthermore, the lower quality of the students who enter preschool teaching is not only clear in the PSU score. In terms of wages, preschool educators are among the lowest earners. For example, see column 2 of **Table 1** where we show that preschool teachers earn only a little more than one-fifth as much as an engineer or a doctor, one-fourth as much as a lawyer, and only about 28% as much as those who graduate from Business and Economics. Additionally, their career offers little scope for advancement or promotion, hence their wage curve is quite flat. All these facts are important for our discussion section below.

[5] https://www.oecd.org/els/soc/PF3_1_Public_spending_on_childcare_and_early_education.pdf

[6] PSU test is the test required for being accepted into any course of studies of a Chilean University. It has a standardized score with an average of 500 points, a minimum of 150 points and a maximum of 850, with a standard deviation of 110 points.

4 Data and Descriptive Statistics

4.1 Data

The data we use has several sources. First, we use administrative information from the Chilean Ministry of Education, which includes information about students regarding their performance on the SIMCE, which is a standardized national test that started in 1988 and evaluates learning results in some subjects, such as Language and Mathematics, among others. Using related questionnaires, it also collects information regarding teachers, students, and parents. This information is used by the Ministry of Education to contextualize and analyze students performance. The scale used by this test ranges from 230 to 350 points, and one standard deviation represents around 50 points. These tests are administered by the Ministry of Education to the entire population of students. Although the SIMCE does not follow students over time, recent available data allows us to identify students that took the tests on more than one occasion. Using data from SIMCE 2010 and 2014, we identified students with test scores in Math and Language when they were in the 4^{th} and 8^{th} grades.

Second, we used variables at the municipality level from the Sistema Nacional de Información Municipal (SINIM) for the year 2000 and from the Encuesta de Caracterización Socioeconómica (CASEN) also for the year 2000. Both of these datasets allow characterizing the municipality where the parents were living at the moment of the decision to enroll or not their children in a nursery care center (i.e. one year before or in some cases the same year the child was born).

Third, we use administrative data from JUNJI and INTEGRA to know the number of public nursery care centers by municipality (including JUNJI+INTEGRA+VTFs) in 2000 and its evolution until 2014.

Fourth, we use information about parents who are surveyed by a complementary questionnaire of the SIMCE and include socio-economic information about the household and a very important question for our study, namely, whether or not the student has attended to a nursery, playgroup, or transitional level center. Unfortunately, parents do not specify whether the childcare was public or private. This is important, as the information regarding childcare supply only refers to public childcare centers (JUNJI and INTEGRA inlcluding VTFs). Therefore, if we take into considerations all the students who took the SIMCE in 2014, the approximation would be imprecise, as there would not be a suitable instrumental variable for an unknown percentage of students who attended private childcare centers. In order to minimize this risk, we have decided to only keep in our final sample students who study in public and voucher schools, implicitly assuming that children who attended private childcare centers were in their vast majority enrolled in private (non-voucher schools). In other words, parents with a willingness to pay for childcare higher than zero are the same as those who have a positive willingness to pay for primary schools. Thus, our treated group would be children of public and voucher schools who attended nursery care when they were 0-2 years old while our control group would be those children from the same schools who did not attend nursery care. This assumption seems likely to be, as of all children who attended childcare centers of JUNJI and INTEGRA, only around 3% belonged to the richest quintile. In the same way, around 5.5% of the students of public and private-voucher schools belonged to the richest quintile (CASEN 2013). In other words, the segmentation by income of the Chilean educational system makes it likely that our assumption holds.

Finally, and also from the SIMCE database, we use the information regarding non-cognitive skills recently collected (and for the first cohorts) by the Agencia de la Calidad de la Educación. This information consists of a series of questions to evaluate students' self-esteem and motivation. Each question allows four possible options: 1= strongly disagree, 2=disagree, 3=agree and 4=strongly agree. The score is calculated by using a Likert scale, where the higher the score, the higher will be the student's self-esteem or motivation. Unfortunatelly, the number of questions given to students when they were in the 4^{th} grade (eight questions) was increased to 11 when the questionnaire was given again in the 8^{th} grade. Thus, we have rescaled each of the scores to 100 to make them comparable.

4.2 Descriptive Statistics

Columns 1 and 2 of **Table 2** present the summary statistics for treated and untreated individuals in our sample respectively. As we can see, in most variables there are no significant differences. Among those few variables which present differences are the SIMCE score for Language and Mathematics in the 8^{th} grade (i.e. one of the outcome variables), being negative in both cases. These results are in line with what we find in our estimations below. The only control variable (that is not an instrument) with a significant difference between treated and control individuals is the dummy variable indicating if the childcare center is rural or not. Our statistics suggest that, on average, treated individuals are slightly more urban than individuals in the control group.

From the descriptive statistics of the instruments also described in **Table 2**, we observe that most of them do not present significant differences between the treated and control individuals except for the average educational level in the municipality. Our descriptive statistics suggest that our treated individuals live on average in municipalities with slightly higher educational levels.

5 Empirical Strategy

5.1 Framework

In order to test for the medium run effect of nursery care (0-2 years old) on cognitive and non-cognitive skills, we consider a generalized Roy model (**Roy, 1951**), following **Heckman and Vytlacil (1999, 2005)** and **Carneiro, Heckman and Vytlacil (2011)**. Let us consider two possible scenarios. In the first one, individuals do not attend nursery care (0-2 year old) but they do attend the following preschool care (3-5 years old). In the second scenario, we have the same individuals but who attended nursery care (0-2 years old) and also the following levels of preschool care (3-5 years old). The equations that determine the level of the student's outcomes in this context are the following:

$$Y_1 = \mu_1(X) + U_1 \tag{1}$$

$$Y_0 = \mu_0(X) + U_0 \tag{2}$$

where Y_1 and Y_0 denote the potential outcome for individual i in the treated versus non treated state (i.e. outcomes that individuals who attended and did not attend to nursery care obtain in 8^{th} grade respectively), $\mu_1(X)$ is a function that determines 8^{th} grade outcomes for those who did attend nursery care (0-2 years old). Similarly, $\mu_0(X)$ is a function that determines outcomes for those individuals who did not attend nursery care. X is a vector of observable characteristics that affect the outcome (child and family characteristics, care center quality characteristics and municipality and year fixed effects). Finally, U_1 and U_0 are error components that affect the outcome of the individuals who attended, and did not attend, nursery care, respectively. Thus, the returns to attending nursery care (in terms of the score) will be given by $R = E(Y_1 - Y_0|X) = \mu_1(X) - \mu_0(X) + E(U_1 - U_0|X)$. In order to be able to model these returns, we must analyze the part of the equation that depends on the selection of individuals ($E(U_1 - U_0|X) \neq 0$). We assume that the decision to attend nursery care is modeled by the following latent index model:

$$A = \begin{cases} 1 & \text{if} \quad A^* > 0 \\ 0 & \text{if} \quad A^* \leq 0 \end{cases}$$

Where the decision to attend, A, is equal to 1 if the individual attends a nursery care facility (0-2 years old) and 0 if this is not the case (i.e. to attendance will be our *treatment*). Thus, we have that $Y = A \cdot Y_1 + (1 - A) \cdot Y_0$. The decision variable depends upon a latent variable, A^*, which determines the utility level that the individual will perceive in both scenarios. We model this latent utility as follows:

$$A^* = \gamma Z - V \tag{3}$$

Where Z is a vector of observable variables that affect the decision to attend (or not) a nursery care facility. It includes the same covariates as the outcome equation and the instruments excluded from the outcome equation. We consider different variables as instruments in the choice equation (and that are excluded from the outcome equation). According to the method presented above, considering several instruments allows us to expand the range in which the MTE is identified. In our application, the first instrument is local nursery care supply (at the municipality level) as measured by the nursery care coverage rate 14 years prior to 8^{th} grade, which is when the decision to attend or not was made (i.e.in 2000 which is $t-14$). This variable directly affects the decision to attend or not nursery care, as **Rojas et al. 2014 and Cornelissen et al. 2018** suggest).This variable has been widely used in the literature[7]

Another source of variation considered in our empirical strategy is the potential demand for nursery care (0-2 years old) at the municipal level in the year when the decision to send the child to nursery care was made (i.e. the year 2000). This is captured as the Proportion of $\left(\frac{0-2\ years\ old}{0-6\ years\ old}\right)$ in Municipality i in $t-14$.[8]. The rationale is that the higher the potential demand, the higher will be the incentive to provide nursery care services in the municipality (as in **Bucarey et al. 2014**). A third instrument used is the average level of education in the municipality the year when the decision to send the child to nursery care was made (in $t-14$) as a proxy for the average human capital in the municipality. As the information comes from the year 2000 (14 years before the scores of the 8^{th} grade were recorded), we can argue that our variables can be used as instruments (i.e. they affect the decision to attend early childcare, but not necessarily the outcome variable 14 years later (the student's test scores in the 8^{th} grade). γ is a parameter that measures how important are the previously mentioned variables for the studied choice, and V is an unobservable component. Because the error term V enters the selection equation (3) with a negative sign, it embodies the unobserved characteristics that make individuals less likely to receive treatment. We thus label V "unobserved resistance" or "distaste" for treatment (as in **Cornelissen et al. 2018**).

