Comprehensive Early Childhood Development Support Systems and Academic Achievement: The case of Chile Crece Contigo

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Abstract

This paper studies the effects of a comprehensive early childhood support system on human capital accumulation. Specifically, we explore differences in educational achievement of the first generations of children exposed to the comprehensive child development support system "Chile Crece Contigo." To study this, we exploit the gradual implementation of the policy and the age eligibility requirements to estimate the returns of availability of the policy on data from seven cohorts (2012-2018) of fourth-grade students in Chile. We find sizable positive effects in mathematics (0.21 of a standard deviation) and language (0.23 of a standard deviation) test scores for children in municipalities that started the program during or before their prenatal stage compared to children that the program began when they were older than sixty months. Estimates from an event-study design show that the exposure returns dissipated for children thirty-six months old or older when the policy started. This result is consistent with the schedule of interventions and early detection instruments established. When we look at the difference in the returns to exposure across gender and socioeconomic status, we find evidence that (i) comprehensive child support system has higher returns on boys, which could be explained partially by differences in access to need-based services, (ii) these differences across gender differences occur in children with higher levels of exposure, and (iii) we do not find relevant differences between students classified as low-socioeconomic background and not classified in this category.

Keywords: Chile Crece Contigo, long-term return, early childhood interventions.

JEL Code: I38, J13, J18

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1 Introduction

From conception, parents face constraints and limitations in their investment decisions shaping their children's future. Constraints such as lack of parenting skills (Brooks-Gunn et al. (2000)), financial constraints (Duncan et al. (2010)), environmental factors ((Meaney et al. (2007), Weaver et al. (2004)), lack of information (Mayer et al. (2018)) or poor-quality nutrition (Bhargava (2016)) create an unequal start in life. Based on this evidence, policymakers had implemented over the last decades multiple types of interventions such as early childhood education programs[1], nutritional complements[2], and home visits[3]. However, as Shonkoff and Philips (2000) described, these policies are often fragmented, with multiple en try points due to the lack of institutional infrastructure. The previous makes it difficult to have consistent early detection systems and interventions that complement more complex problems. Comprehensive child support systems aim to integrate multiple services and resources with early detection mechanisms to deliver effective and appropriate interventions.

Based on this evidence, in 2007, the Chilean government implemented a national comprehensive child development support system (CCDSS) called *Chile Crece Contigo* to promote the development of every child in the country, independent of their condition. Furthermore, this support system expanded the supply of services for children under five through new institutions and funding to coordinate the timely delivery of materials and interventions at a national level. Following this example, different countries in the region started implementing similar policies such as Uruguay Crece Contigo (Uruguay), de Cero a Siempre (Colombia), Programa Nacional Cuna Más (Peru), Crianca Feliz (Brazil), and Plan Nacional Primera Infancia (Argentina). In addition, in the US, similar initiatives have been funded through the Program for Infants and Toddlers with Disabilities (Part C of IDEA) which offers federal grants for states to provide early interventions for children under three and their families (Sanborn and Giardino (2014)).

This paper examines the differences in educational achievement generated by exposure to the first comprehensive child development support system in Latin America. Specifically, we look at the different indicators of educational outcomes of the first generations of children exposed to the policy. To achieve this, we combine information from standardized test scores (language and mathematics) and administrative records (annual attendance) from seven cohorts of fourth-graders in Chile between 2012 and 2018 containing children born between 2000 and 2009 to implement our empirical strategy. In order to identify the effects of having availability to this comprehensive support system, we combine two institutional characteristics of the policy in our identification

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[1]Currie (2001) Heckman et al. (2013a) McCoy et al. (2017) García et al. (2020) Drange and Havnes (2018)

[2]Nutritional interventions could be found in different developing countries (Behrman (1993), Popkin et al. (1980), Walker et al. (1991), Selowsky and Taylor (1973),Maluccio et al. (2009)) and in the US Currie and Rajani (2015), Sonchak (2016), Bersak and Sonchak (2018).

[3]Olds (2002),Health Resource and Service Administration (2015), Michalopoulos et al. (2019), Paradis et al. (2018), Doyle et al. (2017))

strategy. The first characteristic is the gradual roll-out across different municipalities used to implement the policy between July 2007 and June 2008. This staggered implementation allows us to separate time trends from the age from which the child starts to be exposed. The second characteristic of the policy is the Chile Crece Contigo target population. The system aims to support children from their prenatal stage until 59 months of life. Given our sample's range of birth dates, it is possible to define a control group from all children who were not eligible to receive services when the policy started. Combining both features lets us determine the level of exposure for all children eligible to receive policy compared to all children not eligible to receive services through the period that the policy was being introduced.

Our main results show that a child for whom the policy was available in her municipality since the perinatal stage had a positive return of 0.23 of a standard deviation in language test scores and 0.21 of standard deviation in mathematics in fourth grade compared to children who were not exposed to the policy (sixty months or older at the time of implementation). Furthermore, when we relax the assumption of linearity on the level of exposure using an event-study design, we conclude that the returns decrease with the child's age at first exposure until there are no returns for children exposed from thirty-six months or older. This result is consistent with the policy's schedule of early detection mechanisms and interventions, such as psycho-motor screening tests, parental skills workshops, and home-visits services.

Our second set of results explore the heterogeneity across subgroups in the sample. First, we observe relatively modest differences between students classified as low-socioeconomic students and students who are not. Specifically, we observe a difference of 0.02 standard deviations in standardized test scores in language and mathematics, favoring low-SES students and one additional percentage point in annual attendance. Second, we perform an analysis by gender. We find considerable differences across male and female students. In the first place, we show evidence that the returns for male students are higher than for female students in all three domains. Moreover, these differences are more prominent for children with higher levels of exposure, dissipating for children exposed after 12 months in the case of mathematics and for children exposed after 24 months for language.

This paper contributes to various strands of the literature. First of all, we can contribute to the general literature on the effects of early childhood interventions and their effects later in school (Brooks-Gunn (2003), Currie (2001), Brooks-Gunn et al. (2000), Olds et al. (1998), Avellar et al. (2013), Connell and Prinz (2002)). More specifically, we contribute to the emerging literature of comprehensive child support systems in Latin America that compares to similar experiences like the Integrated Child Development Service in India (Vikram and Chindarkar (2020), Nandi et al. (2020)). Second, we build on the existing literature that estimates the returns of national policies based on cumulative exposure models (Hoynes et al. (2016), Bailey et al., Bailey et al. (2020)) and extends the framework for policies with multiple services and heterogeneity in take-up rates.

Finally, this paper contributes to the literature about returns of the Chile Crece Contigo in early childhood development (Carneiro et al. (2019), CIGES (2013), and Clarke et al. (2020)). We contribute to the literature exploring the differences in human capital accumulation five years after these children become ineligible to continue to receive services from the system. Previous research was able to provide evidence for shorter periods. Furthermore, previous research focused on specific services offered by the policy, such as stimulation and parental skills workshops. Our paper looks at the exposure to the policy as the treatment that these children are receiving. This approach has its downsides since it cannot provide information about the impacts of specific interventions. However, our approach can estimate the returns on the system at a national scale rather than on one specific intervention.

The rest of the paper goes as follows. In Section 2, we present the institutional background of the policy, describe the different services and interventions offered through the system, and discussed previous literature. Section 3 describes the data used in the analysis. In Section 4, we described the identification strategy and the empirical model. In Section 5, we describe the empirical results. Finally, in Section 6, we conclude and present further discussion about the interpretation of our results.

2 Chile Crece Contigo

2.1 Institutional Background

Chile Crece Contigo (ChCC onward) is a national comprehensive early childhood development support system. This system comprises an integrated network of services to *promote the development of children who participate in the public health network* (MIDEPLAN (2009))—supporting parents and children from conception until they enter preschool at the age of five. Policymakers chose this target population based on the empirical evidence showing that the highest return to investment in terms of human capital accumulation occurs in the first years of life (Heckman et al. (2005)).

Before creating ChCC, services that target children under five were scattered across different agencies without any coordination, such as the Ministry of Health, Ministry of Social Development, and local governments. The first change that this comprehensive early childhood support system was to establish a national coordination and monitoring scheme (MIDEPLAN (2009)) in the Ministry of Social Development and Family (MSDF, and formerly known as the Ministry of Planning (2005-2012) or Ministry of Social Development (2012-2019)). This allow the management and delivery of interventions by different government agencies under one common framework. The second change was the program's expansion and diversification in the supply of services provided, changing the framework from a purely biomedical approach to a bio-psychosocial considering children's specific environments for their development.

The inter-agency coordination of the system was committed to the Ministry of Social Development and Family. The inter-agency coordination of the system was committed to the Ministry of Social Development and Family. Funding of this policy is provided through the MSDF, assigning the total amount to their annual budget, and then is distributed across the different government institutions[4] that offer the individual services. The principal government agency that receives these transfers is the Ministry of Health, which received 36.95 million USD in 2009 for the two main components of the program: the Biopsychosocial Development Support Program and the Newborn Support Program. From 2010 and onward, the total cost of the agenda has been 46.07 million USD (with an exchange rate of 814 CLP = 1 USD).

2.2 Services Provided

The support system ChCC provides a large-scale range of services to promote the development of children who participate in the public health network. These services supplied through ChCC could be classified into three main components: The Newborn Support Program (PARN), Biopsychosocial Development Support Program (PADB) and, the Mental Health Support Program (PASMI) (Gobierno de Chile (2018)). All these services are available through the public health system. The first component, the Newborn Support Program (or PARN for *Programa de Apoyo al Recien Nacido*), consists of materials (trousseau) and educational workshops about newborn care and basics of early parenting and respectful parenting. The set of materials delivered to each family consist of a transportable crib with mattress and sheets, a stimulation mobile, an EVA foam carpet, a baby carrier, clothes, and information brochures about parenting and stimulating play.

The second component of services provided by ChCC is the Biopsychosocial Development Support Program (or PADB for *Programa de Apoyo al Desarrollo Biopsychosocial*). Which have had a constant annual cost of around 24 million USD (in 2021 dollars), constituting approximately 40% of the annual budget of the system (Budget Office of the Finance Ministry of Chile (2010)). This program's primary goal is to provide intensive support through surveillance and promote children's environment and development. In terms of management, this component of the policy introduced standardized detection instruments such as psycho-motor evaluations during the first three years of life (Bedregal (2008)), postpartum depression evaluations (Cox et al. (1987)), mother-infant attachment (Massie (1977)), and screening surveys to detect the vulnerable condition at the household. On the other hand, the programs offer multiple interventions to promote children's development. These services range from workshops to support parenting skills ("Nadie es Perfecto"), workshops for stimulation support, and home visiting. Additionally, the program also includes a nutritional component (new milk formula for expecting mothers called "Purita Mama" and for children under 12 months "Purita Fortificada") and educational material.

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[4]There is a fraction of the annual budget below 1% that goes to a private institution, Fundación Integra, to hire the service *Fono Infancia*.

