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Middle-run Impacts of Comprehensive Early Childhood Interventions: Evidence from a Pioneer Program in Chile*

Abstract

This paper analyzes the impact of comprehensive and universal early childhood development programs on outcomes in middle childhood. I exploit the birth eligibility cutoff of a pioneer intervention of this type in Chile and use administrative data on grade point averages, standardized test scores, and an extensive early childhood development survey. Program exposure raises standardized math scores by 1.8 percent of a standard deviation, standardized reading scores by 4.0 percent of a standard deviation and grade point averages by 0.03 percent of a standard deviation. However, the effect is less pronounced for girls and socioeconomically vulnerable children. Impacts on several other child development outcomes also differ by gender and socioeconomic status. A cost-benefit analysis suggests that targeted programs might be more cost-effective than comprehensive programs.

JEL Code: I24, I28, I38, J13, J24, O15
Keywords: Education and inequality; government policy; children; human capital

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1 Introduction

There is substantial evidence showing that the first years of a child's life lay the basis for sustainable development (Daelmans et al. 2017). It is these early years during which children lay the foundation for their human capital accumulation and labor market outcomes during the rest of their lives (Currie and Almond 2011). At the same time, estimates by the World Health Organization (2020) find that 250 million children, or 43 percent of all children from low- and middle-income countries, were unable to fulfill their full development potential in 2016, a worrisome finding given the importance of childhood development for sustainable growth.

While there is an increasing literature studying the potential of early childhood interventions to close these development gaps, the focus is mainly on targeted programs.[1] However, several scholars have recently pointed out the need for universal and comprehensive early childhood development (ECD) programs (Richter et al. (2017); Black et al. (2017); Daelmans et al. (2017)). Comprehensive ECD programs are interventions that incorporate multi-sectoral entry points, which include a variety of coexisting components, such as health, nutrition, security and safety, responsible care, and early learning.[2] However, to date, there is limited evidence on the effectiveness of these types of programs, largely due to the absence of such programs and data limitations.

This paper provides novel evidence on the effects of universal and comprehensive early childhood interventions by quantifying the impact of a pioneer ECD program of this type, *Chile Crece Contigo*[3] (hereinafter ChCC), on multiple measures of child development. ChCC was rolled out in 2007 as one of the first comprehensive and universal ECD programs. Using administrative data on grade point averages for the entire student population in Chile and standardized test scores in reading and math of all 4th graders, I analyze the program's impact on educational outcomes in middle childhood 12 years after its introduction.

In a second step, I leverage data from the Longitudinal Survey of Early Childhood (ELPI), which contains rich and standardized information on child development outcomes and the home environment of children, to investigate potential channels behind my findings on educational outcomes. Following the current state of the literature and the multi-sectoral setup of the program, I explore three key channels, which could drive my results. First, based on

[1]Examples include the Perry Preschool program (Heckman et al. 2010), the Jamaica study (Gertler et al. 2014), the Abecedarian experiment (Campbell et al. 2014), or targeted programs in Colombia (Attanasio et al. 2020).

[2]The researchers highlight that families who cannot provide their children with the necessary input to reach their developmental potential need support. This support should consist of materials, financial resources, knowledge, time and professional assistance, as well as protection, prevention and education.

[3]In English: Chile Grows With You.

work by Cunha, Heckman, and Schennach (2010) showing the importance of cognitive and non-cognitive skills for school performance, I investigate ChCC's impact on these skills. Second, following the literature on the significant influence of the home environment on learning outcomes (Currie and Almond (2011); Almond, Currie, and Duque (2018)), I analyze its effects on parent-child relationships and the home environment. Third, given the work on the impact of early childhood education (Temple and Reynolds (2007); Carneiro and Ginja (2014); Williams (2019)), I analyze if ChCC results in increased attendance rates in early childhood education facilities.

ChCC is a pioneer program based on two characteristics. First, the program is universal, meaning that it targets the full universe of children in Chile. Children are integrated into the program from the first prenatal checkup until they enter the school system. Second, ChCC takes a comprehensive approach. This means that ChCC offers a variety of services to children and their families, such as access to the public health system, technical help, nurseries, kindergartens, and the *Chile Solidarity* program, which supports vulnerable families. ChCC gives families preferential access to the whole network of social services of the State. Thus, ChCC implemented an approach which was recently identified as a best practice for child development in the literature already back in 2007. Hence, I can examine whether these best practices do indeed work as predicted by experts. To the best of my knowledge, this is the first paper to study the overall impact of ChCC on child development in middle childhood.

Studying ChCC is of high policy-relevance since it has been the basis for the design of several similar programs in numerous countries.[4] It is one of the showcase models used by international organizations (Richter et al. 2017). Chile offers a relevant context for the underlying research question as it is a benchmarking country for Latin American countries, but also other developing countries.[5] To date, there is only one other paper studying the effect of ChCC by Clarke, Méndez, and Sepúlveda (2020). Unlike my work, Clarke, Méndez, and Sepúlveda (2020) study the effect of one specific component of *Chile Crece Contigo* on different health variables at birth. They find that the health components of ChCC have a positive effect on birth weight and the rate of fetal deaths.

My empirical strategy exploits the birth eligibility cutoff of the program. I apply a regression discontinuity approach by matching the date of ChCC's introduction by municipality with children's dates of birth and places of residence. I create a staggered eligibility threshold based on treatment variation by county and birth cohort. This staggered eligibility threshold allows me to compare children born before and after the program's roll-out. To

[4] ChCC has inspired similar programs in Colombia, Peru, Uruguay, El Salvador and South Africa (Ministry of Health 2017).

[5] Chile is a high-income OECD member country in Latin-America. Although it joined the OECD in 2010, it is still considered a developing country (United Nations 2022).

limit concerns about potential treatment manipulation, I show that there is no discontinuity around the cutoff. Besides, in the setup of this paper, treatment manipulation might be of low concern given that the staggered roll-out of ChCC took place at the monthly level and it might be difficult to time the birth of children to an exact month. I also provide suggestive evidence that children around the cut-off are similar to each other, at least on observable characteristics. In addition, I build upon approaches by Almond, Hoynes, and Schanzenbach (2011), Hoynes, Schanzenbach, and Almond (2016) and Bailey et al. (2020) and estimate an event study to confirm results from my regression discontinuity design (RDD). They also hold when estimating a linear local randomization approach. I verify that my findings are robust to varying the size of bandwidth, different polynomial specifications, the financial crisis in 2008, the development of copper prices, migration patterns, school entry dates, and children's maturity.

I find that the program has positive effects on educational outcomes. Program exposure increases standardized math scores by 1.8 percent of a standard deviation, standardized reading scores by 4.0 percent of a standard deviation and grade point average by 0.03 percent of a standard deviation. Analyzing potential mechanisms behind these positive effects suggests that they are due to important improvements in intra-household relations and raising attendance rates in early childhood facilities. I do not find evidence in favor of improved cognitive and non-cognitive skills.

I examine heterogeneity in my estimates by sex and socioeconomic status. Overall, improvements in school performance are more marked for boys. Standardized math scores increase by 2 percent of a standard deviation for boys (1.6 percent for girls), standardized reading scores by 4.3 percent of a standard deviation (3.6 percent for girls) and grade point averages by 3.4 percent of a standard deviation (2.5 percent for girls). The program's impact on educational outcomes is larger for socioeconomically non-vulnerable children. Standardized math scores increase by 3.5 percent of a standard deviation for the non-vulnerable (1.3 percent for the vulnerable), standardized reading scores by 6.0 percent of a standard deviation (versus 3.2 percent) and grade point averages by 6.4 percent of a standard deviation (versus 2.0 percent). These results indicate that pre-existing gaps between different socioeconomic groups could increase under comprehensive, universal early childhood development programs.

The heterogeneity in effect sizes could be partly driven by the fact that the program's impact on potential mechanisms behind improved schooling outcomes differs by socioeconomic group. For girls, I find significant improvements in several of the parental outcomes investigated. The program also raises girls' executive functioning.[6] For boys, I find sig-

[6]Executive functioning refers to mental skills, which allow us to remember instructions, to mentally play

nificant improvements in the availability of learning material at home. Moreover, there is some evidence pointing towards increased attendance rates in early childhood education for boys. There are significant differences by socioeconomic group. I find barely any beneficial effects for socioeconomically vulnerable children. They experience improvements in their executive functioning, but there are no changes in parental outcomes or attendance rates in early childhood education facilities. In addition, they even experience some adverse effects with respect to dental care and the space at home available for toys. In contrast, the more privileged children report improvements in several of the parental outcomes and the home environment as well as increased attendance rates.

My analysis has important implications for valuing ChCC as a long-term public investment. To assess the cost-effectiveness of the program, I follow Hendren (2016) and Hendren and Sprung-Keyser (2020) and calculate the program's Marginal Value of Public Funds (MVPF), which is the benefit of the policy in relation to its net costs. I find that ChCC's MVPF is 1.41. The value is low in comparison to the MVPF for early childhood interventions in the US, such as the Food Stamps, the Perry Preschool Program and the Carolina Abercedarian (Hendren and Sprung-Keyser (2020); Bailey et al. (2020)). The relatively low MVPF for ChCC indicates that targeted and more specific early childhood interventions might be more cost-effective.

My paper contributes to the literature studying effects of having access to social safety nets during early childhood. While one literature stream analyzes the impact on health outcomes early in life[7], a large number of papers assess long-term effects[8]. My paper talks to this literature by exploring the potential of multi-sectoral early childhood interventions. Additionally, most of the work in this field focuses on the developed world.[9] I generate evidence on impacts of ECD programs in developing countries. Another contribution of this paper to the existing literature on ECD is that it analyzes outcomes in middle childhood. Almond, Currie, and Duque (2018) identify a lack of research focusing on middle childhood within this field. My work helps to close this gap by showing that there is a significant interaction between early childhood development and development outcomes in middle childhood.

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with ideas and to plan.

[7]See for example work by Ludwig and Miller (2007), Almond, Hoynes, and Schanzenbach (2011), Hoynes, Page, and Stevens (2011), Amarante et al. (2016), Goodman-Bacon (2018), Ko, Howland, and Glied (2020).

[8]Example studies conducted by Chetty et al. (2011), Campbell et al. (2014), Hoynes, Schanzenbach, and Almond (2016), Akee, Jones, Simeonova, et al. (2020), Bailey et al. (2020), Bailey, Sun, and Timpe (2021), Brown, Kowalski, and Lurie (2020) and Goodman-Bacon (2021) give a great entry to the topic.

[9]One paper by Amarante et al. (2016) analyzes the effect of the PANES program on birth outcomes in Uruguay.

2 Institutional Background and Program Description

2.1 Inequality and Human Capital Gaps in International Context

Chile is a high-income OECD member country in Latin-America. Although it joined the OECD in 2010, it is still considered a developing country (United Nations 2022). This is mainly because of high levels of inequality. While its GDP per capita stood at approximately 25,000 US-Dollar (after adjusting for purchasing power parity in constant 2017 US-Dollar) in 2019, a value close to Bulgaria's GDP per capita, its Gini coefficient is close to the one of other very unequal countries like Mexico or Bolivia (World Bank Group 2022). The persistently high levels of inequality are reflected in low social mobility. Chile only ranks 47th out of 82 countries on the *Global Social Mobility Index* by the World Economic Forum (2020).[10]

Human capital gaps are persistent in Chile. According to the *Human Capital Index* by the World Bank Group (2022) a child is only 65 percent as productive in adulthood as it could be if it enjoyed full access to education and health. This positions the country in the upper second quintile when compared globally. It performs similarly when restricting the index to harmonized test scores or learning-adjusted years of schooling. Educational attainment rates in primary and secondary schooling are close to the Latin-American and OECD average (World Bank Group 2022). Gross enrollment rates in preprimary education stood at 85 percent in 2019, a value slightly above the OECD average and 8 percentage points higher than the Latin-American average (World Bank Group 2022).

To summarize, Chile presents a highly relevant setting for the underlying research question. Not only is it characterized by persistent inequality and human capital gaps, which is the main motivation of this study. Chile is also a widely used bench-marking country for developing countries, especially in the Latin-American region. Comparisons to OECD countries are also reasonable.

2.2 Institutional Background of Early Childhood Development

Early childhood development has been one of the priorities of Chilean politics since the 20th century. As a result, child mortality decreased from 370 per 1,000 births in 1900 to 7.6 per 1,000 births in 2006 (Villalobos 2011). In 2001, Chile introduced its *Integrated Action Plan for Early Childhood and Adolescence*. The plan involved the creation of a public institution with the task of informing the presidency about the progress in the implementation of chil-

[10] Chile assumes a score of 60.3 on the index. In comparison, the US ranks 27th with a score of 70.4 (World Economic Forum 2020).

dren's rights. The institution was established in 2003, at the same time as *Chile Solidario*[11].

In 2006, there were still persistent gaps in early childhood development.[12] This led to the establishment of the *National Advisory Council for the Reform of Policies for Children* in 2006. The mission of the council was to develop a social protection system for early childhood development, laying the foundation for *Chile Crece Contigo*, which President Bachelet announced in October 2006 (Villalobos 2011).

2.3 Program Description

Chile Grows with You (ChCC – *Chile Crece Contigo*) is a comprehensive early childhood protection system which, alongside the social sub-programs *Chile Cuida* and *Chile Seguridad y Oportunidad*, is part of the overall social protection system of the Chilean government. The aim of the program is to accompany, protect and support all children and their families in an integrated manner. The program operates via an integrated network, combining services of several public sector institutions. It was introduced in 2007 with the goal of reducing inequalities during the first years of a child's life in Chile.

ChCC offers a variety of social services for children in their early life stages. The services offered through the program are adapted to the different needs that develop at each stage of life. It also addresses the needs of families, pregnant women, primary caregivers, and the family as a whole. The program is a universal program offered to all children and is part of the public health system (Asesorías para el Desarrollo 2012). Originally, children entered the program at their mother's first prenatal examination and left when they entered kindergarten or preschool. The program was expanded to include children from five to nine years of age in 2017.

ChCC is a program with a strong socioeconomic development focus, trying to address cognitive, emotional as well as behavioral lags in children's development through the program's comprehensive health, education and parental approach. Parental investment, cognitive as well as emotional stimulation, and a comprehensive health program are the entry points of

[11] *Chile Solidario* is the social protection system for the poor population in Chile. It offers several programs and services aimed at improving the living conditions of these people.

[12] The 2006 socioeconomic household survey (CASEN) showed that 21.9 percent of children under the age of four lived in poverty, a higher share than in the overall population (13.7 percent) (Villalobos 2011). Moreover, the National Survey on Life Quality and Health revealed some troubling results. The study found that 30 percent of children below five years old did not meet internationally established development goals, and it revealed that significant developmental gaps existed between income quintiles with respect to child development (Villalobos 2011). Another gap was observed in early education. Coverage of early education in general was low. Only 26.5 percent of children between two and three years old attended kindergarten, while only 6 percent of children under two attended pre-kindergarten (Villalobos 2011). The gaps between income quintiles were marked, with four times more children from the top quintile attending early education facilities than children from the bottom quintile (Villalobos 2011).

ChCC to foster children's development. It therefore diverges from programs trying to lift people out of poverty through cash transfers.

The implementation approach of ChCC is an integrated one, recognizing that the municipality is the environment which forms and fosters the development of its children. The entry point and first contact point with the target population is the health sector, mainly through the Biopsychosocial Development Programme (PADB). The services offered through the program fall into three categories: An educational program for the Chilean citizenship and children's caregivers with the goal of raising awareness of the importance of early childhood development; services for children under the Biopsychosocial Development Programme PADB (Programa de Apoyo al Desarrollo Biopsicosocial), benefiting children from the womb to age four; special services for children belonging to the lowest 40th percentile in terms of income or non-income vulnerabilities.