In order to simplify the interpretation of the *Marginal Treatment Effect* (MTE) presented below, it is

[7] See Berlinsky et. al. (2008, 2009), Bernal et. al. (2009), among others.

[8] To capture potential demand at the municipal level we use the CASEN 2000 survey which is representative at the municipal level. CASEN also allows us to control for several local socio-economic variables. In particular, we use the average per capita income and the average unemployment, both at the municipal level, which allows us to eliminate socio-economic differences as one of the determinants of the students' results.

possible to define the probability of being treated (*propensity score)* as:

$$\Pr(A = 1, Z) = \Pr\left(\frac{V}{\sigma_V^2} < \frac{\gamma Z}{\sigma_V^2}\right) = \Phi\left(\frac{\gamma Z}{\sigma_V^2}\right) = P(Z)$$

In order to identify the treatment effect for those individuals who are at the margin of being treated or not, we must estimate the effect that the treatment would have had on the outcome for different margins (i.e. for different levels of propensity scores). In this regard, articles such as **Heckman and Vytlacil (1999, 2005)** and **Carneiro, Heckman and Vytlacil (2011)** have suggested estimating the *Marginal Treatment Effect* (MTE), which depends on the probability of being treated. The propensity score, as detailed in the literature, is very important in the context of instrumental variables since it satisfies the independence and monotonicity conditions of **Imbens and Angrist (1994)**.

We redefine the selection equation in terms of the observables and unobservables but using the propensity score:

$$A = \begin{cases} 1 & \text{if} \quad P(Z) - U_A > 0 \\ 0 & \text{if} \quad P(Z) - U_A \leq 0 \end{cases}$$

Where $U_A = \Phi\left(\frac{V}{\sigma_V^2}\right)$. Thus, the MTE as a function of the quantiles of the distribution of V can be expressed as follows:

$$MTE(X = x, U_A = u_A) = E(R|X = x, U_A = u_A)$$

We see that the MTE will take different values depending on the levels of the unobservables U_A (**Carneiro, Heckman and Vytlacil, 2011**). In this way, the MTE measures how attending early care affects child outcomes for children whose unobserved determinant of attending care (u_A) is the same as their propensity score (P). This is a marginal effect in the sense that the parents of these children are indifferent between sending their children to nursery care or not doing so.

5.2 Estimation

For the outcome equation different structures can be assumed, some of which are more restrictive than the others. Following Carneiro, Heckman and Vytlacil (2011), the general structure is given by:

$$E(Y|X = x, P(Z) = p) = x\beta_0 + (x(\beta_1 - \beta_0))p + K(p) \tag{4}$$

Where $K(p)$ is a control function, in the sense of Heckman and Robb (1985) and $K(p) = E(U_1 - U_0|A = 1, P(Z) = p)$. For this structure, the MTE will be given by the following equation:

$$MTE(X = x, U_A = p) = \frac{\partial E(Y|X = x, P(Z) = p)}{\partial p} = x(\beta_1 - \beta_0) + \frac{\partial K(p)}{\partial p} \tag{5}$$

The estimation of the MTE then proceeds by making varying assumptions about the functional form of $K(p)$. To estimate the model, we assume normality for $K(p)$ in equations (4) and (5). Due to its flexibility we would like to use a semi-parametric approach to present our results in the following section. However, the use of the semi-parametric approach would require a full common support for the propensity score $P(Z)$, which as noticed in **Figure 4** does not hold (it goes from 0.34 to 0.54). Thus, due to incomplete common support, we use the parametric-normal approach to estimate the model. In particular, this assumes that the unobserved components follow a trivariate normal distribution:

$$(U_1, U_0, V) \sim N(\mathbf{0}, \Sigma)$$

Where Σ is the covariance matrix of the error components. We define the variance of the error component U_i as σ_i^2 (for $i = 1, 2$) and for component V as σ_V^2. On the other hand, the covariance between component U_i and component V is given by $\sigma_{i,V}$ (for $i = 1, 2$) and for components U_i and U_j by $\sigma_{i,j}^2$. According to this specification, the definition of the MTE can be rewritten as:

$$E(Y|X = x, U_A = u_A) = \alpha_1 + \varphi - \alpha_0 + x(\beta_1 - \beta_0) + (\rho_1 - \rho_0)\Phi^{-1}(u_A) \tag{6}$$

Where $\rho_1 = \frac{\sigma_{1,V}}{\sigma_V^2}$ and $\rho_0 = \frac{\sigma_{0,V}}{\sigma_V^2}$. We consider that $\frac{\gamma Z}{\sigma_V^2} = \Phi^{-1}(P(Z))$, that $E(Y_1|A = 1, X, Z) = \alpha_1 + \varphi + X\beta_1 + \rho_1 \cdot \left(-\frac{\phi(\Phi^{-1}(P(Z)))}{P(Z)}\right)$ and $E(Y_0|A = 0, X, Z) = \alpha_0 + X\beta_0 + \rho_0 \cdot \frac{\phi(\Phi^{-1}(P(Z)))}{1-P(Z)}$.[9] **Heckman et al. (2006)** suggest two stages in order to estimate the MTE in the normal model context: (1) Estimate the propensity score through a probit estimation and then construct the predicted probabilities for each individual and (2) replace these probabilities in the MTE equation and estimate it by OLS. The MTE can be aggregated over U_A in different ways to generate several meaningful mean treatment parameters, such as the Average Treatment Effect (ATE), the Treatment on the Treated (TT), among others (see **Heckman and Vytlacil, 2005, 2007**).

[9] See Heckman and Vytlacil (1999, 2005) and Heckman, Urzúa and Vytlacil (2006) for more details.

6 Results

6.1 Cognitive Results.

The estimation results of the choice equation are presented in **Table 3**. We see that gender (male=1) has a positive and significant effect on the probability of attending a nursery care institution. We also see that children with more educated parents, with more books at home and from higher income families are more likely to attend nursery care. The only variable with a negative effect on the probability of attending nursery care services is the rural dummy. One potential explanation for this is that in those areas, the distance to nursery care centers is longer and roads are more complicated to travel, especially during winter.

Regarding the instruments, we observe that the number of nursery care centers in the municipality has a significant effect on the probability of attendance. In particular, we find that the higher the number of nursery care centers, the higher the probability of attendance will be. The other instruments have no significant effects if they are evaluated with their t tests. However, the F test of all the instruments suggests that they are jointly highly significant ($p-value$ of 0.000).

Table 4 presents the results of the outcome equation for the first of the cognitive tests, which corresponds to language skills. In the first two columns we present our results for model A, which does not include the lagged SIMCE score for language or controls for nursery care quality. We observe that higher level of parental education, higher household incomes and more books at home have positive effects on students' language test scores in the 8^{th} grade. However, males have a worse performance than females and students in public schools have a worse performance than students in private voucher schools. Overall, we observe an ATE of -0.47 standard deviations which corresponds to 23.5 points less in the language test. Once we add the lagged SIMCE score (model B in columns 3 and 4 of **Table 4**) as a control, point estimates become slightly smaller but fairly similar to those in model A and the same happens with the ATE, which decreases to -0.36 standard deviations. It is important to notice that the lagged SIMCE score is statistically significant (at 1%), which suggest the importance of controlling for the student's previous language score. Finally, in columns 5 and 6 of **Table 4**, we present model C, which adds childcare quality measures as controls. We observe that both are statistically significant and suggest that a bigger class size (one extra student) decreases students' language scores in 0.01 standard deviations and also that a better technical coefficient (i.e. one more educator and/or assistant per student in nursery care) increases students' performance in 8^{th} grade lenguage score by 0.01 standard deviation.[10] Once we control for childcare quality, the ATE becomes -0.54 standard deviations,

[10] In general the average number of students per class in the Chilean educational system is 30 (http://accioneducar.cl/wp-content/files_mf/1443578310Ana%CC%81lisisAlumnosporCurso_26.6.2015.pdf).

which represents -27 points in the SIMCE score.

To further analyze our results for the language test score we observe **Figures 5 and 6**, which plot the marginal treatment effect obtained in models A and B. In both cases we observe a slightly positive gradient, which indicates a modest reverse selection on gains in unobserved characteristics. However, once quality controls are included, the results change to a downward sloping MTE curve (**Figure 7**) which suggests that low-resistance types (those who are more likely to participate in the treatment due to unobserved reasons) have a higher treatment effect, and high-resistance types have a lower treatment effect. This latter result highlights the importance of controlling for nursery care quality.

Regarding the other cognitive test, which corresponds to Mathematics, the results (presented in **Table 5**) are similar to those for Language except for the effect of gender. In this case, male students perform better in Mathematics than females (the reverse result to that in Language) suggesting observed heterogeneity in test results by gender. The other difference is the slope of the MTE. For Mathematics, the slope is negative in the three models (model A, B, and C presented in **Figures 8, 9, and 10**) indicating that students who are more likely (due to unobserved reasons) to attend nursery care have a higher treatment effect, and students who are less likely (due to unobserved reasons) to attend to nursery care have a lower treatment effect. Similarly, the ATE is negative, which coincides with the result for Language.