The last pillar of the ChCC, and recently introduced in 2017, is the Mental Health Support Program (PASMI for *Programa de Apoyo a la Salud Mental Infantil* in Spanish). The services provided through this pillar aim to detect and support the alterations in the socio-emotional development of children between 5-9 years old. However, this program constituted only 1% of the program's annual budget in 2017 and grew up to 6% in 2020. Therefore, this paper cannot capture the effects of these services based on the age ranges of our sample and the magnitude of spending.

2.3 Implementation

In June 2006, the Presidential Advisory Committee for Early Childhood Reform presented their proposals to the Chilean government. In October of that year, President Bachelet announced the creation of the social protection system Chile Crece Contigo. Nine months later, in July 2007, the execution of ChCC started July 2007. The execution was done gradually across the country's different municipalities (lowest administrative unit) and finished in June 2008.

In Figure 1, it is possible to observe the proportion of the 346 municipalities that were providing ChCC services. The paper uses the implementation dates reported by the Ministry of Social Development and presented in Clarke et al. (2020). Thus, it is possible to observe how only a handful of municipalities started providing services covered by the social protection system during the first months of implementation. Later in August 2007, the Ministry of Social Development introduced this policy in 121 municipalities in different regions of the country. Finally, the remaining 202 municipalities were incorporated gradually between September 2007 and July 2008[5].

The order of entry implemented by the Ministry of Social Development was based on the availability of space to integrate new services, which differs on the quality and quantity of the available infrastructure (in Silva and Molina (2010) it is possible to find a more extensive description of the implementation of the policy). Therefore, it does not imply that the first to implement had better health infrastructure, they just were not facing capacity constraints at that moment. For this reason, it is possible to observe municipalities with lower population densities enter first. In Clarke et al. (2020), the authors test the correlation between being an early adopter of the policy with observable characteristics in 2006. They find that the adoption order is correlated only with the proportion of households with a low socioeconomic status.

2.4 Enrollment

Every child has enrolled automatically in the local ChCC network in their first contact with the public health system. This first contact could be at the first prenatal care appointment[6], at

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[5]Section 3 of the Online Appendix shows that the distribution of the number of municipalities entering each period does not differ from the number of potential new children served by the policy.

[6]In 2006, the coverage of pediatric care in the public health system was 90% of all children born in the public health system, with an average of 6 appointments during the prenatal period (Silva and Molina (2010)).

birth, or regular pediatric appointments at a hospital or clinic part of the public health system[7]. During the encounter, the nurse or health professional in charge of the local ChCC network in that establishment provides the essential information and applies the screening survey. The policy is intended only for children in the public health system, but this does not restrict children from the public health system to request service and material at their local clinic[8].

It is important to note that enrollment in this social protection system does not make ChCC use of services mandatory. Moreover, as described earlier, some services are available only to children with specific needs, such as developmental lags or psychosocial factors affecting their development.

2.5   Previous Research on Chile Crece Contigo

The evidence related to the effects of Chile Crece Contigo is still limited and only being able to study it's the impact of some services on the short and medium-term. This knowledge gap about this policy's impact relates to the complexity of evaluating a comprehensive child support system that combines multiple services and the lack of evaluation strategies embedded in the policy design. The existing evidence shows that the policy have had positive returns for children in their development, expanding the possibilities for the development of children in vulnerable conditions. Carneiro et al. (2019) study the medium-term effects of the parental skills workshop "Nadie es Perfecto" (Nobody is Perfect) offered through ChCC. This intervention has the goal of improving the quantity and quality of parental investments. To study the effects of these workshops the authors use an RCT design in 162 public health centers, with two treatment groups: one that received 6 to 8 group sessions, and the second received two extra sessions focused on responsive play and dialogic language. They find that three years after the intervention, the treatment group presents a 0.43 standard deviation in cognitive development and 0.54 standard deviation in a measure of personal-social development The take-up rate of the interventions in the treatment group was 25% and 30%, and the total cost of each intervention was 22 USD for each family attended. The second study, CIGES (2013), uses a before and after comparison of children attending stimulation workshops. Based on a sample of 299 children who received a referral from the health center to participate in stimulation interventions. The authors also collected information related to the cost to provide this type of intervention, allowing them to estimate the cost-effectiveness ratio of the interventions. Their main finding is that from the 265 children (10% of attrition), 10.2% of children improve their test scores to a normal path of development category. TThe last paper studies the effects of ChCC on children's

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[7]In Chile, access to health providers could be through public health services or private health providers. Based on data from the 2009 National Socioeconomic Characterization Survey (CASEN), 66% of children under the age of 5 received their primary care through the public health system, which includes municipal health clinics, national public health system clinics, rural clinics, and urgency care from the public health system. In addition, around 95% of all these children have insurance through the National Health Fund (FONASA), which is the national public insurance. Moreover, FONASA provides coverage for private health providers, but caregivers must incur out-of-pocket copay.

[8]¿Pueden participar en los talleres de ChCC o recibir materiales quienes no pertenecen al sistema público de salud?

development is Clarke et al. (2020). In their research, they use the gradual implementation of the policy to estimate the impact of the prenatal components of the policy on birth outcomes. Using administrative information on birth outcomes, they find an improvement in birth weight of children eligible (based on their birth dates) to receive the prenatal component of the policy. They also present evidence of the policy's equity since exposure to the policy had higher returns on children of socially vulnerable groups.

3 Data

The primary analysis of the paper combines data on the Chile Crece Contigo implementation at the municipality level with educational administrative records of multiple cohorts of Chilean 4th graders between 2012 and 2018. As described in earlier sections of the paper, the ChCC policy offers services from prenatal care until the child is 60 months old. Therefore, when ChCC become available in a municipality, children 60 months and up were ineligible to receive its services. Based on the implementation dates of the policy, children born before June 2002 should be ineligible to receive those services. (the school year 2012-2012). Including cohorts between 2012 and 2018 will allow observing children with different grades of exposure to ChCC.

The primary source of information comes from the Chilean Ministry of Education (MINEDUC) and the Education Quality Agency (*Agencia de Calidad de la Educación*). The Agency provides annual individual-level data for every student enrolled in the Chilean education system, which achieved a 100% coverage of the projected school-aged population (MINEDUC (2018)). This individual data provides us information demographic information about the student such as date of birth, municipality of residence, gender, identifiers for the school where the child is enrolled, and a masked individual identifier that allow us to join this data with other sources of information from the Ministry of Education. In addition, the Education Quality Agency also provides information on the annual school attendance, reported GPA from the school to the Ministry of Education, and information related to socioeconomic characterization used by MINEDUC to assign differentiated school vouchers.

Added to this information, the Agency administers an annual battery of standardized tests in fourth grade called SIMCE (Sistema de Medición de la Calidad de la Educación). These tests measure the proficiency level in language and mathematics based on the national curriculum established by the Ministry of Education based on an Item Response Theory measurement model (Agencia de Calidad de la Educación (2015)). The objective of these evaluations is to assess improvement in equity and quality of education in the country. Each year the test is administered to around 250,000 children. As part of these standardized tests, each caregiver receives a questionnaire that should be filled at home. This questionnaire consists of around 40 questions about the household characteristics, such as household size, income, parents' level of education, preschool attendance,

and parents' educational expectations for the child. Each year, the information collected through this instrument changes, with only a subset of demographic characteristics asked every year, limiting the information available for all cohorts of this paper.

Sample Restrictions We restrict the sample used for our analysis to 4th-grade students attending a public school or subsidized private schools observed for the first time in the sample. As described in the previous section, ChCC provides its services through each municipality's local public health networks. However, since the data used in this paper comes from the Ministry of Education, there is no information related to where the child's caregiver takes her to receive health services. Therefore, to have a closer sample to the target population of this policy, we use only children enrolled in public schools or subsidized private schools for the analysis[9]. From a total of 1,635,953 unique records between 2012 and 2018, this first restriction reduces the sample size to 1,498,218 (92%).

The second sample restriction was that all observations have measurements in every outcome of interest and background information. This restriction leaves the final number of observations used in the paper to 1,148,296. This restriction operates from children who did not have SIMCE test scores, and there was no information on parental background. As described previously, the questionnaire received by parents was handled through the school and had to be returned by the student later. The rate of non-response to these questionnaires is around 13% for each year.

Outcomes of Interest The goal of this paper is to study the differences generated by exposure to the policy in academic achievement. We use three complementary outcomes to measure academic achievement: school attendance, language standardized test scores, and standardized mathematics tests scores. The first one is annual attendance, reported as the number of school days the student is present at school. Attendance plays a role in the ability to learn of students; if they are not present in the classroom, the student will not learn, and when they return to class, teachers need to invest more time in this group of students (Marcotte and Hemelt (2008),Gottfried (2015),Gottfried (2009)).

The second and third measures of academic achievement are the results of the standardized test SIMCE. As described before, this test measures proficiency in language and mathematics of all 4th-grade students in the school system during the last months of the academic year. Following Neilson (2013), Feigenberg et al. (2019), and Navarro-Palau (2017), it is possible to leverage the comparability of the SIMCE test scores across different years when the scores are normalized. In

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[9]We based this assumption on data from the first and third round of the Early Childhood Longitudinal Survey in Chile (ELPI from its acronym in Spanish). In this nationally representative longitudinal survey, 85% of public school children and 69% attending subsidized private schools were born in a public hospital. On the other hand, 62% of children in private schools that their caregivers declared born in a private hospital. Therefore, the assumption is that excluding children from private schools would reduce the downward bias generated by children living in municipalities affected by the policy who could not receive the treatment.

this paper, we normalize test scores with the mean and standard deviation of 2012, the first year in the sample.

3.1 Descriptive Statistics

Table 1 presents the summary statistics for the sample of children in these seven cohorts for whom we have non-missing values on the outcomes of interest and the background characteristics. The total number of observations in the sample is 1,148,296 ((Column (1)-(2) of Table 1). The first two columns show the mean and standard deviations for the outcome of interest and the background characteristics for the children's sample described in the previous section. We also included the descriptive statistics for children whom the Ministry of Education classifies as low-socioeconomic students, which corresponds to 50% of the original sample.

It is possible to observe that the average attendance rate for children in fourth grade is 93%. In our sample, the rate of chronic absenteeism, defined as being absent more than 10% of school days (equivalent to 20 school days)[10] , in Chilean 4th-grade students, is approximately 25%. When looking at the standard deviation of this outcome, the annual attendance has a standard deviation of 5.9, making all children one standard deviation below the mean chronically absent. When looking at low-SES children, they have a statistically significant difference of .5% lower level of attendance to school compared to the rest of the sample.

Our second set of outcomes of interest are the standardized test scores in mathematics and language. It is possible to observe that the SIMCE test scores in language and mathematics have an average of 266 for language and 260 for mathematics. The standard deviations are 51 points and 48 points, respectively. As expected, low-SES students have a significantly lower score than the rest of the sample (273 vs. 258 in language and 268 vs. 253 in mathematics). A critical aspect of these three achievement measurements measure similar underlying skills (cognitive and socio-emotional skills), but not the same. The estimated correlation between GPA and language is 0.54, GPA and mathematics 0.53, and mathematics and language 0.67.