Appendix B presents a detailed list of the services provided through ChCC. The focus program of ChCC is the PADB, through which all children enter the program.[13] The main changes that ChCC implemented in early childhood services are the following: an increase in the time for prenatal screenings from 10-20 minutes to 40 minutes and the inclusion of psychosocial factors in risk assessments, additional to biomedical factors; a comprehensive home visit program for at-risk patients; educational workshops on pregnancy and parenting as well as the distribution of educational materials; a guarantee of personalized services during childbirth; the availability of local facilities to care for at-risk children or children with developmental delays; the development of a local network to address all children's needs (The World Bank 2018).

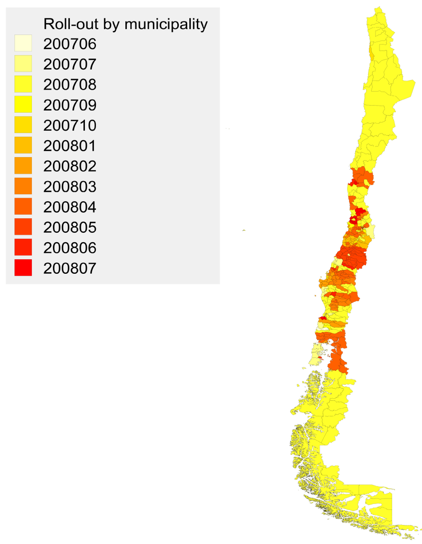
ChCC's roll-out was gradual at the municipality by month level. The system was first implemented in 159 municipalities which were best prepared for its implementation. Experiences gained in the first round of roll-outs were then used for program implementation in the remaining municipalities during the second phase of ChCC's roll-out. Geographically, the roll-out of ChCC was dispersed as shown in Figures 1 and 2.

The inclusion of beneficiaries was also gradual (see Appendix A). First, the first generation of women was included in the system. In the next year, the second generation of women and all newborns were included in the system. By 2011, the system included all pregnant women and children under four years of age. The system also introduced different services gradually, to reflect the aging of beneficiaries. The roll-out of activities took place gradually targeting children according to their age. The system immediately offered these services to

[13] Importantly, ChCC did not introduce all services listed in the Appendix, but enhanced them, developed them further, increased their scope and coverage, and improved their coordination and linkage with each other.

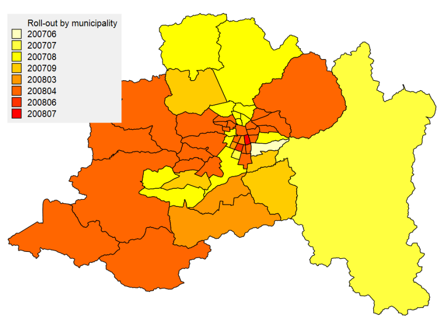
the whole target population. In the first year, the program mainly provided services for pregnant women and newborns. Importantly, there was strong compliance in ChCC's roll-out. Children born slightly before and after program implementation did not form part of ChCC.

Figure 1: Geographic roll-out of ChC



Notes: The figure plots ChCC's roll-out over time by municipalities in Chile. ChCC's roll-out took place at the month by municipality level. Importantly, there was strong compliance in the monthly roll-out and the exclusion of children born slightly before the program. Source: Clarke, Méndez, and Sepúlveda (2020).

Figure 2: Geographic roll-out of ChCC (metropolitan area of Santiago de Chile)



Notes: The figure plots ChCC's roll-out over time by municipalities in the metropolitan area of Santiago de Chile. ChCC's roll-out took place at the monthly basis at the municipality level. Source: Clarke, Méndez, and Sepúlveda (2020)

3 Previous Literature on Early Childhood Development

This paper contributes to three different strands of the existing literature.

First, my results empirically manifest predictions made by theoretical models of early childhood development, such as those developed by Heckman (2006) and then later Almond, Currie, and Duque (2018). Heckman (2006) states that early investments strongly affect the productivity of later inputs and that they are dynamic complementarities[14] rather than perfect substitutes (Cunha and Heckman 2007). Consequently, investments in early childhood are especially important. The framework developed by Almond, Currie, and Duque (2018) confirms this. The authors highlight that a reallocation of resources from later to earlier in life creates pareto improvements. My results show that investments made in early childhood translate into positive human capital outcomes in middle childhood. Thus, my findings confirm the theory of dynamic complementarities.

Moreover, my paper builds on previous research showing positive effects of having access to social safety nets. The program design of ChCC links the paper at hand to this literature by comparing these findings on the impact of specialized social safety nets to a comprehensive ECD program. To the best of my knowledge there is only one paper so far analyzing the causal effect of ChCC. Clarke, Méndez, and Sepúlveda (2020) study the neonatal health component of *Chile Crece Contigo* and show that it has significant positive effects on birth weight and other early human capital outcomes.

Several studies within the literature on social safety nets focus on infant health. Almond, Hoynes, and Schanzenbach (2011), for example, show that participation in the Food Stamp Program three months prior to pregnancy leads to increased birth weight, with the largest gains at the lowest birth weights. Similarly, Hoynes, Page, and Stevens (2011) show that the implementation of WIC results in an increase in average birth weight. Related to that Amarante et al. (2016) study the effects of transfers to poor pregnant women in Uruguay, that are part of the PANES program. They find that the incidence of low birth weights decreases by 20 to 19 percent. A paper by Goodman-Bacon (2018) analyzes the effect of Medicaid on infant and child mortality. The paper shows that infant and child mortality decline due to the program. Ko, Howland, and Glied (2020) examine the Supplemental Security Income (SSI) program, which includes cash transfers for poor children with disabilities. They find positive effects on a variety of health outcomes for children in the first eight years of life.

A related literature studies the impact of social safety nets on other dimensions besides

[14] Dynamic complementarities refer to the fact that early inputs in human capital affect the productivity of later inputs, a phenomenon that Cunha and Heckman (2007) call self-productivity.

infant health. Milligan and Stabile (2011) study the effect of an increase in child benefits, that translates into higher family income. They find significant positive effects on test scores, maternal health, and mental health, among other measures, with significant differences by gender.[15] Similarly, Akee et al. (2018) evaluate the impact of quasi-experimental unconditional household income transfers on children's emotional and behavioral health and personality traits, as well as on parental relationships. They find large positive effects.

Similarly, a connected stream of literature looks at the long-term impact of access to social safety nets during early childhood. Chetty et al. (2011) investigate the effects of the project STAR during kindergarten on earnings and find positive effects. Hoynes, Schanzenbach, and Almond (2016) illustrate that participation in the Food Stamp Program leads to a reduction in the incidence of metabolic syndrome and an increase in economic self-sufficiency. Bailey, Sun, and Timpe (2021) study the long-term effects of the Head Start program[16]. Deming (2009) follows up and finds positive effects on adult human capital, adult economic self-sufficiency, the quality of adult neighborhoods and an increase in life-expectancy. The program leads to a large increase in adult human capital and economic self-sufficiency. The author demonstrates a positive effect of 0.23 standard deviations on a summary index of young adults' outcomes. Moreover, Akee, Jones, Simeonova, et al. (2020) study how the EITC program affects the next generation. They find significant and mostly positive effects, varying by household type and gender. Similarly, Brown, Kowalski, and Lurie (2020) study the effects of childhood Medicaid and find positive effects on college enrollment, wage income and lower mortality, while Goodman-Bacon (2021) shows that it reduces mortality and disability and increases employment in the long-run. Related work by Bharadwaj, Eberhard, and Neilson (2018) documents positive effects of parental investment on academic outcomes.

Most of the interventions outlined in the literature above focus on the effect of income or in-kind transfers on children's short or long-term outcomes. Additionally, most of them are located in developed countries like the US or Canada. My paper contributes in that it goes beyond looking at the income component of child development by studying a comprehensive, integrated early childhood intervention. It also examines whether the positive effects found in the literature to date also apply to developing countries, where human capital needs are greatest.

Next, my work builds on previous research studying the effect of policy interventions for children. Two examples are the well-known Perry Highschool Project[17] (Heckman et al.

[15]While benefits have stronger effects on educational outcomes and physical health for boys, for mental health, they are larger for girls.

[16]Head Start is a nationwide preschool program for poor children in the US, established in 1965 as part of the federal government's "War on Poverty".

[17]The Perry Highschool Project is a pre-school intervention targeting socioeconomically disadvantaged

(2010) or Heckman, Pinto, and Savelyev (2013)) and the ABC/CARE program (García, Heckman, and Ziff 2018). In the same way, Attanasio et al. (2020) study the impact of a targeted early childhood intervention in Colombia and find significant gains in cognitive and socio-emotional skills among disadvantaged children. Felfe and Lalive (2018) analyze the expansion of early child care in Germany, showing strong but diverging effects on children's motor and socio-emotional skills. Most of these interventions are programs that target vulnerable children. My work contributes by asking whether universal programs can have similar effects and how they differ.

While there is a number of papers that investigate the effects of universal childhood interventions, none of these interventions follows the comprehensive approach of ChCC. Moreover, most of these studies analyze ECD programs in developed countries. One example is work by Baker, Gruber, and Milligan (2008) who analyze the introduction of universal child care in Quebec. According to their study, the provision of universal child care leads to an increase in maternal labor supply, but leaves children worse off. On the contrary, Cascio (2017) finds that attending a state-funded universal preschool in the US leads to increased test scores, particularly for the poor. Similarly, in the case of Germany, universal child care has larger treatment effects for disadvantaged children (Cornelissen et al. 2018). Furthermore, a universal ECD program in Norway is associated with long-term improvements in educational outcomes, as well as labor market outcomes (Havnes and Mogstad 2011). Similarly, Havnes and Mogstad (2015) show that the childcare expansion in Norway results in income gains during adulthood for children from the lower and middle parts of the income distribution, but income losses for those in the upper part.

My paper also talks to the literature which analyzes how to improve children's school performance. One example is the influential paper by Duflo (2001) that studies the impact of education supply on schooling outcomes. Black et al. (2014) ask how childcare subsidies impact student performance and several papers investigate the interaction between initial endowments and educational outcomes[18]. Neidell and Waldfogel (2010) demonstrate that peer interactions play a crucial role in early childhood education. A stream within this literature

children. The High/Scope Perry Preschool Project started in 1962 to analyze the influence of pre-school education on children's learning outcomes (Weikart et al. 1970). The project was created when David Weikert noticed that poor children were doing much worse in school and formed a committee to address these gaps. As part of the project, a randomly selected group of vulnerable, ultra-poor children ages three to four were given access to pre-school as well as a weekly 90-minute home visits by a social worker, while a second group of vulnerable, ultra-poor children with similar characteristics served as a control group. Decades later, researchers compared several socioeconomic outcomes of both groups, such as criminal activities, income, and educational outcomes (Manning and Patterson 2006).

[18]See, for example, the work by Bharadwaj, Løken, and Neilson (2013), Bharadwaj, Eberhard, and Neilson (2018), Almond, Mazumder, and Van Ewijk (2015) or Johnson and Jackson (2019).

analyzes the effect of income increases.[19] Similar to my contribution to the social safety net literature, my work expands this literature by looking beyond a pure income channel and analyzing the effects of a more comprehensive approach, bringing together several income and non-income channels.

Finally, Almond, Currie, and Duque (2018) single-out the necessity to further study the effect of the "missing middle" years, meaning trajectory effects of early childhood and middle childhood. They identify a lack of knowledge about how early childhood, middle childhood and adulthood interact. My paper contributes to this identified gap in the literature.

4 Data

In this section, I document the data I use to analyze ChCC's program impact on child outcomes in middle childhood. I mainly rely on administrative datasets provided by different entities of the government of Chile. I additionally use a rich survey on early childhood development as well as data on standardized test scores.

Standardized test scores. The first dataset used in this paper is from the national student achievement testing system (SIMCE). The data is provided by the National Agency of Educational Quality in Chile (Agencia de Calidad de la Educación 2021) and measures educational achievements along several dimensions, such as math or reading skills. The evaluation takes place every year and evaluates all second, fourth, sixth and eighth graders in elementary school, as well as the second and third graders in secondary school. For the purpose of this paper, I focus on standardized test scores in reading and math of fourth graders tested between 2015 and 2018. To enter the schooling system in Chile a child must be at least six years old on March 31st of the respective school year (Ministerio de Educación 2021b). The treated children in 2007 would therefore enter primary education in 2013 at the earliest and be in fourth grade in 2016. The treated children in 2008 would be in fourth grade in 2017. Including the 2015 and 2018 evaluation years allows me to include children born one year before to one year after the introduction of ChCC. My resulting sample size consists of 835,042 children.

Student register. The second dataset is the Student Register, which contains information on the entire student body based on administrative school registry data provided by the Ministry of Education of Chile (Ministerio de Educación 2021a). The data contains information about students' municipality of residence, date of birth, grade point average, school

[19] For a good introduction to the topic, see studies by Dahl and Lochner (2012), Aizer et al. (2016), Muralidharan and Prakash (2017), Barrera-Osorio, Linden, and Saavedra (2019), Millán et al. (2020) or Barr, Eggleston, and Smith (2022).

assistance rate, whether they passed the school year, the school and class they attend, and more. It also contains information on the socioeconomic status of students, divided into priority and preferential students. Priority students are those who belong to households with a socioeconomic background that make it more difficult for them to manage the educational process. These are students who are part of the social protection system *Chile Solidario*, students who belong to the most vulnerable 30-percentile as defined by the Social Protection Scorecard (in Spanish: Ficha de Protección Social - FPS); students who do not have a Social Protection Scorecard and are group A beneficiaries in the benefit system of the National Health Fund, Fonasa, which are from families in poverty and receiving a family subsidy; students whose household income is below the poverty line; students whose mothers have less than four years of education; and students living in rural or poor communities. Preferential students are students who belong to the 80-percentile of the population, as defined by the social characterization score (in Spanish: Instrumento de caracterización social vigente del Registro Social de Hogares). The key outcome variable of interest is school performance, that is, the grade point average achieved by a student in a respective year. I use data on grade point averages from 2015-2018 and merge the data with SIMCE data based on the electronic student ID (MRUN).

Roll-out data. I use data on the monthly roll-out of ChCC data at the municipality level provided by Clarke, Méndez, and Sepúlveda (2020). The main explanatory variable is an indicator equal to one if a student was born after the implementation of ChCC in her respective community of residence. Table 1 gives an overview of the underlying student population by treatment group. The largest difference between both groups is the share of vulnerable students.

Survey data. To analyze potential channels through which ChCC affects school outcomes, I look at intermediate factors that could impact a child's performance in school. To this end, I use data from the Longitudinal Survey of Early Childhood (ELPI) published by the Ministry of Social Development (Ministerio de Desarrollo Social y Familia 2021). The ELPI Survey consists of several questionnaires, addressed both to the children themselves and to their families. It also includes the use of child evaluation instruments that measure child development, as well as caretaker development and the interaction between the two.