6.2 Non-Cognitive Results

Once we move towards non-cognitive skills, the results change relative to those reported above for cognitive skills. **Table 6** reports results where students from rural areas perform better in motivation than those in urban areas. This result is the opposite of what we observed for cognitive skills. Other differences are the insignificant results of household income and public schools in students' motivation. Despite these differences there are other results which are similar to those for cognitive skills. A household with more books improves the student's performance in motivation. Also,men perform worse than women. The role of the father seems to be important, as his presence and his education have positive effects on the student's motivation. Also, it continues to be important to control for nursery care quality measures and previous test scores as they are all statistically significant. The ATE are also negative in the three models for motivation. When we look T the MTE presented in **Figures 11, 12, and 13,** we observe that the gradients are negatively sloped in the same way than those presented for Mathematics, suggesting that students who are more likely (due to unobserved reasons) to attend nursery care have a higher motivation score, and students who are less likely (due to unobserved reasons) to attend nursery care have a lower motivation score.

When we look at the other non-cognitive skill presented in our data, the results do change. **Table 7** displays the results for self-esteem, suggesting (in model C, our preferred model) that males perform better than females, that neither parental education, household income nor public schools were significant, but that the number of books at home, the lagged self-esteem score and nursery care quality measures, remain important. As well as with the other skills (Language, Mathematics and Motivation), the ATE is negative and of similar magnitude (all approximately between -0.54 and -0.59 standard deviations except in Mathematics, for which it is smaller in magnitude). The MTE presented in **Figures 14, 15 and 16** have negative slopes in all three figures, suggesting a similar pattern to those displayed for Mathematics and Motivation, and suggesting that students who are more likely (due to unobserved reasons) to attend nursery care have a higher self-esteem score, and students who are less likely (due to unobserved reasons) to attend nursery care have a lower self-esteem score.

6.3 Threats to the Identification

6.3.1 Relevance of the Instrument

For the empirical strategy presented above to be valid, some conditions must be met. First, the instrument (Z) should cause variation in the probability of treatment after controlling for (X, year and municipality dummies). In our case, we use the nursery care supply in the municipality in $t-14$. (i.e. 14 years before the 8^{th} grade, which is in 2000) as one instrument for nursery care attendance conditional on year and municipality dummies, thereby accounting for time invariant differences across municipalities. Other instruments used are the potential demand for nursery care in $t-14$ and the average years of education in the municipality in $t-14$.

We observe from **Table 3** the relevance of the instrument used in this study. We see that some of the instruments increase the probability of attending nursery care, supporting in this way the claim that higher nursery care supply in the municipality before the birth of the child increases the chances of attending nursery care. Furthermore, we observe that the F test (for the joint significance of all instruments) has a $p-value$ of 0.000,.which suggests that we do not have weak instruments.

6.3.2 Exogeneity of the Instrument

A second important condition for our setup is the assumption that the instrument included in Z must be independent of the unobserved component of the outcome and selection equation conditional on the observed characteristics and the municipality and year dummies This assumption requires that the instrument be as good as randomly assigned conditional on (X , year and municipality dummies). It also embodies the exclusion restriction that the nursery care supply in the municipality in $t-14$ must not directly affect the outcome conditional on A and (X , year and municipality dummies). To check this, we follow **Cornelissen et al (2018)** who regress the change in nursery care coverage (**2000-2014**) on several observable baseline (in 2000) municipality characteristics including municipality dummies. We observe in **Table 8** that the change in nursery care supply (2000-2014) is associated with the proportion of the rural population and the average level of schooling in the municipality. In other words, the increase in nursery care supply was stronger in rural and less educated municipalities. However, even if the municipality characteristics at the baseline did predict nursery care expansion in the municipality, this would not generally invalidate our identification strategy because these characteristics at the baseline mostly reflect time-constant differences, which are taken into account by the inclusion of municipality dummies in our estimation.

6.3.3 Childcare Quality

A third threat to this kind of analysis is that nursery care expansions might negatively change nursery care quality, affecting not only children pulled into nursery care by the creation of new slots but also those whose nursery care attendance is unaffected. In order to deal with this threat, we include in our preferred specification some nursery care quality measures, such as class size and the technical coefficient ($\frac{Educators}{Children}$) (model C). As is possible to see in columns 5 and 6 of **Tables 4, 5, 6 and 7** the results change when quality measures are included versus models A and B where quality was excluded. In particular, the ATE becomes more negative in all the cases.This highlights the importance of controlling for nursery care quality measures as suggested by the previous literature (e.g. **Cornelissen et al. 2018**).

6.3.4 Endogenous Mobility

The last threat to be considered is endogenous mobility. This refers to the possibility that some non-random families may move to municipalities with a larger supply of nursery care. In our case, this is unlikely to be a problem, since not many people change municipality for the availability of nursery care services in Chile. Furthermore, the mobility rate 2000-2014 is uncorrelated with changes in municipal nursery care availability ($p-value$ of the coeficient is 0.27).

6.4 Identification of the heterogeneous returns of attending at nursery care (ATE, TT, TUT, MPRTE)

So far, we have presented results based on ATE and the MTE. However we would like to go further in our analysis and go beyond the ATE. To do so, we use the MTE obtained above as an input to calculate different parameters of interest. We follow Heckman and Vytlacil (2001), who define the *Policy Relevant Treatment Effect* (PRTE) as a function of the MTE:[11]

$$PRTE = \frac{E(W^*) - E(W)}{E(A^*) - E(A)} = \int_0^1 MTE(u_A)\omega_{\mathrm{PRTE}}(u_A)du_A \tag{7}$$

Where $\omega_{\mathrm{PRTE}}(u_A) = \frac{F_P(u_A) - F_{P^*}(u_A)}{E_{F_{P^*}}(P) - E_{F_P}(P)}$ is the weight that is given to the MTE, which depends on the policy change. In this case, $E(W^*)$ is the expected test score of an individual once the policy change has been made, $E(W)$ is the expected test score under the base policy, $E(A^*)$ is the average probability of being treated in the new scenario, $E(A)$ is the probability of being treated in the base scenario, F_{P^*} and F_P are the cumulative distribution functions of the probabilities of being treated, with and without the policy change, respectively, while $E_{F_{P^*}}(P)$ is the expected value of the probability of being treated under the new scenario, which is equivalent to that of the case of the base scenario.

By using the parameters of the structural model, we calculate the*Treatment on the Treated* (TT), which is equivalent to the economic returns that the treated obtained. Following Heckman and Vytlacil (2005), the TT can be defined as a function of the MTE and is specified by the following equation:

$$TT = \int_0^1 MTE(u_A)\omega_{\mathrm{TT}}(u_A)du_A \tag{8}$$

Where $\omega_{\mathrm{TT}}(u_A) = \frac{\int_{u_A}^1 f(a)da}{E(A)}$, $f(a)$ is the probability density of being treated, and $E(A)$ is the expected probability of being treated. Since we do not have a full common support for the propensity score, it is not possible to identify the TT according to the semiparametric model. However, we follow Carneiro, Heckman and Vytlacil (2011) and estimate it by re-calibrating the weights, so that they add up to 1 in the support that we will work in. All the relevant weights (including those of the other treatment parameters, such as the *Average Treatment Effect*, ATE, the *Treatment on the Treated*, TT, and the *Treatment on the Untreated*, TUT) are presented in **Table 9.**

Regarding the estimation of the conditional probability density function, which is necessary for the

[11] We suppress the conditioning on X for the sake of simplicity.

construction of the weights, it is important to notice the following. The multidimensionality of X introduces a problem at the moment of estimating the conditional density of the propensity score. Given this, following Carneiro, Heckman and Vytlacil (2010, 2011), we condition on an index $X(\widehat{\beta_1 - \beta_0})$ instead of conditioning on X.[12]

With these two parameters it is possible to test whether the PRTE is greater than the TT. If this is the case, then this could be an indication of the presence of constraints, since the returns of those treated (attending nursery care) are lower than those to the controls (those who are at the margin of attending nursery care).

It is important to note that, as Carneiro, Heckman and Vytlacil (2010) shows, in those cases in which a full support for the propensity score is not reached, it is not possible to identify the PRTE. Instead, the *Marginal Policy Relevant Treatment Effect* (MPRTE) is proposed. The MPRTE allows identifying the effects of marginal changes in policies despite not having a full common support. The MPRTE assumes marginal changes in policies and is defined as follows:

$$MPRTE = \int_0^1 MTE(u_A)\omega_{\text{MPRTE}}(u_A)du_A \tag{9}$$

Where:

$$\omega_{\text{MPRTE}}(u_A) = -\frac{\frac{\partial}{\partial\delta}F_0(u_A)}{\frac{\partial}{\partial\delta}E_{F_0}(A)} \tag{10}$$

The definition of the weight depends on the type of policy change that is simulated. More formally, we define the MPRTE as in Carneiro, Heckman and Vytlacil (2010). For this, consider a sequence of policies indexed by a scalar variable δ, with $\delta = 0$ denoting the baseline, status quo policy. We associate with each policy δ the corresponding fitted probability of attending P_δ , where $P_0 = P(Z)$, the baseline propensity score. For each policy δ,we define the corresponding PRTE parameter for going from the baseline status quo to policy δ. We define the MPRTE as the limit of such a sequence of PRTEs as δ goes to zero. We will consider the following examples of such sequences of policies: (i) a policy that increases the probability of attending nursery care by an amount δ, so that $P_\delta = P_0 + \delta$; and (ii) a policy that changes each person's