For our analysis, we included the background characteristics of the students and their households. The first characteristic is the gender of the child. We observe approximately the same proportion of male and female students in the sample. From the parent surveys, we can observe the distribution of the level of schooling of the child's mother. Around 24% of the children in the sample, their mother has a level of education below 12 years of schooling. We can observe that 38% of mothers of children in the sample completed high school. This sample's average years of mothers' schooling is similar to the 11.1 national average in 2017 (Ministerio de Desarrollo Social (2018)). The age of children in this sample is 9.57 years at the moment of the administration of

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[10]This differs from the definition used in the US for chronic absenteeism, which is 15 days of absent unlawful days is considered chronically absent. The rate of chronically absent students for Elementary schools in the US is 13.6% accordingly with data from the Department of Education.

the SIMCE. The children's observed age is consistent with the age cutoffs used by the Chilean schooling system, where children should be nine by March 31st of the year in 4th grade.

4   Empirical Strategy and Estimation

In this paper, our main research question is, did exposure to the comprehensive early childhood support system Chile Crece Contigo generate differences in human capital accumulation? Specifically, in this work, we attempt to answer the following question: Did students exposed to the policy have higher academic achievements by 10? The following section describes the empirical strategy used to answer this question.

4.1   Measuring Exposure to ChCC

The setup is the following: child i who lived in municipality m born in period t, had an age (in months) A_{mt} (Equation 1) when the policy ChCC was implemented in their municipality E_m. In Figure 2, we can see the distribution of A_{mt} of the sample.

$$A_{mt} = t - E_m \tag{1}$$

Based on A_{mt}, we can define the level of exposure to the policy $D_{imt} \in [0, 1]$ as the share of days since the estimated first prenatal control (In Utero (IU)) and 59 months of life (Equation 2). Unfortunately, the data sources described in the previous section do not contain information about the gestational length that allows us to calculate when the gestational period started. So to estimate the first prenatal control date, the paper calculated a general rule of 224 days before the date of birth as an approximate date for the first prenatal control at eight weeks of gestation for a child born with 40 weeks of gestation[11]. Since the target population of this policy, at least in the first years of implementation[12], are children under five, the paper defines that children were older than 59 months when the $E_m = 1$ had exposure of $D_{imt} = 0$.

$$D_{imt} = \begin{cases} 1 & \text{if } A_{imt} < -8 \\ (67 - A_{imt})/67 & \text{if } -8 < A_{imt} \leq 59 \\ 0 & \text{if } A_{imt} \geq 60 \end{cases} \tag{2}$$

The data described in the previous section includes seven cohorts of fourth-graders in Chile

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[11]Based on the Chilean Ministry of Health reports, around 92% of children born in Chile between 2002 and 2008 were born between 37 and 41 weeks of gestation. To access the data report `shorturl.at/sxL12`

[12]The target population of the ChCC social protection system today includes a mental health module for children between 6 and 9 years, but it wasn't implemented until August 2017.

between the years 2012 and 2018[13]. These cohorts were born between August 1999 and May 2009. This range of birth dates allows us to observe children with levels of exposure to the policy along with the complete range [0,1]. In Figure 2, based on the definition of exposure D_{imt}, we can observe that 27% of children have a level of exposure under 10% (less than seven months of exposure). Also, 18% of the children had 90% or above (corresponding to exposure since six months of gestation). The remaining 65% of the sample distributes uniformly between not exposure and total exposure to the policy.

4.2 Empirical Model

To estimate the differences in school achievement of children i with different levels of exposure to the policy D_{imt}, we estimate the specification presented in Equation 3.

$$Y_{imt} = \alpha + \varphi D_{imt} + X_{imt}\beta + \gamma_m + \tau_r t + \delta_s + \epsilon_{imt} \tag{3}$$

The specification in Equation 3 indexes i for a child, m for the municipality, r region, s for the school where the child is enrolled, y for the year of birth, and t for the month of birth. We define the outcome of interest as a function of the exposure to the policy D_{imt}, a vector of individual characteristics such as gender of the child, a set of dummies of the age of the child in months[14], the level of education attained by the mother of the child, and a dummy variable that indicates if the child lives in a household classified as a low-socioeconomic status by the Ministry of Education.

One of the critical features of the implementation of ChCC was the staggered adoption in different periods, allowing us to compare children with varying levels of exposure to the policy due to their municipality and date of birth. In this specification, the model includes dummy variables γ_m for each municipality that captures time-invariant characteristics such as income, public school availability, and public health infrastructure that create differences in educational achievement and human capital accumulation. In addition, we included regional time trends (based on year of birth). To capture variation in educational outcomes due to differences in school quality, we have dummy variables δ_s for the child's school. The parameter of interest in this model is φ, which captures the linear effect of exposure to the policy. Identification of this parameter comes from the variation within municipalities across cohorts[15]. This variation allows us to separate the time trends based

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[13]This is the last year of data available that includes the SIMCE evaluations. Unfortunately, the Agency of Education Quality could not administer the 2019 SIMCE to 4th graders due to the social unrest after the October 18th protest.

[14]Including the child's age allows us to consider the relative age of the child and not add this to the coefficient of D_{imt}. Since younger students in each cohort have a higher probability of having a higher exposure to the policy $Corr(D_{imt}, A_{imt}) > 0$, not accounting for age could include a downward bias of $\hat{\varphi}$. At the same time, including age as fully saturated variable allow us to estimate non-parametrically the relation between age and school performance.

[15]Since the level of exposure to the policy in each cohort doesn't have the full range in the space [0,1] it is not possible to include year-of-birth dummies. Changing the interpretation of our estimates, since it will reduce the variation to a within-year of birth comparison.

on year-month of birth and exposure to the policy. The standard errors were estimated using a covariance structure clustered at the municipality level (Bertrand et al., 2004).

Using a continuous approach to exposure allows us to only generate comparisons "from above" like the ones described in Hoynes et al. (2016) and Bailey et al.. Using this "dosage" definition of treatment status captures the cumulative exposure effect of the policy. This feature of the paper departs from the approach of other early childhood interventions evaluations, where treatment groups are exposed from a specific period rather than different starting points for a limited time. This approach does not allow us to provide any conclusions related to the optimal intervention time, but allow us to understand the compounding effect of the multiple services children and their families could receive when the systems covers them. In the context of comprehensive support systems, whose goal is to detect factors that could alter the potential normal path of development, the conclusions from this approach help to understand the gains of starting as earlier as possible. In this case, the coefficient of interest $\hat{\varphi}$ can be interpreted as the difference between children fully exposed and children not eligible to be supported by ChCC (accounting for all possible levels of exposure), since the values that D can take are between $[0, 1]$. So the gains of exposure to the policy is $\hat{\varphi} = E[Y|D = 1, X] - E[Y|D = 0, X]$.

One of the limitations of the first empirical model is the assumption of constant returns to exposure to the policy. To relax this assumption, we use a second approach to estimate the differences in educational achievement. This second approach is an event-study specification that allows us to estimate the returns of the policy based on a fully saturated model. To estimate this model, we use dummies for each possible age (in months) of the child at the moment of implementation (Equation 1) using 60 as the baseline (first month of non-eligible for ChCC services) coefficients since the target population of ChCC is children under five.

$$Y_{imt} = \alpha + \sum\nolimits_{a=-18[a\neq60]}^{70} \pi_a \mathbb{1}[b - E_m = a] + X_{imt}\beta + \gamma_m + \tau_r t + \delta_s + \epsilon_{imt} \qquad (4)$$

The event-time coefficients range from 20 months before birth up to 81 months old. In addition, we include, similar to the first approach in Equation 3, a set of dummies for each municipality to time-invariant characteristics, a set of dummies variable for each school to capture differences in outcomes due to school quality and practices. Also, we include regional month-of-birth trends at regional level. This set of coefficients $\{\pi_a\}_{a=-18[a\neq60]}^{70} = E[Y|A_{mt} = a, X] - E[Y|A_{mt} = 60, X]$ captures the effect on educational achievement of being exposed to ChCC since age a ($A_{mt} = a$) relative to age 60 months. As the cumulative exposure model, we use clustered standard errors at the municipality of residence level.

4.3 Threats to Identification

The estimation strategies described rely on several assumptions. The first assumption is that the timing used to implement the policy across the country is uncorrelated with factors correlated with the outcomes of interest. Thus, if the correlation between the order used to implement the policy and the quality of services provided through the local public health network is different from zero, we could expect biased estimates for the returns to ChCC (Equation 3). This question was asked before by Clarke et al. (2020), where they test differences in time of entry based on municipal characteristics in 2006 (before the start of the intervention). They find no evidence that could indicate that factors systematically correlated with improvements in health and development.

The second threat to identifying the effect of exposure to ChCC is confounding social programs enacted around the same time. During the last three decades, the Chilean government has implemented several social policies with a proxy means targeting method to reduce poverty, especially in vulnerable groups such as children under the age of 3, who in 2006 had a poverty rate of 21.8% compared to the 13.7% national poverty rate (based on the 2006 National Socioeconomic Characterization Survey). The first program is the *Chile Solidario* policy enacted in 2002 (Larranaga et al., 2012), which was a combination of conditional cash transfers, psycho-social support for families, and coordination of social services around recipients of the policy. In our sample, only 1% of children were born before 2002. The older students from the 2012 cohort were born before between 2000-2001 which, if eligible, they would still receive this monetary transfers within the first two years of life not imposing a risk of confounding to our empirical strategy.

5   Empirical Results

Table 2 shows our first set of results coming from the estimation of Equation 3 on the sample described earlier in the paper. Each column of the table presents the estimation results for each of the outcomes of interest: annual attendance, standardized test scores for language, and standardized test scores for mathematics. The estimated coefficients show in the first place the role of socioeconomic background in educational achievement and performance. The coefficients associated with students categorized as a low-socioeconomic status are negative, indicating lower attendance and test scores for less privileged students. However, the magnitude of these coefficients is relatively small compared to other coefficients. One possible explanation can be the fact that Equation 3 includes time-invariant dummies for each school. This feature interprets the coefficients associated with low-SES status as the average difference between children classified as low-SES students and children who do not enter under this classification within the same school. Given the segregation in the Chilean school system (Treviño et al. (2016), Kutscher et al. (2020), Santos and Elacqua (2017)), when we include school fixed effects, we attenuate the differences by low-socioeconomic

status.

Regarding gender differences in educational performance, we can observe that the difference in annual attendance is unfavorable for male students; the magnitude of the coefficient makes these differences irrelevant. In the case of standardized test scores, the results align with previous research (Bharadwaj et al. (2016), Reilly et al. (2019)): as early as fourth grade, girls outperform boys in reading test scores, and boys show higher test scores in mathematics. In this case, we observe male students performing 0.17 standard deviations lower than female students. On the other hand, we evidence a smaller gap in performance between male and female students with an advantage for the first one of only 0.07 standard deviations.

