The Effect of Participation in Public Childcare Centers: Evidence from Chile

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Abstract

This paper analyzes the effectiveness of public investments in early childhood education programs in the developing world. The empirical study employs a unique quasi-experimental longitudinal dataset from Chile containing detailed information on the family background and developmental outcomes of young children eligible to participate in public childcare centers. We focus on estimating the average causal effect of attending a public childcare center on specific components of a child's cognitive and noncognitive development, allowing for heterogeneous treatment effects and endogenous selection into childcare. We implement various empirical approaches, including instrumental variables and control function methods which use the exogenous growth in the public supply of childcare centers as sources of exclusion restrictions.

Our analysis demonstrates the importance of accounting for sources of selection bias, particularly as we find that unobservable factors dominate the selection process. Failure to account for such bias leads to largely underestimated and highly statistically significant effects. Based on a control function approach, we estimate a positive average treatment effect over time in nearly all areas of child development, particularly those concerning motor and cognitive skills. Negative effects appear in the area of adult interactions and we deduce this may be related to the shortage of quality staff at public childcare centers. Finally, our findings suggest the magnitude of the effects is highly dependent on the age of the child and the length of exposure to the program.

KEYWORDS: Education Economics, Early Childhood, Program Evaluation, Treatment Effects, Control Function.
JEL: C31, I21, O15, O54.

1 Introduction

Increasingly, a number of global business and economic leaders, including Fortune 500 CEOs, Nobel Laureates in Economics, Federal Reserve bankers, and even Grammy Award-winning artists have led the call to increase public investments in early childhood. During the 2008 presidential campaign, Barack Obama pledged $10 billion for early childhood education (Dillon, 2008). Earlier that year, economists in Latin America cited early childhood development (ECD) programs as the top priority for their governments if they had $10 billion to solve their most urgent problems (Inter-American Development Bank, 2008). And just recently, the World Bank launched a $300 million joint initiative with the ALAS foundation and Columbia University's Earth Institute aimed at expanding cost-effective ECD policies and programs for young children in Latin America and the Caribbean (The World Bank, 2010).

Early childhood (ages 0-6 years) is a crucial time to invest in interventions that improve a child's welfare in several dimensions, including physical, intellectual, and social. Research in neuroscience and psychology has found that cognitive and noncognitive stimulation in early life are critical for long-term skill development as key brain pathways for subsequent learning and lifelong capabilities begin to form (Shonkoff and Phillips, 2000). In the field of economics, the human capital literature has also placed emphasis on and demonstrated empirically the importance of investing in children at early ages (See Becker, 1993; Heckman et al., 2003; Cunha and Heckman, 2007, among others for details). Cunha and Heckman (2007), for example, introduce an economic model for the technology of skill formation in which home inputs and innate endowments of the child (i.e. genetic factors and innate abilities) are directly linked to ECD outcomes. They also estimate a version of this model, documenting the relative importance of a comprehensive set of variables describing family environments as well as the cognitive and noncognitive skills of a child.

Numerous studies demonstrate the importance of cognitive skills, as measured by achievement tests and IQ scores, in explaining a variety of economic and social outcomes, including schooling attainment, earning profiles, health status, and participation in crime (See Cawley et al., 2001, for a summary of recent evidence). More recently, noncognitive abilities, such as patience, self-esteem, risk aversion, persistence, attention, and social behavior skills, have also been shown to be important predictors of these outcomes (See Heckman et al., 2006, 2008, for details). Heckman et al. (2008), for instance, conclude that the Perry Preschool Program operates primarily through improving the noncognitive traits of participants.[1] Despite the fading of initial gains in IQ, in the long-term, participants had higher achievement test scores, high school graduation rates, and earnings, as well as lower rates of participation in welfare, teenage pregnancy, and crime. The acquisition of noncognitive skills at early stages in life therefore promotes the formation of cognitive skills later on.

Consequently, there is a strong multiplier effect associated with public investments in early childhood, whereby investments in the early years, particularly for disadvantaged children, can make investments in the later years more productive. Moreover, remediating early disadvantages later may be prohibitively costly.[2] Therefore, investing in early childhood initiatives promotes fairness and social justice and at the same time promotes productivity in the economy and in society at large, by impacting schooling, labor market, and behavioral outcomes (Heckman, 2006). Overall, comprehensive early childhood intervention policies appear to be sound investments that may offer the greatest development impact per dollar spent and may begin to break the cycle of poverty that hinders a nation's quality of human capital and consequently its economic growth.[3]

Nevertheless, despite the appeal of public investments in ECD relatively few rigorous and systematic evaluations of early childhood education (ECE) programs have shown the effects of these interventions in developing countries, particularly on cognitive and noncognitive skill indicators. Therefore, the purpose of this paper is to evaluate the impact of public childcare

[1]See Appendix A for a detailed review of the Perry Preschool Program.

[2]Due to the dynamic nature of the skill formation process (*Skill begets skill; learning begets learning*), remediating early disadvantages at later ages is often prohibitively costly (i.e. the opportunity cost of funds greatly exceeds the rate of return) (Cunha and Heckman, 2007).

[3]For example, Hanushek and Woessmann (2009) perform a growth analysis on several regions of the world and find that school attainment is associated with economic growth only insofar as it produces cognitive skills. The study emphasizes the poor growth performance of Latin America despite relatively high levels of schooling attainment and reconciles this fact with evidence of low levels of cognitive skills in the region.

centers in Chile on various aspects of early child development. Specifically,

- We present a comprehensive empirical analysis of the average causal effects of attending public childcare centers on cognitive and noncognitive dimensions of child development.
- Our empirical model allows for heterogenous treatment effects and endogenous selection into childcare centers. We focus our analysis on the average treatment effect and examine whether there are dynamic effects associated with the age of the child and the length of program exposure.
- We employ a unique quasi-experimental longitudinal dataset from Chile containing a rich set of family and child characteristics including cognitive and noncognitive scores of the child prior to and after entering a public childcare center.
- We supplement the analysis with administrative records containing information on the local availability of public childcare centers. We exploit the significant increase in Chile's public supply of childcare centers as sources of instruments/exclusion restrictions.
- We document the presence of selection and its effects. We do this by directly testing for the presence of selection and by comparing the results obtained from different estimation strategies: OLS, Instrumental Variables (IV), and Control Function (CF) approach.
- We show that it is imperative to account for selection bias as the effects of participation in a public childcare center would otherwise be largely underestimated. We also find that selection bias drives the magnitude and significance of the effects estimated by OLS and IV.
- Our results reveal a positive average treatment effect over time in nearly all areas of child development, particularly those concerning motor and cognitive skills. Negative

effects appear in the area of adult interactions and we deduce this may be related to the shortage of quality staff at public childcare centers. The magnitude of these effects is highly dependent on the age of the child and the length of exposure to the program.

- The policy implications of our results point to the challenge of expanding ECE coverage, particularly for the younger and economically disadvantaged children in the population, while continually improving and rigorously evaluating the quality of services provided, considering the higher level of expenditure associated with creating an age-appropriate curriculum and providing an adequate number of trained teaching staff.

The paper is organized as follows. Section 2 presents a detailed literature review and explains why Chile is a case of interest. Section 3 describes our data from Chile, including family and child characteristics as well as the cognitive and noncognitive measures of child development. Section 4 introduces the econometric strategy along with the identification assumptions. Section 5 discusses the implementation and advantages of our empirical model relative to conventional regression models. Section 6 presents the empirical results associated with the demand for public childcare centers, the presence of selection, and the effects of attending a public childcare center, as well as a discussion of these results in the context of the literature. Section 7 concludes.

2 Review of the Literature

In general, the evidence from the U.S. experience shows that the effects of ECE programs are more consistently positive in the short-term for cognitive outcomes than for noncognitive outcomes.[4] Nevertheless, it is difficult to generalize these results to the experience of developing countries. Both the kinds of ECE programs and the families and children they serve differ in multiple respects, especially considering the heterogeneous market, policy, and cultural contexts in developing economies (i.e. program expenditure per child, training of

[4] Appendix A contains a detailed review of the U.S. literature.

care providers, child health and development, family behavior and preferences, etc.) Such differences could significantly affect the extent and type of benefits experienced by children who attend a childcare center in the developing world. Therefore, as Behrman et al. (2007) emphasize, it is crucial to systematically expand and rigorously assess evaluations of ECE programs in different developing country contexts.

At present, however, the knowledge base on the relative effectiveness of public ECE programs and policies in the developing region of Latin America is alarmingly scarce. This is highly worrisome as 46 million children aged 0 to 6 years in Latin America and the Caribbean are not enrolled in any type of ECE or readiness-to-learn program (IADB, 2010). The large majority of these children are poor and run the risk of not reaching their full developmental potential due to poverty, poor health and nutrition, and deficient care. In fact, Grantham-McGregor et al. (2007) estimate that more than 10 million children under the age of 5 in Latin America are not fulfilling their developmental potential.[5] Hence, early childhood interventions could remedy the situation of disadvantaged children in developing countries, by improving cognitive and noncognitive outcomes both in the short run and in the long run. Recent experimental studies in Guatemala, for instance, document a significant positive effect of a nutritional intervention in early childhood (0 - 2 years of age) on adult economic productivity and educational outcomes (See Hoddinott et al., 2008; Maluccio et al., 2009, for details).[6]

Furthermore, the most recent and methodologically sound evaluations of public ECE programs in the region of Latin America also report largely positive short-run and long-run

[5] Risk factors for loss of potential include stunting, iodine and iron deficiency, and inadequate cognitive stimulation. These indicators are closely associted with poor cognitive and educational performance as children as well as a prevalence of low income, high fertility, and poor parental behavior as adults.

[6] Hoddinott et al. (2008) explores the effect of the early childhood experimental nutritional intervention a quarter century later on annual income, annual hours worked, and wages. They find that atole supplementation during 0-24 months led to a 46 percentage increase in average hourly wage rates for men. There was also a tendency for hours worked to be reduced and for annual incomes to be greater for those exposed to treatment. Maluccio et al. (2009) do a follow-up study to investigate the effects of the same nutritional intervention on educational outcomes and they find that exposure to treatment between 0-24 months increased schooling by 1.2 grades for women, and it also increased reading comprehension and nonverbal cognitive test scores by one-quarter of a standard deviation for both men and women.

impacts on cognitive and noncognitive skills. These programs include the *Proyecto Integral de Desarrollo Infantil* (PIDI, or Integrated Child Development Project) program in Bolivia, the expansion of the public preschool system in Argentina and Uruguay, and the *Hogares Comunitarios de Bienestar Familiar* (HCBF, or Community Welfare Homes) program in Colombia.[7]

Behrman et al. (2004) use a large nonexperimental dataset to assess the impact of the Bolivian PIDI program on multiple child outcome measures related to motor, anthropometric, language, and psychosocial development.[8] Using generalized propensity score matching methods to allow program impacts to be estimated as nonparametric functions of age at the time of entry and duration of participation in the program, the study finds that the program has positive impacts on participants' gross and fine motor skills, psychosocial skills, and language acquisition.[9] Impacts are found to be cumulative, with greater impacts associated with longer program exposure, particularly longer than a year. Moreover, positive and statistically significant effects are concentrated among children aged 30 months or older at the time of entry into the program who participated in the program for more than 7 months.[10] For younger children (younger than 30 months of age), the program effects are generally insignificant and are as likely to be positive as negative.

In Argentina, Berlinski et al. (2009) took advantage of the dramatic 1990s preschool construction program aimed at increasing primary school attendance for children between

[7]This is not a comprehensive review of more general ECD studies in Latin America. Although programs with a primary focus on child nutrition, maternal health, parenting support, and cash-transfers, for example, are of prime importance to the ECD literature, we will solely focus on preprimary education programs sponsored by the government as it is the most relevant literature for our line of inquiry. For a comprehensive review of ECD studies in Latin America, see Vegas and Santibáñez (2010); Schady (2006).

[8]In line with the government of Bolivia's Social Strategy Statement and its 10-year action plan to improve the lives of women and children, PIDI is a home-based daycare program that was implemented in the 1990s and offers full-time daycare plus nutritional and education services to children between the ages of 6 - 72 months in poor urban areas.

[9]In terms of anthropometric outcomes (i.e. height-for-age and weight-for-age percentiles), the study estimated program impacts on height are positive at ages up to 36 months, but mostly negative for older children. For weight percentiles, estimated impacts are negative at ages younger than 36 months. However, the study reports that the impacts on the anthropometric outcomes are not precisely estimated as no baseline data were available.

[10]For this age group, the program is estimated to increase test scores by roughly one additional correct item, which is 3% to 4% of the average score within age classes of the untreated group.

the ages of 3 and 5 to study the effects of a national, publicly-funded ECE program on primary school achievement.[11] Using an identification strategy similar to Duflo (2001), the study exploits the variation in program intensity across regions and cohorts and finds positive effects on subsequent third grade standardized Spanish and Mathematics test scores. In particular, they find that one year of attending preschool increases average third grade test scores by 23 percent of the standard deviation, with similar gains for boys and girls. Preschool attendance also has a positive impact on a third grade student's behaviors such as attention, effort, participation, and discipline in class as reported by his teacher. Moreover, these effects appear to be relevant to the population at large, not just to the most disadvantaged children, although the effects are twice as large for students from poor backgrounds.

A similar analysis was carried out by Berlinski et al. (2008) using the national household survey (*Encuesta Continua de Hogares*) in Uruguay which collected retrospective data on preschool attendance. In the context of a rapid expansion in the public supply of preprimary education, the study exploits the exogenous variation in preschool attendance rates by locality of residence and birth cohort across siblings to predict the effects of participation in preschool on subsequent school outcomes.[12] The results show significant and positive effects of preschool attendance on completed years of primary and secondary education via a reduction in grade retention rates since early school years and a reduction in dropout rates among teenagers. In particular, by age 15, treated individuals have accumulated around 0.8 more years of education and are 27 percentage points more likely to be in school compared to their nontreated siblings. They also find substantial heterogeneity in the effect of treatment. In particular, children whose mothers have lower than average education or who live outside of the capital appear to benefit largely from exposure to preschool.

[11] Under the compulsory law established for preschool education, Argentina constructed enough classrooms for approximately 175,000 children between 1993 and 1999. Comparing 1991 to 2001, all provinces increased enrollment in preprimary education by at least 10 percentage points.

[12] Between 1995 and 2004, the *Administration Nacional de Educación Pública* (ANEP, or Nation Administration of Public Education) increased enrollment in public preschools from 49,618 to 87,237 pupils, a rise of 76% over nine years. Moreover, the expansion attracted children from more disadvantaged backgrounds. While in 1991 attendance rates of 4 year olds belonging to the lowest income quintile was in the order of 20%, by 2002 this figure was in the order of 60%.

Lastly, in Colombia, Bernal et al. (2009), in partnership with Profamilia, collected quasi-experimental data for approximately 26,000 children aged 0 to 6 years, half of whom participated in the HCBF program, to evaluate the effects of the intervention on the nutritional status, health, cognitive and psychosocial development of children.[13] Relying on choice-based sampling, the evaluation employed nonparametric propensity score matching methods to estimate the impact of the program while taking into account the length of duration. The results indicate that there is a positive and significant effect of the program on nutritional status measured by a reduction in the probability of chronic malnutrition of around 2% for children between the ages of 2 and 4. In addition, there is a negative effect of the program on children's health as measured by incidence of diarrhea and respiratory illness.