[12] In the estimation of the conditional density function $f(P|X)$ we follow Carneiro, Heckman and Vytlacil (2010). We estimate a local linear regression of $\frac{1}{h}K\left(\frac{\widehat{p}-p}{h}\right)$ on the index $X(\widehat{\beta_1 - \beta_0})$, where $K(\cdot)$ is a Gaussian kernel and $h = 1.06 \cdot (\widehat{Var}(P))^{1/2} \cdot n^{-1/5}$. For the local linear regression we consider a bandwidth equal to $h = 1.06 \cdot (\widehat{Var}(X(\beta_1 - \beta_0)))^{1/2} \cdot n^{-1/5}$.

probability of attending a nursery care institution by the proportion $(1+\delta)$, so that $P_\delta = (1+\delta)P_0$ In each of these two cases, we consider the corresponding PRTE for going from the status quo to policy δ, and consider the limit of such PRTEs as δ goes to zero. All the relevant weights for each of the two policies mentioned above are presented in **Table 10**.[13]

The parameters of interest (ATE, TT, TUT) and the different types of MPRTEs are presented in **Table 11**. In columns 1 to 6 of row 1 we observe the ATE under the parametric model for each of the the skills (Language, Mathematics, Motivation and Self-esteem respectively). They are the summary of the model C of the previous tables and show that attending nursery care (0-2 years old) negatively affects each of the skills by -0.54 to -0.59 standard deviations, except for Mathematics, which is around -0.24 standard deviations. In the second and third rows we present the Treatment on the Treated (TT) and the Treatment on the Untreated (TUT) and find that in all cases, the former is higher (less negative) than the latter. These results were expected, as the MTE presented in **Figures 7, 10, 13 and 16** display negative slopes for all the skills analyzed. Recall that an MTE curve that falls in U_D would suggest that low-resistance individuals (those who are more likely, due to unobserved reasons, to participate in the treatment) have a higher treatment effect, and high-resistance individuals have a lower treatment effect. Thus, a falling MTE curve would indicate positive selection in unobserved characteristics based on gains—or in other words, what we find is that those who are more likely to attend nursery care (due to low resistance) would benefit the most from the treatment (attending nursery care) while those who are less likely to attend nursery care (due to higher resistance) would benefit the least.

These results suggest that students who are more likely (due to unobserved reasons) to attend nursery care would benefit more, in Language, Mathematics, Motivation and Self-esteem, than students who are less likely (due to unobserved reasons) to attend nursery care. Along the same lines, the MPRTE are presented in the fourth and fifth rows of **Table 11** and suggest that individuals who are at the margin of atending nursery care also present negative effects, although less negative than those of the Treatment on the Untreated (TUT). In summary: TT>MPRTE>TUT. These results are important from the public policy point of view, as improvements would be small for childrens with a high resistance to nursery care attendance, which basically implies that nursery care attendance would not act as an equalizer. They also imply that policies that successfully attract children with high resistance not currently enrolled in nursery care may yield low returns.

[13] Notice that the treatment parameters and even the instrumental variable estimations can be written as weighted average of the MTE. For more details see Heckman and Vytlacil (2005) and Heckman, Urzúa and Vytlacil (2006).

7 Conclusion

In this study, we contribute to the literature by analyzing the medium run (for 14 years of age) cognitive and non-cognitive effects of nursery care considering observed and unobserved heterogeneity. In particular, we analyze the effect of attending nursery care (children between 0-2 years old) on Language and Mathematics for cognitive skills, and Motivation and Self-esteem for non-cognitive skills. This is important, as most of the literature analyzes the effect of attending childcare (i.e.when children are older (3-6 years old)) and usually only considering cognitive skills at the start of elementary school. Therefore, we contribute to the understanding of the impact of very early out-of-home care on a child's abilities, which is crucial, since early childhood skills are important determinants of future outcomes, and early interventions to remediate deficiencies are more cost-effective than policy interventions at later ages. Furthermore, unlike most of previous literature, we not only consider observed heterogeneity but also unobserved heterogeneity.

We base our analysis on a two-sector Roy model, which helps us to model the decision to attend nursery care and also the impact on the students who attended versus those who did not attend. The Roy model allows us to analyze the case of observationally equivalent toddlers that might benefit in an heterogeneous way due to unobservable variables. This method also allows us to estimate the different treatment parameters used in the treatment literature, such as: Average Treatment Effect (ATE), Treatment on the Treated (TT), and Treated on the Untreated (TUT) which allows us to analyze marginal changes in policies that expand nursery care coverage.

Our first set of results suggests that attendance in a nursery care center positively depends on the availability of nursery centers in the municipality as well as the parents' years of education, the average household income, and the number of books in the household. Also, we find that the probability of attending nursery care is smaller in rural areas of the country.

Our second set of results suggests that attending a nursery care center has, on average, a negative effect on children's cognitive and also non-cognitive scores at the age of 14 (i.e. 8^{th} grade). In particular, the ATEs are -27, -12, -7.4, and -7.8 points in Language, Mathematics, Motivation and Self-esteem respectively, which in turn represent -0.54, -0.24, -0.57, and -0.59 standard deviatons respectively. A potential explanation for these results may be found in the expansion of the nursery care supply and the marginal population that has been obtained access. For example, the MTE obtained in our preferred specifications for all the skills considered have a negative slope, suggesting that those individuals with lower resistance to attending a nursery care center benefit more than those with higher resistance. Hence, succesive expansions of the public nursery care center supply may allow the attendance of people who do not benefit much from attending to nursery care centers. This may be one plausible explanation, as the MTE for low resistance individuals is positive, becoming negative as we move towards higher resistance individuals. This kind of result stresses the necessity to focus on quality when nursery care public supply is expanded.

Also, we find unobserved heterogeneity in treatment effects, although in all cases they are negative. In particular, we find that results for TT are less negative than those obtained for the TUT. Furthermore, we find that policies that (i) increase the probability of attending nursery care by a small amount, and policies that (ii) change slightly each person's probability of attending a nursery care institution, that marginally switch individuals into treatment, will have also negative effects, suggesting that policies that successfully attract children with high resistance not currently enrolled in nursery care may yield low returns.

References

Almond, D., J. Currie and V. Duque (2018) “Childhood Circumstances and Adult Outcomes: Act II” *Journal of Economic Literature*, forthcoming.

Baker, M., J. Gruber, and K. Milligan (2008)."Universal child care, maternal labor supply, and family well-being". *Journal of Political Economy* 116 (4), 709-745.

Baker, M., J. Gruber, and K. Milligan (2015). "Non-cognitive deficits and young adult outcomes: The long-run impacts of a universal child care program". *Working Paper 21571, National Bureau of Economic Research.*

Behrman, J., Y. Cheng and P. Todd (2004): "Evaluating Preschool Programs When Length of Exposure to the Program Varies: A Nonparametric Approach.," *Review of Economics and Statistics*, 86(1), 108-32.

Berlinski, S., S. Galiani, and P. Gertler (2006): "The Effect of Pre-Primary Education on Primary School Performance.," *Working paper no.838*, William Davidson Institute.

Berlinski, S., S. Galiani, and M. Manacorda (2008): "Giving children a better start: Preschool attendance and school-age profiles," *Journal of Public Economics*, 92(5-6), 1416-1440.

Berlinski, S., Galiani, S., and P. Gertler (2009). “The Effect of Pre-primary Education on Primary School Performance”, *Journal of Public Economics*, Vol. 93, N 1, pp. 219-234.

Bernal, R., C. Fernandez, C. E. Florez, and A. Gaviria (2009): "Evaluacion de impacto del Programa Hogares Comunitarios de Bienestar del ICBF," *Documentos CEDE 005854*, Universidad de los Andes-CEDEF.

Bernal, R., and M. Keane (2010): "Quasi-structural estimation of a model of childcare choices and child cognitive ability production," *Journal of Econometrics*, 156(1), 164-189.

Bucarey, A., G. Ugarte and S. Urzua (2014) "El Efecto de la Educacion Preescolar en Chile". *Draft.*

Carneiro, P., J. Heckman and E. Vytlacil (2011) "Estimating Marginal Returns to Education", *American Economic Review*, 101 (6)

Cascio, E. and D. Schanzenbach. (2013). "The Impacts of Expanding Access to High-Quality Preschool Education," Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution. 47 (2):127-192.

Contreras, D., Bustos, S., and P. Sepulveda. (2010). When schools are the ones that choose: The effect of screening in Chile. *Social Science Quarterly*, 91: 1349–1368.

Cornelissen, T., C. Dustmann, A. Raute and U. Schönberg (2018) "Who benefits from universal child care? Estimating marginal returns to early child care attendance" Draft,accepted at *Journal of Political Economy.*

Cunha, F., J. Heckman, L. Lochner, D. Masterov (2006). "Interpreting the evidence on life cycle skill formation". In: Hanushek, E., Welch, F. (Eds.), *Handbook of the Economics of Education*. North-Holland, Amsterdam, pp. 697-812.

Cunha, F. and J. Heckman (2007): "The Technology of Skill Formation," *American Economic Review*, 97(2), 31-47.

Elango, S., J. García, J. Heckman and A. Hojman. (2016). "Early Childhood Education." Forthcoming in *Economics of Means-Tested Transfer Programs in the United States*, Volume 2, ed. by Robert A. Moffit. Chicago, IL: University of Chicago Press.