Finally, the gradient of mother schooling level shows a positive relationship between the highest educational level achieved and school performance. This result is consistent with previous research that shows a correlation between a mother's level of education and vocabulary development in early childhood (?). The magnitude of the education gradient for annual attendance and GPA are statistically significant but not relevant in terms of magnitude. The gradient for language and mathematics shows a difference of 0.4 standard deviations between children with a mother with a four-year college degree and a child whose mother did not finish middle school.

The results for our parameter of interest, $\hat{\varphi}$, are the following. In the case of annual attendance, the estimation results from column 2 of Table 2 show a statistically significant difference of 1 percentage point between children eligible to receive services from ChCC since prenatal care compared ineligible to be enrolled in ChCC. Based on the definition of chronic absence, 20 days correspond to 10% of absenteeism, so an increase of 1.5 in attendance corresponds to 2 extra days that the child is at school.

Columns 3 and 4 of Table 2 show considerable improvements in children's performance when they are eligible to be exposed to the policy. Regarding the performance in language standardized test scores, we can observe that exposure to the policy increases performance in the SIMCE test score by 8.46. As shown in Table 1, the standard deviation for the full sample is 51.09 for reading and 48.10 for mathematics. Therefore, we can interpret these estimates as an increase in 0.16 standard deviations. Additionally, the effects of exposure to the policy are higher in mathematics test scores. The estimated difference between children fully exposed and children without exposure to the policy is 0.083 standard deviations. To put these results in context, we could compare these results to the one shown in Bharadwaj et al. (2013). They show that new protocols established in 1991 for newborns who weigh less than 1,500g can generate returns of 0.15 standard deviations in fourth-grade SIMCE mathematics test scores using a regression discontinuity design. These magnitudes are promising when we weigh in that our empirical strategy identifies the effect of availability services rather than using these, a discussion that we will come back to later.

As described in the previous section, the model estimated in Equation 3 imposed a constant return of exposure to the policy. In which, the parameter $\hat{\varphi}$ estimates the difference between children

fully exposed (program implemented in the municipality at the moment of the prenatal period started) and children not eligible for being exposed to the policy (program implemented in the municipality when children older than 60 months). This assumption can be strict if we think about the discussion of brain plasticity and sensitive periods (or "critical periods") of child development (Johnson (2005)) and the dynamics of skills accumulation (Cunha and Heckman (2007)). In order to relax this assumption, we estimate the event-study specification described in Equation 4.

Figure 4 presents the estimated coefficients $\{\pi_a\}_{a=-18[a\neq60]}^{70}$ for each outcome of interest using the full sample[16]. Recall from Figure 2, children that their age (A_{imt}) was -8 or less at the moment when ChCC implementation are eligible to be fully exposed to the policy. As we move from left to right, children have lower levels of exposure to the policy. Moreover, at the moment of ChCC implementation in each municipality, children 60 months or older were not eligible to receive services through the policy. As explained earlier, the system's design provides services from prenatal care up to fifty-nine months of life. If the estimation strategy used in this paper is valid, we should observe that the subset of coefficients $\{\pi_a\}_{a=61}^{70}$ should not be different from the base comparison age. From the results of the estimates in Figure 4, it is possible to observe that there is no significant difference for children not eligible to be exposed by the policy for language and mathematics. However, the results for attendance show some variation in this subset of the sample.

In the case of mathematics (Figure 4 (a)), we can see that the returns of ChCC in this domain occur in the period after birth and three years of life. One interesting comparison to the results from the cumulative exposure model is the differences in magnitude. In the results from Table 2, the return from being fully exposed was 12.71. From Figure 4 (c), if we take the estimated coefficient in $A_{imt} = 10$ and $A_{imt} = 40$, the estimated difference is 10.14. Using an average of the estimated coefficients between [-18,10], the expected difference with reference to the baseline month is $E[\{\pi_a\}_{a=-20}^{10}] = 8.44355$. And the average of the estimated coefficients between [40,60] the expected difference with respect to the baseline month is $E[\{\pi_a\}_{a=60}^{70}] = .04$. Based on these two averages, we can calculate that the return of exposure to ChCC in mathematics is 8 points, which is smaller than the estimated return based on the model from Equation 3.

Lastly, the estimates for language standardized test scores (Figure 4 (d)) shows returns of exposure to the policy in the order of magnitude of 15 points, higher than the results of Table 2. When we look at the distribution of these returns across the age of exposure to the policy, it is possible to see that most of these returns come from the first three years of life (including the return from prenatal care). These last observations are consistent with the distribution along the life cycle of the services provided through ChCC (the online appendix offers a more detailed description of services provided). For example, the instruments used to detect motor and cognitive development lag are between two and thirty-six months.

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[16]The figure only shows coefficients between -17 and 70 to keep the number of observation in each possible A_{imt} balanced across the support.

Figure 4 (c) shows the estimates of Equation 4 for annual attendance. It is possible to observe that the positive returns from Table 2 can be explained by the slope for children with high levels of exposure ($A_{imt} < 10$) and children with partial levels of exposure ($10 < A_{imt} < 60$). In this outcome, when we relax the assumption of linear returns, it is possible to see that ChCC has no significant positive returns for children under 60 months at the moment of implementation.

The sample size on each possible value of A_{imt} is approximately 13,000 observations. Despite the sample size, the estimates from the specification in Equation ?? still suffer from month-to-month variations. To complement the results from the even-study, we use a similar approach as Lafortune et al. (2018), estimating a linear spline regression model. Based on the results from Figure 4 we select the 12-months intervals that capture the slope on each year of development. The spline regression model in Equation 5. The coefficients $\{\omega_s\}_{s=1}^{7}$ represents the slope for A_{imt} on each subsection of the support.

$$
\begin{aligned}
Y_{imt} &= \alpha + \omega_1 1[A_{imt} < -0]A_{imt} + \omega_2 1[0 \leq A_{imt} < 12]A_{imt} + \omega_3 1[12 \leq A_{imt} < 24]A_{imt} + \\
&\quad \omega_4 1[24 \leq A_{imt} < 36]A_{imt} + \omega_5 1[36 \leq A_{imt} < 48]A_{imt} + \omega_6 1[48 \leq A_{imt} < 60]A_{imt} + \\
&\quad \omega_7 1[A_{imt} \geq 60]A_{imt} + X_{imt}\beta + \gamma_m + \tau_r t + \epsilon_{imt}
\end{aligned} \tag{5}
$$

The estimation results of Equation 5 are shown in Figure 5, supporting the results from Figure 4. In the case of mathematics and language test scores, the results of the spline estimates reinforce the conclusions from the event-study strategy. In the case of mathematics, it is possible to observe that the returns to exposure are not constant during the first five years of life. The splines estimated gains are 0.2 between the 12 and 24 months of life and 0.65 between 24 and 336 months. We interpret this result as all children who received services at least 36 months or younger perceived the returns to the policy in their mathematics test scores. Looking at the timing of possible interventions in that period, the most salient is the referrals for stimulation workshops due to the cognitive assessment in the two-year pediatric visit. The total return to exposure in the first 60 months of life corresponds to 10.2 points or an equivalent of 0.21 standard deviation in our sample. When we contrast these results with language test scores, we can find similar results with certain peculiarities. Even when we observe the highest annual returns for services in the third year of life, language development services in earlier periods show significant gains. Added to the stimulation workshops, interventions such as the parental workshops who had shown a positive impact on receptive language (Carneiro et al., 2019) or home visiting who had shown improvement in the mother-child relationship (Conti et al. (2021)). The results for language confirm the conclusion from the event-study estimates: exposure to the policy during the prenatal period up to 36 months of life has returns of 12 points, equivalent to 0.23 standard deviations. The estimates slope for the other segments is not statistically different from zero, or their magnitude is relatively small.

In the case of annual attendance, Figure 5 (c), we can reconcile the results from the cumulative exposure and the event study in the following way. First, a change in the slope explains the positive return in annual attendance to the age of intervention around 24 months, but there is a reduction in attendance for children exposed during their last year. Finally, our results from Figure 5 support the internal validity of the identification strategy. Concretely, we can observe that even estimates of ω_7 for attendance, mathematics, and language are not different from zero, or the magnitude of the slope is statistically (an in magnitude) small compared to the slope of the eligible groups.

5.1 Estimates Heterogeneity

In the following section, we test for heterogeneity of the previous results across different groups: socioeconomic status and gender of the child. To explore these sources of heterogeneity, we estimate the cumulative exposure model (Equation 3) and the event-study design (Equation 4) for each different group separately. The results of this cumulative exposure model for socioeconomic status are in Table 3. We observe in Table 1 that our sample of students consists of 50% of students classified (by the Ministry of Education for subsidies assignment) as low socioeconomic status. The first row of Table 3 shows the estimated effect of being exposed to the policy for each group for each outcome of interest. It is possible to observe that the estimated coefficients for low-SES students are higher compared to the estimated coefficient for non-low-SES students.

The estimation results in language and mathematics test scores show that the returns to exposure are slightly larger for low-SES students. We can observe that the difference across groups ranges between 0.01 standard deviation (language) and 0.03 standard deviation. Figure 6 shows the event-study design (Equation 4) separated by group. The results for annual attendance show that for non-low-SES students, there are no differences in the control group and for exposure before 24 months of life. We also evidence that children exposed later in the intervention period (3-5 years old) have a lower attendance level than the control group. The results for language and mathematics test scores (Figure 6 (a)-(b)) shows that a slight difference across the first three years of life explained the differences in the cumulative model.

These results have two possible explanations. The first one relates to the probability of actually receiving services and interventions through the policy. Recalling from the description in Section 3 about sample selection, not every child in the sample attends the public health system for primary care (even when all children can attend to the local clinic to receive the services of the policy). Therefore, we can assume that low-SES students have a higher probability of using the public health network, increasing their exposure to the policy. A second complementing explanation is that children from low-SES households have a higher probability that their parents face constraints (financial and information) in their parental investments. This reasoning has two conflicting drivers: low-SES should benefit the most since they face higher constraints (returns higher

for low-SES students). However, changing their circumstances (to improve their outcomes) can be more challenging than changing the circumstances of non-low-SES students who can benefit from the policy (returns higher for non-low-SES). This tangled hypothesis is relevant to future research, but we can not answer based on the current data.

The second difference across groups that we test is across the gender of the student. Recent literature have seen higher return to early childhood interventions for girls compared to boys (for example Conti et al. (2019), García et al. (2018), Magnuson et al. (2016), Heckman et al. (2013b)). To test these differences, we estimate the same model in Equation 3 by gender of the student (Table 4). Columns (2) and (3) of Table 4 display the result from the estimates for each of the outcomes of interest. The difference between attendance estimates shows a difference close to zero. When we look at the results in Figure 7 (c), it is possible to observe that the cumulative exposure model hides away some differences across gender. Specifically, in the event-study results, we can explain that the results for female students can be because of a reduction in attendance for children exposed in the last years. In the case of male students, children exposed before first-year life experience an increase of 0.5 percentage points in annual attendance. If we go back to the results from 4, we can see how this heterogeneity can explain the not significant results across gender.