In terms of cognitive and psychosocial development, the results in Bernal et al. (2009) were restricted to the sample of children aged 3 to 6 years (roughly 6,000 children and 50% participated in HCBF). The results indicate that there are short-term positive and significant effects on the cognitive and psychosocial development of children of all ages who had at least 16 months of program participation.[14,15] The study also implements an instrumental variables technique to estimate the medium-term effects of the program on cognitive development. Instrumenting for program participation with the number of HCBF capacity spots at the municipality level and using a sample of 1,890 students who took standardized tests in primary school and were once eligible to participate in HCBF, the study finds positive effects of participating in HCBF on academic achievement in fifth grade, particularly in the area of language, conditional on participating in HCBF for a longer period of time.

The conclusions that can be drawn from these papers are open to consideration given

[13]Implemented in 1986 by the *Instituto Colombiano de Bienestar Familiar* (ICBF, or Colombian Family Welfare Institute), the community-based program uses *madres comunitarias* (community mothers) to provide childcare services with an important nutritional component to approximately 1 million children under the age of 6 who belong to the poorest sectors in the population.

[14]The measures of cognitive and psychosocial development include: the Early Development Instrument (EDI), the Penn Interactive Peer Play Scale (PIPPS), the Batería III Woodcock-Muñoz, and the Spanish Peabody Picture Vocabulary Test (PPVT).

[15]These effects appear to depend to some extent on the pedagogical resources available at the home of the *madre comunitaria* (community mother) as well as the knowledge she has of early childhood development practices, as measured on the KIDI (Knowledge of Infant Development Inventory) scale.

the small number of studies. On one hand, it appears that the preliminary evidence does demonstrate that particular ECE interventions may plausibly benefit a child's cognitive and noncognitive development. On the other hand, explicit efforts to secure the quality of ECE programs have not accompanied the growing levels of preschool enrollment rates in Latin America and the Caribbean (see Figure 1). In addition, according to Behrman et al. (2007), there is the challenge of carrying out a rigorous empirical analysis which (1) takes into account the multiple dimensions of ECD programs, (2) estimates relations that would be informative for improving understanding within a life-cycle behavioral framework with unobservable factors (i.e. genetic endowments), (3) provides adequate resolutions to estimation problems, and (4) deals with different types of data effectively. This paper seeks to address these challenges by providing empirical answers on the effectiveness of public investments in ECE programs in Latin America with particular attention to the case of Chile.

2.1 Why Chile?

Chile is one of South America's most stable and prosperous nations. Recently, it was invited to join as the first OECD member in South America (OECD, 2010). Moreover, in 2007, it achieved the status as the region's richest country in terms of gross domestic product per capita, which has increased at an average annual growth rate of 3.6% since 1990.[16] Chile also leads regionally in terms of low poverty rates, high literacy rates, low infant stunting and mortality rates, and high preprimary education investments.[17] For instance, Chile has a 1% incidence of moderate to severe stunting and a 9% mortality rate among children under 5 years of age compared to a 14% and 26% average in Latin America in these measures, respectively (UNICEF, 2010). In addition, expenditures on preprimary education services per student represent 20% of its GDP per capita, well above the OECD countries average of

[16] Based on GDP per capita at market prices in US dollars as reported in IMF (2008) and GDP per capita average annual growth rate as reported in UNICEF (2010).

[17] According to CIA (2010), 18% of the population in Chile is below the national poverty line and 96% of the total population is literate.

18% (OECD, 2009).[18] Moreover, the government accounts for 70% of the total expenditures on preprimary education and this amount represents close to 10% of its total spending in the education sector (MINEDU, 2006).

Nevertheless, Chile continues to rank high in the level of income and educational inequality.[19] For instance, Chilean data from the most recent national household survey, CASEN (2006), show that only six percent of children under two years of age and a quarter of the children between two and four years of age attend a childcare center (Medrano, 2009). These low preprimary enrollment rates are also highly unequal across income levels. For example, children between two and four years of age who belong to the bottom income quintile had roughly half of the coverage relative to children in the same age range who belong to the top income quintile.[20] Moreover, children under two years of age belonging to the first income quintile had a 15% difference in coverage with their peer group in the fifth quintile.[21] Therefore, the challenge lies in expanding early childhood education coverage, especially for the younger and economically disadvantaged children in the population, while maintaining and continually improving the quality of services provided, considering the higher level of expenditure associated with creating an age-appropriate curriculum and providing an adequate number of trained teaching staff.

Recently, the Chilean government has taken serious steps to remedy the situation of young children, particularly the most vulnerable, by increasing ECE coverage with equity and quality. As soon as the Bachelet administration (2006-2010) took office, it established a national ECD policy, *Chile Crece Contigo* (Chile Grows with You), and it organized the Presidential Advisory Council for Infant Policies. One of the main objectives for the Council was to considerably increase the supply of public childcare center for children from the

[18] This represents expenditures on preprimary education only for children 3 years of age and older. As a percentage of total GDP, expenditures at this level of education constitute 0.5% of Chile's GDP.

[19] Income inequality based on the Gini coefficient of 0.55 in 2007 (UNDP, 2007).

[20] Coverage for children between 2-4 was 3% for the bottom income quintile while 13% for the top income quintile (Medrano, 2009).

[21] Coverage for children between 0-2 was 24% for the bottom income quintile while 39% for the top income quintile (Medrano, 2009).

poorest households in Chile. The commitment was to increase spots in the *Sala Cuna* (crib room) program designed for the youngest children (those under two) by 70,000 between March 2006 and December 2009. Thus far, Chile has nearly tripled coverage at this level of education between 2005 and 2007 (Encina and Martínez, 2009).[22] Figure 2 shows the growth in enrollment levels in the *Sala Cuna* program by public childcare center provider from 2005 to 2007.

The *Junta Nacional de Jardines Infantiles* (JUNJI) and the *Fundación Nacional para el Desarrollo Integral del Menor* (INTEGRA) are the two public providers of childcare centers in Chile and they account for 45% of the total enrollment at the preprimary level (MINEDU, 2006).[23] During 2006, JUNJI increased by 320 the number of classrooms for infants between 0 and 2 years. INTEGRA, made a similar number of new classrooms available (Medrano, 2009). This first expansion was made mostly by refurnishing old classrooms that were used by pre-kindergarten and kindergarten children, since these levels are now offered in school buildings. Therefore, an important part was the renovation of existing facilities. Additionally, they made use of the previously-approved local funds at the municipality level to build new facilities and to buy the required equipment.

At the beginning of 2007, JUNJI also focused on improving the early development of children in Chile by evaluating the effectiveness of current programs in the context of the expansion policy. In partnership with the *Centro de Estudios de Desarrollo y Estimulación Psicosocial* (CEDEP),[24] JUNJI set out to implement a longitudinal study to evaluate the effects of participation in their childcare centers on a young child's development outcomes as measured by the Battelle Developmental Inventory Test. Characteristics of a child's family and particular childcare center were also collected at the beginning of the study as possible

[22]Enrollment in public childcare centers increased by 240% between 2005 and 2007 (Encina and Martínez, 2009).

[23]JUNJI is a public organization of the Ministry of Education responsible for imparting the country's early education for children under four years of age who live in a situation of poverty or social vulnerability. INTEGRA is a non-profit organization and it aims to provide quality education to children from disadvantaged backgrounds who are younger than five years of age. For further information on these organizations visit their web links http://www.junji.cl/ and http://www.integra.cl/

[24]For organization information visit the web link http://www.cedep.info/

sets of predictors on program participation.

In December 2007, CEDEP completed its final report regarding the results of the first year of the longitudinal study (CEDEP, 2007). Much of the analysis presented various summary statistics, qualitative information, and multivariate regression analysis without a rigorous examination of the effects of participation in JUNJI childcare centers on a young child's learning and development. Most importantly, the analysis failed to account for selection into the program and the child's family background. Hence, our purpose is to use this unique dataset to rigorously evaluate the static and dynamic effects of JUNJI childcare centers on the cognitive and noncognitive development of the children it serves by controlling for family and child characteristics as well as correcting for the selection bias inherent to the quasi-experimental design of the study described in the next section.

3 The JUNJI Longitudinal Study (JLS)

3.1 Data Description

The longitudinal study implemented by JUNJI in 2007, the JLS, followed a quasi-experimental approach. The researchers first constructed a regionally stratified random sample of 41 public childcare centers from the 164 centers under JUNJI's direction from across the nation. Table 1 presents the distribution of the childcare centers and treated sample in the JLS at the municipality level.[25] The treatment group was selected randomly from children, 2-14 months of age, who attended the *Sala Cuna Menor* program (designed for those in their first year of life) in JLS childcare centers for the first time in April 2007 and did not exhibit signs of severe disability. The control group was selected from healthy children of roughly the same age range who did not previously enroll in any childcare center but attended a

[25]Chile is composed of 15 regions, 53 provinces, and 346 municipalities. According to the data from the national household survey CASEN (2006), the sample of municipalities in the JLS range in size from 6,100 households to 79,300 households. On average the number of households in these municipalities is around 40,000.

public health clinic corresponding to the selected JLS childcare centers.[26] The purpose was to implement choice-based sampling in order to match socioeconomic conditions across the treatment and control groups (similar to Bernal et al., 2009).

In April 2007 (date of baseline interview), 720 children were part of the JLS, 466 were assigned to treatment and 254 were assigned to control.[27] In November 2007 (date of second interview), however, an attrition rate of approximately 24% in the treatment group and 28% in the control group resulted in 355 treated and 183 untreated remaining. Attrition, according to the report by CEDEP, was mainly due to a child experiencing health issues after attending the center or a change of home address (CEDEP, 2007). As a result of a reduced sample size, and in order to maintain the desired sampling error, CEDEP researchers decided to add 72 children that met the same requisites as those in the treatment group to obtain a base sample for analysis with a total of 427 children in the treatment group and 183 children in the control group. In our analysis, however, we consider only the group of children older than 4 months of age for whom baseline socieconomic data were collected and Battelle Investory outcomes were assessed in both periods of measurement. This yields a total sample size of 482 children, 331 treated and 151 untreated.[28]

Table 2 presents descriptive statistics of family characteristics for the treatment and control groups collected at the beginning of the JLS via interviews with the child's mother (95% of the cases), father (2%), or guardian (3%). The child's mother was counted as present if researchers interviewed the biological or adoptive mother at baseline, or interviewed the father/guardian who reported that the mother currently lived or had contact with the child. Father's presence was concerned only with whether the biological father lived with the child.

[26] Public health clinic data was provided by the Ministry of Health. No further details are provided on how the researchers matched these clinics to the JLS childcare centers. However, these centers tend to function next to public institutions, including clinics. Thus, we expect that the clinics were selected accordingly.

[27] CEDEP researchers selected sample size based on setting a margin of error of roughly 6.5% (CEDEP, 2007).

[28] We were unsure of how informative the test results for children younger than 4 months old could be and since there were few data points in the range of 2-4 months old (48 observations) we decided to exclude them. Further sample reductions were as follows: 181 observations without Battelle Inventory outcomes in both periods, 78 observations without baseline socioeconomic data, 72 observations added after baseline, 3 observations missing father's education although the father was present.

The highest level of education of the child's parents was computed in years and only if the parent was present. The type of occupation held by the child's parents was surveyed and categorized into four types: out of the labor force, unemployed, unstable job (i.e. temporary workers), and stable job (i.e. non-temporary workers who generate a stable income stream). Finally, mother's age was reported for all mothers and it was recorded in four age ranges: less than 18 years, 19-25 years, 26-35 years, and older than 36 years.

A comparison of family characteristics across treatment and control groups reveals that there exist mean differences (Table 2, Column 5). Statistically significant differences are notable for father's presence, mother's age, and mother's job. In particular, children assigned to the control group are more likely to have their biological father present and a younger mother who is also out of the labor force. On the other hand, children assigned to treatment are more likely to have an older mother who has a stable job. This suggests that families who decide to send their child to a JLS childcare center are different from those who refrain from doing so. As a result, in the estimation of the effect of attending a JLS childcare on a child's development outcomes we must: (1) control for family background and child characteristics, and (2) control for the potential selection bias that might arise from observed and unobserved factors that influenced the parents' decision to send their child to a JLS childcare center.

Besides the information on family characteristics, the data contains information on child development outcomes for both the treatment and control groups. Specifically, the children in the sample took the Battelle Developmental Inventory test (BDIT), which evaluates fundamental dimensions of development for children ages 0 to 8 based on the concept of milestones.[29] The information was collected both at baseline (April, 2007) and follow-up (November, 2007) interviews. The BDIT is a comprehensive, standardized, norm-referenced and criterion-referenced assessment that yields valid and reliable information about the child's relative standing when compared with other children of the same chronological age and has been widely used as a tool for measuring child development changes over time for population-

[29]Translated to Spanish by De la Cruz and González (1996) from its original version by Newborg et al. (1984).

based longitudinal studies (See Berls and McEwen, 1999, for details).[30] The test is comprised of 22 subdomains and the JLS selected the following nine subdomains: gross motor skills and fine motor skills, receptive and expressive communication, cognitive reasoning and memory, adult interaction and expression of feelings, and adaptive eating behavior.

In the noncognitive domain, the area of gross motor skills measures the coordination of large muscle systems used in locomotion skills such as crawling, walking, running, and jumping, and coordinated movements such as throwing and intentionally dropping objects. The area of fine motor skills assesses the development of a child's fine muscle control and coordination, particularly the small muscles in the arms and hands that allow performance of increasingly complicated tasks.[31] In the area of communication, the child's receptiveness is evaluated in terms of recognition and understanding of sounds, words, and gestures.[32] The child's expressive communication is assessed by observing how he/she conveys information to others using sounds, words, and gestures.[33] The level of personal-social skills are determined by the child's ability to initiate social contact to interact with adults as well as by his ability to express his feelings in an appropiate manner and setting.[34] Last, the measure of adaptative behavior evaluated in this study is eating which assesses the child's ability to carry out food-related tasks effectively.[35]

In the cognitive domain, the data contain information on skills and abilities most commonly thought of as "mental" or "intellectual," with the exception of language and commu-

[30]For the JLS in particular, CEDEP (2007) reports high internal consistency of the different BDIT measures for the sample examined (i.e. Cronbach's alpha greater than the acceptable threshhold of 0.7). It also reports high intercorrelations among the areas of development evaluated (i.e. greather than 0.8).

[31]Sample milestone in the subdomains of fine and gross motor skills include crawling up four steps without assistance, standing in an upright position without support, transfering objects from one hand to the other, and reaching for and touching an object. Description of subdomains and sample milestones can be found in Newborg (2005).

[32]Sample milestones in the subdomain of receptive communication include responding to different tones of voice, responding to who or what questions, and associating pictures with words.

[33]Sample milestones in the subdomain of expressive communication include waving, imititating speech sounds, and clearly articulating familiar words.