The survey consists of three survey waves from 2010, 2012, and 2017. I include those children into my sample who are in the 2010, 2012, and 2017 survey waves and exclude children who are only reported in 2010 or 2012, as no information is available for them on their place or date of birth. The final sample size consists of 31,695 children, but survey questions and evaluation tools differ by age group (UNICEF 2018). Consequently, the sample size varies by variable. I weight the observations using the sample weights provided by the

Table 1: Summary statistics of 4th-graders (2015-2018)

	Control Group			Treatment Group		
VARIABLES	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Stand. math score	565,928	261.6	48.55	269,114	261.3	47.76
Stand. reading score	565,928	267.2	52.06	269,114	271.7	52.69
Rural	565,928	0.0977	0.297	269,114	0.101	0.301
Age (Years)	565,907	9.501	0.849	269,093	9.107	0.322
GPA	565,928	5.808	1.006	269,114	5.886	0.997
Assistance (%)	565,928	91.06	14.79	269,114	91.49	14.69
Female	565,928	0.490	0.500	269,114	0.514	0.500
Retention	565,928	0.0108	0.103	269,114	0.00660	0.0809
Vulnerable student	565,928	0.824	0.381	269,114	0.737	0.440

Notes: The information above is based on SIMCE data and the National School Register from 2015-2018. Treated children are all children born after the implementation of ChCC in the respective municipality of residence. Standardized math scores range from 93 to 395 points. Standardized reading scores range from 115 to 406 points. Grade point averages represent the grade point average achieved by the respective child in a given school year and range from 1.0 (lowest) to 7.0 (highest). The retention rate is a dummy variable that takes the value of one once a child has not successfully completed the school year. Vulnerability refers to socioeconomic vulnerability based on a variety of characteristics defined by the Ministry of Education in Chile.

ELPI evaluation team. Table D1 in Appendix D shows some basic characteristics of the underlying sample by treatment group.

The package of evaluation instruments for children consists of a set of tests measuring the following areas of child development: psychomotor development, executive functioning, socio-emotional functioning, as well as anthropometric measures. For the purpose of my analysis, I focus on instruments that were used with children who were part of the treatment as well as control group[20]

1. *Children's cognitive development*:

    - TEPSI (Psychomotor Development Test): The TEPSI measures the psychomotor development of children and was part of the survey in 2010. A higher score indicates a better psychomotor development.
    - TVIP (Peabody Picture Vocabulary Test): The TVIP Score consists of 145 questions, and the ELPI gives an overall score generated from these questions. It is

[20] For an overview of all instruments see the ELPI User Manual (UNICEF 2018). For a detailed explanation and description of all instruments see a report published by the Universidad de Chile (2015).

a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. A score below 70 is considered extremely low, and a score of more than 145 is considered extremely high. Instructors used this instrument with children in all three survey waves.

- TADI (test of general infant learning): The TADI score evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. This evaluation instrument was part of the 2012 survey. It consists of a task given to the child, a set of questions for the primary caregiver and a professional observation of the child. The TADI score is standardized for the Chilean population.

2. *Children's non-cognitive development:*

- BDST (Backward Digit Span Task): The BDST consists of 16 questions and measures the working memory. The ELPI reports an overall score based on these questions.
- HTKS (Head Toes Knees Shoulders Task): The HTKS is a game for children, in which they are asked to do the opposite of what an instructor says.

3. *Children's socio-emotional development:*

- CBCL1 (Child Behavior Checklist 1): The CBCL1 is a caregiver report identifying behavioral problems in children, based on the following symptoms: aggressive behavior, anxiety, attention problems, rule-breaking behavior, somatic complaints, social problems, thinking problems, and depression. The CBCL1 consists of 99 questions. The ELPI, in turn, generates an overall test score from these questions. A percentile score of less than 93 is considered normal, and a score greater than 98 is considered clinical range. A total scale score of less than 60 is considered normal, while a total scale score of greater than 83 is considered clinical range. This evaluation instrument was part of all three rounds in the ELPI survey.

4. *Anthropometric measures:*

- Abnormal height: A dummy variable that equals one if the interviewer observes some kind of abnormality in a child's height.

5. *Parental interactions:*

- PSI (Parental Stress Index): The PSI consists of 36 questions answered directly by the principal caregiver. Each question relates to a subdomain of parental stress and is scored on a five-point scale. A score of less than 80 is considered normal, while a score greater than 90 is within the clinical range.
- PSCS (perceived self-confidence scale): The PSCS consists of 17 items measuring the self-assessment of parenting skills. Higher scores represent greater parent confidence in their parenting skills.
- CESD-10 (Center for Epidemiologic Studies Depression Scale 10): The CESD-10 is based on 10 items. People with higher scores are more prone to depression.
- HOME Index (Home Observation Measurement of the Environment Index): The HOME Index consists of 13-43 questions. It measures several dimensions of household quality, such as the emotional interaction between principal caregivers and children, the presence of learning material, as well as maternal commitment. The interviewer assigns points for each dimension, with eight points being the maximum score.
- Parental practices: I retrieve information on parenting practices (such as inadequate dental care)

6. *Early childhood education:*

   - Attendance: A dummy variable, which is equal to one if a given child attends an early childhood education facility.

Table D2 in Appendix D gives an overview of the evaluation instruments under consideration.

5 Identification Strategy

5.1 Regression Discontinuity Design

In this section, I describe the identification strategy I use to empirically assess the intention-to-treat (ITT) effect of ChCC on school performance in middle childhood. Simply regressing an indicator variable, which is equal to one if a child was born after ChCC's roll-out, and zero otherwise, on child outcomes in middle childhood might lead to biased estimators. Children from earlier birth-cohorts might significantly differ from children in later birth-cohorts. This is problematic especially if they differ on unobservable dimensions, which also affect the outcome variables of interest. To give an example, children of the pre-treatment group might be subject to different education policies than children of the treatment group. These policies might significantly affect schooling outcomes, but are unobservable in the data at hand. Therefore, a simple ordinary least square regression might mistake the effects generated from changes in education policies for changes generated through the implementation of ChCC.

To address these endogeneity concerns, I follow other scholars in the early childhood development literature (Barr, Eggleston, and Smith (2022); Ludwig and Miller (2007)) and exploit the fact that there is a random cutoff for potential exposure to ChCC, that is, the date of birth of a child, and apply a regression discontinuity design (RDD). The intuition behind RDDs is that students close to the cutoff are very similar to each other. Hence, the potential existence of unobservable confounding factors is less likely. Comparing outcomes of students located closely below the cutoff to outcomes of students located closely above the cutoff delivers the local treatment effect of ChCC. Hence, I estimate the following equation:

$$Y_i = \alpha + \beta ChCC_i + \gamma_1(X_i - c) + ChCC_i\gamma_2(X_i - c) + \varepsilon_i \tag{1}$$

, where:

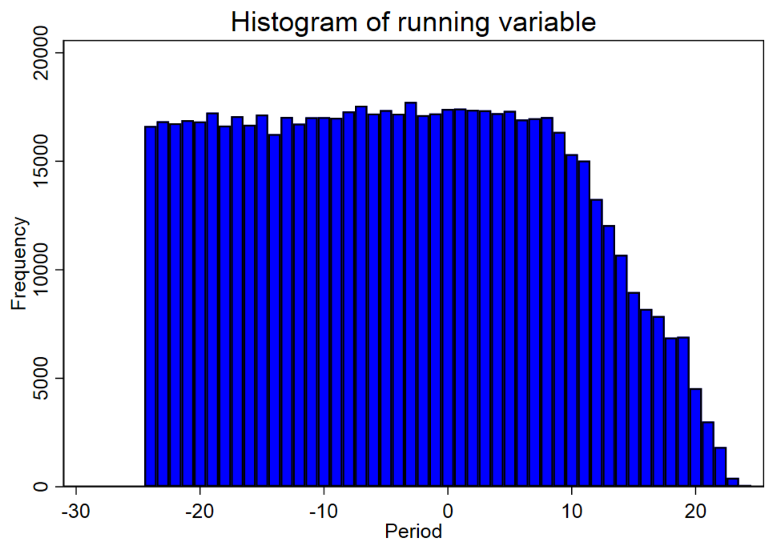
$$ChCC_i = \begin{cases} 1, & X_i \geq c \\ 0, & X_i < c \end{cases} . \tag{2}$$

Being exposed to ChCC is determined by the threshold c (being born after ChCC) of the discrete variable X_i, the date of birth of the respective child. As ChCC's roll-out was staggered, I first normalize the threshold. I do so through setting the roll-out date to zero and then calculating the difference between each child's date of birth and the roll-out date. The running variable is equal to the number of months ChCC was in place in a respective municipality. X_i depends on the bandwidth b of the data used. The bandwidth is equal to the number of periods under consideration before and after ChCC's implementation took place. X_i is therefore as follows:

$$c - b \leq X_i \leq c + b \tag{3}$$

RDDs were originally designed for settings with continuous running variables. Importantly, it is only possible to apply RDDs to settings with discrete running variables when the number of mass points is large (Cattaneo, Idrobo, and Titiunik 2019). If the number of mass points is small, a local randomization approach might be more appropriate than a RDD. Figure 3 shows a histogram of the running variable. I restrict the sample to all chil-

Figure 3: Histogram of the running variable (months since roll-out)



Notes: The figure shows a histogram of the running variable. The x-axis presents the running variable. The running variable is the number of months relative to ChCC's roll-out. 0 is the staggered roll-out period. The y-axis indicates the frequency in absolute numbers. Source: SIMCE (2014-2018).

dren born 18 months before to 18 months after ChCC's roll-out, a setup under which there are sufficient observations in each of the cells of the underlying dataset. This results in 37 mass points, a relatively small number. Hence, I decide to implement a local randomization approach instead of a continuity-based method.

I employ finite-sample methods to determine the cutoff window under which the assumption of randomized treatment assignment is most plausible. I follow Cattaneo, Titiunik, and Vazquez-Bare (2016) and implement a window-selection procedure based on balance tests. I find that the optimal window is equal to four periods around the cutoff.[21] This means that the optimal cutoff window consists of the two birth cohorts previous to ChCC's implementation and the first three birth cohorts exposed to ChCC. For the underlying figures and details behind the optimal window length selection see Appendix E.

My baseline estimation strategy relies on the assumption that the relationship between exposure to ChCC and schooling outcomes in middle childhood has a regression slope equal to zero. But if the true relationship is linear or even non-linear, the local randomization approach could mistake linear and non-linear relationships for discontinuities. To account

[21]This applies to a functional form of polynomial order zero. The optimal cutoff window of a local randomization approach with higher polynomial orders is the minimum cutoff window. As it is challenging to estimate the slope with only two data points, I consider a bandwidth of ten as the main empirical specification. In these cases, I show that findings are robust to specifications, which only consider the minimal cutoff window.

for this caveat, I employ a parametric regression specification of the local randomization approach as robustness tests and estimate the following regression:

$$Y_i = \alpha + \beta ChCC_i + \sum_{p=1}^{n} \gamma_p c_i^p + \varepsilon_i \tag{4}$$

, where:

$$ChCC_i = \begin{cases} 1, & c_i \geq c \\ 0, & c_i < c \end{cases} . \tag{5}$$

I follow Pei et al. (2022) and select the optimal polynomial order p based on a mean squared error estimation. I find that an increase in the polynomial order does not lead to a lower mean squared error. Thus, I rely on a local randomization approach, which does not include slope terms, as my baseline estimation. I later account for higher polynomial orders to test the validity of my findings.

5.2 Testing the Validity of Identification Assumptions

The underlying assumption of the local randomization approach is that the assignment of each child to the treatment was random and that there was no manipulation into treatment. To test this assumption I conduct a falsification test. I find that there are 17,203 observations in the month before ChCC's roll-out, 17,410 observations during its roll-out and 17,426 observations after its roll-out, which suggests that there is no manipulation or non-random selection into the treatment. The ratio of observations close to the cutoff is nearly 1, showing consistency with the assumption that treatment assignment is random and close to a probability of 0.5. Additionally, in the specific setup of this paper manipulation might be of low concern, as it is difficult to time child birth to an exact month. A pregnancy takes 10 months and it is unlikely that the roll-out date of ChCC played a role in the monthly timing of pregnancies. I conduct a binomial test to confirm that treatment manipulation is of low concern. The resulting p-value is close to 1, speaking for the validity of the estimation strategy.

Next, I investigate whether the chosen window around the cutoff potentially drives my empirical results. I consider different nested windows, namely up to 20 months around the cutoff and find that the ratio of observations around the cutoff remains balanced (see Figure 3). Consequently, the probability of treatment assignment remains around 0.5 and it is unlikely that the window size drives my results.

Another important assumption of the local randomization approach is that individuals close to the cutoff are similar on observable and unobservable characteristics. While I cannot analyze the similarity of unobservable student characteristics around the cutoff, I can do so for observable covariates. I test if treated and control groups close to the cutoff are on average similar in terms of observable characteristics. I observe three covariates in the data at use, namely students' gender, socioeconomic vulnerability and the degree of urbanization of the school they attend.

Table 2 shows the mean values of the three observable student characteristics in the optimal window around the cutoff. The table also presents the resulting p-value of a t-test, which investigates the equality of means in the optimal cutoff window in Column 3. I cannot reject the null hypothesis of no significant difference in the means in the minimum cutoff window for none of the three observable covariates. Moreover, there is no discontinuity of observable student characteristics around the threshold (see Figure 4 to Figure 6).

Table 2: Baseline municipality characteristics (4 periods around cutoff)

	Control mean	Treatment mean	T-test p
Female	0.50	0.50	0.50
Vulnerable student	0.74	0.74	0.20
Rural	0.10	0.10	0.37
Standardized math score	262.36	263.24	0.36
Standardized reading score	270.35	272.41	0.00
Grade point averages	5.86	5.89	0.05
Observations	34,324	52,206	86,530

Notes: The table shows the baseline characteristics of children in the treatment and control group. I restrict the window to the optimal bandwidth (4 periods around the cutoff). Column 1 presents the mean value for children in the control group, Column 2 for children in the treated group and Column 3 the p-values for a two-sample t-test that tests for systematic differences between both groups in each variable in the table. Standardized math scores range from 93 to 395 points. Standardized reading scores range from 115 to 406 points. Grade point averages represent the grade point average achieved by the respective child in a given school year and range from 1.0 (lowest) to 7.0 (highest). Source: SIMCE (2015-2018), MINEDUC (2015-2018).

Figure 4: Regression Discontinuity Plot (female)

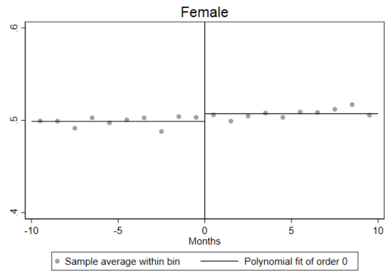


Figure 5: Regression Discontinuity Plot (vulnerable)

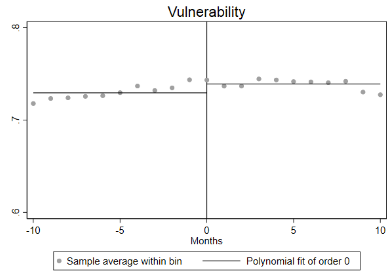
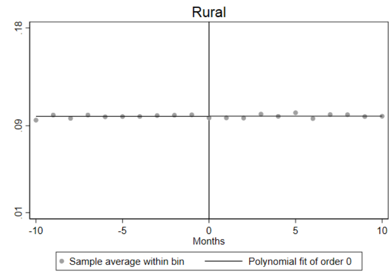


Figure 6: Regression Discontinuity Plot (rural school)



Notes: The figures above show the local randomization design plots for observable control variables. I do not include a slope in this case. The left panel shows the plot for gender, the middle panel the one for socioeconomic vulnerability, and the right panel the one for urbanity. *Female* is a dummy variable equal to 1 for girls and 0 otherwise. *Vulnerable* is a dummy variable equal to 1 for socioeconomically vulnerable by definition of the Ministry of Education and 0 otherwise. *Rural school* is a dummy variable equal to 1 for students who attend a school in a rural area and 0 otherwise. I restrict the periods shown to a bandwidth of 20. This means that the figures show the average values of the socioeconomic controls for all children born ten months previous to ChCC's roll-out to ten months after its roll-out. The black horizontal line features the threshold of the local RD approach, namely zero. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

6 Impacts on Schooling Outcomes

6.1 Results

After establishing the plausibility of the underlying identification assumptions, I analyze the local randomization discontinuity (RD) effect of exposure to ChCC on the main outcome variables of interest, namely standardized math and reading scores as well as grade point averages. If the program successfully increases school performance in middle childhood, I expect to see positive and significant effects of program exposure.