Felfe, C. and R. Lalive. (2015). "Does Early Child Care Help or Hurt Children's Development?" *Unpublished Manuscript*, University of St. Gallen.

Fort, M., A. Ichino and G. Zanella (2016) "Cognitive and Non-Cognitive Costs of Daycare 0–2 for Girls". *IZA Discussion Papers Series* 9756, February.

Havnes, T. and M. Mogstad (2011). "No child left behind: Subsidized child care and children's long-run outcomes. *American Economic Journal: Economic Policy* 3 (2), 97-129.

Heckman, J. J. (2008). "Schools, skills and synapses". *Economic Inquiry* 46 (3), 289-324, July.

Heckman, J., R. Pinto, and P. Savelyev (2013). "Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review* 103 (6), 2052-2086.

Kline, P. and C. Walters. (2016). "Evaluating Public Programs with Close Substitutes: The Case of Head Start." *Quarterly Journal of Economics*, 131 (4): 1795-1848.

Loeb, S., M. Bridges, D. Bassok, B. Fuller and R. Rumberger (2007) "How much is too much?: The influence of preschool centers on children's social and cognitive development". *NBER Working Paper* 11812.

Noboa-Hidalgo, G. and S. Urzua (2012): "The Effects of Participation in Public Child Care Centers: Evidence from Chile" *Journal of Human Capital*, 6(1), 1 - 34.

Nonoyama, Y. and Y. Ota (2011) "Early Childhood Development in Developing Countries: Pre-primary Education, Parenting, and Health Care". Background paper prepared for the Education for All Global Monitoring Report 2011 The hidden crisis: Armed conflict and education. UNESCO.

Rojas, E., R. Sanchez and I. Zapata (2014) "El impacto de la educación temprana en el mediano plazo". *Draft.*

Valenzuela, J., Bellei, C. and D. De los Ríos (2013) “Socioeconomic Segregation in a market-oriented Educational System. The Case of Chile”. *Journal of Educational Policy*, 29 (2):217-241

Table 1

PSU Scores and Wages

Degree	**PSU Score**	**Average Monthly Wage**
	(1)	(2)
Medicine	787.8	4,031.7
Civil Engineering	726.9	4,340.7
Business & Economics	716.4	3,230.6
Law	702.1	3,868.6
Psychology	704.9	1,992.4
Journalism	656.1	1,817.8
Preschool Education	602.6	928.4

Note: PSU scores are the average score of the last enrolled student in Pontificia Universidad Católica de Chile and Universidad de Chile, the two best universities in Chile, 2013-2017. Monthly wages are the average monthly wage of the first 10 years and are from mifuturo.cl. They are calculated in US dollars with an exchange rate of 603 chilean pesos per dollar (Central Bank of Chile 02/12/2018)

Table 2

Summary Statistics

Variables	**Treated**	**Untreated**	**Difference**
	(1)	(2)	(3)
SIMCE Lenguage 8th	251.02	255.34	-4.32*
	(50.01)	(49.62)	
SIMCE Mathematics 8th	274.59	279.05	-4.46*
	(48.34)	(49.73)	
Gender (Male=1)	0.47	0.47	0.00
	(0.50)	(0.49)	
Mother's Presence in the Household	0.90	0.91	-0.01
	(0.30)	(0.28)	
Father's Presence in the Household	0.51	0.57	-0.06
	(0.49)	(0.49)	
Number of Books in the Household	18.07	16.01	2.06
	(35.9)	(40.0)	
Mother's Education (years)	12.55	12.54	0.01
	(2.97)	(2.99)	
Father's Education (years)	12.32	12.54	-0.22
	(3.27)	(3.38)	
Average Household Income (thousands of pesos)	856,321	845,777	10,544
	(86,223)	(85,653)	
Rural childcare center (rural=1)	0.04	0.06	-0.02**
	(0.20)	(0.23)	
Public (public childcare=1)	0.30	0.29	0.01
	(0.46)	(0.45)	

continue

Note: The scale used by the SIMCE ranges from 230 to 350 points, and 1 standard deviation represents around 50 points. Standard errors are provided in parentheses. *($p < 0.1$), **($p < 0.05$), ***($p < 0.01$)

Table 2

Summary Statistics(cont.)

Variables	**Treated**	**Untreated**	**Difference**
	(1)	(2)	(3)
SIMCE Lenguage 4th	251.01	274.39	-23.38*
	(50.01)	(47.89)	
SIMCE Mathematics 4th	274.59	269.17	5.42
	(48.34)	(47.58)	
Motivation 8th	64.95	66.30	-1.35
	(15.88)	(15.51)	
Self-esteem 8th	71.41	72.97	-1.56
	(14.49)	(14.22)	
Motivation 4th	23.77	23.73	0.04
	(16.79)	(19.60)	
Self-esteem 4th	28.14	27.40	0.74
	(14.70)	(17.23)	
% rural population in Municipality	0.18	0.18.	0.00
	(0.13)	(0.13)	
Average Education in Municipality	9.79	9.69	0.10*
	(1.11)	(1.10)	
Proportion of $\left(\frac{0-2\ years\ old}{0-6\ years\ old}\right)$ in Municipality	0.31	0.31	0.00
	(0.04)	(0.04)	
Number of Childcare Centers in Municipality	7.47	6.54	0.93
	(5.35)	(5.23)	
Obs	5,063	6,651	

Note: The scale of the non-cognitive skills test (motivation and self-esteem) ranges from 0 to 100, with 0 being no motivation or self-esteem and 100 the maximum level of motivation or self-esteem. The scale used by the SIMCE ranges from 230 to 350 points, and 1 standard deviation represents around 50 points. Standard errors are provided in parentheses. $^{*}(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

Table 3: Results of the Choice Equation

Variables	Coefficient
Gender (Male=1)	0.08**
	(0.04)
Mother's Presence in the Household	-0.05
	(0.05)
Father's Presence in the Household	0.07
	(0.05)
Number of Books in the Household	0.03***
	(0.01)
Mother's Education (years)	0.11***
	(0.04)
Father's Education (years)	0.08**
	(0.04)
Average Household Income (thousands of pesos)	0.06**
	(0.03)
Rural (rural municipality=1)	-0.09***
	(0.03)
Public (public childcare=1)	0.09
	(0.08)
Number of Childcare Centers in Municipality	0.08***
	(0.01)
Proportion of $\left(\frac{0-2\ years\ old}{0-6\ years\ old}\right)$ in Municipality	0.16
	(0.12)
Average Education in Municipality	-0.06
	(0.06)
Obs.	10,596
F-Test (all instruments)	84.33
P-value	0.000

Note: The last three variables: Number of Childcare Centers in the municipality, proportion of 0-2 years olds relative to 0-6 years olds in the municipality, and the average education in the municipality, are the instruments used which are only present in the choice equation. The others are control variables also present in the output equation It also includes municipality and year fized effects. Standard errors clustered at the municipal level are provided in parentheses. $^{*}(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

Table 4:SIMCE score in Language

(in standard deviations)

SIMCE 8^{th}Grade	Model A		Model B		Model C	
Variables	Treated	Untreated	Treated	Untreated	Treated	Untreated
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (Male=1)	-0.21***	-0.24***	-0.11***	-0.14***	-0.12***	-0.10***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Mother's Presence	0.01	0.06	0.02	0.05	-0.00	-0.01
	(0.05)	(0.04)	(0.06)	(0.03)	(0.05)	(0.05)
Father's Presence	0.09***	0.01	0.05**	0.02	0.07**	0.04
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Number of Books	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mother's Education	0.03***	0.03***	0.01*	0.01**	0.08	0.56
	(0.01)	(0.01)	(0.00)	(0.00)	(0.33)	(0.35)
Father's Education	0.03***	0.03***	0.02***	0.01**	0.01*	0.01**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Household Income	0.06**	0.10***	0.02	0.06***	0.03	0.03
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Rural	0.07	0.04	0.04	0.07	0.12	0.04
	(0.08)	(0.07)	(0.06)	(0.06)	(0.08)	(0.09)
Public	-0.12***	-0.14***	-0.07**	-0.07***	-0.07**	-0.10***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
SIMCE 4^{th}Grade	-	-	0.01***	0.01***	0.01***	0.01***
			(0.00)	(0.00)	(0.00)	(0.00)
Class Size	-	-	-	-	-0.01**	-0.01
					(0.00)	(0.01)
Technical Coefficient	-	-	-	-	0.01*	0.01
					(0.00)	(0.01)
ATE	-0.47		-0.36		-0.54	
Obs	10,129		10,129		6,211	

Note : This table shows the results for the Language SIMCE test. Columns 1 and 2 display results for model A which does not include the SIMCE lagged score or nursery quality controls. Columns 3 and 4 display the results for model B which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Columns 5 and 6 display results for model C which is the same as model B plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers). .Technical coefficient is measured as $\left(\frac{Number\ of\ educators}{Number\ of\ toddlers}\right)$. It also includes municipality and year fixed effects. Boostrapped standard errors are provided in parentheses. $^{*}(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

Table 5: SIMCE score in Mathematics

(in standard deviations)