[34]Sample milestones in the subdomains of adult interaction and feeling expression include infant attachment, awareness and identification of familiar people, expressing ownership or possession, and appropiately communicating positive and negative emotions.

[35]Sample milestones in the subdomain of eating include being able to drink from a cup without spilling and being able to use eating utensils without assistance.

nication skills. These skills are interrelated, with the acquisition of earlier skills providing the foundation for the development of increasingly complex and higher-level cognitive abilities. In the area of memory skills the test evaluates the child's ability to visually and auditorily attend to environmental stimuli for varying lengths of time and to retrieve information when given relevant clues.[36] In the area of reasoning the test measures the child's ability to solve problems in academic (math, reading,and writing) and social contexts.[37]

Performance in each BDIT subdomain uses three methods of examination (structured tests; interviews with parents, caregivers, or teachers; and observations of the child in natural setting) and is evaluated on a three-point objective scoring system which assigns a raw score and converts it to an age-adjusted and subdomain-specific standardized score, a T score ($\mu = 50, \sigma = 10$).[38] For the purpose of our analysis, we convert T scores to Z scores ($\mu = 0, \sigma = 1$) for ease of interpretation.

In Table 3 we present descriptive statistics for the JLS sample of children we analyze. In terms of baseline measures of child characteristics, we observe minor differences across the treatment and control groups but only the difference in mean age is statistically significant. However, as far as child development outcomes, we do find several significant differences in means across treatment and control, both pre-program and post-program. In particular, at baseline it appears the control group has significantly higher outcomes in the areas of expressive and receptive communication, adult interaction, feeling expression, and eating. However, the data from the follow-up interview suggests that the control group performs significantly lower than the treated group in the areas of fine motor skills, expressive communication, and adult interaction.

These results or the related difference-in-differences (DD) estimates, however, cannot be attributed to treatment effects. As is well known, only if the experiment was randomized

[36]Sample milestones in the subdomain of memory include identifying and recalling auditory and visual stimuli, uncovering hidden objects, or selecting the hand hiding a toy.

[37]Sample milestones in the subdomain of reasoning include naming and matching colors, searching for a removed object, reaching around a barrier to obtain a toy, putting together pieces of a puzzle, grouping and sorting similar objects, showing interest in age-appropriate book, and demonstrating basic math skills.

[38]The BDIT uses 6-month age-norm intervals for infants under 2 years of age.

would DD estimates yield the precise treatment effects (See Heckman and Robb, 1986; Heckman and Smith, 1995, for details). Since the JLS data were obtained using the quasi-experimental approach described, a simple comparison of mean differences is not informative on the causal effect of attending a public childcare center. Instead, a rigorous empirical approach which models the endogeneous selection mechanism and accounts for family and individual characteristics is necessary. We present our empirical model and econometric identification strategy in the section that follows.

4 Empirical Model and Identification Strategy

4.1 Model

We start out by constructing a model of self-selection into public childcare centers. The model has the same structure as a Roy Model (Roy, 1951). First, we introduce a standard selection model with two periods. At $t = 0$, parents decide whether or not to enroll their child i in a public childcare center, and we observe the first set of developmental outcomes. At $t = 1$, the enrollment decision remains the same and we observe the second developmental outcomes of the child. To begin, let D_i^0 denote a binary decision variable indicating whether or not the child i attends a public childcare at $t = 0$.[39] Specifically,

$$D_i^0 = \begin{cases} 1 & \text{if family sends child } i \text{ to a public childcare center} \\ 0 & \text{if family does not send child } i \text{ to \textit{any} childcare center} \end{cases}$$

We model this decision using a standard choice model. In particular, if we denote by $\mathbb{I}_i^0$ the latent index driving the decision, we write,

$$D_i^0 = \mathbb{1}[\mathbb{I}_i^0 \geq 0] \tag{4.1}$$

[39]Given the structure of our quasi-experimental study, we do not consider participation in private childcare. Thus, the child can stay at home or attend a public childcare center only.

where we assume $\mathbb{I}_i^0 = Z_i^0\gamma - V_i^0$. Z_i^0 denotes a vector of observable components, which is independent from V_i^0, the unobservable components associated with the static decision rule.

We use a model of counterfactual outcomes to study child (cognitive and noncognitive) development. Given that we consider a two-period model, we denote Y_{1i}^t (Y_{0i}^t) as a vector of outcomes associated with child i in the event of attending (not attending) the public childcare center at time t. Due to the data limitations on historical input measures and test score measures, we use a contemporaneous production function model to determine cognitive and noncognitive achievement outcomes (See Todd and Wolpin, 2003, for details). In particular, we assume,

$$
\begin{aligned}
Y_{1i}^t &= \alpha_1^t + X_i^t\beta_1^t + \epsilon_{1i}^t \qquad (4.2)\\
Y_{0i}^t &= \alpha_0^t + X_i^t\beta_0^t + \epsilon_{0i}^t \qquad (4.3)
\end{aligned}
$$

where X_i^t represents a vector of observable inputs in period t, β_1^t (β_0^t) represents the parameter associated with individuals who attend (do not attend) a public childcare center at time t, and $(\epsilon_{0i}^t, \epsilon_{1i}^t)$ represent the unobservable components which influence the developmental outcomes of child i in period t. Notice that we do not impose any assumptions on the correlations between $\epsilon_{1i}^t, \epsilon_{0i}^t$ and V_i^0. This means we allow the unobserved components from outcomes and parents' choices to be correlated. As a consequence of this, any comparison of outcomes across schooling groups would be contaminated by potential sample selection problems. Also, notice that although Z_i^0 and X_i^t can share elements, they are fundamentally different objects. Following the standard identification argument, we assume at least one variable in Z_i^0 to be excluded from X_i^t, that is, a valid exclusion restriction (See Heckman, 1978, for details). Section 5 discusses the exclusion restrictions.

The fundamental inference problem in the model described by equations (4.2) and (4.3) is that we do not observe Y_{0i}^t and Y_{1i}^t simultaneously. We only observe Y_{0i}^t if $D_i^0 = 0$ or Y_{1i}^t if

$D_i^0 = 1$. In other words, at time t the researcher observes,

$$Y_i^t = (D_i^0)Y_{1i}^t + (1 - D_i^0)Y_{0i}^t \tag{4.4}$$

which under the contemporaneous specification becomes,

$$Y_i^t = \alpha_0^t + (\alpha_1^t - \alpha_0^t)D_i^0 + X_i^t(\beta_1^t - \beta_0^t)D_i^0 + X_i^t\beta_0^t + \nu_i^t \tag{4.5}$$

where ν_i^t is the error term on the regression and equals $\epsilon_{0i}^t + (\epsilon_{1i}^t - \epsilon_{0i}^t)D_i^0$. Estimating this equation using ordinary least squares (OLS) would yield unbiased estimates if selection of D_i^0 is independent of ν_i^t conditional on X_i^t. However, given the structure of our model and the quasi-experimental nature of the data this may not be a plausible assumption and requires the correction of the potential selection bias.

4.2 Selection in Levels and Gains and the Treatment Effect

There are two sources of potential selection bias when considering equation (4.5). Both of them are due to the fact that ν_i^t is correlated with the decision of treatment variable D_i^0. The first one is the standard selection bias from the correlation between ϵ_{0i}^t and D_i^0 (i.e. selection in levels). The second one comes from the presence of D_i^0 in ν_i^t (i.e. selection based on gains).

The consequences of these two sources of bias are analyzed in Heckman and Vytlacil (2005) and Heckman et al. (2006). As we discuss below, our approach addresses these two issues of selection. In addition, our model is consistent with a heterogeneous treatment effect set-up as a main consequence of allowing for selection based on unobserved gains, which allows observationally equivalent individuals receiving the same treatment to respond in different ways.

Moreover, observe that the individual treatment effect in period t can be represented as,

$$Y_{1i}^t - Y_{0i}^t = (\alpha_1^t - \alpha_0^t) + X_i^t(\beta_1^t - \beta_0^t) + (\epsilon_{1i}^t - \epsilon_{0i}^t) \tag{4.6}$$

In this context, we can explore a variety of different treatment effects. We focus our analysis on the average treatment effect (ATE). First, as noted in Manski (2007), from the perspective of welfare economics, the relevant population for analysis of treatment response is the population that will be subjected to treatment, as opposed to a subpopulation of the treated. Thus, in the context of Chile's expansionary ECE policy, ATE is a parameter of interest as it captures the average of the individual treatment effects in the entire population. Our ATE estimates are informative of the expected outcomes a randomly chosen individual from the population at large would experience as the government expands the provision of childcare centers and an increasing fraction of the population starts to gain access to these centers.

More formally, in period t we can define the average effect of the treatment on a child drawn randomly from a population of individuals with observable characteristics X. Specifically,

$$\begin{aligned} ATE^t(X) &= E(Y_{1i}^t - Y_{0i}^t | X_i^t) \qquad (4.7) \\ &= (\alpha_1^t - \alpha_0^t) + X_i^t(\beta_1^t - \beta_0^t) \qquad (4.8) \end{aligned}$$

Additionally, since we are interested on the dynamic effects of attending the public childcare center, we define the incremental average treatment effect as,

$$\Delta ATE(X) = ATE^t(X) - ATE^{t-1}(X) \tag{4.9}$$

where $\Delta ATE(X)$ estimates the incremental average treatment effect between period t and $t-1$ controlling for the differences observed in $t-1$. The parameter is analogous to a difference-in-differences estimate. In our empirical results we present $ATE^0(X)$, $ATE^1(X)$

and $\Delta ATE(X)$ for each dimension of child development studied in this paper.

Furthermore, knowledge of $ATE^t(X)$ and the selection mechanism involved enables us to gain insight into another treatment parameter that would be of interest for future research. The treatment on the treated (TT) parameter is the effect of treatment on those attending a public childcare center. It is defined as a function of $ATE(X)$ and the sorting gain/loss (i.e. selection based on gains) as follows,

$$\begin{aligned} TT^t(X) &= E(Y_{1i}^t - Y_{0i}^t | X_i^t, D_i = 1) && (4.10) \\ &= E(Y_{1i}^t - Y_{0i}^t | X_i^t) + E(\epsilon_{1i}^t - \epsilon_{0i}^t | D_i = 1) && (4.11) \end{aligned}$$

In Section 6 we briefly discuss how this treatment parameter and its dynamic version, $\Delta TT(X)$, compares to $ATE(X)$ and $\Delta ATE(X)$.

4.3 Identification Strategy

Our main empirical strategy is based on the presence of exclusion restrictions and on the assumption of a normal selection model. Based on these premises, we first implement a control function approach for our contemporaneous outcome model (See Heckman and Robb, 1986, for details). This framework allows us to formally deal with the selection issues.

More precisely, we assume $(\epsilon_{1i}, \epsilon_{0i}, V_i) \sim N(0, \Sigma)$ and $(\epsilon_{1i}, \epsilon_{0i}, V_i) \perp (Z_i)$. Thus, conditioning the expected treatment outcomes on observable characteristics (X, Z), denoting $\Pr(D_i = 1 | X_i, Z_i)$ as $\mathbb{P}_i$ (the propensity score), and leaving out the sub-index t, from equation (4.4) we have,

$$\begin{aligned} E[Y_i | X_i, Z_i] &= (\alpha_1 + X_i\beta_1)\mathbb{P}_i + (\alpha_0 + X_i\beta_0)(1 - \mathbb{P}_i) \\ &\quad + E[\epsilon_{1i} | D_i = 1, X_i, Z_i] \times \mathbb{P}_i \\ &\quad + E[\epsilon_{0i} | D_i = 0, X_i, Z_i] \times (1 - \mathbb{P}_i) \end{aligned}$$

Under the assumption of joint normality, we can show that,

$$Y_i = \alpha_0 + X_i\beta_0 + (\alpha_1 - \alpha_0)\mathbb{P}_i + X_i(\beta_1 - \beta_0)\mathbb{P}_i + (\theta_1 - \theta_0)\cdot\phi(\Phi^{-1}(\mathbb{P}_i)) + \eta_i \tag{4.12}$$

where $E(\eta_i \mid \mathbb{P}, X_i) = 0$, $\phi(\cdot)$ represents the standard normal density function, $\Phi(\cdot)^{-1}$ is the inverse of the standard normal cumulative density function, and $\theta_j = \frac{Cov(\epsilon_{ji}, V_i)}{\sqrt{Var(V_i)}}$. Hence, under the assumption of a normal selection model, we can obtain unbiased estimates for $ATE^0(X)$, $ATE^1(X)$, and $\Delta ATE(X)$.

We compare the results from this approach with those obtained using conventional regression models, including OLS and Instrumental Variables.[40] The next section details the implementation of the different empirical approaches.

5 Empirical Implementation

We consider the following linear model for the child development outcomes observed in period t for child i,

$$Y_i^t = \gamma_0^t + \gamma_1^t D_i^0 + \gamma_2^t D_i^0 \cdot Age_i^t + \gamma_3^t D_i^0 \cdot (Age_i^t)^2 + X_i\gamma_4^t + \nu_i^t \tag{5.1}$$

where we allow ν_i^t to be correlated with D_i^0 (even conditional on Age and the vector of observable characteristics X_i^t). This specification follows from equation (4.5) with the only difference that, for simplicity, here we do not include all the interactions of the treatment indicator D_i^0 with the vector of observable characteristics X_i. [41] We only include the interaction of treatment with the child's age and child's age squared since we are particularly interested in age-specific effects.[42] The variables contained in X_i include baseline family char-

[40]Since our exclusion restrictions are determinants of the decision to attend a public childcare center but do not affect the development outcomes of the child, we use them as sources of instruments. See Section 5 for details.

[41]The results are fairly robust to the inclusion of additional interaction terms.

[42]Due to the rapid development of young children at early ages, a quadratic rather than a linear specification of age is deemed more appropriate.

acteristics such as mother's presence, education, and age; father's presence and education; and baseline child characteristics such as birthweight and gender.

While OLS accounts for the observable characteristics of the child and his family, it does not solve the more serious selection issues. In our case, these may stem from a number of sources, including unobserved heterogeneity associated with the decision to attend a JLS center and, at the same time, with child development outcomes (i.e. parenting practices, family preferences and behavior, unobserved abilities, peer effects, community characteristics, cultural factors, etc.)

A typical approach in addressing the kind of endogeneity problems just described involves Instrumental Variables (IVs). However, the interpretation of IV methods is generally problematic, particularly in the context of a heteregoneous response model (as it is our case). According to Heckman et al. (2006), in such a model, IV methods do not estimate any of the standard treatment effects and in fact they can produce misleading inference. Formally, IV estimates control only for one source of potential selection bias discussed in Section 4, they only control for selection in levels.

In contrast, the normal selection model based on the method of control functions (CF) accounts for selection in levels as well as for selection in gains.[43] Thus, in this paper we estimate equation (4.12), which in the context of our empirical model (equation (5.1)) becomes,

$$Y_i^t = \gamma_0^t + \gamma_1^t \mathbb{P} + \gamma_2^t \mathbb{P} \cdot Age_i^t + \gamma_3^t \mathbb{P} \cdot (Age_i^t)^2 + X_i \gamma_4^t + \gamma_5^t \phi(\Phi^{-1}(\mathbb{P})) + \eta_i^t \tag{5.2}$$

where γ_5^t is the coefficient associated with the term controlling for selection (i.e. $\gamma_5^t = \theta_1^t - \theta_0^t$).

