Child development and obesity prevention: evidence from the Chilean School Meals Program

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Abstract

Childhood obesity is one of the major public health challenges of the 21st century. Evidence suggests that timely nutrition and stimulation interventions can prevent excessive weight gain, however little is known about the effects of scaled-up programs. I use a national administrative dataset to explore the short- and long-run exposure effects to the Chilean School Meal Program (SMP) on the nutritional status of children attending public and subsidized schools. I estimate the effects on the standarized body mass index (BMI) using a Regression Discontinuity design based on the SMP eligibility cutoffs over a household vulnerability score. Participation in 1st grade reduces average BMI of girls but not boys in the same year. Effects are concentrated among overweight or obese children. Effects are driven by improvements in nutritional quality of meals. Non-sedentary students, children with higher socioemotional skills, and those receiving mental health services reap larger benefits from the SMP. Continued participation from 1st grade reduces boys' average BMI at 5th grade, relative to never participants.

Keywords: Nutritional Status, socioemotional development, Human capital, School meal program, Health, Child development

JEL Codes: I12, J13, J24

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1 Introduction

Socioeconomic vulnerability, inadequate nutrition and psychosocial deprivation prevents nearly one of every two children from reaching their developmental potential worldwide (Grantham McGregor et al. 2014; Black et al. 2017).[1] In middle- and high-income countries, early gaps in health are often reflected as excessive weight gain, particularly among resource-constrained households (Popkin 2002; Popkin et al. 2012). Childhood obesity has long-lasting effects in physical, cognitive and socioemotional development (Ebbeling et al. 2002; Conti et al. 2015; Palermo and Dowd 2012; Wang et al. 2016). From a life-cycle perspective, the costs of overweight and obesity are substantial: decreased quality of life, elevated risk of mortality, chronic physical and mental health conditions, increased health-care consumption, productivity losses and absenteeism, and social stigma (OECD 2019; Dee et al. 2014; Puhl and Brownell 2006; Withrow and Alter 2011). Obese individuals spend roughly 30% more on direct medical costs alone, compared to normal weight peers.

Obesity has increased dramatically since 1980 (Ng, Fleming et al. 2014). 60% of adults and nearly 30% of children are overweight or obese in the OECD area (OECD 2019). Changes are particularly striking in developed and developing countries that experienced rapid growth in disposable income (see Figure D.1). The Chilean case is of particular concern as childhood obesity rates nearly doubled in the last two decades, and one of every two children attending public or subsidized schools is overweight by the time they reach first grade of school (JUNAEB 2017). The World Health Organization (WHO) declared childhood obesity one of the most serious public health challenges of the 21st century (WHO 2016).

The scientific community has emphasized the importance of integrated strategies to address developmental gaps, given the dynamic complementarities between physical, cognitive and socioemotional development (Alderman and Fernald 2017; Grantham McGregor et al. 2014; Black et al. 2017). Evidence from small, randomized controlled trials (RCT) suggests

[1] Productivity losses from gaps in early development are estimated on an average loss of 19.8% in adult annual income (Grantham McGregor et al. 2007).

that integrated interventions (nutrition and stimulation) reduces developmental gaps on both nutrition and socioemotional skills during pre-school (Conti et al. 2015; Grantham McGregor et al. 2014; Attanasio et al. 2015a; Campbell et al. 2014). However, it is unclear whether similar school-based programs can successfully promote healthy nutritional status once scaled to the population level. To date, causal evidence on the impact of school meal programs (SMP) on weight gain is rather inconclusive (Millimet and Tchernis 2013; Schanzenbach 2009; Gundersen et al. 2012). Some studies suggests that SMP with high nutritional standards can improve weight status (Fung et al. 2013; Schwartz et al. 2015). However, to date there is little evidence on population characteristics that drive program effectiveness. For example, students with higher socioemotional development or those who engage in healthy behaviors (e.g. physical activity outside school) could benefit more prom the program. Similarly, children who received higher parental stimulation or mental health services at school could also be more susceptible, all else equal. Effects can also be larger among overweight students, if the SMP replaces high-calorie, less nutritious foods at home. Finally, as noted with other targeted programs, concern has been raised on whether SMP eligibility could induce bullying and stigma, negatively impacting socioemotional skills accumulation and program participation (Bhatia et al. 2011).

This study contributes new evidence connecting large early childhood interventions, parental behavior, socioemotional skills and nutritional status in a context of high overweight status prevalence, using rich administrative data from the National Board of School Aid and Scholarships (JUNAEB, spanish acronym). The analysis follows two cohorts of children that started Pre-Kindergarten in 2012 and 2013, with repeated measurements at Pre-Kindergarten, Kindergarten, First and Fifth grade. I estimate the local Intent-to-Treat effects of short- and long-run exposure to the Chilean SMP on the z-score of the body mass index (BMI-z) of boys and girls attending public and subsidized schools in urban areas, under a fuzzy regression discontinuity (RD) framework. The running variable approximates a household vulnerability score and treatment status is determined at the individual level based on two pre-determined cutoffs. Alongside with local Intent-to-Treat effects, I also estimate local treatment effects across the BMI-z distribution based on the quantile RD method proposed by Frandsen et al. (2012).