Table 4 (4) to (7) shows the results for language and mathematics favoring again male students compared to female students. Specifically, male students have a return of availability of the policy all of their life 0.2 standard deviations in language and 0.3 in mathematics, compared to the 0.12 standard deviation in language and 0.24 in mathematics for female students. The results for language test scores show that the results from Table 2 reflect the weighted average between both groups. Figure 7 (a) and (b) show the event study for these outcomes separately by gender. We can observe that in the case of mathematics, the differences across gender are for children exposed before the twelve months of life, and there are no differences for the later level of exposure. In the case of language, the window of time that creates differential returns by gender extends up the two-year-old mark. Figure 7 (b) shows how there is a difference of 5 points in returns for children exposed since their prenatal care, and this difference shrinks around the 24 months of life.

These overall results show an overall higher return for boys, deviating from the earliest literature that looks at gender differences in early childhood interventions. To understand the mechanisms behind this difference, we explore the 2018 Monthly Statistical Reports (or *REM* for its acronym in Spanish). These reports encompass all information reported from the local health networks to the Ministry of Health. On each monthly report, each local health network has to inform the health authority of the number of services provided on each clinic using a unified coding system. One of the features of these reports is that clinics have to report some services by the recipients' gender. For example, one of the services recorded is the total number of psycho-motor screening tests applied as part of *strengthening health control for integral development* component described in Section 2 of the paper. The second indicator recorded in these reports is the number of children

referred to stimulation services by age and gender due to lags in their development.

Figure 3 shows the ratio of children referred to stimulation services after evaluation at the national level. It is possible to observe a difference of at least 5% across child's gender for children 12 months and up. For example, suppose male children have worse results in their cognitive and motor skills assessments, and therefore, are referred more than female children. A possible explanation for these differential results comes from the following reasoning: estimated higher returns for boys are by a combination of differences in the probability of receiving services and differential returns. In Appendix A), we derive an expression for the treatment effect of exposure to the policy as a function of the treatment effect of receiving services (which is the parameter shown in previous that look at gender differences) and the probability of receiving services provided by the policy. Equation 6, shows the results of this exercise.

$$1 \quad < \quad \frac{Pr(S=1|M)}{Pr(S=1|F)} \frac{\Delta_{1M}}{\Delta_{1F}} \tag{6}$$

Using as a reference the differences observed in Figure 3, we can assume that $\frac{Pr(S=1|M)}{Pr(S=1|F)} > 1$. Therefore we can't conclude that the $\frac{\Delta_{1M}}{\Delta_{1F}} > 1$ since there is a set of values of $\frac{\Delta_{1M}}{\Delta_{1F}}$ for which the condition in Equation 14 still holds. Moreover, this difference in stimulation service referrals (based on their needs) across gender is only one of the multiple services offered by the policy. This analysis allows that the results presented in Table 4 still be consistent with previous results from the literature on early childhood interventions.

6   Conclusions and Further Discussion

During the last decades, research on early childhood interventions has shown their effectiveness in reducing early inequalities. However, when we think about implementing large-scale interventions to promote the flourishing of human capabilities and reduce inequalities of opportunities, beneficiaries could benefit from complementarities between interventions and clear guidelines on which is the most suitable action plan. These arguments are the reasoning behind the implementation of comprehensive child support systems. In 2007, the Chilean government started implementing the first comprehensive early childhood support system, Chile Crece Contigo, creating the institutional infrastructure to detect and provide children and their families services.

Our paper explores whether the availability of a large-scale system supports children and their families to promote their development in the first five years of life. To answer this question, we examine the educational outcomes in fourth-grade of the first generations of children that had access to the policy. Previous studies have looked only at short-term effects (birth outcomes) or medium-run outcomes (cognitive test. at age 3), so this paper is the first one looking at the most

recent outcomes for these children.

Our results show relevant returns for children exposed from prenatal care up to 5 years old compared to children ineligible to receive these services. Specifically, we observe gains in standardized test scores for language (0.23 of a standard deviation) and mathematics (0.2 of a standard deviation). Moreover, the exposure returns are concentrated in the first three years of life, consistent with the timetable of available interventions and detection instruments. Finally, when we look at the heterogeneity of these results across socioeconomic status and gender, first, we document minor differences across socioeconomic status. In the second place, we document higher returns for male students in mathematics for exposure before the 1-year old and in language test scores before the 2-year olds. Finally, we offer a possible channel for these differences based on the observed probability of receiving a recommendation of a stimulation intervention due to lags in cognitive development.

Based on these estimates, we can inform policymakers about the importance of this specific policy in advancing human capital accumulation. However, the challenges of this type of policy remain the ability to recover the average treatment on the treated (TOT) parameters. Other policies which consist of a single treatment, the recovery of this treatment parameter is relatively straightforward, combining the estimation results as Intention to Treat (ITT) parameters and take-up rates based on aggregate data (Bailey et al.). However, in the case of comprehensive support systems that combine multiple services with different bundles based on the child's need and their families, recovery of these parameters is complex. Appendix B derives an expression from recovering the bound for the 2-service case. Further analysis to disentangle the different mechanisms through Chile Crece Contigo (and all other policies implemented in the last decade) has improved human capital accumulation poses as an exciting avenue for future research.

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Figure 1: Roll-out dates distribution
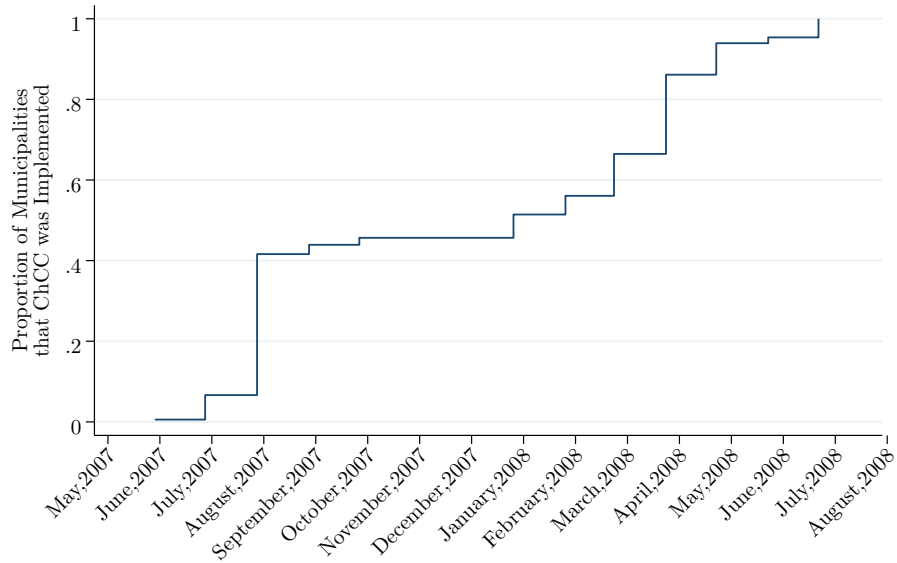
Note: Author's calculations based on entry dates from the Ministry of Social Development presented in Clarke et al. (2020).

Figure 2: Distribution of Age at Implementation of ChCC
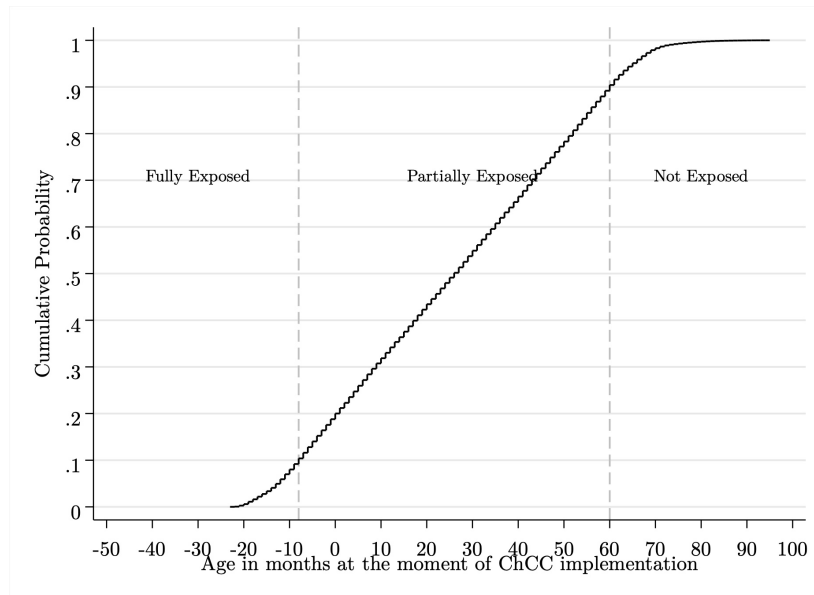
Note: The figure shows the distribution of the age of the child at the moment when ChCC was implemented A_{mt}. The implementation dates used to calculate this are the ones reported by Clarke et al. (2020) from the Ministry of Social Development.

Figure 3: Ratio of Tested Children Referred to Stimulation Services, by gender and age
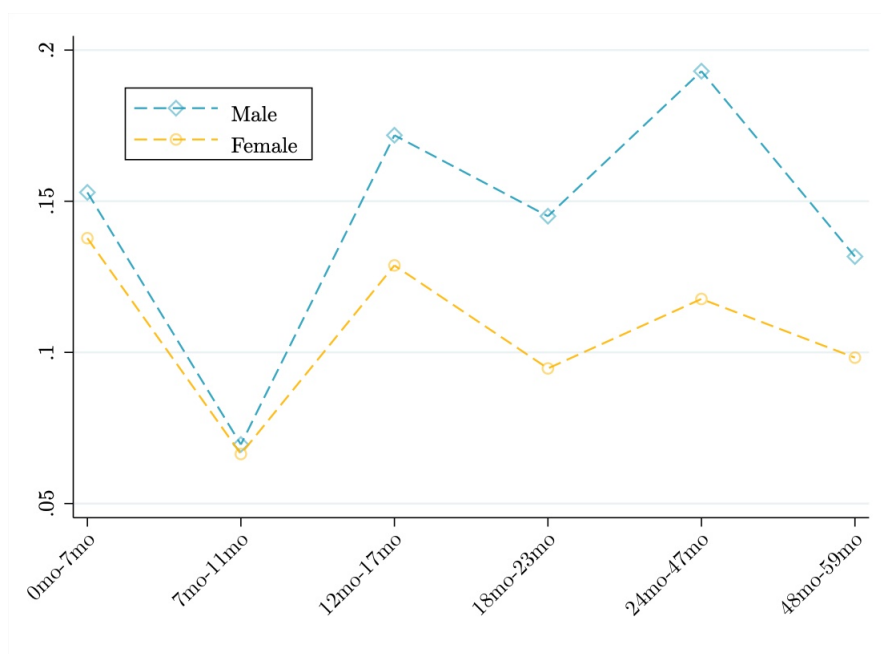
Note: Author's calculation based on the 2018 Monthly Statistical Reports from the Chilean Department of Health Statistics and Indicators (DEIS). Each point represents the proportion of children that a psycho-motor screening test was applied and receive a referral to assist to stimulation services. This can be calculated based on the sum of service code 06902601, 06902602, and 06902603 divided service code 02021740 for each age and gender group.