[43] To better understand selection in levels and in gains, consider a simplified version of equation (4.5). In particular, consider a linear outcome model which depends only on the treatment indicator (D). That is, leaving out the subindex for t and i, let $Y = \alpha + \beta D + \epsilon_0 + (\epsilon_1 - \epsilon_0)D$. Then, OLS computes $\beta + \{E(\epsilon_0|D=1) - E(\epsilon_0|D=0)\} + \{E(\epsilon_1 - \epsilon_0|D=1)\}$, where β corresponds to the average treatment effect (ATE), the first term in curly braces represents the bias due to selection in *levels*, and the second term in curly braces represents the bias due to selection in *gains* (See Carneiro et al., 2005, for details). Now, for IV assume for simplicity a binary instrument $Z = \{z, z'\}$. Then IV computes $\beta + \frac{E(D(\epsilon_1 - \epsilon_0|Z=z) - E(D(\epsilon_1 - \epsilon_0|Z=z'))}{Pr(D=1|Z=z) - Pr(D=1|Z=z')}$, where the term in curly braces represents the bias due to selection in gains (See Imbens and Angrist, 1994, for details). Finally, CF computes only β, i.e., ATE.

The estimated coefficients on the propensity score and its interaction with age and age squared are then useful for obtaining an unbiased estimate of $ATE(X)$ in each period, i.e, $ATE^t(X) = \gamma_1^t + \gamma_2^t(\overline{Age}^{\,t}) + \gamma_3^t(\overline{Age}^{\,t})^2$, where $\overline{Age}^{\,t}$ is the average age of all children (in months) in period t.

Notice that using this specification we can also gain insight into another treatment parameter, the treatment on the treated (TT). Following equation (4.11) we can estimate,

$$TT^t(X) = ATE^t(X) + \gamma_5^t \phi(\Phi^{-1}(\mathbb{P})) \tag{5.3}$$

Ultimately, our parameter of interest is $\Delta ATE(X)$. Differencing the estimates of equation (5.2) for each period t across treatment and control groups and subsequently differencing across periods yields,

$$\begin{aligned} \Delta ATE(X) \;=\; & (\gamma_1^1 - \gamma_1^0) + (\gamma_2^1 - \gamma_2^0) \cdot \overline{Age}^{\,0} + 6\gamma_2^1 \\ & + (\gamma_3^1 - \gamma_3^0) \cdot \left(\overline{Age}^{\,0}\right)^2 + \gamma_3^1(12\overline{Age}^{\,0} + 36) \end{aligned}$$

where $\overline{Age}^{\,0}$ is the average age of all children (in months) at baseline and $\overline{Age}^{\,1} = (\overline{Age}^{\,0} + 6)$ represents the average age of children after 6 months in the program.[44] Finally, for the purpose of statistical inference, we use bootstrap techniques.[45]

5.1 Conventional Caveats and Exclusion Restrictions

The CF approach is sensitive to misspecification of the model for the decision rule and misspecification of the functional form of the control function. Nevertheless, misspecification of the decision rule affects both the IV and CF approaches in the context of a heterogeneous response model. The more central assumption is that of functional form. In our model, we impose the assumption of joint normality. Thus, identification is obtained through functional

[44] The average length of program exposure is 6.2 months.

[45] The bootstrap technique draws 200 random samples (with replacement) using 100% of the observations in the original dataset.

form (nonlinearities) rather than through exclusion restrictions. Thus, formally, we do not need exclusion restrictions. Still, it is often advisable to use an exclusion restriction to avoid potential multicollinearity and sensitivity to the functional form assumption (Winship and Mare, 1992).

In this paper we identify a pair of exclusion restrictions to enhance our identification strategy when using the CF approach. In particular, we use historical administrative records to capture the exogenous variation over time in the supply of public childcare centers. Specifically, we construct time series of municipality-level growth in the number of public childcare centers offering the *Sala Cuna Menor* program and the municipality-level growth in capacity spots at those centers. To do this, we first gather monthly information on the number of centers available and their capacity at each municipality. For each child in our data, we then construct the municipality-level change in the number of public childcare centers over a variable period of time, starting at the time of the child's month of birth (January - December 2006) and ending at the time of the child's enrollment in the public childcare center (April 2007).[46] Presumably, this is the time period in which the child's parents are considering the decision of sending their child to a public childcare center.[47]

These variables are sources of variation that are arguably uncorrelated with unobservable factors which determine both program participation and the developmental outcomes of the children in our sample.[48] First, we do not expect aggregate-level measures of childcare

[46]Since the JUNJI data were only available for the months of March through December, we proxy the number of centers in January 2006 and February 2006 with data for December 2005. The same procedure was applied to compute the growth in capacity spots.

[47]The formal enrollment process starts in September with an application for the upcoming year and ends with a final confirmation of enrollment during the last week of March (Medrano, 2009). Even though the public childcare centers are open to any child, the scarcity of vacancies forces them to use certain selection criteria. The basic criteria is having less than 11,734 points in the Social Protection Score Card, which is highly correlated with the first two income quintiles. Ideally, we would like to model this in the decision rule. Due to data limitations, however, we simplify the selection process and use socioeconomic characteristics of the child's family as proxies (i.e. parental presence, education, and occupation). Moreover, although there is no formal restriction on which centers families can apply to, there is an implicit policy to accept only application forms from the home municipality. In fact, over 90% of the children attend a public childcare center in their home municipality.

[48]Similar instruments can be found in the literature. See Berlinski et al. (2008) which uses average enrollment by cohort and locality as an instrument for treatment; Bernal et al. (2009) which instruments for program participation with the number of HCBF capacity spots at the municipality level; and Loeb

supply to be linked to individual variables. Second, we use lagged measures of childcare supply which affect the parents' decision to send their child to a public childcare center but should not be expected to affect the subsequent outcomes of the child. Finally, as previously mentioned in Section 2.1, during 2006, the growth in capacity spots was mainly driven by a renovation of the existing public childcare facilities and the growth of brand new facilities was dependent on previously-approved local funds at the municipality level. Thus, it is reasonable to assume that a systematic allocation rule was not yet in place.

As further evidence of this, in Table 4 we show the correlation of a few relevant municipality-level characteristics found in the CASEN (2006) with our instrumental variables/exclusion restrictions. For the 36 municipalities in the JLS, we find that while there is a significant correlation between preschool coverage and the percent of households in poverty at the municipality level, there is not a significant correlation between the growth in the number of public childcare centers and preschool coverage or the percent of households in poverty. We also do not find a significant correlation between the growth in capacity spots at these centers and the percent of households in poverty, though the correlation coefficient with preschool coverage is significant but small (0.15). Consequently, we view this as an indication that our instruments are exogenous from socioeconomic characteristics at the municipality level.

In Figure 3 we show the percentage distributions for these two instrumental variables at the municipality level. While the distribution for the growth in the number of public childcare centers is highly concentrated around zero, the distribution for the growth in capacity spots is more dispersed. This is consistent with the historical fact mentioned previously, indicating that the growth in spots was mainly driven by the rennovation of centers rather than by the construction of new centers. Finally, we find that neither instrument is highly correlated with child development outcomes (correlations are under 0.1).

et al. (2007) which uses information on childcare supply at the zip code level in the instrumental variables estimation. These studies are described in Section 2 or in Appendix A.

6 Empirical Results and Discussion

6.1 The Demand for Childcare

Table 5 presents the marginal effects results from the estimation of a probit model of childcare attendance on individual characteristics (including family background), the municipality-level growth in the number of public childcare centers, and the municipality-level growth in capacity spots at those centers. The results show that the instrumental variables are strongly significant both individually and jointly. The growth in the number of centers is significant at the 10% level and it has a positive coefficient which suggests that as the number of public childcare centers within a given municipality increases parents are more likely to send their child to a JLS childcare center. The growth in the number of capacity spots is highly significant at the 1% level and it has a negative coefficient. This suggests that parents are less likely to send their child to a JLS childcare center if the number of capacity spots at public childcare centers within their municipality is high, perhaps signaling to them that their child will not receive appropriate attention or is more likely to contract illness due to a large population of children at the center.

In addition, mothers who are unemployed are 22 percentage points more likely to send their child to a JLS center compared to mothers who are out of the labor force. This probability increases as the mother secures a job, either unstable (0.23) or stable (0.36). The effect of the father's occupation is also significant but highly negative. Relative to fathers who are out of the labor force, fathers who have a stable job are 96 percentage points less likely to send their child to a JLS childcare center. This probability decreases as the father has a less stable job (-0.85) or is unemployed (-0.76). In addition, a child who does not live with his/her father is 96 percentage points less likely to attend a JLS center while the comparable effect for a child who does not live with his/her mother is insignificant and essentially zero.[49] Finally, we also find that the age of the mother, particularly in the early

[49] The relative magnitudes of these effects are not surprising given the large fraction of children in the sample who have a missing father (38%) relative to the fraction of children who have a missing mother (1%).

20s, and the age of the child at the time of entry are significant predictors of attending a JLS center.[50]

Additionally, Table 5 shows the results of the Wald test which indicates that the instruments are jointly significant at the 1% level. Taken together, these results suggest that the combination of the instruments provide strong support for identification of the effects of attending a JLS childcare center on child development outcomes.

Upon estimation of the probit model, we can predict the probability of attending a public childcare center (i.e. the propensity score) and use it to construct the term that controls for selection.[51] The importance of correcting for the potential selection bias is discussed in the next section.

6.2 Testing for Selection

Table 6 presents the tests for the coefficient associated with the term controlling for selection (γ_5^t in equation 5.2) for each outcome by period. As previously mentioned, we construct the tests using bootstrap techniques. We find evidence of selection, particularly negative selection based on gains ($\gamma_5^t < 0$ for most outcomes). This indicates that the sorting mechanism works in a negative fashion, that is, children who select into treatment experience lower marginal returns compared to children who do not select into treatment, even if they are observationally identical (due to unobserved heterogeneity). Hence, according to equation (5.3), $TT^t(X) < ATE^t(X)$. Plausible explanations and implications of this result are discussed in Section 6.4.

In addition, since we assume that years of education are zero if the parent is missing, the coefficient on missing father might be capturing the unobserved effect of education as well. We estimate that the effect of missing father alone is actually positive and significant and roughly 0.13.

[50] Although it appears parental education is not a significant predictor of attending a JLS center, the estimate assumes that years of education are zero if the parent is missing. Consequently, the predictive power is limited, particularly for fathers, as a large fraction of them are missing data which we coded as zero years of education in the analysis.

[51] The Web Appendix contains the figure which shows the differences in the distribution of propensity scores between treatment and control. While the distribution of the propensity score for the control group does not exhibit a clear direction of skew, the distribution of the propensity score for the treatment group clearly has a positive skew.

In addition, we find that these coefficients are statistically significant for pre-program scores obtained in the area of reasoning and for post-program scores obtained in the areas of expressive communication and adult interaction. The coefficients are also marginally significant at the 10% level for baseline outcomes in the areas of fine motor skills and receptive communication. Given this evidence of sample selection, it is imperative to control for the biases. In the next section we show how different the results are when the researcher fails to account for sources of selection bias.

6.3 The Effects of Attending Childcare

In this section, we present static and dynamic effects estimated using four different empirical approaches: raw data, OLS, IV, and CF. Table 7 presents a summary of the estimated static effects on each child development outcome by period and type of model.[52] Columns 1 and 2 present the observed differences between treatment and control without accounting for observable characteristics or selection (raw data). The results suggest that the mean difference between the treatment and control group at $t = 0$ is negative for all outcomes. This means that, on average, those assigned to treatment exhibit worse developmental outcomes compared to those assigned to control at baseline. In particular, disparities in the areas of expressive communication, adult interaction, feeling expression, and eating are statistically significant beyond the 1% level.[53] However, in the next period ($t = 1$), developmental gaps between the treatment and control groups appear to vanish in most subdomains. We find statistically significant and positive differences between the treatment and control groups in the areas of fine motor skills and feeling expression. Still, some subdomains, such as expressive communication and adult interaction, show statistically significant and negative differences, though lower in absolute magnitude compared to those observed at baseline.

These results would suggest to the naive analyst that the treatment is somewhat effective

[52]The Web Appendix contains the estimates of mean differences which yield the reported static effects for all empirical methods.

[53]The gross motor and memory subdomains are also statistically significant at the 10% and 5% level, respectively.

at improving child development outcomes. But, as mentioned earlier, the quasi-experimental structure of this study impedes the use of evidence based on the data alone in formulating conclusions on *causal* treatment effects. This necessitates the specification and estimation of econometric models which account for family background, child characteristics, and sample selection bias.

Column 3 of Table 7 shows the effects obtained from an OLS regression which controls for child characteristics and family background.[54] As with the raw data, the OLS estimates are all negative at $t = 0$ and highly significant for the subdomains of expressive communication, adult interaction, feeling expression, and eating.[55] Column 4 shows that OLS predicts larger effects on all subdomains except those concerning motor skills (both fine and gross) and communication (both receptive and expressive). These effects are statistically significant and negative in the areas of expressive communication, reasoning, and adult interaction while statistically significant and positive only for the eating subdomain. Therefore, we find that for the most part the static effects of the program were overestatimated using the raw data. We also find that family and child characteristics that are highly significant predictors of OLS effects include mother's education (positive), mother's age (particularly in the 19-25 age range and positive), child's birthweight (positive), child's gender (generally in favor of females), and the age of the child in both periods (generally positive).[56]

Based on the OLS results, we might conclude that attending a JLS childcare center is plausibly detrimental to the development of a child. However, voluntary participation in a JLS childcare center also raises selection issues which may link the decision rule with unobservable factors that influence the developmental outcomes of a child. Hence, we incorporate an IV strategy to shed some light on this issue.

Table 7 shows the effects obtained using the IV method in Columns 5 and 6. Relative to the OLS results, this method reveals amplified effects in general. The finding that IV

[54]See Section 5 for details on the variables included as controls and the Web Appendix for second stage regressions which estimate static treatment effects for all empirical methods.

[55]The memory subdomains is once again statistically significant but at the 10% level.

[56]See Web Appendix for details.

estimation results suggest a downward bias in OLS estimates is consistent with more general findings in the economics of education literature where it has been found that IV methods estimate returns to schooling that are 20-40% above the corresponding OLS estimates, perhaps due to higher marginal returns for relatively disadvantaged groups in the population versus the average marginal returns in the population as a whole (See Card, 1999, for details). In the context of our study, this may be a plausible explanation for the larger effects under the IV estimation as JUNJI serves children who live in a situation of poverty or social vulnerability (mainly those belonging to the first two income quintiles). The IV findings further suggest that the effects are generally negative at baseline, and statistically significant and large in magnitude for outcomes in the expressive communication and eating subdomains. However, in the post-program period, we observe drastic improvements for nearly all outcomes, feeling expression in particular. Only reasoning and adult interaction show declining effects.