Table 3 implies that exposure to ChCC leads to improved schooling outcomes in the optimal window length. Column 2 shows that the program increases standardized math scores by 0.883 points, standardized reading scores by 2.059 points and grade point averages by 0.03 points. The p-values in Column 3 are zero or very close to zero. Consequently, the reported point estimates are significant at the 1 percent significance level. I show that my findings hold when varying the window length to the minimum bandwidth as well as a bandwidth of 20 in Appendix D.

Figure 7 to 9 show the related local randomization design plots for schooling outcomes in a window length of 20. The solid lines give the predicted values from a regression of schooling outcomes on a zero-degree polynomial in months relative to the birth eligibility cutoff. Negative values of months indicate children born before program implementation, positive values of months those born after program roll-out. The figures show that there is a clear jump in standardized reading scores and grade point averages for children born after ChCC's roll-out, which confirms my previous findings. The jump in standardized math scores, on the other hand, seems to be negligible. Figure E2 to E4 in Appendix F show that figures are similar when restricting the window length to the optimal bandwidth of four.

Table 3: Local RD effect of ChCC on schooling outcomes and observable control variables in the optimal window around cutoff

	Variable	RD Estimate	P-Value	N (left)	N (right)
1	Standardized math score	0.883	0.008	34,324	52,206
2	Standardized reading score	2.059	0.000	34,324	52,206
3	Grade point averages	0.030	0.000	34,324	52,206
4	Gender	0.000	0.983	34,324	52,206
5	Vulnerability	-0.000	0.921	34,324	52,206-
6	Rural	-0.003	0.185	34,324	52,206

Notes: The table shows the local RD effect of ChCC in the four months around the cutoff. This means that the estimation considers all students born two months before and after ChCC's roll-out as well as those born during its roll-out. The first column shows the intention-to-treat (ITT) effect of ChCC on the three schooling outcomes and observable covariates. Column 2 presents the related coefficient p-values. Column 3 and 4 show the number of observations N on each side of the cutoff. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

Figure 7: Regression Discontinuity Plot (standardized math scores)

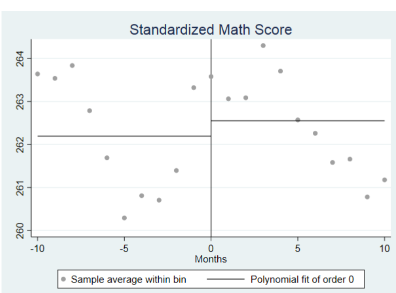


Figure 8: Regression Discontinuity Plot (standardized reading scores)

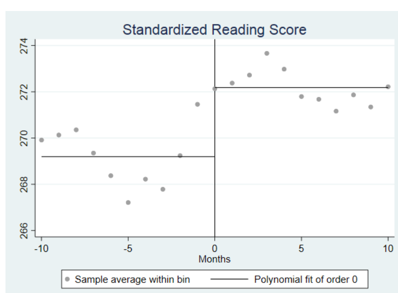
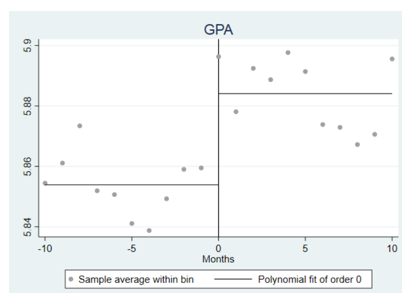


Figure 9: Regression Discontinuity Plot (grade point averages)



Notes: The figures above show the local randomization design plots for schooling outcomes. The left panel shows the plot for standardized math scores, the middle panel the one for standardized reading scores, and the right panel the one for grade point averages. I restrict the periods shown to a window length of 20. This means that the figures show the average values of schooling outcomes for all children born 10 months previous to the roll-out of ChCC to 10 months after its roll-out. The black horizontal line features the threshold of the local RD approach, namely zero. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

To confirm that there are no confounding factors around the cutoff, I estimate the local

RD effect on the three observable student characteristics in the optimal cutoff window. The last three columns in Table 3 suggest that there is indeed no discontinuity in any of the observable covariates in the optimal cutoff window, given that the p-values are larger than any of the most commonly used significance levels. While I cannot make any conclusion about potential unobservable factors, these findings show that the assumption of similarity between observed covariates is plausible.

6.2 Magnitude in Relation to Existing Literature

In terms of magnitudes, impacts correspond to a 1.8 percent of a standard deviation increase in standardized math scores, a 4.0 percent of a standard deviation increase in standardized reading scores, and a 0.03 percent of a standard deviation increase in grade point averages.

Bharadwaj, Eberhard, and Neilson (2018) establish a positive effect of birth weight on academic achievements in school. They establish that a 10 percent increase in birth weight improves performance in math by nearly 0.05 standard deviations and language test scores by around 0.038 standard deviations. According to their study, effect sizes are fairly stable between grades one and eight. My results are similar in magnitude for language test scores, but smaller for math test scores. Bharadwaj, Løken, and Neilson (2013) examine the effect of improved neonatal and early childhood health care on mortality and long-run academic achievement in school. They demonstrate that school performance improves by 0.15 standard deviations in math. An early-life medical intervention in Denmark results in 0.386 and 0.255 standard deviation increases in language and math test scores (Daysal et al. 2022). My results on ChCC are smaller compared to these results.

Analyzing effects of cash transfers, Dahl and Lochner (2012) find that a 1,000 US-Dollar increase in family income raises math and reading test scores by about 6.0 percent of a standard deviation. Similarly, Milligan and Stabile (2011) show that an increase of 1000 US-Dollar in child tax benefits leads to a 6.9 percent of a standard deviation increase in math scores. Black et al. (2014) investigate the impact of child-care subsidies in Norway. Their study demonstrates a positive ITT effect on grade point averages of 0.3 standard deviations. I note that my estimated ITT effects are smaller.

7 Robustness Tests

My chosen functional form or unobservable factors taking place at the same time as ChCC's roll-out could confound my main findings. Hence, I validate my findings by employing three robustness tests. First, I estimate a parametric estimation of the local RD approach. Next, I employ an event study to show that my main results hold under an alternative empirical strategy and that there are no pre-trends. Lastly, I show that my findings are not confounded by the financial crisis, the development of copper prices, migration patterns, school entry dates nor children's maturity.

7.1 Parametric Estimation

To investigate if assumptions about the underlying functional form drive my results, I include slope terms. Table 4 presents the results of a local linear randomization approach. Based on the p-values in Column 2, all three coefficients are significant and positive at the 1 percent significance level. When comparing the point estimates in Column 1 to the point estimates from the baseline specification, the local RD estimator is larger, which could mean that the non-parametric estimation underestimates the true impact of the program. The other way around, accounting for a polynomial order of one could overestimate the intention-to-treat (ITT) effect of ChCC.

Figure 10 and 11 plot the discontinuity for standardized test scores and Figure 12 the one for grade point averages. The solid lines depict the predicted values from a regression of schooling outcomes on a one-degree polynomial in months relative to the birth eligibility cutoff. Similar to previous graphs, while there is a clear jump in standardized reading scores and grade point averages for children born after program implementation, the graph on standardized math scores is less convincing. Note that all graphs have a downward slope. Schooling outcomes decrease as one moves away from the birth eligibility cutoff for children exposed to the program, and similarly increase for children born before program implementation. These slopes are driven by window lengths and disappear when increasing the window size to 11 or 12 periods, which suggests that they are related to the slight periodicity visible in the RD plots.

Table 4: Local RD effect of ChCC on schooling outcomes in the 20 periods around the cutoff with a polynomial fit of order 1

		RD Estimate	P-Value	N (left)	N (right)
1	Standardized math score	3.157	0.000	172,695	186,707
2	Standardized reading score	3.887	0.000	172,695	186,707
3	Grade point averages	0.043	0.000	172,695	186,707

Notes: The table shows local RD effects of ChCC in the 20 months around the cutoff window. This means that the estimation considers all students born 10 months before and after the roll-out of ChCC as well as those born during the roll-out. The results are based on a parametric regression specification of the local randomization approach of degree one. Column 1 reports the point estimates, Column 2 the coefficient p-values, and Column 3 and 4 the number of observations N on each side of the threshold. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

Figure 10: Regression Discontinuity Plot - p=1 (stand. math scores)

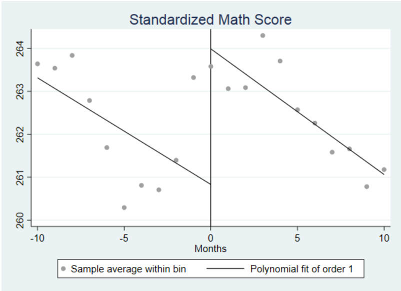


Figure 11: Regression Discontinuity Plot - p=1 (stand. reading scores)

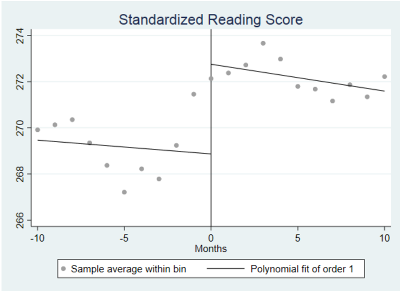
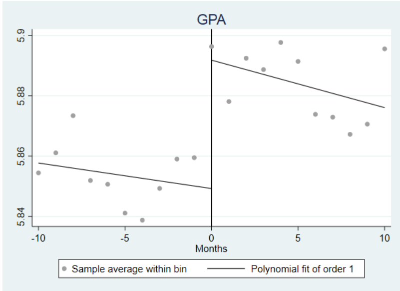


Figure 12: Regression Discontinuity Plot - p=1 (grade point averages)



Notes: The figures above show the local randomization design plots for schooling outcomes assuming a polynomial fit of order one. I consider a cutoff window of ten periods before and ten periods after the actual cutoff. The cutoff is equal to zero and represented by the black horizontal line. The left panel shows the plot for standardized math scores, the middle panel the one for standardized reading scores, and the right panel the one for grade point averages. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

7.2 Event Study

I next employ an event-study design to shed further light on the validity of my findings. My main explanatory variable is the number of months that ChCC had been in place in a certain municipality when a child was born. I explain this further using the example of a child born in August 2008. If ChCC was introduced in her respective municipality in August 2007, the main explanatory variable has a value of 12. If the child was born in August 2006, the main explanatory variable has a value of -12. For computational reasons, I collapse the data to the birthmonth by municipality level and then estimate an event study as follows:

$$y_{mb} = \alpha + \sum_{p=-13}^{13} \beta_p \times I_p + \eta_m + \lambda_b + \theta_s \times b + \delta M_{pre} \times b + \gamma X'_{mb} + \varepsilon_{mb} \tag{6}$$

,where m stands for the municipality, and b for the birth-cohort. One cell in the sample represents a combination of a specific municipality and birth-cohort. y_{mb} is the outcome of interest (as, for example, the average municipality-level standardized test score for a certain birth-cohort) and β_p the effect of leads and lags I_p included in the event study design. η_m is a municipality fixed effect, λ_b a birth-cohort fixed effect, and $\theta_s \times b$ a state-specific linear time of birth trend. Standard errors are clustered at the regional level. I omit period -1. Additionally, I interact some pre-treatment municipality characteristics with a time of birth trend ($M_{pre} \times b$) and control for a set of municipal time-varying controls (X'_{mb}).

Schmidheiny and Siegloch (2019) recommend a binning approach in which the number of pre-periods included in the event study is equal to the first year of data for the dependent variable (in my case, July of 2007) minus the effect window (which in my case is 13 periods). Figure 13 shows the results for standardized math scores, Figure 14 for standardized reading scores and Figure 15 for grade point averages.[22]

Figure 13 shows that there is no pre-trend for standardized math scores and that math scores increase consistently after the introduction of ChCC. The same is true for standardized reading scores (Figure 14), although there might be a small periodic trend in the pre-treatment period. Still, standardized reading scores increase after the introduction of ChCC. Figure 15 illustrates that there is evidence of a slight but negligible pre-trend in the case of grade point averages. Grade point averages increase steadily in the post-treatment period. Overall, my event study confirms the results from the local randomization approach. I conduct a joint significance test of the 13 lags included in the event study. I can reject the null hypothesis that all coefficients are zero at the commonly used levels of significance.

[22] I take advantage of the command *eventdd* provided by Clarke and Tapia-Schythe (2021).

Figure 13: Event Study Graph (standardized math score)

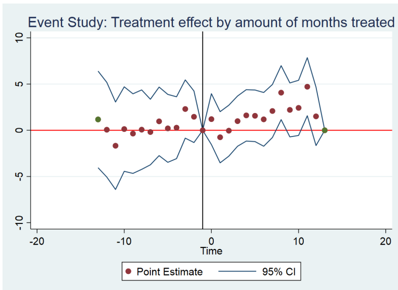


Figure 14: Event Study Graph (standardized reading score)

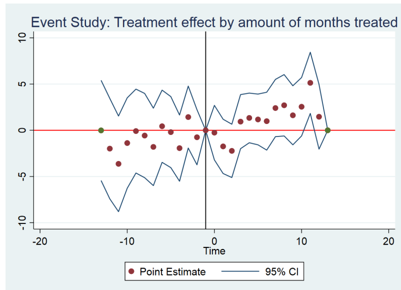
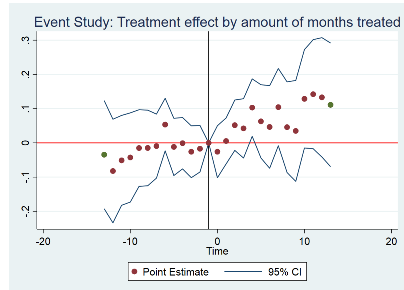


Figure 15: Event Study Graph (grade point averages)



Notes: The plots above show results for an event study on standardized math and reading scores as well as grade point averages. I aggregate data at the date of birth by municipality level. The main explanatory variable is the number of treatment periods relative to ChCC's roll-out. I control for municipality fixed effects as well as date of birth fixed effects. I include an interaction term between birth cohorts and regions of residence, as well as pre-treatment controls. I include the following pre-treatment municipality characteristics: poverty rates at the municipality level, the number of families receiving subsidies, the available budget per municipality, the share of education spending from the Ministry of Education, the type of administrative cooperation in education, the student-teacher ratio, having or not having a primary health unit, the health transfer per capita from the Ministry of Health, and the share of votes in the 2004 mayoral elections. I control for the following individual characteristics: the share of female students, the share of vulnerable students, and the share of students from rural areas. The omitted event time is period -1, represented by the vertical black line. Standard errors are clustered at the regional level. Source: SIMCE and MINEDUC (2014-2018).

7.3 Additional Robustness Checks

7.3.1 Migration as a Confounding Factor

I do not have information on the children's municipality of birth, only on the children's municipality of residence. Therefore, my treatment and control group could be confounded by internal migration patterns. To test this, I analyze these patterns using data from the latest 2017 micro-census. The data shows that 15.8 percent of the population are internal migrants (Instituto Nacional de Estadísticas 2020). Internal migrants are defined as all people who changed their residence between 2012 and 2017 by moving between regions or within one region but between municipalities. Importantly, households with children are less likely to migrate internally, and the share is lowest among the youngest and oldest population (less than 2 percent). Internal migration patterns only begin to take hold for children over age 15. As these groups are not included in my sample, I conclude that internal migration patterns of less than 2 percent for my target group should not be a significant confounding factor in the definition of my treatment and control group.