(a) Mathematics

(b) Language

(c) Annual Attendance

Figure 4: Event Study Parameters, full sample

Note: The parameters presented on each graph correspond to the point estimate of Equation 4. Each the coefficient correspond to the dummy variable associated with the age of the child i in municipality m when the ChCC local network was implemented. The figure only shows coefficients in the range (in months) [-19,70] to maintain a balanced sample in each cell. Children with ages below -8 are considered children who where fully exposed to the policy, from prenatal care to the age of five. And children ages 60 months and up are considered not exposed to the policy. The baseline coefficient of each graph are children 60 months old at the moment of implementation. The dashed line represents the confidence interval of each point estimate at the 95% of confidence using standard errors clustered at the municipality level.

(a) Mathematics

(b) Language

(c) Attendance

Figure 5: Splines Estimates

Note: The parameters presented on each graph correspond to the splines estimate of Equation 5. Children with ages below -8 are considered children who where fully exposed to the policy, from prenatal care to the age of five. And children ages 60 months and up are considered not exposed to the policy. The baseline coefficient of each graph are children 60 months old at the moment of implementation. The caps represents the confidence interval of each point estimate at the 95% of confidence using standard errors clustered at the municipality level.

(a) Mathematics

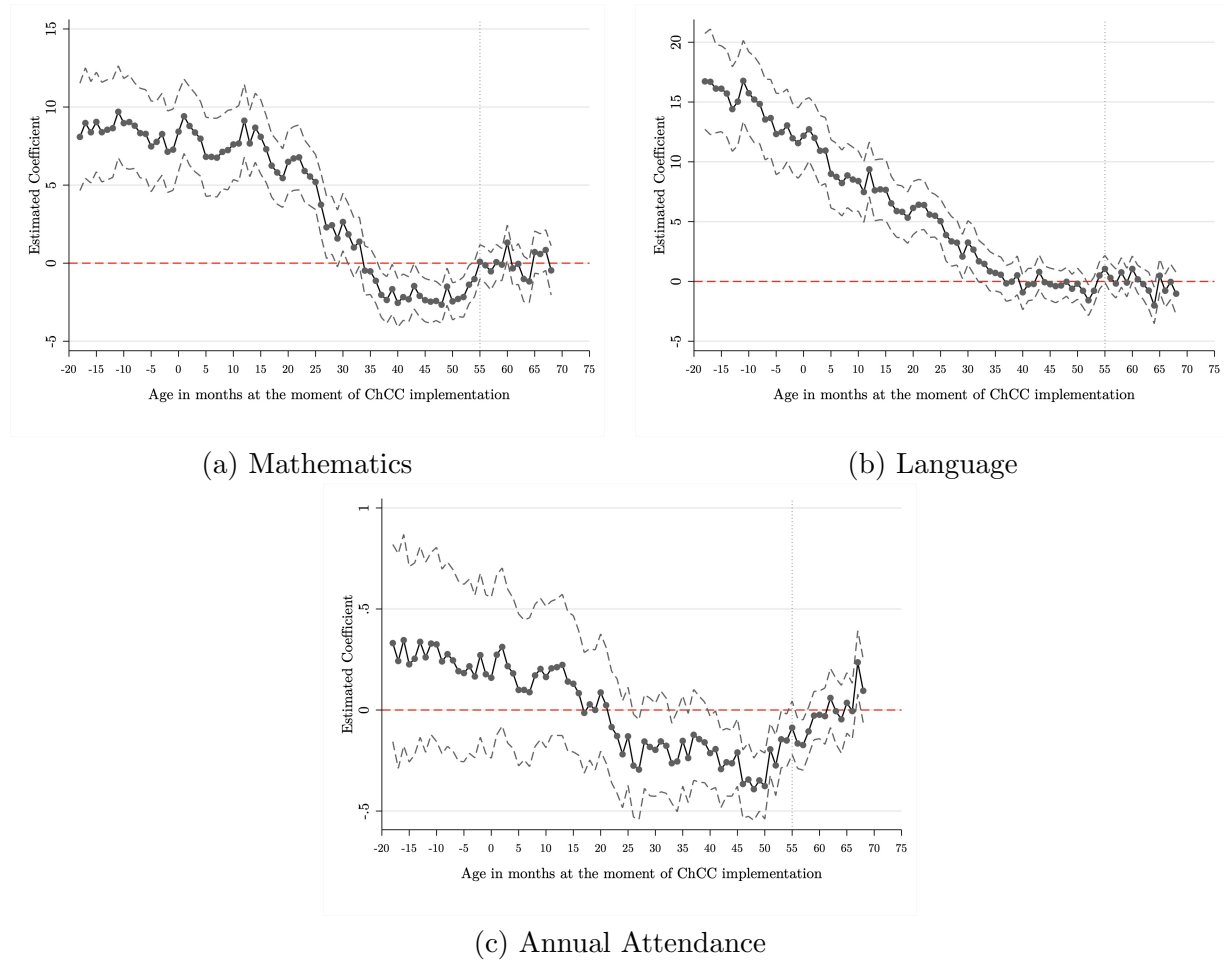(b) Language

(c) Annual Attendance

Figure 6: Event Study Parameters, by low-SES classification

Note: The parameters presented on each graph correspond to the point estimate of Equation 4 by the classification of *priority* received by the student by the Ministry of Education. Each the coefficient correspond to the dummy variable associated with the age of the child i in municipality m when the ChCC local network was implemented. The figure only shows coefficients in the range (in months) [-19,70] to maintain a balanced sample in each cell. Children with ages below -8 are considered children who where fully exposed to the policy, from prenatal care to the age of five. And children ages 60 months and up are considered not exposed to the policy. The baseline coefficient of each graph are children 60 months old at the moment of implementation. The dashed line represents the confidence interval of each point estimate at the 95% of confidence using standard errors clustered at the municipality level.
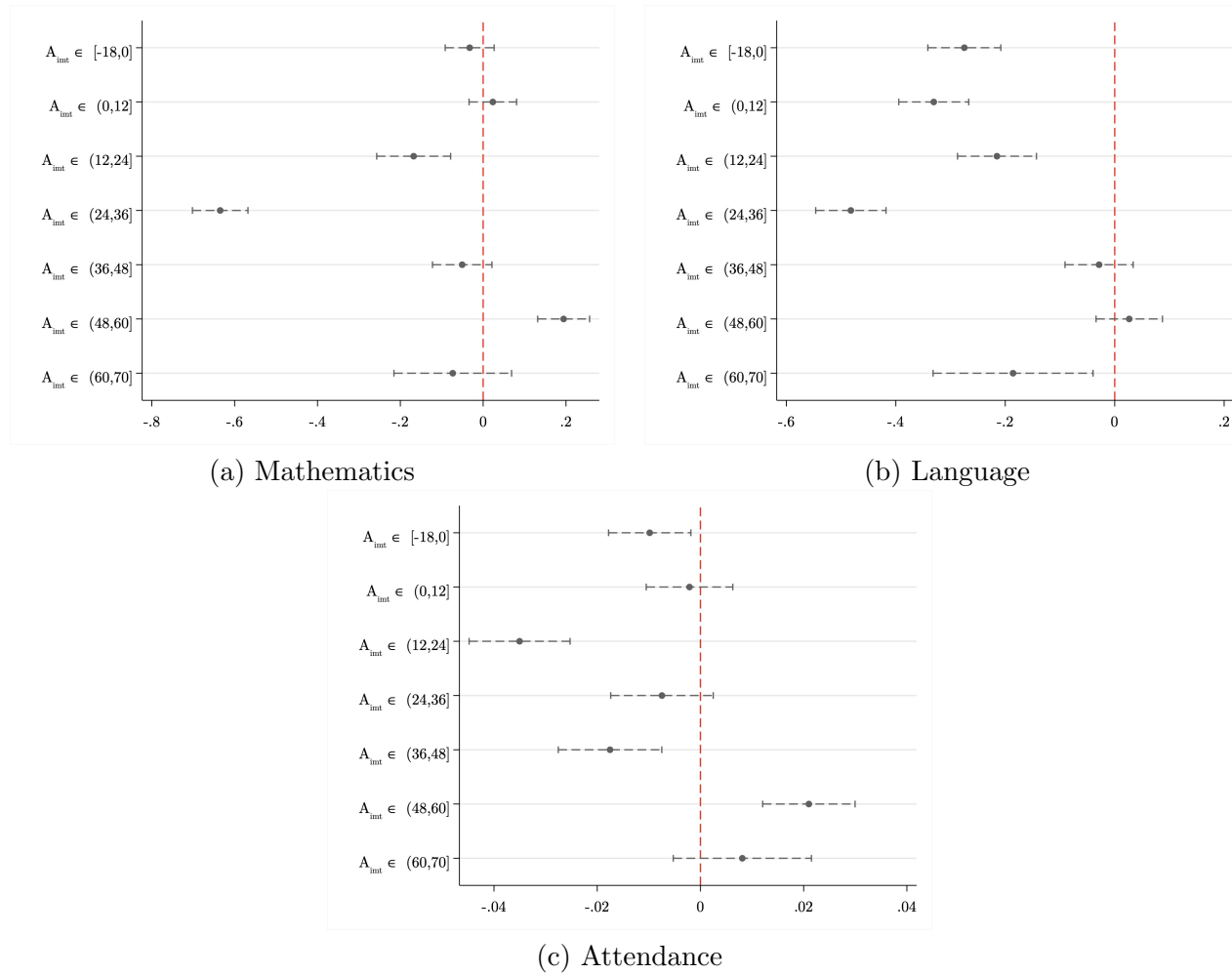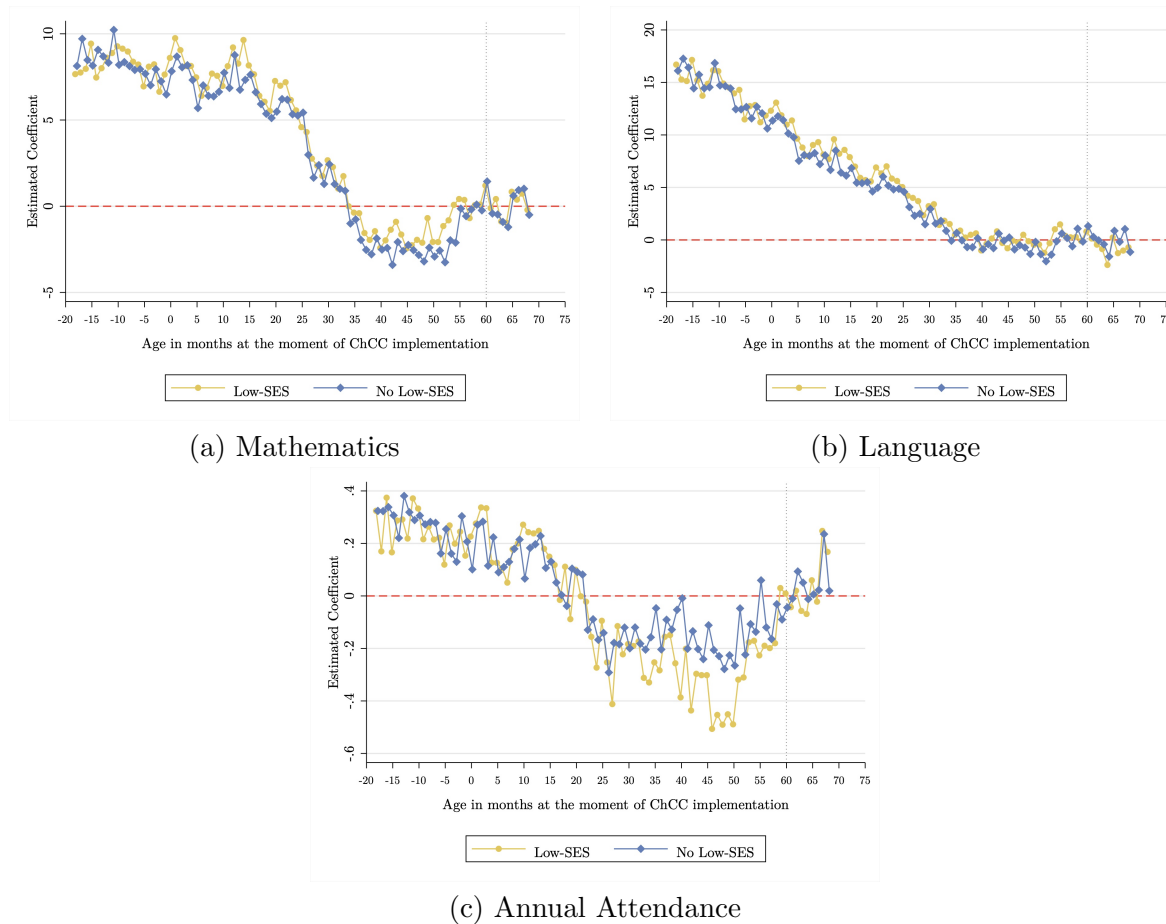
(a) Mathematics