The interpretation of IV methods as estimating actual treatment effects, however, is not without complication. As previously discussed, IV methods do not generally estimate any of the standard treatment effects, particularly in the context of the heteregoneous response model we propose. In addition, IV methods only correct for the bias that results from selection in levels. Therefore, we incorporate the CF approach to correct for the bias that arises due to selection in levels and in gains and to recover interpretable treatment parameters, in this case the average treatment effect (ATE).

Columns 7 and 8 in Table 7 reveal the ATE results under the CF approach. At baseline, CF confirms that the ATE is negative for all outcomes and statistically significant effects exist in the subdomain of expressive communication and eating. But, unlike previous methods, the CF approach reveals that there is also a highly negative and significant effect on reasoning skills. Moreover, in period $t = 1$, there is considerable developmental progress for children attending a JLS childcare center. With the exception of adult interaction skills, which decline and exhibit a statistically significant ATE, all outcomes experience an upward shift and nearly half turn positive. However, in general, these effects are not statistically significant.

Figure 4 illustrates the estimates obtained for ATE relative to the biases associated with the OLS and IV estimates. Compared to ATE, IV estimates are severely more biased than OLS. Both biases appear to be generally positive but the IV bias can be three times as large as ATE estimates, on average, while the OLS bias may be less than twice as large, on average. In addition, recall that OLS estimates will be biased due to selection in levels and in gains, while IV estimates will be biased due only to selection in gains. Once again, this highlights the importance of correcting for both sources of selection bias discussed in the context of a model with heterogeneous treatment effects.

So far, we have examined the static effects associated with attending a JLS childcare center. From a longitudinal perspective, we are also interested in the incremental effects involved. Table 8 presents a summary of the dynamic effects estimated under the different empirical models for each subdomain of child development. Column 1 contains the results obtained using the raw data. These suggest that there are medium-sized positive gains – ranging from 0.13 to 0.69 standard deviations (SD) – on almost all development outcomes for those attending a JLS childcare center, with sizeable increases particularly in the subdomains of feeling expression and eating. Reasoning is the only outcome that experiences a negative but negligible impact (-0.04 SD).[57]

In Column 2 of Table 8 we control for family and child characteristics to assess the impact of the program on a child's development outcomes. We observe a full range of positive incremental effects, some of which are highly significant. Among the outcomes that exhibit statistically significant effects are reasoning (0.01 SD), expressive communication (0.33 SD), feeling expression (0.52 SD), and eating (0.69 SD). Thus, conditional on observable characteristics of the family and the child, these results offer an optimistic view on the dynamic effects of attending a JLS childcare center. However, due to the evidence of selection bias, it is crucial to estimate models that address the issue of sample selection.

[57] We cannot attribute significance levels to the effects estimated using the data alone that would be analogous to those computed for the remaining empirical approaches.

We first perform an IV estimation to provide some insight into dynamic effects that account for the bias resulting from selection in levels. The results are presented in Column 3. This method estimates positive effects for seven out of the nine outcomes. In particular, the effects on reasoning and adult interaction are negative and statistically significant while the effects are positive for the remaining outcomes and statistically significant in the areas of expressive communication, feeling expression, and eating. Largely, the effects are augmented under the IV method relative to OLS estimates. Generally, however, the effects identified by IV are difficult to interpret (Heckman et al., 2006). Therefore, we focus on a CF approach which is more appropriate in the context of our empirical framework and allows us to identify the incremental average treatment effect (ΔATE).

The last column of Table 8 presents the estimated ΔATE. The estimates are generally positive and large. With the exception of adult interaction skills, which seem to be negatively affected (-0.56), substantial gains are observed in the areas of gross and fine motor skills (0.67 SD and 1.05 SD) and in the areas of feeling expression (0.93 SD) and eating (0.57). The program also appears to impact positively the subdomains of receptive and expressive communication (0.26 SD and 0.31 SD) as well as the cognitive areas of memory (0.17 SD) and reasoning (0.33). But despite the wide range of positive effects, the results reveal statistically insignificant effects on most outcomes while marginally significant effects on gross motor skills and feeling expression. Thus, overall it appears that, contrary to the intuitive findings, it is not possible to reject the null hypothesis that the program had no incremental effects on the majority of child development outcomes.

Figure 5 presents a graphical analysis of the incremental effects contained in Table 8 and their associated confidence intervals.[58] The figure indicates that the incremental effects of the program on child development outcomes are consistently positive and similar in magnitude using the raw data and the OLS regression. However, once we control for the sources of

[58]We implement a bootstrap technique to derive the appropriate standard errors and compute 95% confidence intervals according to the percentile method. The boostrapped standard errors along with the corresponding confidence intervals for the incremental effects under all empirical methods previously discussed are presented in table format in the Web Appendix.

selection bias, we find that gains are not uniform in sign or magnitude across dimensions of child development. IV, for instance, predicts sizable negative impacts on reasoning and adult interaction while amplified positive impacts on the remaining outcomes. The CF approach parallels the effects of IV estimates but, unlike IV, it is informative about our parameter of interest, ATE. Compared to the previous methods, CF estimates larger positive impacts on all areas of child development, except adult interaction, which is negatively signed and larger in absolute magnitude. Overall, it is evident that accounting for selection bias is imperative, as the effects of participating in a public childcare center would otherwise be largely underestimated.

Lastly, we are interested in decomposing the significant treatment effects by age.[59] In Figure 6 we plot the age of the child at baseline (ranging between 5 and 14 months) against ΔATE (measured in standard deviations from the mean). The age-specific effects by differing lengths of program exposure ranging between 5, 6, and 7 months are represented by three separate functions. The subdomains considered are those for which we find evidence of significant effects under at least one of the empirical approaches (i.e. reasoning, expressive communication, feeling expression, and eating). The figures illustrate the effects on these subdomains behave as concave functions of age. This suggests that children on the extremes of the age range do not tend to benefit from the program relative to those in the middle age range (roughly 7-12 months). In general, we also find that the estimated age-specific ΔATE depend highly on the length of treatment exposure. These effects tend to be amplified as exposure to treatment increases. Overall, these graphs suggest that the bulk of the positive effects are concentrated among younger children (7-12 months old) who receive the longest exposure to treatment (7 months).

[59] While here we will only illustrate the age-specific ΔATE results for the subdomains with significant effects, the Web Appendix contains illustrations of all the ΔATE and ATE results by age as well.

6.4 Discussion of the Results

The previous section documented a negative average treatment effect of attending a public childcare center on most child development outcomes assessed at two points in time. Particularly upon entering the public childcare center ($t = 0$), the treated group exhibits serious developmental delays compared to their peers who remain at home. However, the negative effects diminish in the following period ($t = 1$). A plausible explanation for these findings can be found in the field of psychology. Bowlby (1982) discusses the theory of infant attachment suggesting that a young child who experiences temporary detachment from his mother for the first time will exhibit a predictable sequence of behaviors. During the initial phase, the child will show extreme distress at having "lost" his mother and will reject alternative caregivers. In the next phase, the child is still preoccupied with his missing mother but his behavior suggests increasing hopelessness of expecting her return. He will become withdrawn, inactive, and quiet, indicating, erroneously, a diminution of distress. In the last phase, the child begins to show some signs of recovery and shows more interest in his surroundings but mainly he remains self-centered and, instead of directing his attention towards people, he will become preoccupied with material things such as toys and food. Thus, in the end, the child may successfully adapt to the new environment at the childcare center but he will show deficient sociability unless care is taken to foster these skills.[60]

Hence, it is not surprising to find that there is a positive incremental average treatment effects of attending a public childcare center on most areas of child development over time. The only outcome that appears to be affected negatively is adult interaction. This could relate to the child's deficiency in social behavior as well as to the quantity and quality of educators available at the public childcare center. Given the major increase in enrollment at public childcare centers, children may not have received proper levels of care and stimulation needed to effectively interact with their educators on an individual basis. CEDEP (2007)

[60]The intensity of these reactions can be reduced by the presence of a sibling and the care of a single mother-substitute, especially one the child has met before in the presence of his mother. These reactions also depend on the length of a child's separation from his mother and the quality of the new environment.

does cite that the number of children per staff (educators and helpers) is high and that this is an area that needs improvement. JUNJI does not report an exact child-to-staff ratio but in a report submitted to the Chilean Budget Office (DIPRES) it is estimated to be around 11:1 in 2006 which falls short of the norms set by the Chilean Ministry of Education – a 6:1 ratio in *Sala Cuna* programs (DIPRES, 2008).[61] Thus, we expect the quantity and quality of teaching staff available at public childcare centers to be a major determinant of child development outcomes.

To further delve into the effects of a public childcare center, we briefly explore another treatment parameter, the effect of public childcare centers on the subsample being treated (i.e. $TT(X)$), but we leave the details of estimation and testing of this parameter as focus for future research. Given that we have information on the sorting mechanism, we can estimate $\Delta TT(X)$ using equation (5.3) and compare it to $\Delta ATE(X)$.[62] In general, we find that $\Delta TT(X)$ reinforces $\Delta ATE(X)$ in most dimensions. In particular, we find that the positive effects observed in the areas of motor skills (fine and gross), cognitive skills (memory and reasoning), receptive communication, and feeling expression, are even larger for the subsample being treated, on average, compared to the sample drawn at random from the population at large.

However, we find that $\Delta TT(X)$ is lower relative to $\Delta ATE(X)$ for the subdomains of adult interaction, expressive communication, and eating.[63] One possible explanation that may account for this is the presence of peer effects in the public childcare center. Given that we found presence of a negative sorting mechanism, we could expect that peer effects exacerbate low-quality environments for the subsample that is treated leading to setbacks in

[61]The report further cites that only 59% of these programs meet the requirement.

[62]For a table with $\Delta TT(X)$ by outcome please see the Web Appendix.

[63]At first, it may appear contradictory that $\Delta TT(X) > \Delta ATE(X)$ for feeling expression while $\Delta TT(X) < \Delta ATE(X)$ for expressive communication. Although these areas of child development overlap, the opposing effects may be explained by Bowlby's attachment theory. As previously mentioned, the child may become withdrawn, inactive, and quiet, indicating, erroneously, a diminution of distress. Expressive communication thus appears to deteriorate but feeling expression, which is evaluated based on the apparent feelings of the child, may show, imprecisely, a positive effect.

social behavior skills, precisely the type of outcomes that experience negative effects.[64]

Overall, we find consistent patterns on the effects of public childcare centers, despite a lack of statistical insignificant results indicated by $\Delta ATE(X)$. We conclude that effects are uniformly positive for subdomains of child development associated with motor skills and cognitive skills but negative on a child's ability to interact with adults. One possible explanation for the positive effects we find may be that center-based care offer some distinct advantages over informal care at home: (1) trained care providers and learning environments that may foster more cognitive simulation among children, and (2) a higher degree of peer interactions as well physical and educational activities that may enhance the cognitive and noncognitive skills of children attending a childcare center (Bernal and Keane, 2007). Nonetheless, negative social behaviors may potentially undermine the benefits of center-based care, particularly among very young children, as our evidence suggests and as cited by Loeb et al. (2007).[65]

Lastly, our findings compare favorably with those in the literature of developing countries. Behrman et al. (2004), for example, find that the PIDI program in Bolivia significantly increases cognitive achievement and psychosocial test scores, especially for children who participate in the program for at least 7 months. To measure cognitive development, the authors use bulk motor skills, fine motor skills, language and auditory skills. The positive effects on gross and fine motor skills are comparable to our results.[66] However, our findings associated with negative effects on adult interaction and possibly negative peer effects are at odds with their finding of a positive effect on psychosocial skills. This may be due to the differing test measures and structures of the programs. In particular, PIDI offers home-based care by local women and allocates approximately one staff member per five children. This is in sharp contrast with the approximate child-to-staff ratio of 11:1 in JLS centers, and points

[64]There is no reason to believe that peer effects are particularly harmful when the population of interest is beyond the sample being treated. That is, we do not expect peer effects to explain $\Delta ATE(X)$.

[65]See Appendix A for details on the studies by Bernal and Keane (2007) and Loeb et al. (2007).

[66]Behrman et al. (2004) finds 0.8 - 0.9 average marginal impacts for children 6-24 months with 13-18 months of program exposure.

to the importance of increasing the number of educators to improve psychosocial skills as well as the overall development of children attending public childcare centers.

Moreover, our findings suggest that the magnitude of the program impacts are highly dependent on the age of the children and the length of exposure to the program. We find that the group that benefits the most from attending a public childcare center is the one which receives the longest exposure to treatment (7 months) and falls in the age range of 7 to 12 months. Similar findings have been suggested in a review of ECD programs in developing countries (Engle et al., 2007). Evidence from two of these studies (in Bolivia and the Philippines) finds important effects of child's age at the time of program initiation (with the largest effects for initiation in the second year of life) and the duration of program exposure (with relatively large effects for exposure of at least 12 to 24 months, but diminishing marginal effects thereafter) (See Behrman et al., 2004; Armecin et al., 2006, for details).

Although, the structure of this study is not entirely comparable to that of Behrman et al. (2004), it does provide some clues as to why the CF approach, which is similar to the matching methodology in the sense that it establishes the central role of the propensity score in correcting for potential selection bias, yields statistically insignificant incremental effects in the context of childcare programs that serve low-income populations in Latin America. In particular, their results on the marginal impacts of the PIDI program reveal that for children younger than 2 years of age there are no significant effects if the duration of treatment is less than 12 months.[67]

Similarly, Bernal et al. (2009) find that the effects on the cognitive and psychosocial development of children aged 36-48 months with 5-15 months of program exposure at the time of evaluation are generally positive but not significant. However, independent of age, there are generally short-term positive and significant effects on children who have at least 16 months of program participation. Finally, Bernal and Keane (2007) also report that formal childcare (center-based) during the first two years of life has no detrimental effect on child

[67] They also find negative effects on gross motor skills and positive effects on fine motor skills, language and auditory skills, and psychosocial skills among children younger than 2 years of age.

cognitive outcomes, while informal childcare use after the age of 2 does produce significant and negative effects on child cognitive development.[68]

7 Conclusion

This paper presents a rigorous empirical analysis of a unique quasi-experimental longitudinal study initiated in Chile in 2007 to uncover the effects of participation in public childcare centers on a range of cognitive and noncognitive child development outcomes. We derive the average causal impacts of the intervention using various empirical approaches while allowing for heterogeneous treatment effects. A pair of exclusion restrictions measuring the contemporaneous and exogenous growth in the supply of public childcare centers enhance our identification strategy and account for endogeneous selection into childcare centers.

Although we find the effect of attending a public childcare centers is initially negative, our analysis suggests that the average effect over time is positive for nearly all areas of child development. We suspect that this is an indication that participation in public childcare center over time improves the development of young children or, at the very least, it does not have detrimental impacts compared to informal care at home.[69] We also find statistically significant effects estimated by OLS and IV, although the effects estimated by CF methods exhibit more limited statistical significance.

Implementing CF methods that correct for the selection bias, however, is an imperative as we document the presence of selection both in levels and in gains. Failure to account for selection bias would lead to largely underestimated effects, relative to conventional regression models such as OLS and IV. Hence, our findings support the logic behind our model, which is that selection based on levels and gains plays a major role in determining the effects of

[68]This seems to be consistent with the idea that child-mother interactions are more valuable when the child is ready to engage in more challenging tasks like language learning, and less so during initial stages when the child requires more basic care (Bernal and Keane, 2007).