7.3.2 The Influence of the Financial Crisis and Copper Prices

Since the implementation of ChCC took place just before the onset of the financial crisis in 2008, I analyze the potential effect of the financial crisis as a confounding factor. The financial crisis would be a problem for my estimation strategy if it had a systematically different effect on schooling and developmental outcomes of children in municipalities introducing ChCC earlier than those municipalities introducing ChCC at a later stage. This channel could arise from a transitory effect of the financial crisis on income and poverty and then on schooling outcomes.

The implementation of ChCC was completed in August 2008. Like most emerging economies, the financial crisis hit Chile later than developed countries. This is why Chile did not enter a severe recession until late 2008 (Cortés 2016). Real GDP growth (year-to-year) began to fall in the third and fourth quarter of 2008 (3.5 percent and 0.9 percent respectively), and quarterly growth was negative by the first quarter of 2009 (-2.6 percent) (OECD 2021). Based on this data I conclude that the financial crisis is no threat to my identification strategy.

With respect to copper prices, the same reasoning applies. If municipalities that introduced ChCC earlier are municipalities which depend heavily on the Chilean copper industry, and if these industries were hit harder by a negative development of copper prices, the development of copper prices might be a confounding factor. As the copper price did not start to fall sharply until September 2008, I can rule it out as a confounding factor.[23]

7.3.3 School Entry Date and Maturity

One important requirement for RDDs is that there exists a clear cutoff which divides the population of interest into treated and control units. One concern could be that there is an alternative unobservable cutoff which coincides with ChCC's birth threshold but refers to another program. If this alternative program affects educational outcomes I might confound its effects with the impact of ChCC. Because of the staggered rollout of ChCC I am less concerned about potential unobservable programs that were rolled out on one specific date. School entry dates, for example, are not a concern.[24]

Another possible identification concern is the maturity of children. Children born after the birth cutoff in a respective municipality are automatically older than those born before

[23] For the detailed development of copper prices see `https://tradingeconomics.com/commodity/copper`, and for a graphical overview see Figure C1 in the Appendix.

[24] School entries are defined via the 31st of March of each year. To enter school, children must be at least six years old on this day. I do not account for cohort-fixed effects in my regression, as more than 99 percent of all children belong to 4th grade.

the cutoff. If maturity plays a role in educational outcomes the increase in schooling outcomes could be due to the underlying age structure. Again, because of the staggered nature of ChCC's roll-out, I am less concerned about this potential confounding factor. I verify that maturity does not play a role in my findings by controlling for the age of children. I find that my estimates more than double in size when including age as a control variable.[25]

8 Impact on Schooling Outcomes by Subgroups

Next, I analyze the program's effects on educational outcomes by gender and socioeconomic vulnerability. I do so to investigate if comprehensive early childhood development programs have the potential to reduce inequalities between these groups. I divide the treatment group by gender and socioeconomic vulnerability. I then estimate the local RD effect of the program's impact in the optimal window, namely in the four periods around the cutoff.

Table 5 shows that the program's impact significantly differs by gender. Comparing the point coefficients in Column 1 and 2 of Panel 1 reveals that the program has larger effects on boys' standardized math scores than on girls'. The local RD estimate is barely significant at the 10 percent significance level for girls. According to Column 2, exposure to ChCC increases standardized math scores by 0.996 points for boys but only by 0.771 points for girls. In terms of magnitude, this effect is a 2 percent of a standard deviation increase for boys compared to 1.5 percent for girls. Turning attention to Panel 2 and 3, similar patterns become apparent for the other two schooling outcomes investigated. While in the case of standardized reading scores and grade point averages all RD estimators are significant at the 1 percent significance level, exposure to ChCC results in smaller effects for girls than for boys. Column 2 shows that the program increases standardized reading scores by 2.315 points for boys, but only by 1.805 points for girls, which is equivalent to a 4.3 percent of a standard deviation increase for boys and 3.6 percent of a standard deviation increase for girls. The impact on grade point averages is also lower for girls (see Column 2 and 3 in Panel 3). Program exposure increases grade point averages by 3.4 percent of a standard deviation for boys, but only 2.5 percent of a standard deviation for girls.

Differences are even larger when making a distinction by socioeconomic vulnerability. Table 5 shows that the program's impact on standardized math scores is insignificant for socioeconomically vulnerable children. The p-value reported in Column 3 is above 0.1. Column 3 and 4 in Panel 1 present the respective point estimates. While the program raises standardized math scores by 1.639 points for non-vulnerable children, this same effect is

[25]The RD coefficient is 7.836 for standardized math scores, 7.342 for standardized reading scores, and 0.106 for grade point averages.

only 0.615 points for vulnerable children. The effect is therefore nearly three times larger for the socioeconomically privileged group. The effects are equivalent to a 3.5 percent of a standard deviation increase for non-vulnerable children, but only 1.3 percent of a standard deviation increase for vulnerable children. Similarly, the program's impact on standardized reading scores is 1.8 times larger for the socioeconomically privileged group (3.107 points versus 1.689 points). ChCC results in an increase of 6.0 percent of a standard deviation increase in standardized reading scores for non-vulnerable children, compared to 3.2 percent of a standard deviation increase for vulnerable children. There is also heterogeneity in the effect on grade point averages. The impact of ChCC is 2.8 times larger for non-vulnerable children (0.056 points versus 0.020 points). Program exposure increases grade point averages by 6.4 percent of a standard deviation for non-vulnerable children and only 2.0 percent of a standard deviation for vulnerable children.

These findings hold when accounting for a larger cutoff window, as well as for polynomial orders of degree one by subgroups. Appendix D.4 presents the details.

Table 5: Local RD effect of ChCC in the optimal window around the cutoff on schooling outcomes by groups

	Subgroup	Boys	Girls	Vulnerability	Non-vulnerability
	Panel 1: Standardized math scores				
1	RD Estimate	0.996	0.771	0.615	1.639
2	P-Value	0.037	0.094	0.116	0.008
3	Panel 2: Standardized reading scores				
4	RD Estimate	2.315	1.805	1.689	3.107
5	P-Value	0.000	0.000	0.000	0.000
6	Panel 3: Grade point averages				
7	RD Estimate	0.034	0.025	0.020	0.059
8	P-Value	0.000	0.000	0.000	0.000
9	N (left)	17,039	17,285	25,375	8949
10	N (right)	25,912	26,294	38,579	13,627

Notes: The table shows the local RD effects of ChCC in the optimal window by subgroups. The optimal window consists of four months around the threshold. This means that the estimation considers all students born two months before and after the roll-out of ChCC as well as those born during the roll-out. Panel 1 shows the results for standardized math scores, Panel 2 for standardized reading scores, and Panel 3 for grade point averages. I first report the local RD estimator, and then the coefficient p-value. Column 1 reports the results for boys, Column 2 the ones for girls, Column 3 the ones for socioeconomic vulnerable children, and Column 4 for non-vulnerable children. For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016). Source: SIMCE (2015-2018) and MINEDUC (2015-2018).

The diverging effects by gender and socioeconomic status are partly in line with findings from the previous literature. Similar to my findings, Dahl and Lochner (2012) demonstrate larger effects for boys than for girls. However, contrary to my findings, they show that more disadvantaged children benefit more. Bütikofer, Løken, and Salvanes (2019) also demonstrate larger effects for children from low socioeconomic backgrounds when increasing access to mother and child health care centers. Milligan and Stabile (2011) find significant effects of child tax benefits on standardized math scores for boys but not for girls. Similarly Barham, Macours, and Maluccio (2013) only report significant effects of benefits from a conditional cash transfer program for boys. In contrast, Hoynes, Schanzenbach, and Almond (2016) analyze the impact of the food stamp program and demonstrate larger effects for women. In line with this research, Bhalotra et al. (2016) demonstrate larger effects of exposure to an infant health intervention in Sweden for girls.

9 Potential Drivers of Improved Schooling Outcomes

ChCC is a comprehensive program addressing several different aspects of early childhood development. To shed some light on the mechanisms that could drive the positive outcomes on education in middle childhood, I analyze the program's impact on intermediate outcomes. Following the current state of the literature and the multi-sectoral setup of the program, I explore three key channels, which could drive my results. I also investigate if these channels could explain the heterogeneous impact of ChCC on school performance by gender and socioeconomic status.

First, based on work by Cunha, Heckman, and Schennach (2010) which shows that cognitive and non-cognitive skills are important drivers behind school performance[26], I investigate ChCC's impact on these skills. Second, work by Currie and Almond (2011) and Almond, Currie, and Duque (2018) stresses the importance of the home environment for learning outcomes. Hence, I analyze ChCC's effects on parent-child relationships and the home environment.[27] Third, the literature shows that early childhood education significantly influences child development outcomes and educational outcomes later in life (Temple and Reynolds (2007); Carneiro and Ginja (2014); Williams (2019)). Due to this, I analyze if ChCC results in increased attendance rates in early childhood education facilities.

I apply the same local randomization approach described earlier in this paper. I report local RD estimators in the optimal cutoff window of four periods when abstracting from polynomial orders. I also present results on the linear local randomization approach using a

[26]Cunha, Heckman, and Schennach (2010) analyze the interaction between cognitive and non-cognitive skills and their importance for learning outcomes. They find that students with higher cognitive and non-cognitive skills in the early years of life are more successful in learning these skills later in life. These skills then affect a variety of outcomes, as, for example, test scores, schooling, and wages.

[27]A number of papers within the early childhood development literature studies parental outcomes, such as Brown, Kowalski, and Lurie (2020) who analyze the impact of the Earned Income Tax Credit on maternal health.

bandwidth of 20 periods. Table 6 presents summary statistics for the two scenarios. In what follows, I report local RD estimators and coefficient p-values for these model specifications. Table 7 presents the results. For a detailed description of the variables at use see the data section.

Table 6: Summary Statistics of intermediate outcomes in optimal windows

	Bandwidth=4		Bandwidth=20	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Psychomotor dev. (TEPSI)	52.639	11.479	52.960	11.853
Hearing vocabulary (TVIP)	102.222	17.124	102.265	17.185
TADI	50.091	9.009	50.529	9.011
Executive functiong (BDS)	44.630	7.506	44.931	7.360
Executive functiong (HTKS)	49.039	10.841	49.380	10.846
Abnormal behavior (CBCL1)	57.581	10.969	57.392	11.208
Abnormal height (ECD)	0.196	0.397	0.207	0.405
Parental Stress Index (PSI)	40.223	34.892	41.346	35.332
Self-confidene (PSCS)	67.307	10.428	66.801	10.428
Depression Scale (CESD)	7.203	5.271	7.205	5.417
Gender-neutral parenting	0.831	0.375	0.834	0.372
Space for toys	0.889	0.314	0.894	0.308
Learning equipment	0.715	0.452	0.708	0.454
Books	0.878	0.327	0.872	0.334
Reading (Mom)	0.453	0.498	0.451	0.498
Sharing meals	0.855	0.352	0.860	0.347
Lacking dental care	0.367	0.482	0.363	0.481
Early childhood educ. (ECE)	0.503	0.500	0.499	0.500

Notes: The table shows summary statistics of the intermediate outcomes investigated in this paper. I restrict the sample to the optimal window. The first two columns report summary statistics in a window length of four while the last two columns report them in a window length of 20. I leverage data from the ELPI survey. For this purpose, I pool survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* is a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluate children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. I weight each variable by the survey weights. Source: ELPI (2010-2017).

There is limited evidence in favor of significant effects of ChCC on cognitive and non-cognitive child development. Table 7 shows that exposure to ChCC decreases TEPSI Scores. The coefficient reported in Column 1 and 3 is -1.89 and the p-values reported in Column 2 and 4 are close to 0.01. This result is surprising as it implies a decline in children's cognitive

Table 7: Local RD effect of ChCC on intermediate outcomes

Specification	Bandwidth=4	P=0	Bandwidth=20	P=1
Variable	RD Estimate	P-Value	RD Estimate	P-Value
Panel 1: Cognitive child development outcomes				
Psychomotor dev. (TEPSI)	-1.894	0.012	-1.891	0.013
Hearing vocabulary (TVIP)	-0.139	0.875	0.971	0.251
TADI	0.631	0.304	0.818	0.165
Panel 2: Non-cognitive child development outcomes				
Executive functioning (BDS)	0.446	0.353	0.428	0.362
Executive functioning (HTKS)	1.168	0.102	1.325	0.055
Abnormal behavior (CBCL1)	-0.704	0.157	-0.102	0.834
Abnormal height (ECD)	-0.025	0.212	-0.015	0.431
Panel 3: Home environment and parent-child interventions				
Parental Stress Index (PSI)	-2.278	0.3	-1.986	0.352
Self-confidence (PSCS)	0.656	0.317	0.852	0.176
Depression Scale (CESD)	-0.596	0.077	-0.583	0.078
Home environment (HOME)	0.083	0.612	0.028	0.859
Gender-neutral parenting	0.006	0.473	-0.003	0.744
Space for toys	0.006	0.006	-0.010	0.235
Learning Equipment	0.005	0.005	0.027	0.001
Books	0.016	0.07	0.028	0.001
Reading (mother)	-0.023	0.336	0.037	0.106
Sharing meals	-0.008	0.637	-0.005	0.768
Lacking dental care	0.011	0.365	0.036	0.003
Panel 4: Early childhood education				
Attends ECE	0.005	0.665	0.027	0.021

Notes: The table shows two different local RD estimators and the respective coefficient p-values on intermediate outcomes of exposure to ChCC. The first two columns refer to a local randomization approach considering the optimal window around the cutoff and abstracts from polynomial orders (P=0). The next two columns consider 20 windows around the cutoff and a polynomial order of one (P=1). Panel 1 presents the results on cognitive child development outcomes. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* is a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluate children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. Panel 2 presents the results on non-cognitive child development outcomes. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. Panel 3 reports estimators and coefficient p-values on parent-child interactions and the home environment. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016). Source: ELPI (2010-2017) and Clarke and Tapia-Schythe (2021).

development. These negative effects could be related to a more rigorous evaluation of this dimension after the roll-out of ChCC or to unintended adverse effects. The program does not alter children's TEVI or TADI score. These findings are in contrast to previous findings from the literature, which mainly focused on the interaction between health interventions during early childhood and cognitive child development and established a positive link (Rothstein (2013); Figlio et al. (2014); Barham, Macours, and Maluccio (2013)).

To shed further light on potential drivers behind the program's diverging impact on educational outcomes by gender, I investigate its effects for boys and girls separately. I find that the negative impact on TEPSI Scores is only significant for boys (see Table D9 and D10). Similar patterns arise when dividing the sample by socioeconomic vulnerability (see Table D11 and D12). Privileged children experience declines in TEPSI Scores, while there is no significant impact of ChCC on socioeconomically vulnerable children.

In addition, the program increase children's executive functioning when measured via the HTKS. The coefficient is 1.2 and significant at the 10 and 5 percent significance level. My analysis by gender illustrates that this effect is driven by positive effects on girls' executive functioning (see Table D10). The impact is significant at the 5 percent significance level. Boys do not experience positive effects on their executive functioning (see Table D9). Similarly, executive functioning only improves for socioeconomically vulnerable children (see Table D12).