SIMCE 8^{th}Grade	Model A		Model B		Model C	
Variables	Treated	Untreated	Treated	Untreated	Treated	Untreated
	(5)	(6)	(7)	(8)	(7)	(8)
Gender (Male=1)	0.16***	0.10***	0.06***	0.04**	0.07***	0.07**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Mother's Presence	0.02	0.08**	0.03	0.04	0.01	0.02
	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)
Father's Presence	0.09***	0.05**	0.04*	0.04***	0.06**	0.05***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
Number of Books	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mother's Education	0.04***	0.04***	0.01**	0.02***	0.01*	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Father's Education	0.03***	0.04***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Household Income	0.14***	0.16***	0.07***	0.08***	0.07***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Rural	0.12*	-0.10**	0.14***	-0.03	0.30***	-0.03
	(0.07)	(0.05)	(0.04)	(0.02)	(0.08)	(0.07)
Public	-0.26***	-0.28***	-0.19***	-0.20***	-0.19***	-0.20***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
SIMCE 4^{th}Grade			0.01***	0.01***	0.01***	0.01***
			(0.00)	(0.00)	(0.00)	(0.00)
Class Size			-	-	-0.01**	-0.01
					(0.00)	(0.01)
Technical Coefficient			-	-	0.01**	0.01
					(0.00)	(0.00)
ATE	0.06		-0.04		-0.24	
Obs	10,503		10,252		6,297	

Note : This table shows the results for the Language SIMCE test. Columns 1 and 2 display results for model A which does not include the SIMCE lagged score or nursery quality controls. Columns 3 and 4 display the results for model B which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Columns 5 and 6 display results for model C which is the same as model B plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers). .Technical coefficient is measured as $\left(\frac{Number\ of\ educators}{Number\ of\ toddlers}\right)$. It also includes municipality and year fixed effects. Boostrapped standard errors are provided in parentheses. $^{*}(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

Table 6: Motivation Score

(in standard deviations)

Motivation 8^{th}Grade	Model A		Model B		Model C	
Variables	Treated	Untreated	Treated	Untreated	Treated	Untreated
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (Male=1)	-0.08**	-0.12***	-0.04	-0.07**	-0.03	-0.04
	(0.04)	(0.02)	(0.04)	(0.03)	(0.05)	(0.08)
Mother's Presence	-0.06	0.05	-0.03	-0.02	-0.10	-0.11
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
Father's Presence	0.10**	0.08***	0.07**	0.07**	0.08*	0.07
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Number of Books	0.01***	0.01***	0.01***	0.01***	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Mother's Education	-0.01	-0.01	-0.01	-0.01	0.01	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Father's Education	0.01**	0.01**	0.01	0.01	0.01	0.01*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Household Income	-0.02	-0.03	-0.03	-0.03	-0.02	-0.04
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Rural	0.21**	0.01	0.23**	0.21	0.53***	0.10
	(0.10)	(0.06)	(0.11)	(0.14)	(0.16)	(0.14)
Public	0.01	0.01	0.03	-0.01	-0.01	-0.07
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)
Motivation 4^{th}Grade	-	-	-0.01***	-0.02***	-0.01***	-0.02***
			(0.00)	(0.00)	(0.00)	(0.00)
Class Size	-	-	-	-	-0.03***	0.01
					(0.01)	(0.01)
Technical Coefficient	-	-	-	-	0.02**	-0.01
					(0.01)	(0.01)
ATE	-0.49		-0.39		-0.57	
Obs	9,064		8,264		4,933	

Note : This table shows the results for the Language SIMCE test. Columns 1 and 2 display results for model A which does not include the SIMCE lagged score or nursery quality controls. Columns 3 and 4 display the results for model B which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Columns 5 and 6 display results for model C which is the same as model B plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers). .Technical coefficient is measured as $\left(\frac{Number\ of\ educators}{Number\ of\ toddlers}\right)$. It also includes municipality and year fixed effects. Boostrapped standard errors are provided in parentheses. $^{*}(p<0.1)$, $^{**}(p<0.05)$, $^{***}(p<0.01)$

Table 7: Self-Esteem Score

(in standard deviations)

Self-Esteem 8^{th}Grade	Model A		Model B		Model C	
Variables	Treated	Untreated	Treated	Untreated	Treated	Untreated
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (Male=1)	0.03	0.01	0.06	0.05^{*}	0.08^{**}	0.10^{**}
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Mother's Presence	-0.02	0.05	-0.01	0.01	-0.03	-0.08
	(0.06)	(0.06)	(0.07)	(0.05)	(0.08)	(0.08)
Father's Presence	0.07^{*}	0.09^{***}	0.04	0.09^{***}	0.04	0.08^{*}
	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Number of Books	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{**}	0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mother's Education	0.01	0.01^{**}	0.01	0.01^{***}	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Father's Education	0.01	0.01	0.01	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income	0.03	0.00	0.04	-0.01	0.05	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Rural	0.21^{**}	0.03	0.22^{***}	0.06	0.54^{***}	0.19
	(0.06)	(0.09)	(0.07)	(0.08)	(0.14)	(0.13)
Public	-0.01	-0.01	0.01	-0.01	-0.03	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)
Self-esteem 4^{th}Grade	-	-	-0.01^{***}	-0.02^{***}	-0.01^{***}	-0.02^{***}
			(0.00)	(0.00)	(0.00)	(0.00)
Class Size	-	-	-	-	-0.03^{***}	0.01
					(0.01)	(0.01)
Technical Coefficient	-	-	-	-	0.01^{*}	-0.00
					(0.00)	(0.00)
ATE	-0.37		-0.33		-0.59	
Obs	9,426		8,733		5,276	

Note : This table shows the results for the Language SIMCE test. Columns 1 and 2 display results for model A which does not include the SIMCE lagged score or nursery quality controls. Columns 3 and 4 display the results for model B which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Columns 5 and 6 display results for model C which is the same as model B plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers). .Technical coefficient is measured as $\left(\frac{Number\ of\ educators}{Number\ of\ toddlers}\right)$. It also includes municipality and year fixed effects. Boostrapped standard errors are provided in parentheses. $^{*}(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

TABLE 8

Exogeneity of the Childcare Expansion

Variables	Change in the supply of nursery care by municipality 2000-2014
Average Income (per capita)in municipality	0.011
	(2.74)
Proportion of $\left(\frac{0-2\ years\ old}{0-6\ years\ old}\right)$ in municipality	1.174
	(0.47)
Proportion of Rural Population in municipality	0.077***
	(3.75)
Average Education in municipality	-2.158***
	(6.56)
Proportion of male students (male=1)	0.041
	(1.21)
Area of municipality (km^2)	0.035
	(1.01)
Obs.	1,908

Note: This table displays the results of a regression of the change in nursery care centers by municipality 2000-2014 on several covariates measured at the municipality level: number of nursery care centers by municipality, proportion of 0-2 year old students relative to 0-6 years old students by municipality, average income by municipality, average per capita income by municipality, proportion of rural population and the area of the municipality. $^*(p < 0.1)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$

TABLE 9

Weights for Treatment Parameters

Parameter	**Weight**
Average Treatment Effect (ATE)	$\omega_{ATE}(x,u) = 1$
Treatment on the Treated (TT)	$\omega_{TT}(x,u) = \left[\int_u^1 f(a \vert X=x)da\right] \frac{1}{E(P \vert X=x)}$
Treatment on the Untreated (TUT)	$\omega_{TUT}(x,u) = \left[\int_0^u f(a \vert X=x)da\right] \frac{1}{E(1-P \vert X=x)}$
Marginal Policy Relevant Treatment Effect ($MPRTE$)	$\omega_{MPRTE}(x,u) = -\frac{\frac{\partial F_0(u \vert X=x)}{\partial \delta}}{\frac{\partial E_{F0}(A \vert X=x)}{\partial \delta}}$

Source: Carneiro, Heckman and Vytlacil (2010).

TABLE 10

Weights for different MPRTE

Type of Policy	**Weight**
$P_\delta = P + \delta$	$\omega_{MPRTE}(x,u) = f_{P \vert X}(u)$
$P_\delta = P(1+\delta)$	$\omega_{MPRTE}(x,u) = \frac{u f_{P \vert X}(u)}{E(P \vert X)}$

Source: Carneiro, Heckman and Vytlacil (2010). $P = P(Z)$, the baseline propensity score.