[69]It may be that the initial evaluation conditions were not optimal and children did not show accurate levels of development. In this case, the positive effects may be interpreted as a return to "normal" conditions rather than actual improvements. We thank Marta Edwards for pointing this out.

public childcare centers on the developmental outcomes of participants. More specifically, our evidence points the presence of negative selection based on unobservable gains. Given that without controlling for sources of selection the impacts would be underestimated, this suggests that some of the negative selection on unobservables is offsetting the positive selection on observables. This is an interesting result as the general impression is that enrollments are positively selected on parental schooling and income (Checchi, 2006). But, unobservable factors appear to dominate the selection process in our case.

Furthermore, we consider the interpretation of our results useful as we find consistent positive effects on incremental treatment parameters, despite the size of our sample which limits the power of statistical tests. Inference based on the dynamic effects of treatment across various empirical methods coupled with a brief exploration of the dynamic effects associated solely with the subsample of children being treated, reveals that gains are most evident in the areas of motor skills and cognitive skills. Negative effects, however, are found in the area of adult interaction and we deduce this may be related to the low quality of individual care provided by a limited number of teachers and caregivers at public childcare centers. Significant increases in the quantity and quality of public childcare center educators will need to be made in order to counteract this detrimental effect.[70]

Our findings also suggest that the significance and magnitude of the program impacts is highly dependent on the age of the children and the length of exposure to the program. This is consistent with general findings in the literature as well. We find that treatment gains are particularly high for the middle age group of children (ages 7-12 months at the time of entry into the program) who participate in the public childcare center for a longer period of time (7 months). A possible explanation for this could be related to a curricular structure that aims to maximize the benefits of the program for the middle age group and therefore lacks an age-appropriate curriculum for the much younger and older children. Further research on the effectiveness of the curricular bases and educators' training and teaching in these public

[70] A report submitted to the Chilean Budget Office cites a shortage of 2,500 educators which is equivalent to 38% of the total number of educators in 2006 (DIPRES, 2008).

childcare centers would prove useful in testing this hypothesis and in informing ECE policy in Chile in the future.

Overall, the policy implications of our results point to the challenge of expanding ECE coverage, particularly for the younger and economically disadvantaged children in the population, while continually improving and rigorously evaluating the quality of services provided, considering the higher level of expenditure associated with creating an age-appropriate curriculum and providing an adequate number of trained teaching staff.

Undoubtedly, this body of research is still in a premature stage. Nonetheless, it aims to contribute to the ultimate goal of understanding the causal pathways and the ideal set of cost-effective inputs that will improve outcomes in ECD programs. A combination of economic theory, experimentation, data collection, and rigorous evaluation will be needed to guide policymakers and researchers in finding and implementing the most effective kinds of interventions that will allow young children to fulfill their developmental potential and escape the intergenerational poverty trap that continues to hinder the quality of human capital and economic development of all nations.

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8 Appendix A: Review of the U.S. Literature

In the U.S., economic evaluations of the Perry Preschool Program, Head Start, and the Chicago Child-Parent Center Program have been informative about the effects of public ECE programs. The Perry Preschool Program was a two-year experimental intervention started in the 1960s in the Ypsilanti public school system in Michigan which involved morning programs at school and afternoon visits by the teacher to the home of 123 disadvantaged African-American children initially ages 3 to 4. Head Start is a program that began in 1965 as part of President Johnson's War on Poverty and currently provides comprehensive education, health, nutrition, and parent involvement services to more than 800,000 low-income children (0-5 years old) and their families. The Chicago Child-Parent Center Program was established in 1967 through funding from Title I of the Elementary and Secondary Education Act of 1965 and now provides comprehensive educational and family support services to 5,600 economically disadvantaged children from preschool (ages 3+) to early elementary school (grade 3) in 24 centers throughout the Chicago Public School system.

Heckman et al. (2008) conclude that the Perry Preschool Program operates primarily through improving noncognitive traits which increased achievement test scores of participants despite the fading of gains in IQ. And even though IQs were not higher, the Perry treatment group performed better on achievement tests at age 14 compared to the control group. In addition, followups of the participants into age 40 reveal positive effects for a wide range of cognitive and noncognitive behaviors including: higher rates of high school graduation, higher salaries, higher percentages of home ownership, lower rates of receipt of welfare assistance as adults, fewer out-of-wedlock births, and fewer arrests than the control group (Schweinhart et al., 2005). Crime reduction, in particular, is a major long-term benefit of the program which accounts for more than a third and up to two-thirds of the benefit-cost ratios estimated in the study by Heckman et al. (2010).[71] Moreover, the overall rates of social return range from 7 to 10 percent per annum (above the historical yield on equity) and are statistically significant different from zero in most cases.

In contrast to the previous example, Head Start and the Chicago Child-Parent Center Program are two non-experimental large-scale public ECE interventions in the U.S. that are also worth considering, particularly in the context of our study. Currie and Thomas (1995) and Garces et al. (2002) find that Head Start programs produce substantial and significant gains in test scores for children of all racial and ethnic backgrounds.[72] These effects persist into adolescence for white children (including hispanics) but are wiped out by age ten for African-Americans. In addition, whites who attended Head Start are significantly more likely to complete high school, attend college, and possibly have higher earnings in their

[71] The study estimates benefit-cost ratios under typical discount rates (3-5%) and also takes into account the corruption of the randomization protocol which resulted from a reassignment of treatment and control status after random assignment.

[72] Currie and Thomas (1995) use nonexperimental data drawn from the National Longitudinal Survey's Child-Mother files to evaluate the short-term effects of Head Start. They attempt to control for unobserved characteristics of children by comparing siblings who participated in Head Start with those who did not. Garces et al. (2002) use data from the Panel Study of Income Dynamics to provide evidence on the longer-term effects of Head Start. Their methodology follows Currie and Thomas (1995) and the authors claim that this method is likely to provide lower-bound estimates on the positive effects of Head Start.

early twenties, relative to their siblings who did not attend the program. African-Americans who participated in Head Start are less likely to have been booked or charged with a crime and males are more likely to have completed high school. Lastly, Currie (2001) provides a simple cost-benefit analysis of Head Start and suggests that the program would pay for itself in terms of cost-savings to the government if it produced even a quarter of the estimated long-term gains in educational attainment and reduction in crime.

After Head Start, the Chicago Child-Parent Center (CPC) program is the second oldest federally-funded preschool program in America. Reynolds et al. (2007) use data from the Chicago Longitudinal Study of the CPC program to investigate the lifecourse development of 1,539 children, 989 of whom participated in the program between 1983-1985 and 550 of whom enrolled in full-day kindergarten programs in five randomly selected schools outside of the CPC. Employing a quasi-experimental approach which compared a matched group of students at age 24, the study concludes that, relative to participation in full-day kindergarten intervention, participation in CPC was associated with a higher rate of school completion and 4-year college attendance; lower rates of felony arrests, conviction, incarceration, and depressive symptoms; higher rates of full-time employment, health insurance, and lower rates of disability. Overall, participation in CPC for 1 or 2 years was associated with nearly all child outcomes up to age 20, among them, greater cognitive skills at kindergarten entry, higher school achievement leading to reductions in need for school remedial services, lower rates of delinquency and higher rates of school completion.[73]

Nevertheless, some recent studies in the U.S. have shown that not all impacts of ECD programs are uniformly positive. In particular, Bernal and Keane (2010) find that one year of full-time work and daycare use reduces child cognitive ability test score at ages 4-6 by roughly 0.14 standard deviations. This result is robust to econometric approaches that rely on somewhat different identifying assumptions.[74] Further, they find evidence of substantial observed and unobserved heterogeneity in daycare effects, where negative effects are larger for better educated mothers and children with higher skill endowments. Bernal and Keane (2007), on the other hand, find that only informal care (i.e. non-center based care by grandparents, siblings, other relatives and non-relatives) leads to significant reductions in cognitive outcomes for children who are at least 2 years old. Formal care (i.e. center-based care), however, does not produce adverse effects on child cognitive development.[75]

[73] The intervention group was matched on age of kindergarten entry, eligibility for and participation in government-funded programs, and neighborhood and family poverty. At age 20 years, 83.2% of the original sample had data on educational attainment with no evidence of selective attrition. The intervention effects were estimated via probit and negative binomial regressions. The authors report that corrections for non-random attrition and clustering did not affect estimates, nor did alternative analyses using propensity score and latent variable selection models.

[74] The study uses the 1996 welfare reform as an instrument to measure childcare time and a sample of single mothers in the National Longitudinal Survey of Youth (NLSY 1979) to examine the effects of maternal vs. alternative care provider time inputs, and household income, on child cognitive ability test scores recorded at ages 4-6. The study undertakes a quasi-structural approach which implements a dynamic selection correction by approximating decisions rules for employment and childcare use and estimating these jointly with the child's cognitive ability production function. It also implements a single equation instrumental variable approach which leaves implicit the exact form of the decision rules for work and childcare.

[75] They claim that this is supported in the literature which finds two main advantages of center-based care over informal care: (1) trained care providers that may foster more cognitive simulation among children, and (2) a higher degree of peer interactions and educational activities.

Alternatively, Loeb et al. (2007) use data from the Early Childhood Longitudinal Study (ECLS-K) and reports that while exposure to a center-based childcare program prior to starting kindergarten is associated with a 0.1 SD difference in reading and math skills, on average, it is also associated with approximately the same size negative effect on a teacher-reported behavioral measure that captures approaches to learning, self-control and a variety of other interpersonal skills.[76] Overall, the study concludes that for both low- and high-income children, starting a center program before the age of two is not particularly beneficial for cognitive development and appears to be detrimental for social development.

[76]The ECLS-K contrasts different types of early education and care in the year before kindergarten in nationally representative surveys, notably center-based day care including pre-kindergarten programs, preschools, nursery schools, Head Start, and other non-parental center-based care. Loeb et al. (2007) implement a kernel matching approach as well as instrumental variables estimation based on measures of childcare supply at the zip code level.

9 Appendix B: Tables and Figures

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Table 1: Distribution of JLS Childcare Centers and Treatment Group, by Municipality

		JLS Childcare Centers	Sample Attending JLS Childcare Center	
No.	**Municipality**	**No.**	**No.**	**% Treated**
		(1)	(2)	(3)
1	Antofagasta	3	22	27
2	Arica	2	15	38
3	Cerrillos	1	8	39
4	Cerro Navia	1	10	17
5	Copiapo	1	5	38
6	Coquimbo	1	7	46
7	Coihaique	1	10	23
8	Curico	1	9	31
9	El Bosque	1	12	20
10	Estacion Central	1	7	30
11	Hualpen	1	7	36
12	Huechuraba	1	11	35
13	Iquique	1	10	29
14	La Granja	1	5	44
15	La Pintana	1	7	36
16	Linares	1	14	22
17	Llaillay	1	4	50
18	Lo Barnechea	1	8	43
19	Lo Prado	1	11	27
20	Nunoa	1	9	36
21	Osorno	1	13	13
22	Ovalle	1	7	30
23	Penalolen	1	10	17
24	Pudahuel	1	10	38
25	Punta Arenas	2	12	37
26	Quilicura	1	10	38
27	Rancagua	1	7	50
28	Recoleta	1	6	25
29	Renca	1	2	67
30	San Joaquin	1	9	31
31	Talca	1	7	22
32	Temuco	2	15	12
33	Valdivia	1	12	20
34	Vallenar	1	4	33
35	Valparaiso	1	9	31
36	Vina del Mar	1	7	36
	Chile	41	331	31

Source: JLS sample data.

Table 2: Family Characteristics in the JLS Dataset, by Treatment Status

Variable	Control Group Mean	Control Group SD	Treatment Group Mean	Treatment Group SD	Mean Difference
	(1)	(2)	(3)	(4)	(5)
Mother's Presence	0.99	0.08	0.99	0.08	0.00
Mother's Education	10.92	2.54	10.98	2.77	-0.06
Mother's Age					
18 years or less	0.12	0.33	0.08	0.27	0.04
19-25 years	0.46	0.50	0.34	0.47	0.12*
26-35 years	0.32	0.47	0.40	0.49	-0.07
36 years or more	0.10	0.30	0.18	0.39	-0.08*
Mother's Job					
Out of the labor force	0.65	0.48	0.23	0.42	0.42*
Unemployed	0.07	0.25	0.10	0.30	-0.04
Unstable job	0.12	0.33	0.17	0.38	-0.05
Stable job	0.16	0.37	0.49	0.50	-0.33*
Father's Presence	0.72	0.45	0.57	0.50	0.14*
Father's Education	10.99	3.07	11.07	2.49	-0.08
Father's Job					
Out of the labor force	0.00	0.00	0.01	0.10	-0.01
Unemployed	0.02	0.14	0.05	0.22	-0.03
Unstable job	0.18	0.38	0.13	0.33	0.05
Stable job	0.81	0.40	0.81	0.39	0.00
Number of Observations	151		331		

Notes: Parent's presence is equal to 1 if the parent is present. Parent's education is highest attained and in years. Parent's education and job were tabulated only if the parent was present. Column 5 computes the difference in means and * denotes rejection of the equality of means with greater than 95-percent confidence.
Source: JLS sample data.

Table 3: Child Characteristics in the JLS Dataset, by Treatment Status

	Control Group		**Treatment Group**		**Mean**
	Mean	**SD**	**Mean**	**SD**	**Difference**
	(1)	(2)	(3)	(4)	(5)
Baseline measures					
Age	9.30	2.65	10.17	2.59	-0.87*
Male	0.54	0.50	0.56	0.50	-0.01
Female	0.46	0.50	0.44	0.50	0.01
Birthweight	3,396	634	3,382	520	13.10
Pre-Program measures					
Gross Motor	39.92	11.23	38.14	10.50	1.78
Fine Motor	41.22	9.88	40.40	9.29	0.81
Receptive Communication	38.70	10.06	38.35	10.60	0.35
Expressive Communication	45.01	10.78	35.51	10.56	9.51*
Memory	42.13	9.83	40.05	9.67	2.07*
Reasoning	42.71	11.40	42.20	11.39	0.51
Adult Interaction	44.20	11.37	39.27	10.94	4.93*
Feeling Expression	45.58	10.44	41.23	12.04	4.34*
Eating	45.45	12.61	37.46	11.12	7.99*
Post-Program measures					
Gross Motor	44.44	11.21	46.13	11.68	-1.69
Fine Motor	50.30	13.83	53.85	14.10	-3.55*
Receptive Communication	40.71	10.02	41.03	9.85	-0.32
Expressive Communication	42.17	10.37	36.93	9.36	5.24*
Memory	38.78	11.27	37.83	11.58	0.95
Reasoning	42.94	9.44	42.08	9.64	0.86
Adult Interaction	48.12	11.31	45.44	13.49	2.68*
Feeling Expression	45.04	11.03	46.94	11.70	-1.90
Eating	43.93	10.50	44.33	11.80	-0.41
Number of Observations	151		331		

Notes: Child's age is measured in months. Birthweight is measured in grams. Pre-program and post-program measures are T scores ($\mu = 50, \sigma = 10$) obtained in the Battelle Developmental Inventory test in April and November 2007, respectively. Column 5 computes the difference in means and * denotes rejection of the equality of means with greater than 95-percent confidence.
Source: JLS sample data.