The results in Table 7 indicate that the program alters parental outcomes. The p-value of the CESD reported in Column 2 and 4 is below 0.1. This indicates that program exposure significantly decreases the incidence of parental depression at the 10 percent significance level. The point coefficient in Column 1 and 3 suggests that the program decreases the index by approximately -0.595 index points. My findings are in line with those by Akee et al. (2018) who demonstrate a positive effect of unconditional cash transfers on parental mental health.

When restricting the sample by gender, it becomes evident that the program improves parental outcomes for girls but not for boys. Girls' parents report a lower parental stress index, higher self-confidence, and less depression as a result of ChCC (see Table D10). These effects are significant at the 1 percent significance level for most coefficients. A different picture emerges for boys. There is no significant improvement on these dimensions for boys' parents (see Table D9). Similarly, these indicators only report significant improvements for socioeconomic non-vulnerable children (see Table D11). There are no significant changes for parents of less privileged children on these dimensions (see Table D12). Similar to my findings, Gensowski et al. (2020) show that parental responses to public investments in children differ for children from different backgrounds.

In addition, the program seems to increase the availability of learning equipment and books at home. The p-value on these two coefficients is below 0.1 in the case of learning equipment for both model specifications. Exposure to ChCC increases the probability that a household disposes of learning equipment for children by 0.005 (0.027) percentage points. Compared to the mean, this is an increase of 0.711 (3.762) percent. Similarly, ChCC alters the probability to have children books at home by 0.016 (0.028) percentage points. This is equivalent to a relative increase of 1.839 (3.248) percent. Lastly, while the p-value on available space for toys in Column 2 is below 0.01 it decreases to 0.235 in Column 4. Consequently, while there is some evidence on the program increasing the share of households with available space for toys, this evidence does not hold under the local linear randomization approach.

My heterogeneity analysis shows that these improvements in parental outcomes are solely significant for boys but not for girls (see Table D9 and D10). Analyses that make a distinction by socioeconomic status confirm that there are significant and positive effects for the more privileged children (see Table D11). Socioeconomically vulnerable children experience a significant increase in the number of children books at home, but also some adverse effects (see Table D12). There is a significant decrease in the space available for toys. In addition, dental care deteriorates for these children.

As part of ChCC, there was an increase in the supply of early childhood education provided by the public sector. To measure the effectiveness of this channel, I analyze the program's impact on the attendance rate of children in early childhood education facilities. Panel 4 in Table 7 shows that there is some evidence supporting increased attendance rates as a result of the program. The p-value in Column 4 is below 0.05. Therefore, the point estimate of the local linear randomization approach is significant at the 5 percent significance level. ChCC increases the probability to attend an early childhood education facility by 0.027 percentage points. This is a relative increase of 5.294 percent when compared to the average. Still, the significance of this result does not hold when abstracting from polynomial orders. The p-value in Column 2 is 0.665.

The analysis by gender suggests that attendance rates only increase for boys and not for girls (see Table D9 and D10). Socioeconomically vulnerable children do not benefit from the increased supply of early childhood education (see Table D12). Raising attendance rates are limited to the more privileged children (see Table D11).

10 Cost-Benefit Analysis

To compare the costs and benefits of ChCC to alternative programs, I use a framework developed by Hendren (2016) and Hendren and Sprung-Keyser (2020) to calculate the marginal value of public funds (MVPF). Benefits are captured by beneficiaries' willingness to pay and costs capture initial program spending and fiscal externalities. The MVPF is the ratio of both.

To calculate beneficiaries' willingness to pay, I estimate the average lifetime earnings in Chile based on the 2017 socioeconomic household survey (CASEN). I first calculate the mean income of all individuals included in the survey by age. I restrict the working population to all individuals between the ages of 18 and 64. I then assume a discount rate of 3 percent and calculate the average present value of lifetime earnings (PVLE) in Chile. I estimate that the PVLE in Chile is 220,312.4 US-Dollar.[28]

Based on data provided by the government of Chile, the estimated average unit cost of ChCC is 23,647.2 US-Dollar. Distributing these 23,647.2 US-Dollar over the life of an average person in Chile yields a present value of the annual average unit costs of 12,864.5 US-Dollar. Work by French et al. (2015) shows that a 1 percent increase in GPAs leads to an average increase in income of around 12 to 14 percent. The average GPA in my sample is 5.8 (see Table 1). Based on the different model specifications investigated in this paper, the average impact of ChCC on GPAs is approximately 0.031 points. This corresponds to an increase of 0.53 percent. The equivalent increase in income would therefore be approximately 7.5 percent.

A 7.5 percent increase in lifetime earning leads to a difference in the present value of lifetime earnings between the pre- and post-program world of 16,523 US-Dollar per participant and an additional present value of tax revenues of 1,156.6 US-Dollar per participant. The MVPF is then 1.41 per participant.

The MVPF is lower than the MVPF of the Food Stamp Program in the US of 56.25 (Bailey et al. 2020) or the Perry Preschool Project's MVPF of 43.61 (Hendren and Sprung-Keyser 2020). This could be due to the fact that girls and the socioeconomically vulnerable do not benefit equally from the program and that several of the intended channels seem to be unaffected by the program.

11 Conclusion

This paper presents novel evidence on the impact of comprehensive and universal early childhood development programs. So far, evidence on the effects of these type of programs is limited by the small number of such programs currently in place and data limitations. I study the effect of the pioneer program *Chile Crece Contigo* on school performance 12 years after its introduction. The program is universal and combines components of health, education and parental care. I find that exposure to ChCC has positive effects on grade point averages as well as standardized math and reading test scores. Effects are more marked for boys than for girls. The program's impact is smaller for socioeconomically vulnerable children. My findings pass several robustness tests including alternative polynomial orders and variations in the underlying bandwidth. Furthermore, my results hold when employing an alternative empirical estimation strategy, namely an event study design.

The heterogeneous impact of ChCC by subgroups could mean that the program fails

[28] Appendix F presents a detailed overview of the methodology.

to address important human capital gaps between different groups and benefits those who are already more privileged most, which hints towards important shortcomings in the inclusiveness of universal, comprehensive early childhood interventions. Less privileged groups might be less likely to comply with the program, or the inclusion error might be larger for these groups. Another possible explanation is that the quality and quantity of the services offered might differ. The heterogeneous impact of exposure to ChCC could also be evidence of the program falling short on addressing important drivers behind human capital gaps between groups, such as gender stereotypes (Andersen et al. 2013). I generate evidence on potential reasons for the heterogeneity in effect sizes by analyzing the program's impact on intermediate child development outcomes.

The positive impact on school performance seems to be driven by improvements in intra-household relations and increased attendance rates in early childhood education facilities. However, these effects differ by gender and socioeconomic status. For girls, I find significant improvements in several parental outcomes as well as in their executive functioning. Boys seem to benefit by an increase in the availability of material goods. Raising attendance rates are limited to the more privileged children and boys. The latter could explain why the program's impact on educational outcomes is larger for boys and socioeconomically non-vulnerable children. The program barely affects intermediate child development outcomes for less privileged children and these children also experience some adverse effects.

My work contributes to a large literature analyzing early childhood development. I show that a comprehensive approach to early childhood development can lead to improvements in child development across several dimensions. My findings illustrate that, in addition to targeted programs for poor children, universal and comprehensive interventions have positive effects on child development. However, the relatively low MVPF indicates that targeted programs with a higher MVPF might be more cost-effective. This paper fills the gap of the "missing middle years" (Almond, Currie, and Duque 2018) by showing positive effects of investments in early childhood on outcomes observed during middle childhood.

Policymakers should use the insights of this paper to design more integrated and comprehensive approaches to early childhood development. My work illustrates potential limitations of these types of programs. I show that several of the multi-sectoral entry points might not work as intended. In addition, policymakers should pay special attention to the gender dimension of such programs so that boys and girls benefit equally. Additionally, there is a need for mechanisms, which maximize the effect of such programs on the most vulnerable children. The results presented cast doubt on the effectiveness of universal, comprehensive programs like ChCC in closing human capital gaps between socioeconomic groups. While the program's impact is overall positive for all groups investigated, the heterogeneous impact by vulnerability and gender is worrisome.

Further research should analyze if trajectory effects carry over from early to middle childhood into adulthood, and study the impact of ChCC on long-term outcomes, like tertiary education, wages and health in the long run.

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Appendices

A Program Roll-out

The table below details the inclusion of beneficiaries into the program during the early years of ChCC.

Table A1: Beneficiaries of ChCC (roll-out)

Coverage	2007	2008	2009
Municipalities	159	345 (all)	345 (all)
Pregnant women	47,683	202,729	205,935
Births	40,119	160,643	171,373
Children under 1		168,823	173,733
Children aged 1 to 2		174,286	176,854
Children aged 2 to 4			324,338

Notes: The table presents the roll-out of ChCC over time and by municipality. Source: Adapted from The World Bank (2018).

B Detailed Program Description

B.1 Summary of the Program

The social subsystem ChCC is a decentralized program that operates locally through municipal networks (called *Red Comunal*). Children and their mothers start to form part of the social subsystem ChCC during the first prenatal control check-up. From that moment onwards, children are part of the program, with special services offered to them and their families. The services offered start during gestation. They consist of regular health check-ups, parental education programs, the hand-over of materials for stimulation, as well as the assessment of risk factors and the development of personalized health plans. Additionally, pregnant women who are part of the socioeconomically vulnerable population have access to a family subsidy, and home visits. The program also includes a personalized birth-giving process, which is facilitated through a number of actionable items.

ChCC offers a variety of services and benefits to children under five and to their parents. These services range from the handover of didactic materials on how to stimulate children to the introduction of educational group workshops, personalized hospitalization, the development of individual health plans and special services offered to children with disabilities or development lags. It also gives children who are part of the 40 percent most vulnerable population free access to early childhood education.

In the following, I will describe the different components of ChCC in more detail.

B.2 Pregnancy and Childbirth

ChCC offers special services to pregnant women. It also significantly improved the birth-giving experience. The program increased the time of prenatal checkups from 20 to 40 minutes.[29] The program also introduced psycho-social risk factors into the risk screening of pregnant women. ChCC introduced the development of a personalized health plan and personalized home visits. These plans are applied to all women who suffer from any kind of risk factor.[30]

Another entry point of ChCC is the guarantee of equal access to information about pregnancy and birth-giving. Families receive a so-called Gestation Guide during their first prenatal check-up.[31] Moreover, ChCC provides the possibility to participate in prenatal workshops targeted at pregnant women and their partners. The workshops consist of six sessions and provide information about birth-giving and child-care, as well as cognitive and emotional support. Also, ChCC introduced the transfer of educational materials about pregnancy and birth-giving to expectant parents. Additionally, ChCC personalized the birth-giving process and launched a campaign with the goal to raise awareness about the importance of being accompanied while giving birth. It introduced a variety of actionable items aiming at the facilitation of birth-giving. Additionally, ChCC introduced an additional education session with information about the child-bed. In 2008, a nutritional component was developed, called *Purita Mamá*.

B.3 Newborns

In 2009, ChCC introduced a component specifically addressing the needs of newborns, called PARN (*Programa de apoyo al recien nacido*). The program consists of in-kind transfers of materials that are useful for the care-taking of a newborn (as oils, creams, a towel, clothes, and a blanket, among others). It also includes educational materials for parents with information on how to take care of newborns.

[29] The so called EPsA (Psycho-social evaluation) is an evaluation of risk factors, such as depression or gender-based violence. ChCC increased the duration of the pregnancy control from 20 minutes to 40 minutes. Pregnant women are subject to the EPsA twice, once during their first pregnancy control and then again during the third gestation trimester.

[30] These women get access to personalized social services through the municipality network ChCC.

[31] The Gestation Guide contains information about the pregnancy, birth-giving, labor rights, and other practical advice.

B.4 Health

In 2007, the government of Chile introduced evaluation tools that aim to detect risk factors for the development of children under four.[32] Similarly, ChCC introduced the evaluation of psycho-motor deficits.[33] As part of ChCC the attention of children in hospitals was revisited. ChCC introduced a concept that aimed at minimizing the stress experienced by children hospitalized during early childhood. This involved, among others, the introduction of a special technical orientation of medical staff.

B.5 Parental Education

ChCC offers several other group education programs targeted at caregivers, addressing topics such as a child's socio-psychological stimulation, educational child-rearing guidelines, and more. It introduced a variety of workshops targeting socioeconomically vulnerable children. Moreover, ChCC diffuses information as well as materials on child-care for free. These are available through the web portal of ChCC [34], a telephone line, through which it is possible to clarify doubts, a radio program, a TV program, educational booklets, TV campaigns, and a manual of best practices. The goal of these components is to create easy access to experts and informational materials about early child development. In 2008, ChCC launched a special musical program directed at children between zero and five years old.

In 2009, the program *Nadie es perfecto* (Nobody is perfect) was introduced. *Nadie es perfecto* is a workshop series, which consists of six to eight sessions directed at all caretakers. The program was inspired by a similar program in place in Canada. It also involved in-kind transfers directed at the cognitive stimulation of children between zero and five years old.

B.6 Early Childhood Education

Another set of actions forming part of ChCC are the ones addressing early childhood education. These policies aim to achieve equal access to early childhood education through increasing its coverage and quality. The goal was to create 70,000 new places in nurseries and 43,000 new places in kindergardens between 2006 and 2010 through the network of preschools and kindergardens *INTEGRA* (in Spanish: Red de Salas Cuna y Jardines Infantiles) as well as Chile's national daycare association *JUNJI* (in Spanish: Junta Nacional de Jardines Infantiles). Moreover, there was an increase in opening hours. Early childhood ed-

[32] The risk assessment includes the detection of neurological problems and maternal depression.

[33] The evaluation is conducted through the EEDP (Scale of Psycho-motor Development Evaluation), as well as the TEPSI (Test of Psycho-motor Development).

[34] www.crececontigo.cl

ucation facilities also increasingly open during holidays. They also offer parental education, and a special educational program for rural children.

The number of early childhood education facilities with increased opening hours increased from 484 in 2006 to 655 in 2009. Moreover, the number of facilities opening exclusively during the summer holidays augmented from 82 in 2006 to 102 in 2009. Also, ChCC introduced a mobile kindergarden, which reached 187 children in 2009. From 2005 to 2010 *JUNJI* increased its number of daycare centers by 505 percent (from 539 to 3,259) and its number of kindergartens by 92 percent (from 46,990 spots to 85,690 spots). *JUNJI* also introduced a new educational program in its facilities.

B.7 Special Services for the Most Vulnerable Children

ChCC comprises special services and benefits offered to children forming part of the vulnerable population in Chile. Health officials develop a personalized action plan addressing deficits and risks detected through thorough professional evaluations. These health action plans consist of a set of psycho-social actionable items targeting both children and their families.[35] In addition to that, ChCC grants special social protection services to families characterized by some form of socioeconomic vulnerability.[36] These special services are the inclusion of socioeconomically vulnerable pregnant women into the the *Unified Family Subsidy* (in Spanish: Subsidio Único Familiar). The program also offers these families prioritized access to social services offered by the public sector.