TABLE 11

Results for Different Treatment Parameters

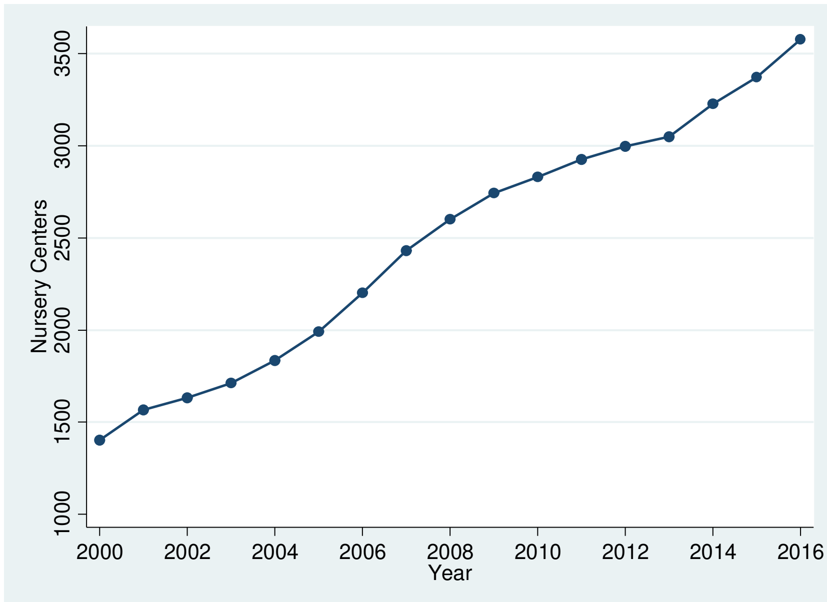
(in standard deviations)

Treatment Parameter	**Language**	**Mathematics**	**Motivation**	**Self-Esteem**
	(1)	(2)	(3)	(4)
ATE	-0.54***	-0.24**	-0.57***	-0.59***
	(0.22)	(0.12)	(0.21)	(0.22)
TT	-0.38*	-0.10*	-0.35**	-0.39**
	(0.21)	(0.06)	(0.17)	(0.19)
TUT	-0.62*	-0.37**	-0.66**	-0.71**
	(0.37)	(0.17)	(0.32)	(0.35)
MPRTE: $P + \delta$	-0.45*	-0.19*	-0.44*	-0.48*
	(0.24)	(0.11)	(0.24)	(0.27)
MPRTE: $P(1 + \delta)$	-0.48*	-0.24*	-0.49*	-0.52*
	(0.26)	(0.13)	(0.27)	(0.29)

Note: For the ATE, TT and TUT we consider results of model C which includes as controls the lagged value of the student's test and childcare quality variables. For the MPRTE, we consider the following: (i) a policy that increases the probability of attending childcare by an amount δ and (ii) a policy that changes each person's probability of attending into a childcare center by the proportion $(1 + \delta)$. In each case, we consider the corresponding PRTE for going from the status quo to policy δ, and consider the limit of such PRTEs as δ goes to zero. Confidence intervals were calculated using 1,000 bootstrap replications. Source: Authors' calculations.

Figure 1

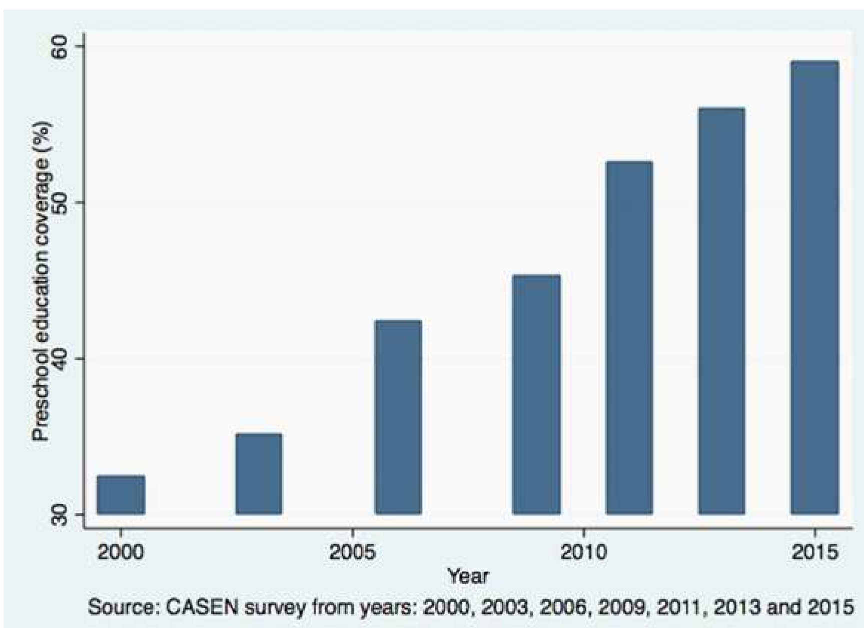
Number of Nursery Centers



Note : Evolution of the number of nursery centers Source: Chilean Ministry of Education

Figure 2

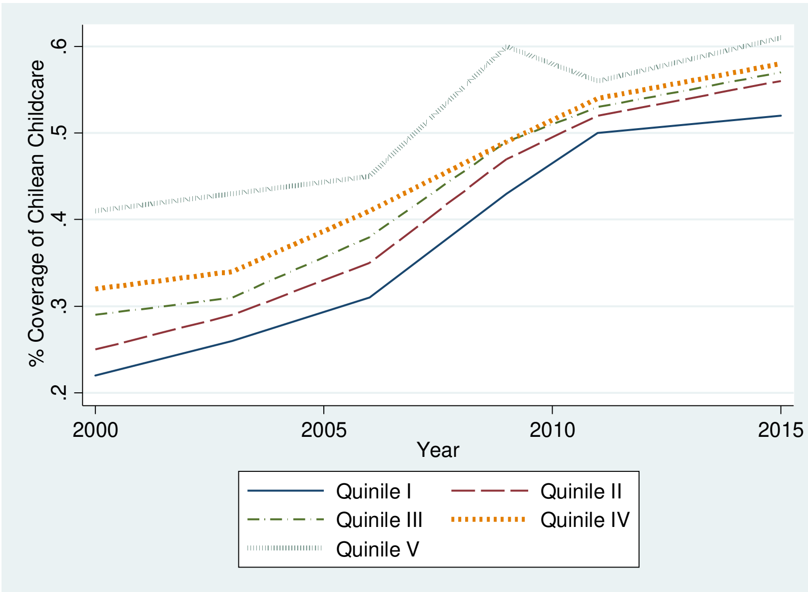
Percentage Coverage of Chilean Childcare



Note : This figure shows the evolution of nursery coverage rate Source: CASEN from several years. CASEN is a national survey which is representative at the municipal level.

Figure 3

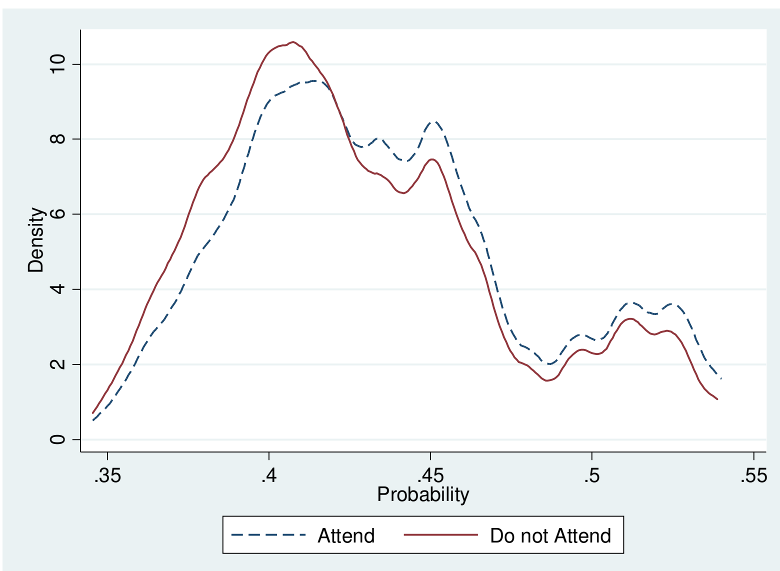
Percentage Coverage of Chilean Childcare by Quintile



Note : This figure shows the evolution of the nursery coverage rate by quintiles of income. Source: CASEN from several years. CASEN is a national survey which is representative at the municipal level.

Figure 4

Common Support of the Propensity Score



Note : This figure shows the common support between those who attend and those who do not attend nursery care. Source: SIMCE dataset and the complementary questionnaire.

Figure 5: Language Score Model A

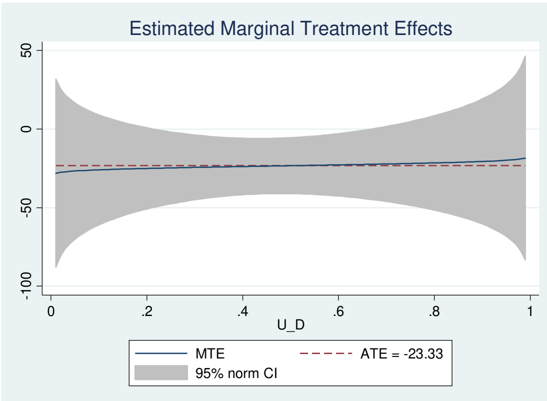


Figure 6: Language Score Model B

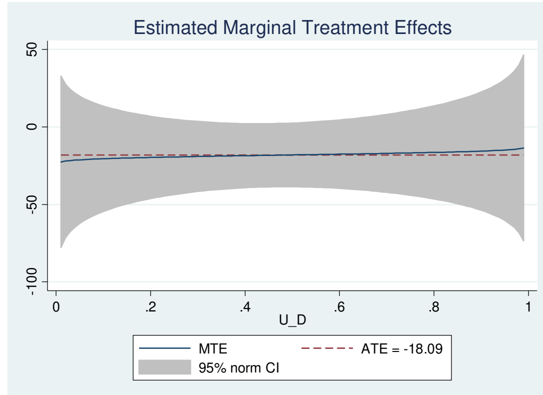
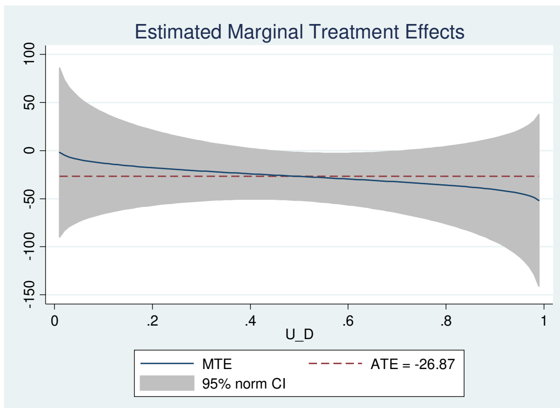


Figure 7: Language Score Model C



Note : These figures show the MTE for the language SIMCE. Figure 5 displays the MTE for model A of Table 4 which does not include the SIMCE lagged score or nursery quality controls. Figure 6 displays the MTE for model B of Table 4 which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Figure 7 displays the MTE for model C which is the same as model B of Table 4 plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers).