(b) Language

(c) Annual Attendance

Figure 7: Event Study Parameters, by student gender

Note: The parameters presented on each graph correspond to the point estimate of Equation 4 individually for gender of the student. Each the coefficient correspond to the dummy variable associated with the age of the child i in municipality m when the ChCC local network was implemented. The figure only shows coefficients in the range (in months) [-19,70] to maintain a balanced sample in each cell. Children with ages below -8 are considered children who where fully exposed to the policy, from prenatal care to the age of five. And children ages 60 months and up are considered not exposed to the policy. The baseline coefficient of each graph are children 60 months old at the moment of implementation. The dashed line represents the confidence interval of each point estimate at the 95% of confidence using standard errors clustered at the municipality level.
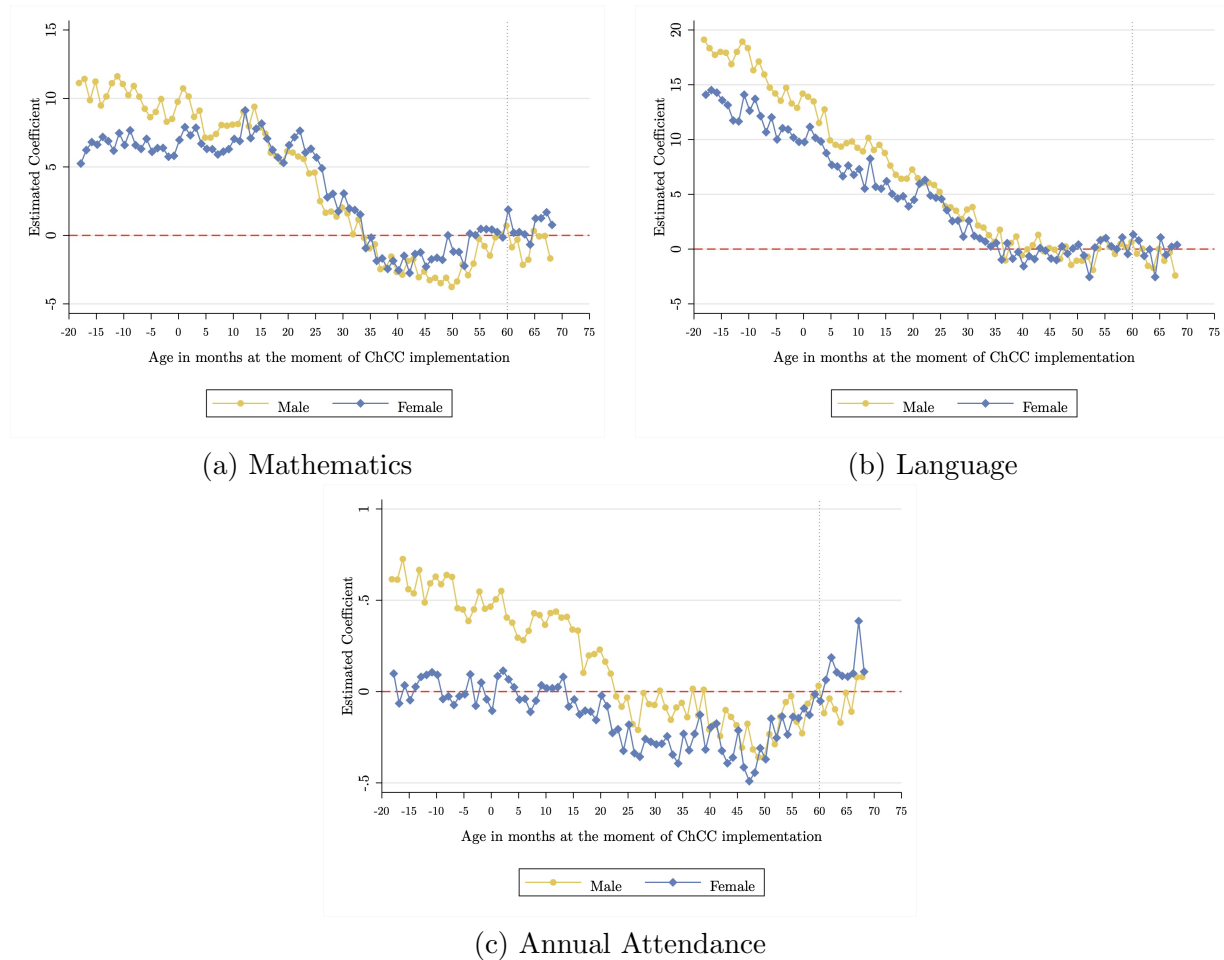
Table 1: Descriptive Statistics

	Full-Sample		Low-SES Sample		Fully Exposed		Not Exposed	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Outcomes								
Attendance	93.20	(5.89)	92.91	(6.21)	93.53	(5.70)	93.03	(6.19)
Language	266.04	(51.09)	258.98	(50.78)	270.50	(52.44)	263.45	(51.89)
Mathematics	260.76	(48.10)	253.71	(48.02)	261.99	(46.83)	259.07	(50.07)
Background Characteristics								
Gender (Male=1)	0.50	(0.50)	0.49	(0.50)	0.48	(0.50)	0.52	(0.50)
Attended PreK	0.88	(0.33)	0.85	(0.35)	0.90	(0.30)	0.79	(0.41)
Attended Kindergarten	0.95	(0.22)	0.93	(0.25)	0.94	(0.24)	0.89	(0.31)
Mother MS Dropout	0.09	(0.28)	0.13	(0.33)	0.06	(0.23)	0.13	(0.34)
Mother HS Dropout	0.23	(0.42)	0.30	(0.46)	0.19	(0.39)	0.28	(0.45)
Mother HS Graduate	0.38	(0.49)	0.38	(0.49)	0.42	(0.49)	0.36	(0.48)
Mother College Dropout	0.11	(0.31)	0.08	(0.28)	0.09	(0.29)	0.07	(0.25)
Mother Two-Year College	0.11	(0.32)	0.07	(0.26)	0.14	(0.35)	0.10	(0.30)
Mother Four-Year College	0.08	(0.28)	0.03	(0.17)	0.10	(0.30)	0.06	(0.23)
Low SES	0.51	(0.50)	1.00	(0.00)	0.51	(0.50)	0.50	(0.50)
Age	9.58	(0.58)	9.60	(0.60)	9.51	(0.51)	9.82	(0.66)
N	1,148,296		584,716		215,796		124,089	

Notes: The descriptive statistics presented in this table are based on all children in fourth grade between years 2012 and 2018. The universe of children is restricted to all student who has no missing values in all variables.

Table 2: Estimation Results of Cumulative Exposure to ChCC on Educational Achievement

	Attendance	Language	Mathematics
Exposure to ChCC IU-5	1.069	8.457	12.708
	(0.179)***	(1.557)***	(1.105)***
Low SES	-0.729	-4.527	-3.335
	(0.030)***	(0.116)***	(0.107)***
Gender (Male=1)	-0.071	-8.846	3.758
	(0.011)***	(0.163)***	(0.151)***
Mother HS Dropout	-0.238	3.754	3.946
	(0.028)***	(0.208)***	(0.186)***
Mother HS Graduate	0.294	10.780	10.914
	(0.032)***	(0.231)***	(0.248)***
Mother College Dropout	-0.312	14.234	13.173
	(0.041)***	(0.292)***	(0.280)***
Mother Two-Year College	0.264	14.972	14.123
	(0.037)***	(0.313)***	(0.322)***
Mother Four-Year College	0.140	22.192	20.359
	(0.040)***	(0.407)***	(0.403)***
R2	0.15	0.16	0.23
N	1,148,296	1,148,296	1,148,296
Municipality Dummy	Yes	Yes	Yes
Age Polynomial	Yes	Yes	Yes
School Dummy	Yes	Yes	Yes
Region Month of Birth Trends	Yes	Yes	Yes

Note: Each column is from a separate regression of Equation 3 of the outcome of interest with respect to the exposure of the child to the policy ChCC between IU and 5 years old (as the percentage of days exposed to the policy). Estimated standard errors clustered at the municipality level are in parenthesis.