B.8 Services Targeting the General Citizenship

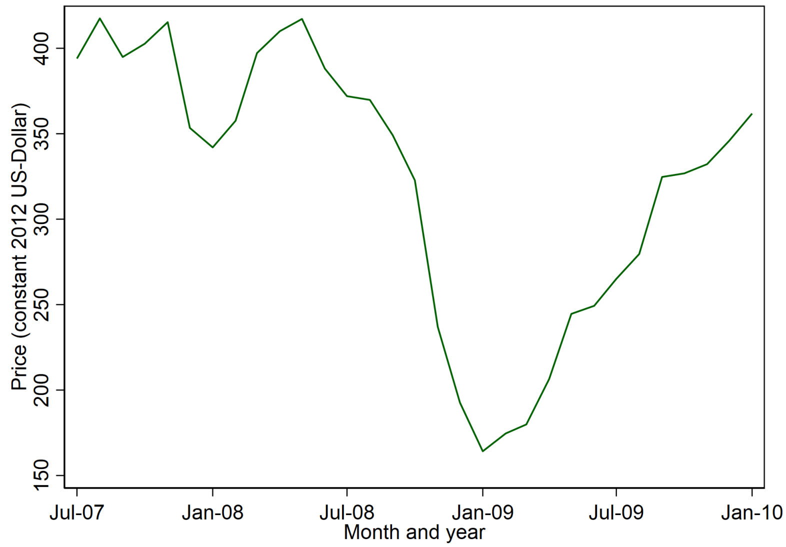
One of ChCC's main goals was to raise the general awareness about the importance of investments in early childhood development. For this purpose, it introduced a website, a free hotline and a radio program targeting the overall Chilean population.

[35] These actionable items consist of home visits, group educational programs, local stimulation centers, playrooms, among others.

[36] From 2007 to 2009 these targeted the 40 percent most vulnerable, in 2010 to the 50 percent, and in 2011 to the 60 percent most vulnerable.

C Copper Prices

Figure C1: Evolution of monthly copper prices (2007-2009)



Notes: The figure plots the evolution of copper prices on a monthly basis for the period between June 2007 to June 2009.

D Additional Tables

D.1 Summary Statistics by socio-demographic group

Summary statistics of 4th-graders by gender (2015-2018)

	Male			Female		
VARIABLES	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Standardized math score	419,505	262.6	48.87	415,537	260.3	47.68
Standardized reading score	419,505	263.8	53.85	415,537	273.5	50.23
Rural	419,505	0.101	0.302	415,537	0.0961	0.295
Age (Years)	419,484	9.416	0.780	415,516	9.332	0.706
GPA	419,505	5.756	1.005	415,537	5.910	0.996
Assistance (%)	419,505	91.08	14.85	415,537	91.32	14.67
Retention	419,505	0.0124	0.111	415,537	0.00645	0.0800
Vulnerable student	419,505	0.796	0.403	415,537	0.796	0.403

Notes: Summary statistics by gender. Source: SIMCE and Chilean Ministry of Education.

Summary statistics of 4th-graders by socio-economic status (2015-2018)

	Non-Vulnerable			Vulnerable		
VARIABLES	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Standardized math score	170,299	262.2	46.26	664,743	261.3	48.80
Standardized reading score	170,299	270.3	51.65	664,743	268.2	52.47
Rural	170,299	0.0827	0.275	664,743	0.103	0.304
Age (Years)	170,299	9.204	0.467	664,701	9.418	0.795
GPA	170,299	5.885	0.927	664,743	5.820	1.022
Assistance (%)	170,299	91.91	13.49	664,743	91.02	15.06
Female	170,299	0.498	0.500	664,743	0.498	0.500
Retention	170,299	0.00702	0.0835	664,743	0.0100	0.0997

Notes: Summary statistics by gender. Source: SIMCE and Chilean Ministry of Education.

D.2 Summary Statistics of ELPI Outcomes

Table D1: Summary statistic of ELPI Sample (2010-2017)

	Control group	Treatment group
Age in months	92.77	59.43
	(42.01)	(33.17)
Male	0.489	0.488
	(0.500)	(0.500)
Vulnerable	0.425	0.398
	(0.494)	(0.489)
Indigenous	0.111	0.126
	(0.314)	(0.331)
Household members	3.621	3.942
	(2.085)	(2.014)
Share of adults with low education	0.121	0.0998
	(0.173)	(0.158)
No. of employed household members	1.658	1.696
	(0.930)	(0.951)
First survey-round	0.247	0.0742
	(0.431)	(0.262)
Second survey-round	0.278	0.185
	(0.448)	(0.389)
Third survey-round	0.475	0.740
	(0.499)	(0.438)
Observations	12404	19291

Notes: The table shows the descriptive statistics of children included in the ELPI survey by treatment status. Treated children are children born after the implementation of ChCC. *Male*, *Vulnerability*, and *Indigenous* are indicator variables. The information on the respective survey round represents the share of people included in the survey round under consideration. I weight each variable by the survey weights. Source: ELPI 2010, 2012 and 2017.

Table D2: Summary Statistics of intermediate outcomes

Variable	Mean	Std. Dev.	Min	Max	N
TEPSI	53.387	12.080	19	80	321,110
TVIP	102.772	17.098	55	145	770,323
TADI	51.337	9.390	23	81	521,280
BDS	45.301	7.772	33	90	503,259
HTKS	49.469	10.592	20	91	507,912
CBCL1	57.376	11.159	28	96	888,009
Abnormal height (ECD)	0.210	0.408	0	1	752,548
PSI (Int.)	41.998	35.325	1	99	734,602
PSCS	66.628	10.360	20	85	734,602
CESD	7.219	5.389	0	30	734,662
HOME	11.785	4.375	0	27	1,745,490
Gender-neutral parenting	0.840	0.367	0	1	3,652,612
Space for toys	0.893	0.309	0	1	3,265,159
Learning equipment	0.704	0.456	0	1	3,264,847
Books	0.872	0.334	0	1	3,263,646
Reading (Mom)	0.457	0.498	0	1	727,518
Sharing meals	0.857	0.350	0	1	730,955
Lacking dental care	0.367	0.482	0	1	3,304,557
ECE	0.497	0.500	0	1	3,652,612

Notes: The table shows the summary statistics of the intermediate outcomes investigated in this paper. I restrict the sample to all children born 18 months before and after the roll-out of ChCC as this allows a large enough sample size on either side of the cutoff. I leverage data from the ELPI survey. For this purpose, I pool the survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* is a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education and is the share of children attending an ECE facility. I weight each variable by survey weights. Source: ELPI (2010-2017).

D.3 Alternative Cutoff Windows

To analyze if the number of windows around the cutoff drive my results, I repeat my analysis using an alternative cutoff window. While the assumption on a similarity of unobserved characteristics is most plausible in smaller cutoff windows, there are downsides to restricting the sample to few windows. I might lose important information on the variation or trends in the data when relying on a window length of less than five. For this reason, I validate my findings considering a larger cutoff window. I choose a cutoff window of 20 months for my robustness check. This means that I consider all students born ten months before and after ChCC's implementation.

Table D3 shows that students systematically differ from each other on observable characteristics when considering the larger cutoff window. The p-values are zero in the case of gender and socioeconomic vulnerability. Consequently, it is not possible to reject the null hypotheses of treatment effects on observable covariates in the larger cutoff window. I confirm this by a t-test on baseline characteristics. Table D4 shows that the related coefficient p-values on gender and socioeconomic vulnerability are zero. The systematic differences in individual controls are an important caveat and might confound my results in the larger cutoff window. The possibility of significant unobservable confounding factors might be more plausible under this model specification.

Turning attention to results reported on the three schooling outcomes, the local RD approach in the larger window confirms my findings from the optimal cutoff window. Table D4 provides evidence that exposure to ChCC significantly improves schooling outcomes. Column 1 illustrates that the program leads to increases in standardized math scores of 0.347 points, in standardized reading scores of 2.987 points, and in grade point averages of 0.03 points. When compared to the local RD estimators in the optimal window length, the point estimates are similar in terms of magnitude in the case of grade point averages, but smaller in the case of standardized test scores. Especially the coefficient on standardized math scores more than halves when compared to the baseline estimator. Furthermore, Column 2 shows that the p-value on standardized math scores increases in the larger window. The point estimate associated with standardized math scores is only significant at the 2.5 percent significance level. In contrast, the coefficient p-values on standardized reading scores and grade point averages remain at zero and are highly significant.

Table D3: Baseline municipality characteristics (20 periods around cutoff)

	Control mean	Treatment mean	T-test p
Female	0.50	0.51	0.00
Vulnerable student	0.73	0.74	0.00
Rural	0.10	0.10	0.60
Observations	172,695	186,707	359,402

Notes: The table shows the baseline characteristics of the control and treatment group in the 20 periods around the cutoff. Column 1 reports the mean of the control group (those children born before the roll-out of ChCC). Column 2 reports the mean of the treatmetn group (those children born after the roll-out of ChCC). Column 3 reports the coefficient p-values of a two-sided t-test. Source: SIMCE (2015-2018), MINEDUC (2015-2018).

Table D4: Local RD effect of ChCC on schooling outcomes in the 20 periods around the cutoff

		RD Estimate	P-Value	N (left)	N (right)
1	Standardized math score	0.357	0.025	172,695	186,707
2	Standardized reading score	2.987	0.000	172,695	186,707
3	Grade point averages	0.030	0.000	172,695	186,707
4	Gender	0.008	0.000	172,695	186,707
5	Vulnerability	0.020	0.000	172,695	186,707
6	Rural	0.000	0.829	172,695	186,707

Notes: The table shows the local RD effect of ChCC in the 20 months around the threshold. This means that the estimation considers all students born ten months before and after the roll-out of ChCC as well as those born during the roll-out. The first column shows the point estimates of exposure to ChCC on the three schooling outcomes and observable covariates. Column 2 presents the related coefficient p-values. Column 3 and 4 show the number of observations N on each side of the cutoff. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

D.4 Additional Heterogeneity Analysis

The below table shows the local randomization approach of estimating the impact of ChCC on schooling outcomes by subgroups in the 20 periods around the cutoff. The findings confirm my results in the optimal window around the cutoff.

Table D5: Local RD effect of ChCC in the 20 periods around the cutoff on schooling outcomes by groups

	Group	Boys	Girls	Vulnerability	Non-vulnerability
	Panel 1: Standardized math scores				
1	RD Estimate	1.056	-0.274	-0.023	1.435
2	P-Value	0.000	0.218	0.902	0.000
3	Panel 2: Standardized reading scores				
4	RD Estimate	3.597	2.237	2.437	4.545
5	P-Value	0.000	0.000	0.000	0.000
6	Panel 3: Grade point averages				
7	RD Estimate	0.040	0.020	0.030	0.040
8	P-Value	0.000	0.000	0.000	0.000
9	N (left)	86,562	86,133	125,975	46,720
10	N (right)	92,026	94,681	137,991	48,716

Notes: The table shows the local RD effect of ChCC in the 20 months around the cutoff window. This means that the estimation considers all students born ten months before and after the roll-out of ChCC as well as those born during the roll-out. I first report the RD estimator and then the coefficient p-value. Panel 1 shows results for standardized math scores, Panel 2 for standardized reading scores, and Panel 3 for grade point averages. Column 1 reports results for boys, Column 2 for girls, Column 3 for socioeconomic vulnerable children and Column 4 for socioeconomic non-vulnerable children. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

The below tables show the parametric estimation of exposure to ChCC in the larger window, using 20 periods around the cutoff. The results confirm the findings from the non-parametric estimation.

Table D6: Local RD effect of ChCC in 20 periods around cutoff window on standardized math scores by groups (p=1)

		RD Estimate	P-Value	N (left)	N (right)	Covariates
1	Boys	3.087	0.000	86,562	92,026	Yes
2	Girls	3.242	0.000	86,133	94,681	Yes
3	Vulnerability	2.899	0.000	12,5975	137,991	Yes
4	Non-vulnerability	3.915	0.000	46,720	48,716	Yes

Notes: The table shows the local RD effect of ChCC on standardized math scores in the 20 months around the cutoff window. This means that the estimation considers all students born ten months before and after the roll-out of ChCC as well as those born during the roll-out. I assume a local polynomial order of degree one. Column 1 reports the RD coefficient, Column 2 the coefficient p-values. N is the number of observations on each side of the eligibility cutoff. I first report results for boys in Row 1, for girls in Row 2, for vulnerable children in Row 3 and for non-vulnerable children in Row 4. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

Table D7: Local RD effect of ChCC in 20 periods around cutoff window on standardized reading scores by groups (p=1)

		RD Estimate	P-Value	N (left)	N (right)	Covariates
1	Boys	3.927	0.000	86,562	92,026	Yes
2	Girls	3.798	0.000	86,133	94,681	Yes
3	Vulnerability	3.498	0.000	125,975	137,991	Yes
4	Non-vulnerability	5.023	0.000	46,720	48,716	Yes

Notes: The table shows the local RD effect of ChCC in the 20 months around the cutoff window on standardized reading scores. This means that the estimation considers all students born ten months before and after the roll-out of ChCC as well as those born during the roll-out. I assume a local polynomial order of degree one. Column 1 reports the RD coefficient, Column 2 the coefficient p-values. N is the number of observations on each side of the eligibility cutoff. I first report results for boys in Row 1, for girls in Row 2, for vulnerable children in Row 3 and for non-vulnerable children in Row 4. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

Table D8: Local RD effect of ChCC in 20 periods around cutoff window on grade point averages by groups (p=1)

		RD Estimate	P-Value	N (left)	N (right)	Covariates
1	Boys	0.042	0.000	86,562	92,026	Yes
2	Girls	0.043	0.000	86,133	94,681	Yes
3	Vulnerability	0.039	0.000	125,975	137,991	Yes
4	Non-vulnerability	0.054	0.000	46,720	48,716	Yes

Notes: The table shows the local RD effect of ChCC on grade point averages in the 20 months around the cutoff window. This means that the estimation considers all students born ten months before and after the roll-out of ChCC as well as those born during the roll-out. I assume a local polynomial order of degree one. Column 1 reports the RD coefficient, Column 2 the coefficient p-values. N is the number of observations on each side of the eligibility cutoff. I first report results for boys in Row 1, for girls in Row 2, for vulnerable children in Row 3 and for non-vulnerable children in Row 4. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

D.5 Analysis of intermediate outcomes by subgroups

The below table shows the Intention-To-Treat (ITT) effect of ChCC on intermediate outcomes by subgroups.

Table D9: The impact of ChCC on intermediate outcomes (boys)

Variable	Bandwidth=4 RD estimator	P-value	Bandwidth=20 RD estimator	P-value
TEPSI	-2.072	0.044	-2.532	0.014
TVIP	-0.046	0.971	1.027	0.389
TADI	1.133	0.198	1.346	0.109
BDS	-0.137	0.834	-0.086	0.893
HTKS	0.297	0.761	0.362	0.702
CBCL1	-1.386	0.047	-0.820	0.234
Abnormal height (ECD)	-0.014	0.616	0.011	0.685
PSI (Int.)	2.851	0.371	2.456	0.423
PSCS	-0.867	0.377	-0.627	0.495
CESD	-0.249	0.616	-0.048	0.920
HOME	0.119	0.603	0.012	0.958
Gender-neutral parenting	-0.003	0.846	-0.008	0.548
Space for toys	0.011	0.372	-0.003	0.830
Learning equipment	0.040	0.021	0.055	0.001
Books	0.025	0.061	0.038	0.003
Reading (Mom)	-0.009	0.793	0.076	0.018
Sharing meals	0.002	0.933	-0.009	0.668
Lacking dental care	0.011	0.533	0.040	0.023
ECE	0.018	0.292	0.049	0.004

Notes: The table shows intention-to-treat (ITT) effects of ChCC on intermediate outcomes for boys. I restrict the sample to the optimal window. The first two columns report results in a window length of four while the last two columns report them in a window length of 20. I leverage data from the ELPI survey. For this purpose, I pool survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* scores are a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. Source: ELPI (2010-2017).