Figure 8: Mathematics Score Model A

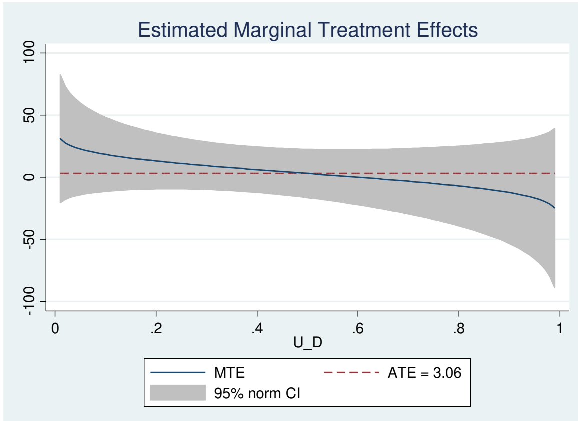


Figure 9: Mathematics Score Model B

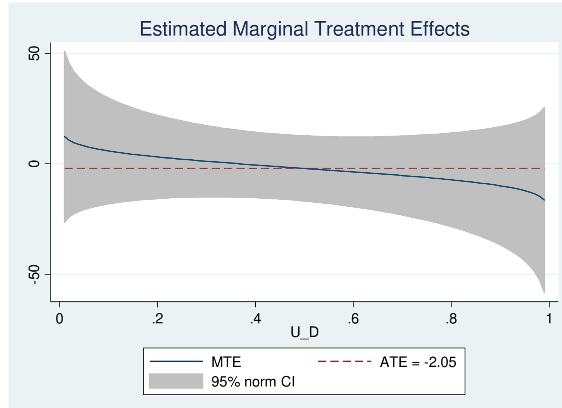
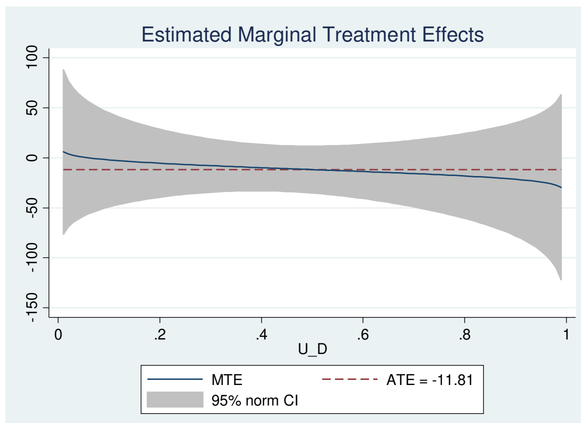


Figure 10: Mathematics Score Model C



Note : These figures show the MTE for the mathematics SIMCE. Figure 8 displays the MTE for model A of Table 5 which does not include the SIMCE lagged score or nursery quality controls. Figure 9 displays the MTE for model B of Table 5 which is the same as model A plus the inclusion of the lagged SIMCE score as a control variable. Figure 10 displays the MTE for model C which is the same as model B of Table 5 plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers).

Figure 11: Motivation Score Model A

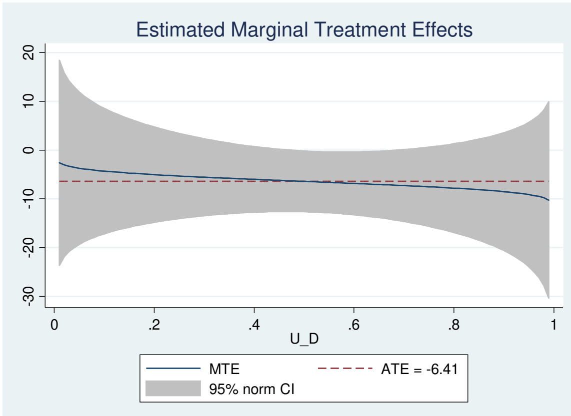


Figure 12: Motivation Score Model B

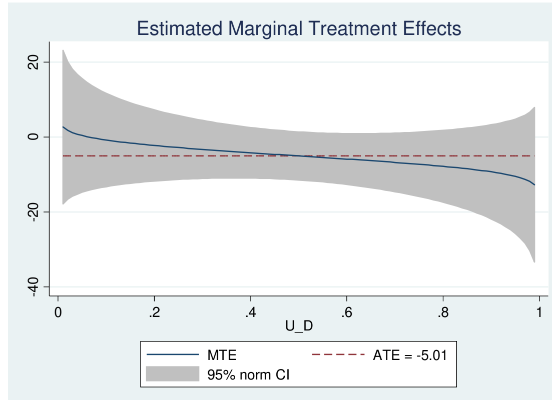
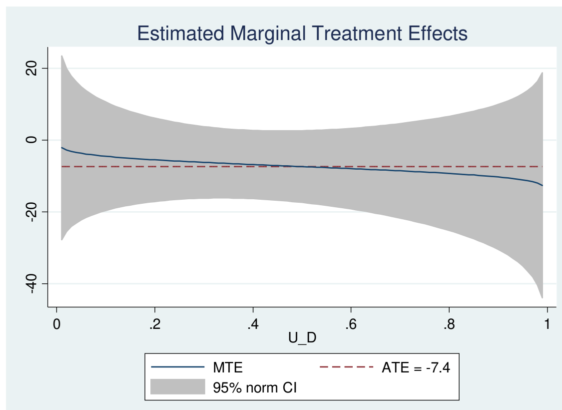


Figure 13: Motivation Score Model C



Note : These figures show the MTE for the motivation test included in the complementary questionnaire of the SIMCE. Figure 11 displays the MTE for model A of Table 6 which does not include the lagged score or nursery quality controls. Figure 12 displays the MTE for model B of Table 6 which is the same as model A plus the inclusion of the lagged score as a control variable. Figure 13 displays the MTE for model C which is the same as model B of Table 6 plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers).

Figure 14: Self-Esteem Score Model A

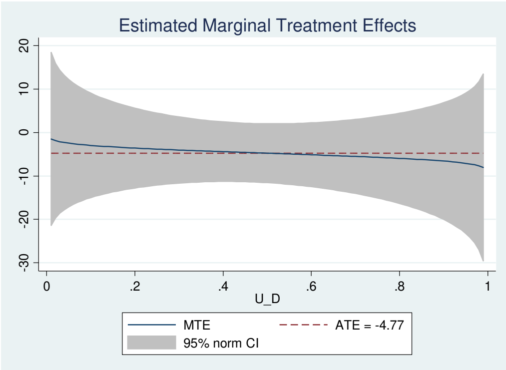


Figure 15: Self-Esteem Score Model B

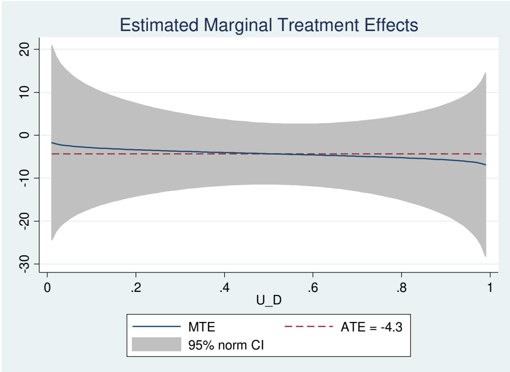
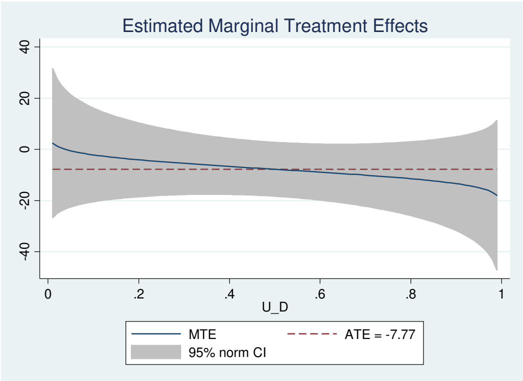


Figure 16: Self-Esteem Score Model C



Note : These figures show the MTE for the self-Esteem test included in the complementary questionnaire of the SIMCE. Figure 14 displays the MTE for model A of Table 7 which does not include the lagged score or nursery quality controls. Figure 15 displays the MTE for model B of Table 7 which is the same as model A plus the inclusion of the lagged score as a control variable. Figure 16 displays the MTE for model C which is the same as model B of Table 7 plus the inclusion of variables that control for nursery quality such as class size and the technical coefficient (i.e. number of educators over number of toddlers).