Table 4: Correlations of Municipality-level Characteristics with Measures of Growth in the Supply of Public Childcare Centers, 2006

	Preschool coverage	HH in poverty	Δ Number of centers	Δ Capacity spots
	(1)	(2)	(3)	(4)
Preschool coverage	1.00			
HH in poverty	-0.25*	1.00		
Δ Number of centers	0.03	0.05	1.00	
Δ Capacity spots	0.15*	-0.01	0.87*	1.00

Notes: All variables are computed for the 36 municipalities in the JLS. Column 1 corresponds to the preschool coverage at the municipality level computed in the CASEN 2006 as the ratio of gross enrollment in preschool to the number of children under 6 years of age in the population who are not enrolled in preschool plus the number of children over 6 years of age who are enrolled in preschool. Column 2 corresponds to the percent of households in poverty at the municipality level which is based on the poverty line computed in the CASEN 2006. Column 3 corresponds to the growth in the number of public childcare centers which is defined as the municipality-level change in the number of public childcare centers serving children in the sala cuna menor over a variable period of time, starting at the time of the child's birth and ending at the time of the child's enrollment in the childcare center. Column 4 corresponds to the growth in the number of capacity spots at the same public childcare centers.
* $p < 0.05$
Source: CASEN (2006), Estadísticas Perfil Comunal. JUNJI Public Childcare Center Data 2001-2007.

Table 5: Propensity Score Estimation for Attending a JLS Center, Probit Marginal Effects

Variables	**Attends JLS Center at $t = 0$**
Δ Number of centers	0.0695*
	(0.0399)
Δ Capacity spots	-0.00509***
	(0.00183)
Child's Age at $t = 0$ (months)	0.0252***
	(0.00870)
Child's Birthweight (grams)	0.0000181
	(0.0000368)
Mother's Age: < 18	-0.156
	(0.118)
Mother's Age: 19-25	-0.188***
	(0.0726)
Mother's Age: 26-35	-0.0749
	(0.0745)
Father Missing	-0.960***
	(0.0278)
Father's Education (years)	0.00137
	(0.0120)
Mother Missing	-0.00960
	(0.266)
Mother's Education (years)	-0.00440
	(0.00798)
Mother's Job: Unemployed	0.224***
	(0.0417)
Mother's Job: Unstable job	0.232***
	(0.0357)
Mother's Job: Stable Job	0.363***
	(0.0402)
Father's Job: Unemployed	-0.759***
	(0.0204)
Father's Job: Unstable job	-0.849***
	(0.0200)
Father's Job: Stable Job	-0.963***
	(0.0295)
Observations	469
Pseudo R^2	0.191
Wald χ^2_2	8.15***

Notes: Omitted category for parent's job is out of the labor force/missing. Omitted category for mother's age is older than 36 years. The growth in the number of public childcare centers is defined as the municipality-level change in the number of public childcare centers serving children in the sala cuna menor over a variable period of time, starting at the time of the child's birth and ending at the time of the child's enrollment in the childcare center. An analogous definition applies to the number of capacity spots at the same public childcare centers. Robust standard errors clustered by municipality in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' analysis based on the JLS sample data and

Table 6: Testing for Selection, by Period

	γ_5^0	γ_5^1
	(1)	(2)
Gross Motor	-0.82	-0.47
	(0.39)	(0.56)
Fine Motor	-1.20	0.30
	(0.15)	(0.73)
Receptive Communication	-1.44	-0.83
	(0.12)	(0.30)
Expressive Communication	-0.60	-1.74**
	(0.55)	(0.04)
Memory	-1.08	-0.88
	(0.25)	(0.35)
Reasoning	-1.57*	-0.09
	(0.06)	(0.91)
Adult Interaction	-0.54	-1.47*
	(0.55)	(0.09)
Feeling Expression	-0.72	-0.26
	(0.44)	(0.78)
Eating	-0.29	-0.81
	(0.71)	(0.30)

Notes: Columns 1 and 2 show the coefficient on the term controlling for selection (γ_5^t from equation (5.2)) at $t = 0$ and $t = 1$, respectively. Effects are measured in Z scores ($\mu = 0, \sigma = 1$).
P values based on Wald tests (χ_1^2) are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Authors' analysis based on the JLS sample data.

Table 7: Summary of Static Treatment Effects on Child Development Outcomes, by Model Type and Period

Outcome	$DATA^0$	$DATA^1$	OLS^0	OLS^1	IV^0	IV^1	ATE^0_{CF}	ATE^1_{CF}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross Motor	-0.17*	0.15	-0.16	0.10	-0.12	0.44	-0.33	0.34
	(0.09)	(0.14)	(0.32)	(0.41)	(0.26)	(0.22)	(0.14)	(0.84)
Fine Motor	-0.09	0.25***	-0.13	0.10	-0.20	0.28	-0.66	0.39
	(0.38)	(0.01)	(0.15)	(0.35)	(0.64)	(0.68)	(0.32)	(0.64)
Receptive Communication	-0.03	0.03	-0.06	-0.01	-0.07	-0.05	-0.59	-0.33
	(0.73)	(0.74)	(0.10)	(0.89)	(0.84)	(0.77)	(0.30)	(0.62)
Expressive Communication	-0.83***	-0.53***	-0.79***	-0.46***	-0.63***	0.06	-0.82***	-0.51
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.60)	(0.01)	(0.39)
Memory	-0.21**	-0.08	-0.14*	-0.01	0.27	0.37	-0.15	0.02
	(0.03)	(0.40)	(0.09)	(0.80)	(0.62)	(0.29)	(0.46)	(0.58)
Reasoning	-0.05	-0.09	-0.11	-0.1**	-0.03	-0.21*	-0.58*	-0.25
	(0.66)	(0.36)	(0.17)	(0.02)	(0.13)	(0.09)	(0.10)	(0.28)
Adult Interaction	-0.44***	-0.21**	-0.45***	-0.3*	-0.01	-0.26	-0.20	-0.76*
	(0.00)	(0.03)	(0.00)	(0.06)	(0.99)	(0.31)	(0.97)	(0.07)
Feeling Expression	-0.37***	0.16*	-0.34***	0.18	0.13	0.92***	-0.08	0.85
	(0.00)	(0.09)	(0.00)	(0.18)	(0.27)	(0.00)	(0.31)	(0.13)
Eating	-0.66***	0.04	-0.62***	0.07***	-0.62*	0.15	-0.68*	-0.11
	(0.00)	(0.72)	(0.00)	(0.01)	(0.10)	(0.27)	(0.10)	(0.29)

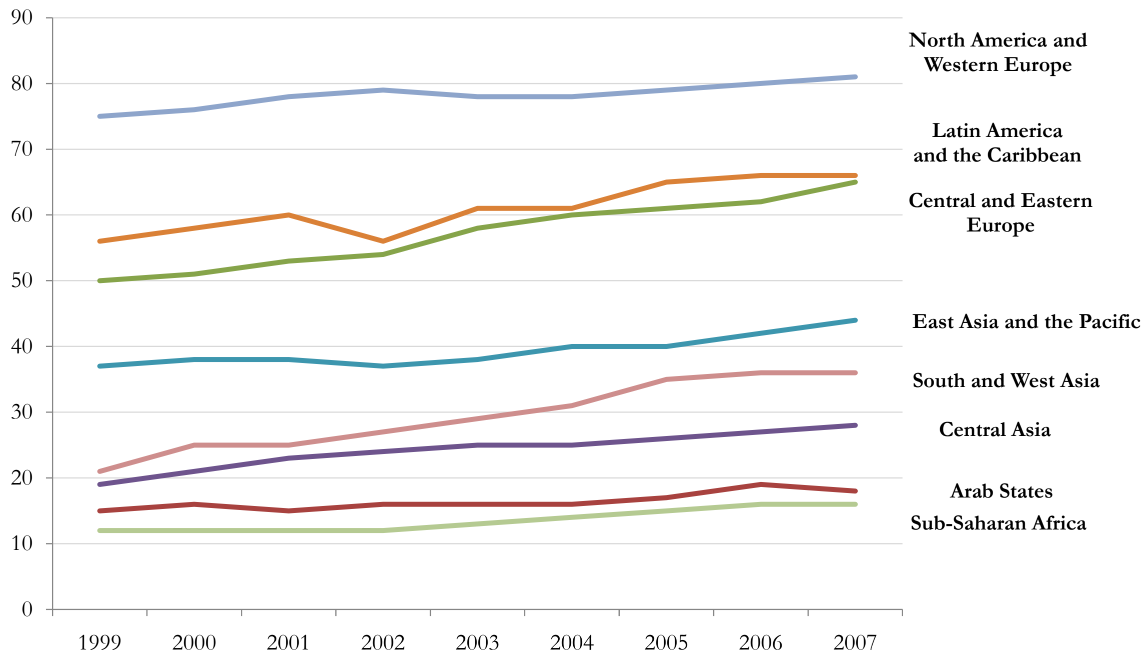
Notes: Odd (even) numbered columns show the mean difference between treatment and control groups at $t = 0$ ($t = 1$) for each type of model. Formally, $DATA^t = E(Y^t|D = 1) - E(Y^t|D = 0)$; $OLS^t = E(Y^t|D = 1, X) - E(Y^t|D = 0, X)$; $IV^t = \frac{E(Y^t|Z=z)-E(Y^t|Z=z')}{\Pr(D=1|Z=z)-\Pr(D=1|Z=z')}$ (See Imbens and Angrist, 1994, for details); and $ATE^t_{CF} = E(Y^t_1 - Y^t_0|X)$. Effects are measured in Z scores ($\mu = 0, \sigma = 1$).
P values based on test of equality of means are in parentheses for Columns 1 and 2. P values based on Wald tests (χ^2_3) are in parentheses for Columns 3-8.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Authors' analysis based on the JLS sample data.

Table 8: Summary of Dynamic Treatment Effects on Child Development Outcomes, by Model Type

Outcome	$\Delta DATA$	ΔOLS	ΔIV	ΔATE_{CF}
	(1)	(2)	(3)	(4)
Gross Motor	0.31	0.25	0.56	0.67
	-	(0.16)	(0.20)	(0.13)
Fine Motor	0.34	0.23	0.47	1.05
	-	(0.11)	(0.60)	(0.43)
Receptive Communication	0.07	0.05	0.02	0.26
	-	(0.26)	(0.86)	(0.76)
Expressive Communication	0.30	0.33**	0.69*	0.31
	-	(0.02)	(0.07)	(0.60)
Memory	0.13	0.13	0.10	0.17
	-	(0.52)	(0.79)	(0.69)
Reasoning	-0.04	0.01**	-0.18**	0.33
	-	(0.05)	(0.04)	(0.19)
Adult Interaction	0.23	0.15	-0.25	-0.56
	-	(0.60)	(0.70)	(0.82)
Feeling Expression	0.54	0.52***	0.79*	0.93
	-	(0.00)	(0.06)	(0.13)
Eating	0.69	0.69***	0.76*	0.57
	-	(0.00)	(0.08)	(0.60)

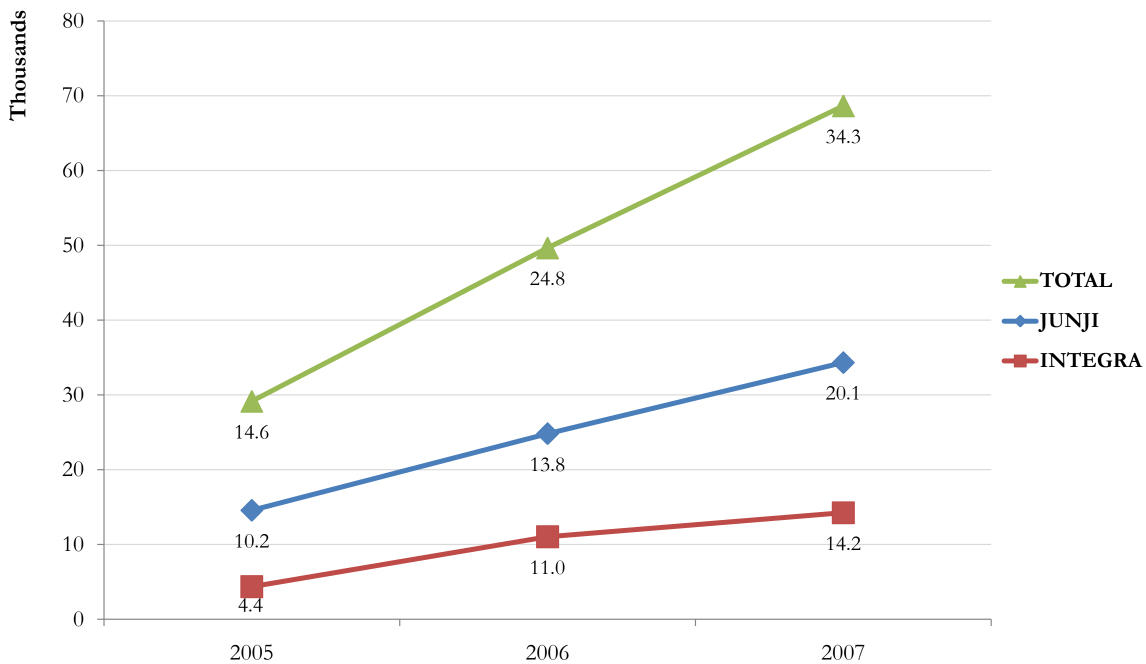
Notes: Columns 1 - 4 show the mean difference-in-differences estimates for each type of model. Effects are measured in Z scores ($\mu = 0, \sigma = 1$).
P values based on Wald tests (χ^2_5) are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Authors' analysis based on the JLS sample data.

Figure 1: Global Trends in Preprimary Gross Enrollment Rates, 1999-2007



Source: UNESCO (2010).