Table 3: Estimation Results Differences across SES

	Attendance Low-SES	Attendance No Low-SES	Language Low-SES	Language No Low-SES	Mathematics Low-SES	Mathematics No Low-SES
Exposure to ChCC IU-5	1.515	0.600	8.632	7.711	13.267	11.877
	(0.228)***	(0.212)***	(1.686)***	(2.057)***	(1.304)***	(1.640)***
Gender (Male=1)	-0.068	-0.074	-9.173	-8.464	3.874	3.677
	(0.016)***	(0.015)***	(0.194)***	(0.173)***	(0.189)***	(0.167)***
Mother HS Dropout	-0.193	-0.360	3.925	3.153	4.081	3.440
	(0.030)***	(0.042)***	(0.227)***	(0.363)***	(0.215)***	(0.330)***
Mother HS Graduate	0.405	0.095	10.895	10.097	10.975	10.424
	(0.035)***	(0.041)**	(0.266)***	(0.335)***	(0.269)***	(0.364)***
Mother College Dropout	-0.231	-0.469	14.742	13.259	13.553	12.476
	(0.050)***	(0.049)***	(0.357)***	(0.394)***	(0.351)***	(0.367)***
Mother Two-Year College	0.276	0.146	15.497	14.045	14.177	13.606
	(0.049)***	(0.048)***	(0.363)***	(0.420)***	(0.374)***	(0.411)***
Mother Four-Year College	0.076	0.043	20.655	21.821	18.819	20.156
	(0.052)	(0.049)	(0.524)***	(0.491)***	(0.500)***	(0.488)***
R2	0.18	0.13	0.15	0.15	0.21	0.22
N	584,716	563,580	584,716	563,580	584,716	563,580
Municipality Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Age Polynomial	Yes	Yes	Yes	Yes	Yes	Yes
School Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Region Month of Birth Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column is from a separate regression of Equation 3 of the outcome of interest with respect to the exposure of the child to the policy ChCC between IU and 5 years old (as the percentage of days exposed to the policy). Estimated standard errors clustered at the municipality level are in brackets. Significance levels: *** 99%, ** 95%, * 1%

Table 4: Estimation Results Differences across Gender

	Attendance Male	Attendance Female	Language Male	Language Female	Mathematics Male	Mathematics Female
Exposure to ChCC IU-5	1.059	1.093	10.406	6.430	13.935	11.696
	(0.218)***	(0.241)***	(1.878)***	(1.774)***	(1.503)***	(1.337)***
Low SES	-0.727	-0.733	-4.464	-4.579	-2.955	-3.677
	(0.033)***	(0.030)***	(0.144)***	(0.146)***	(0.146)***	(0.130)***
Mother HS Dropout	-0.295	-0.188	3.230	4.278	3.428	4.425
	(0.038)***	(0.034)***	(0.273)***	(0.256)***	(0.248)***	(0.238)***
Mother HS Graduate	0.204	0.380	9.897	11.626	9.810	11.946
	(0.041)***	(0.035)***	(0.279)***	(0.290)***	(0.304)***	(0.280)***
Mother College Dropout	-0.399	-0.229	13.505	14.902	12.127	14.131
	(0.051)***	(0.047)***	(0.378)***	(0.349)***	(0.354)***	(0.324)***
Mother Two-Year College	0.152	0.373	14.243	15.677	13.164	15.028
	(0.045)***	(0.045)***	(0.369)***	(0.387)***	(0.402)***	(0.348)***
Mother Four-Year College	0.031	0.250	21.740	22.614	19.388	21.248
	(0.045)	(0.047)***	(0.460)***	(0.470)***	(0.446)***	(0.455)***
R2	0.16	0.15	0.16	0.16	0.23	0.23
N	569,441	578,855	569,441	578,855	569,441	578,855
Municipality Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Age Polynomial	Yes	Yes	Yes	Yes	Yes	Yes
School Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Region Month of Birth Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column is from a separate regression of Equation 4 of the outcome of interest with respect to the exposure of the child to the policy ChCC between IU and 5 years old (as the percentage of days exposed to the policy). Estimated standard errors clustered at the municipality level are in brackets. Significance levels: *** 99%, ** 95%, * 1%

Appendix A   Gender Differences and Referrals

As descried in Section 2, the services provided by the policy have a universal coverage for all children participating of the public health system. Some of the interventions offered by the policy, are universal in coverage but need to be referred by the health professional doing the assessment. We can write Equation 7 the return of the policy as the weighted average of improvement of children receiving services Δ^1 (because they need it), those not receiving them Δ^0 (because they did not need them).

$$\Delta = Pr(S = 1)\Delta_1 + (1 - Pr(S = 0))\Delta_0 \tag{7}$$

We can write Equation 7 for each group, male students (Equation 8) and female students (Equation 9).

$$\Delta_M = Pr(S = 1|M)\Delta_{1M} + (1 - Pr(S = 0|M))\Delta_{0M} \tag{8}$$

$$\Delta_F = Pr(S = 1|F)\Delta_{1F} + (1 - Pr(S = 0|F))\Delta_{0F} \tag{9}$$

Assuming that the returns for children not receiving services is zero $\Delta_{0M} = \Delta_{0F} = 0$, we can write the observed difference in return to the policy as:

$$\Delta_M - \Delta_F = Pr(S = 1|M)\Delta_{1M} - (Pr(S = 1|F)\Delta_{1F} \tag{10}$$

Based on the estimates results from Table 4, we know that $\Delta_M - \Delta_F > 0$. Rearranging Equation 10 we have

$$\underbrace{\Delta_M - \Delta_F}_{>0} = Pr(S = 1|M)\Delta_{1M} - Pr(S = 1|F)\Delta_{1F} \tag{11}$$

$$0 < Pr(S = 1|M)\Delta_{1M} - Pr(S = 1|F)\Delta_{1F} \tag{12}$$

$$(Pr(S = 1|F)\Delta_{1F} < Pr(S = 1|M)\Delta_{1M} \tag{13}$$

$$1 < \frac{Pr(S = 1|M)}{Pr(S = 1|F)}\frac{\Delta_{1M}}{\Delta_{1F}} \tag{14}$$

From Figure 3, can we can assume that $\frac{Pr(S=1|M)}{Pr(S=1|F)} > 1$, therefore we can't conclude that the $\frac{\Delta_{1M}}{\Delta_{1F}} > 1$ since there is a set of values of $\frac{\Delta_{1M}}{\Delta_{1F}}$ for which the condition in Equation 14 still holds.

Appendix B   From ITT to ATT

One important distinction about the estimates in Section 5 is the interpretation as program evaluation parameters. The empirical strategy used defined the treatment to the policy as availability of the policy in the municipality since certain age. As explained in Section 2, the program has universal coverage for all children attending the public health system. Our sample is based on all children attending public schools and private subsidized schools (around 93% of school enrollment), and as we mention in Section 3 not all children in this type of schools were born in public hospitals (as a way to measure participation in the public health system). The rate for each type of school was 85% and 69% correspondingly. This don't restrict children in the private system to participate in services of the policy, since the public health system can not reject patients based on their type of health insurance. Based on this, it is possible to interpret the estimated coefficients as the effect of being exposed to the policy (Equation 15).

$$\Delta = E[Y|D=1] - E[Y|D=0] \tag{15}$$

As explained earlier, the enrollment is automatic for children in the public health system (and opt-in for children in the private health system) services and material offered by ChCC should be accepted by the parents and caregivers. If the policy evaluation parameter that we are interest is the effect on outcomes produced by the services provided by the policy, parameter δ would be the Intention-to-Treat parameter. Since the data available does not allow us to connect program participation and information from the Ministry of Education, it is possible to use aggregate data to estimate the probability of access to services.

In the description of the structure of ChCC, we describe that services and material delivered through the policy can be classified into two categories: universal access and assessment-based. The first one, are offered to all children under the policy and parents need to decide to receive this universal service $Pr(T=1|U)$. The second set of services, assessment-based services, are services only referred for children (and families) for whom is determined they need a specific intervention based on a standardized assessment. For example, the stimulation interventions are offered to children who scored below a certain threshold of the psycho-motor evaluations performed at the primary care appointments. After the referral is made, parents need to take the decision to attend the intervention or not. Formalizing this, a child that is determined to need a specific service will be denoted as $N=1$, and $N=0$ otherwise. If parents, decide to attend the intervention $T=1$ and $T=0$ if they don't.

If we formalize these features of the policy, into the policy evaluation parameters framework we can write the estimate of our empirical results as Equation 16. In this equation we can think of the parameter estimated as the weighted effect of exposure to universal services (U) and need-based

services (N). For each one of these services we can write the change in outcomes as the weighted average between who where exposed and received services $U = 1$, and those who don't in the case of universal services $U = 0$. In the case of need-based interventions, we can write the change on outcomes as a weighted average between children who need these services $(N = 1)$, and children who don't $N = 0$

$$
\begin{aligned}
\hat{\Delta} &= \omega E[\Delta|U] + (1-\omega)E[\Delta|N] \qquad &(16)\\
&= \omega\Big(E[\Delta|U=1] \times Pr(U=1) + E[\Delta|U=0] \times Pr(U=0)\Big) + \\
&\quad (1-\omega)\Big(E[\Delta|N=1] \times Pr(N=1) + E[\Delta|N=0] \times Pr(N=0)\Big) \qquad &(17)
\end{aligned}
$$

Assuming that children who do not received services, should not have any change on their outcomes we assume $E[\Delta|N=0] = 0$. On the other hand, children without a need-based service will not receive any need-based service, allowing us to assume that their outcomes should not experience any change $E[\Delta|N=0] = 0$. These assumptions leave us with the following expression.

$$
\hat{\Delta} = \omega\Big(E[\Delta|U=1] \times Pr(U=1)\Big) + (1-\omega)\Big(E[\Delta|N=1] \times Pr(N=1)\Big) \qquad (18)
$$

As we know, children who based on the assessments at the local health center are classified as children with specific interventions, after parents receive a referral they need to make an active decision to participate in the intervention $S = 1$. With this in mind, we can write the expected value of changes in outcomes for children in need, as the weighted average between children who attend the intervention and children who didn't. Assuming that children not attending should not have changes on their outcomes we can rewrite Equation 20 as Equation 21

$$
\begin{aligned}
E[\Delta|N=1] &= \big(E[\Delta|N=1, S=1] \times Pr(S=1|N=1)\big) + \qquad &(19)\\
&\quad \big(E[\Delta|N=1, S=0] \times Pr(S=0|N=1)\big) \qquad &(20)\\
E[\Delta|N=1] &= \big(E[\Delta|N=1, S=1] \times Pr(S=1|N=1)\big) \qquad &(21)
\end{aligned}
$$

Finally, substituting the results from Equation 21 into Equation 18 we have the following expression for out estimate of changed in outcomes.

$$
\hat{\Delta} = \omega Pr(U=1)E[\Delta|U=1] + (1-\omega)Pr(N=1)Pr(S=1|N=1)E[\Delta|N=1, S=1] \qquad (22)
$$

In Equation 22 it is possible to observe that our estimate can be written as weighted average of the Average Treatment on the Treated of two different services. The values for $Pr(U=1)$, $Pr(N=1)$,

and $Pr(S = 1|N = 1)$ can be recovered from aggregate data. The expression presented poses a technical difficulty in which, the number of unknowns is larger than the number of equations.