Table D10: The impact of ChCC on intermediate outcomes (girls)

	Bandwidth=4		Bandwidth=20	
Variable	RD Estimate	P-Value	RD Estimate	P-Value
TEPSI	-1.549	0.156	-1.041	0.344
TVIP	-0.188	0.877	0.943	0.429
TADI	0.101	0.906	0.264	0.747
BDS	1.032	0.144	0.959	0.160
HTKS	2.008	0.051	2.303	0.020
CBCL1	0.003	0.997	0.653	0.341
Abnormal height (ECD)	-0.035	0.213	-0.042	0.127
PSI (Int.)	-7.289	0.016	-6.167	0.038
PSCS	2.145	0.013	2.281	0.008
CESD	-0.936	0.041	-1.094	0.016
HOME	0.047	0.841	0.045	0.842
Gender-neutral parenting	0.014	0.302	0.001	0.910
Space for toys	0.002	0.894	-0.016	0.146
Learning equipment	0.026	0.115	0.026	0.109
Books	0.007	0.521	0.018	0.129
Reading (Mom)	-0.037	0.273	-0.005	0.889
Sharing meals	-0.018	0.453	0.001	0.979
Lacking dental care	0.011	0.513	0.031	0.060
ECE	-0.006	0.718	0.009	0.595

Notes: The table shows ITT effects of ChCC on intermediate outcomes for girls. I restrict the sample to the optimal window. The first two columns report results in a window length of four while the last two columns report them in a window length of 20. I leverage data from the ELPI survey. For this purpose, I pool survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* scores are a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. Source: ELPI (2010-2017).

Table D11: The impact of ChCC on intermediate outcomes (socioeconomic non-vulnerable children)

	Bandwidth=4		Bandwidth=20	
Variable	RD Estimate	P-Value	RD Estimate	P-Value
TEPSI	-2.434	0.026	-2.456	0.025
TVIP	0.294	0.824	1.913	0.127
TADI	0.841	0.338	1.432	0.093
BDS	-0.250	0.732	0.523	0.466
HTKS	-0.075	0.944	1.001	0.332
CBCL1	-0.513	0.481	0.550	0.440
Abnormal height (ECD)	-0.015	0.620	-0.023	0.433
PSI (Int.)	-5.893	0.038	-3.602	0.191
PSCS	1.314	0.121	1.526	0.060
CESD	-0.928	0.037	-0.699	0.109
HOME	0.185	0.430	0.152	0.502
Gender-neutral parenting	0.007	0.572	-0.008	0.488
Space for toys	0.035	0.001	0.026	0.008
Learning equipment	0.035	0.018	0.052	0.000
Books	0.005	0.632	0.016	0.142
Reading (Mom)	-0.020	0.579	0.032	0.353
Sharing meals	-0.006	0.802	-0.006	0.786
Lacking dental care	-0.006	0.724	0.027	0.101
ECE	0.017	0.312	0.034	0.035

Notes: The table shows ITT effects of ChCC on intermediate outcomes for socioeconomic non-vulnerable children. I restrict the sample to the optimal window. The first two columns report results in a window length of four while the last two columns report them in a window length of 20. I leverage data from the ELPI survey. For this purpose, I pool survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* scores are a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. Source: ELPI (2010-2017).

Table D12: The impact of ChCC on intermediate outcomes (socioeconomic vulnerable children)

Variable	Bandwidth=4 RD Estimate	P-Value	Bandwidth=20 RD Estimate	P-Value
TEPSI	-1.476	0.231	-2.010	0.110
TVIP	1.032	0.461	1.492	0.270
TADI	1.382	0.194	1.440	0.152
BDS	1.035	0.112	0.150	0.823
HTKS	2.541	0.026	1.956	0.080
CBCL1	-0.313	0.724	-0.727	0.392
Abnormal height (ECD)	-0.011	0.745	-0.009	0.791
PSI (Int.)	2.608	0.452	0.108	0.974
PSCS	-0.237	0.819	-0.033	0.973
CESD	-0.147	0.775	-0.448	0.379
HOME	-0.072	0.787	-0.131	0.601
Gender-neutral parenting	0.007	0.629	0.008	0.602
Space for toys	-0.030	0.036	-0.052	0.000
Learning equipment	0.029	0.139	0.025	0.187
Books	0.030	0.039	0.042	0.003
Reading (Mom)	-0.026	0.526	0.036	0.351
Sharing meals	-0.009	0.743	-0.010	0.712
Lacking dental care	0.043	0.029	0.054	0.004
ECE	-0.002	0.896	0.022	0.234

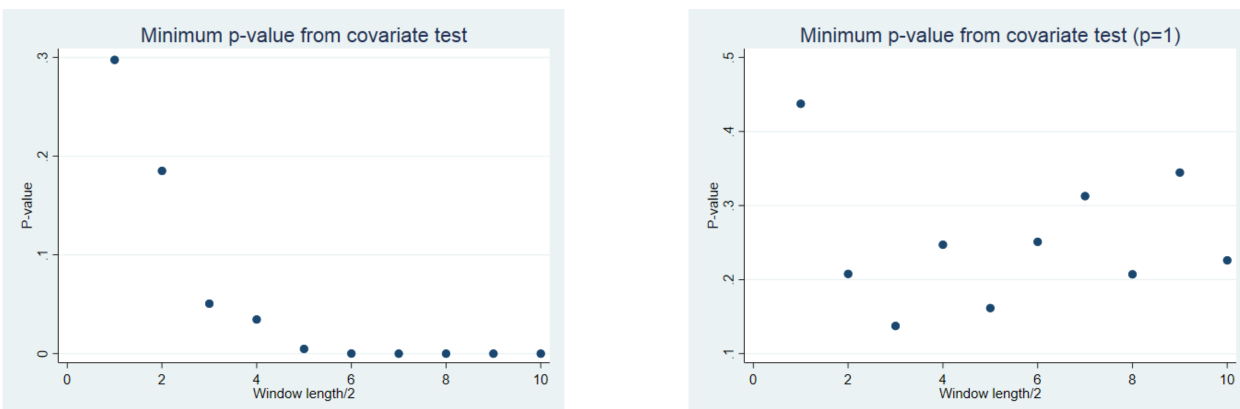
Notes: The table shows ITT effects of ChCC on intermediate outcomes for socioeconomic vulnerable children. I restrict the sample to the optimal window. The first two columns report results in a window length of four while the last two columns report them in a window length of 20. I leverage data from the ELPI survey. For this purpose, I pool survey waves from 2010, 2012, and 2017. *TEPSI* is a score that measures children's psycho-motor development. *TVIP* scores are a norm-referenced measure of Spanish hearing vocabulary analyzing verbal reasoning, as well as language skills. *TADI* scores evaluates children ages three months to six years and measures four dimensions of child development: cognition, motor skills, language and socio-emotional development. *BDS* and *HTKS* measure children's executive functioning and *CBCL1* behavioral abnormalities. *PSI* is an index measuring parental stress, *PSCS* is a perceived self-confidence scale, *CESD* is the Center for Epidemiologic Studies Depression Scale, and *HOME* is the Home Observation Measurement of the Environment Index. All other variables are dummy variables. *ECE* stands for early childhood education. Source: ELPI (2010-2017).

E Additional Figures

E.1 Optimal Window Selection

Figure E1 shows the optimal window selection when abstracting from polynomial orders. The optimal bandwidth is four. Figure E1 repeats this analysis including a linear slope. The optimal bandwidth is the minimum window. As it might be challenging to estimate the slope coefficient with only one data point on each side of the cutoff, I consider a window length of 20 for the linear local randomization approach. The optimal window length is four. This means that the optimal local randomization approach considers the two birth cohorts before and after ChCC's roll-out. Under a polynomial order of one, the optimal window length is the minimum window. This means that the optimal local randomization approach should consider the birth cohort before and after ChCC's roll-out.

Figure E1: Optimal window selection under a polynomial order of 0 and 1



Notes: The graph shows the optimal window selection for the local randomization approach. For a detailed overview of the methodology see Cattaneo, Titiunik, and Vazquez-Bare (2016). I include the following three variables for the covariance balance tests: a child's gender, a dummy variable for socioeconomic vulnerability as well as if the child assists a rural or urban school. The covariate balance test uses a large-sample approximation. The left panel shows the results under an estimation assuming a polynomial order of zero. The right panel shows the results for an estimation assuming a polynomial order of one. Source: ELPI (2010-2017).

E.2 Regression Discontinuity Plots

The figures below show the RD plots of a local randomization approach without slopes in the optimal window of bandwidth four. The cutoff is zero and refers to the date on which ChCC was rolled out.

Figure E2: RD Plot (Standardized math scores)

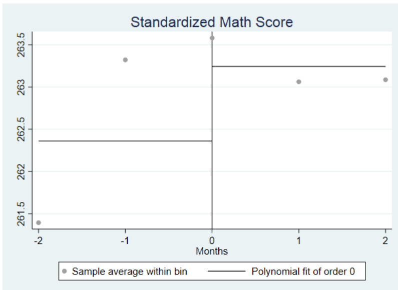


Figure E3: Rd Plot (Standardized reading scores)

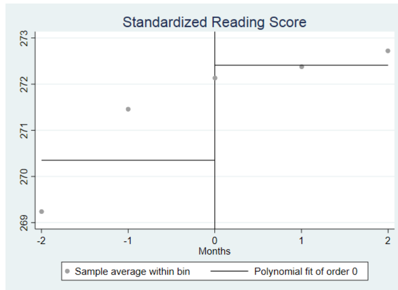
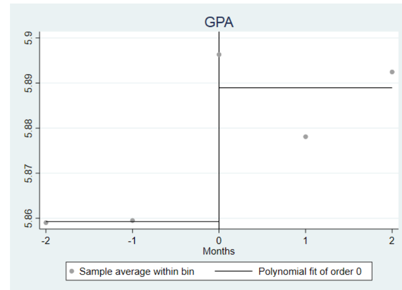


Figure E4: RD Plot (Grade point averages)



Notes: The figures above show the local randomization design plots for schooling outcomes. The left panel shows the plot for standardized math scores, the middle panel the one for standardized reading scores, and the right panel the one for grade point averages. I restrict the periods shown to the optimal window length, namely four periods. This means that the figures show the average values of schooling outcomes for all children born two months previous to the roll-out of ChCC to two months after its roll-out. The black horizontal line features the threshold of the local RD approach, namely zero. Source: SIMCE (2015-2018) and MINEDUC (2015-2018). For details on the estimation procedure see Cattaneo, Titiunik, and Vazquez-Bare (2016).

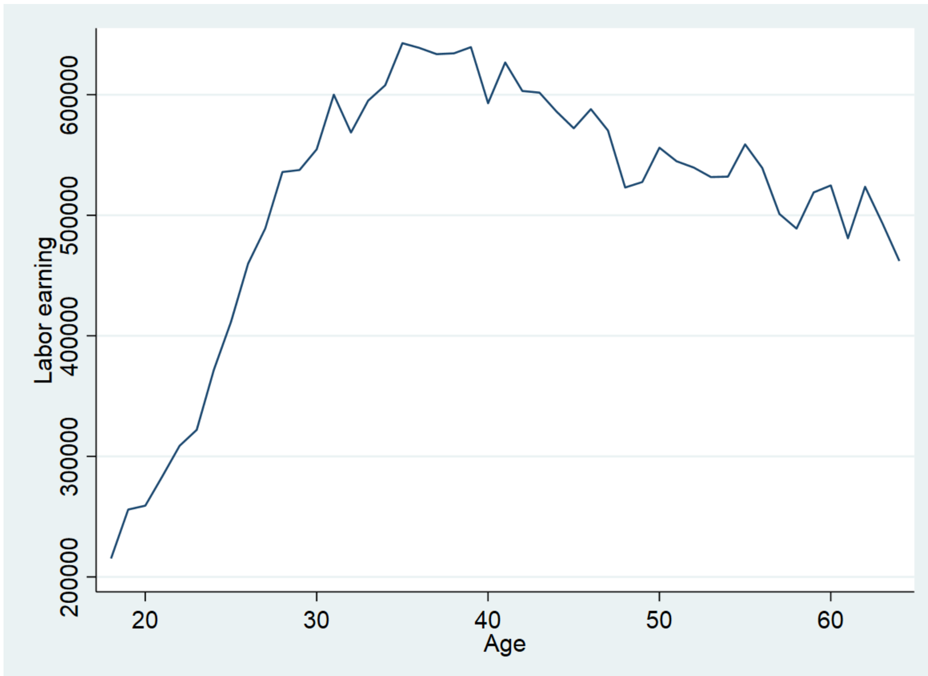
F Appendix G - Detailed Cost-Benefit Analysis

To calculate the program's costs per participant I take advantage of data provided by the government of Chile. I have data on the program's costs per component per year as well as on the number of units benefiting from each component. Depending on the program component these units are children, pregnant women, municipalities or newborns. I restrict my period to the years 2007 to 2017, as the program's target group was expanded in 2017. The total costs of the program for all units amount to 236,472.2 US-Dollar for the period 2007 to 2017. I then calculate the average unit cost per year and convert these values to US-Dollars using data on exchange rates published by the OECD for each year. I then sum up the costs for each respective year from 2007 to 2017. Next, I divide the sum by the number of years. This gives me the average unit cost per year for the period 2007 to 2017. The average unit cost per year is 23,647.2 US-Dollar.

To calculate the marginal willingness to pay for ChCC by program participant I calculate the present value of lifetime earnings in Chile. I take advantage of data published by the Ministry of Social Protection, namely the socioeconomic survey (CASEN) from 2017.

I first calculate the mean labor income of all individuals between 18 and 65 years old in 2017. The results are shown in figure G1. I assume that this distribution is representative for the average lifetime earning distribution in Chile. I then calculate the present value of this earning stream. I assume a discount rate of 3 percent. I then convert the values to 2017-US-Dollar, taking the average exchange rate for 2017 from data on exchange rates published by the OECD. This results in an average present value of lifetime earnings of 220,312.4 US-Dollar.

Figure G1: Average lifetime earnings in Chile (2017 in CL)



Notes: The graph shows the average lifetime earnings in Chile in Chilean Pesos. The x-axis represents the age in years and the y-axis the labor earning in Chilean Pesos. Source: Ministerio de Desarrollo Social y Familia (2017)

Next, I equally distribute the average per year program unit cost of 23,647.2 US-Dollar across a typical lifetime of an individual. I then calculate the present value of this cost stream, which is 12,864.5 US-Dollar. This is 6 percent of the average present value of lifetime earning in Chile. Consequently, participants would need to increase their earnings by 6 percent over the course of the life to meet the program costs of ChCC.

Work by French et al. (2015) shows that a 1 percent increase in the GPA leads to an average increase of around 12 to 14 percent in earnings. The average GPA in my sample is 5.8 (see table 1). Based on the different model specifications investigated in this paper, the average impact of ChCC on grade point averages is approximately 0.3. This is an increase of 0.5 percent over the mean grade point average. The equivalent increase in income would therefore be approximately 7.5 percent. From this information I create the post-program average income flow, adding 7.5 percent to the average income per age year. I then take the net present value of this post-program income flow. A 7.5 percent increase in the lifetime earning leads to a difference in the present value of lifetime earnings between the pre- and post-program world of 16,523.4 US-Dollar per participant and an additional present value of tax revenues of 1,156.6 US-Dollar per participant. The average income tax in Chile was 7.0 percent in 2019[37].

The marginal value of public funds is equal to the ratio of participants' marginal willingness to pay for the program and the initial program costs (costs minus fiscal externalities). I therefore divide the difference in the pre- and post-program NPLE by the difference between the costs per participant and the fiscal revenue generated through the program. The MVPF is then 1.41 per participant.

[37] `https://www.oecd.org/tax/tax-policy/taxing-wages-chile.pdf`