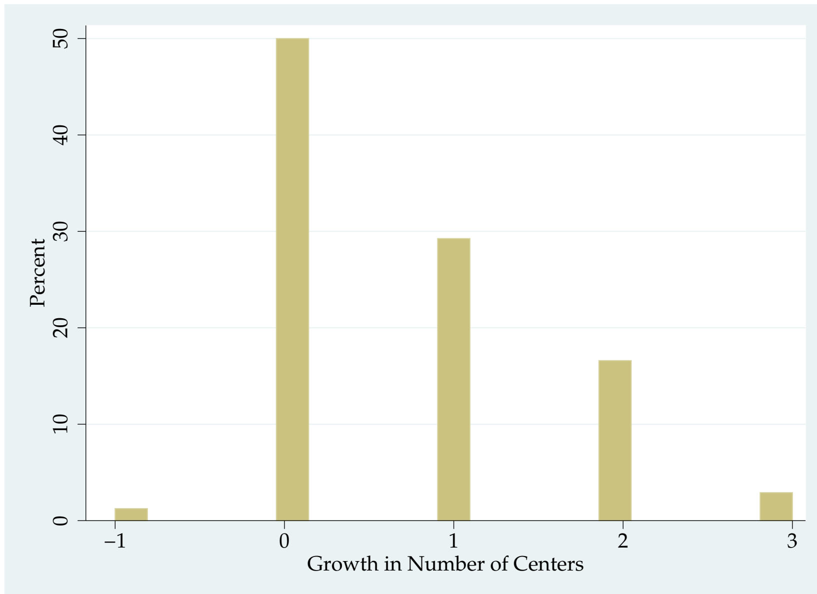
Figure 2: Enrollment in the *Sala Cuna* Program by Public Childcare Center Provider, 2005 - 2007



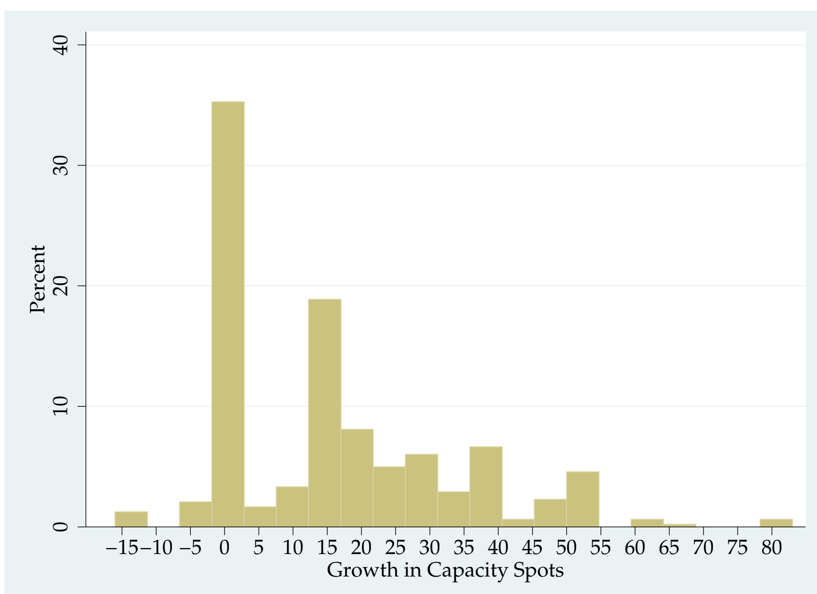
Notes: JUNJI and INTEGRA are the two public providers of childcare centers in Chile. JUNJI is a public organization of the Ministry of Education responsible for imparting the country's early education for children under four years of age who live in a situation of poverty or social vulnerability. INTEGRA is a non-profit organization and it aims to provide quality education to children from disadvantaged backgrounds who are younger than five years of age.
Source: Administrative JUNJI and INTEGRA data provided in Encina and Martínez (2009).

Figure 3: Percentage Distribution of the Growth in the Number of Public Childcare Centers and the Number of Capacity Spots at the Municipality Level

(a) Number of Centers



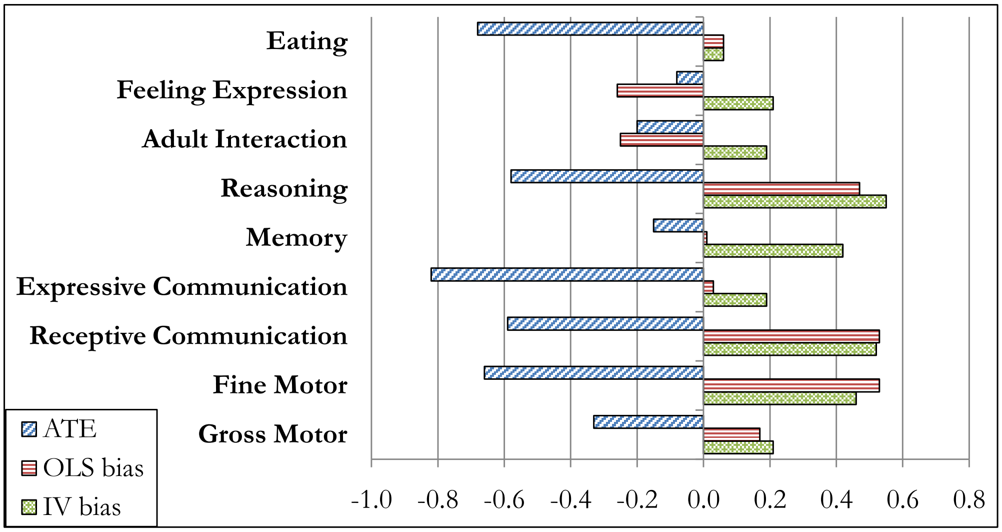
(b) Number of Capacity Spots



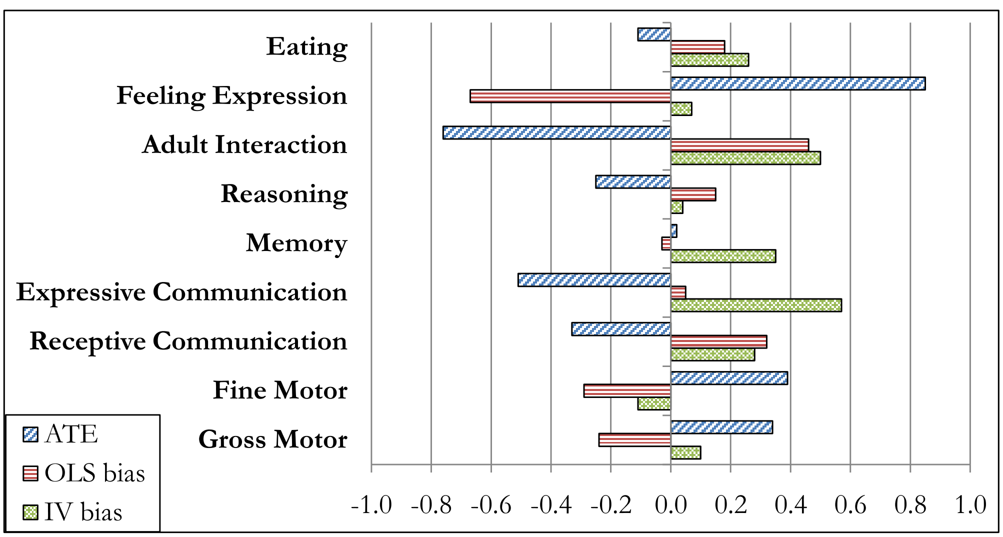
Notes: The growth in the number of public childcare centers is defined as the municipality-level change in the number of public childcare centers serving children in the sala cuna menor over a variable period of time, starting at the time of the child's birth and ending at the time of the child's enrollment in the childcare center. Analogous definition applies to the number of capacity spots at the same public childcare centers. Source: Authors' analysis based on the JLS sample data.

Figure 4: Average Treatment Effects Relative to OLS and IV Bias, by Period

(a) Period 0



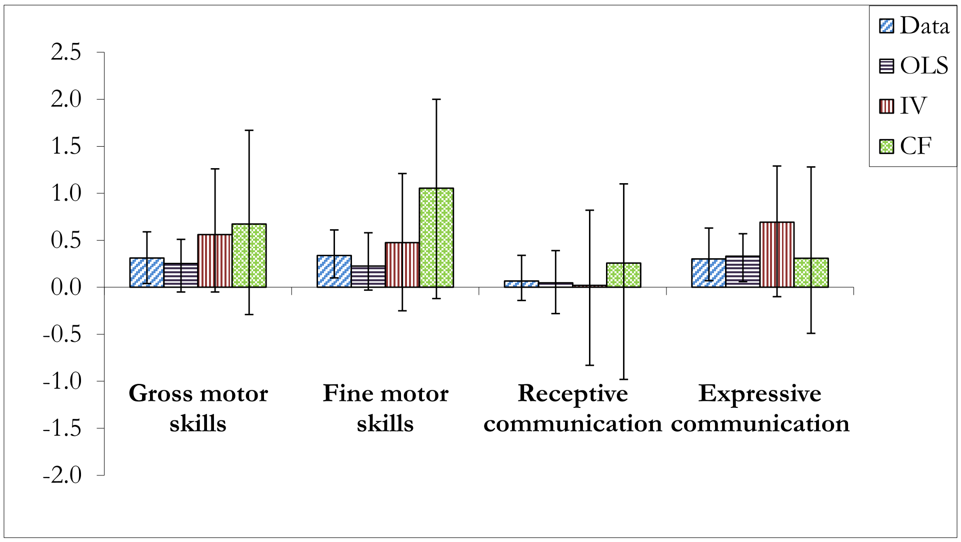
(b) Period 1



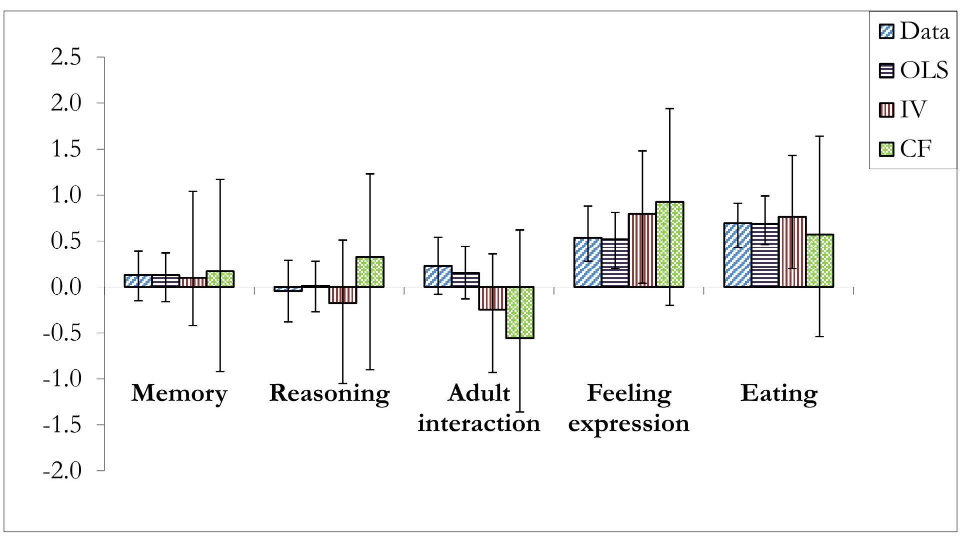
Notes: Effects are measured in Z scores ($\mu = 0, \sigma = 1$). OLS bias refers to the difference between OLS^t and $ATE^t(X)$ estimates. IV bias refers to the difference between IV^t and $ATE^t(X)$.
Source: Authors' analysis based on the JLS sample data.

Figure 5: Dynamic Treatment Effects on Child Development Outcomes, by Model Type

(a) Motor and Communication Skills

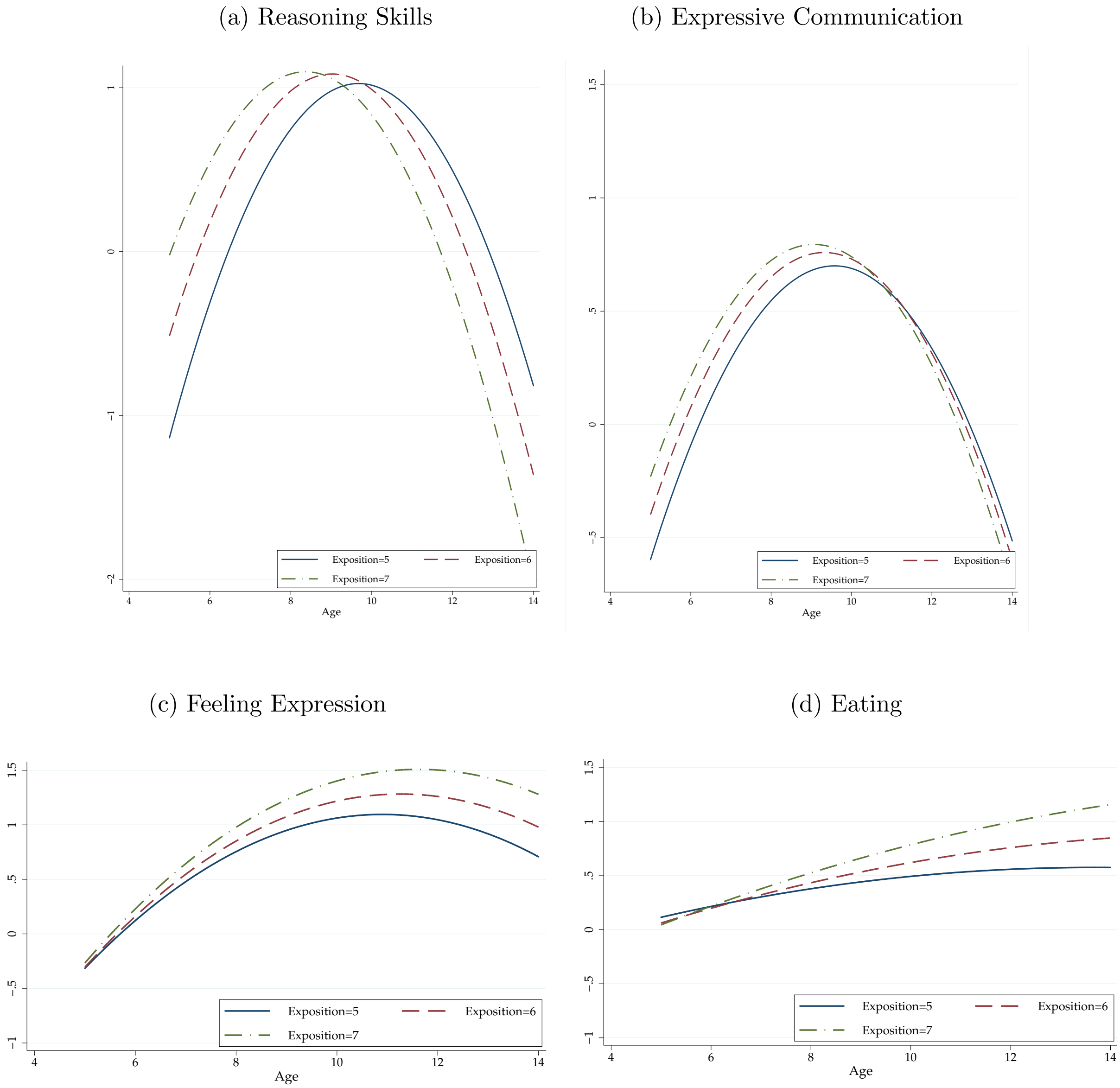


(b) Cognitive and Personal-Social Skills



Notes: Effects are measured in Z scores ($\mu = 0, \sigma = 1$). Error bars show 95 percent confidence intervals computed based on the percentile method for 200 bootstrap samples.
Source: Authors' analysis based on the JLS sample data.

Figure 6: Age-Specific ΔATE for the Selected Child Development Outcomes, by Child's Age at Baseline and Length of Program Exposure



Notes: The horizontal axis measures the age of the child at baseline (5-14 months) and the vertical axis measures ΔATE in Z scores ($\mu = 0, \sigma = 1$). The graph plots three functions corresponding to different lengths of program exposure: 5 months (blue line), 6 months (red line), and 7 months (green line).
Source: Authors' analysis based on the JLS sample data.