In order to understand underlying mechanisms, I estimate heterogeneous effects in different dimensions. First, I explore exogenous variation on the nutritional quality of the meals provided and seasonality in the anthropometric measurement. Secondly, based on the methods discussed by Carril et al. (2017), I estimate the effects for students attending schools that participate in Abilities for Life program (AfLP), a massive mental health intervention covering nearly a third of all schools, based on their vulnerability (Murphy et al. 2017) (see Appendix A). Finally, I conduct sub-group analysis based on the student's socioemotiona lskills, parental investments and health behaviors. To measure socioemotional development and parental investments, I estimate underlying factors from noisy measures contained in the household questionnaire (see Heckman et al. (2013) and Attanasio et al. (2015b)).

Results from the measurement system identify several skills with an analogous interpretation to dimensions of the Big Five Inventory. Local average local effects reveal that girls (but not boys) eligible for the program have a significant post summer decrease in average BMI-z in the 2015 cohort. In contrast, there are no significant effects in the 2014 cohort. Furthermore, the effect occurs at the top half of the BMI-z distribution, i.e., children that are obese or overweight. Additional analysis suggests that effects are mainly driven by improvements in the nutritional quality of meals provided. socioemotional skills, namely Openness to Experience and Neuroticism (a.k.a. Externalizing Behavior), moderate the SMP effects on BMI-z, consistent with prior evidence from observational studies and randomized experiments. Conversely, I find no evidence that program eligibility has any impact on socioemotional development. In addition, children who attend to schools providing additional mental health services (AfLP) exhibit larger reductions in BMI-z. Using data from the 2014 cohort, I show that continuous SMP participation from 1st grade until 5th grade (i.e. long-run exposure) significantly decreases BMI-z on boys, relative to never participants, specially if they are overweight. Exogenous variation in participation status between 4th and 5th grade due to policy changes in 2016 had no significant effects on average BMI-z in 5th grade (during 2018).

This research builds on several studies connecting SMP participation and children's nutritional status in contexts of high obesity prevalence (Schanzenbach 2009; Millimet and Tchernis 2013; Gundersen et al. 2012; Miyawaki et al. 2018; Taber et al. 2013; Bhattacharya et al. 2006). Previous evidence indicates that free meals with high nutritional standards could improve children's' BMI-z through a reduction in the availability of energy-rich foods (Alderman and Bundy 2011; Woodward-Lopez et al. 2010). The latter is consistent with evidence from SMP in the U.S. and elsewhere (Millimet and Tchernis 2013; Gundersen et al. 2012; Bhattacharya et al. 2006).[2]. Overall, I found that the nutritional quality of the Chilean SMP contributes to preventing excess weight among overweight students in the short- and long-run. This study also contributes additional evidence regarding the impact of scaling-up pre-school integrated nutrition and stimulation interventions (Alderman and Bundy 2011; Kautz et al. 2014). The effectiveness of the program is higher for students with high socioemotional development. Results also suggest the presence of complementarities with a stimulation intervention delivered at the school level.

The paper proceeds as follows. Section 2 provides background on the biological basis of weight gain in early life and describes the particular characteristics of the Chilean school meal program. Section 3 introduces the theoretical framework and its empirical implementation. Section 4 discusses the estimation approach. Section 5 describes the SMP data, with emphasis on the measures of child development. Section 6 presents the main results, sub-analysis and robustness tests. Section 7 concludes.

[2]Methodologically, the closest study is Schanzenbach (2009), which shows an increase in obesity prevalence for children that are eligible for the U.S. National School Lunch Program (NSLP), based on a sharp discontinuity in eligibility status. However, it is important to note that in the U.S. there is large heterogeneity in the nutritional quality of meals provided at each school given that food operations are managed at the school-level.

2 Background

2.1 Early development and excessive weight gain

Individual obesity risk can increase since conception due to epigenetic characteristics that can be triggered by factors such as maternal overnutrition during pregnancy or absence of exclusive breastfeeding in the first six months of life (Anderson and Butcher 2006; Lillycrop and Burdge 2011). Later, food preferences and eating habits are shaped in the first years of life by the experiences provided by caregivers within their ”food environment” (Birch 1999). In particular, increased availability and marketing of foods high in critical nutrients (i.e. sugars and fats) can have a substantial effect on weight gain among children (Wyatt et al. 2006; Birch and Anzman 2010; Swinburn et al. 2011; Anderson et al. 2019). As such, the rise in childhood obesity through the last decades can be explained substantially by striking changes in health behaviors (increased sedentarism and energy intake) as a response to environmental cues, particularly among vulnerable households. Across the globe, different structural policy schemes have emerged, aiming to transform obesogenic environments to promote nutritional health (OECD 2019; Vandevijvere et al. 2019). The WHO recognizes the school environment as key to introduce policies and interventions aimed to prevent obesity (WHO 2016).

Another important factor associated with early weight gain is insufficient social and emotional development. socioemotional skills, such as self-regulation, are strong predictors of obesity among children (Graziano et al. 2010). This result is striking, as there is substantial evidence of an increase in the prevalence of emotional and behavioral problems among children and adolescents in recent decades (Tick et al. 2007; Collishaw et al. 2004). Insufficient nurturing care to promote socioemotional development and nutritional health create a vicious circle: limited socioemotional skills leads to unhealthy behaviors that promote obesity. In turn, overweight children are more likely to be marginalized and bullied, stunting their socioemotional development (Strauss and Pollack 2003; Cornette 2011). There is also relevant documentation of seasonal effects in weight gain. Particularly, children gain weight during the summer, and are also likely to lose weight starting the school year as the is more structure in their diet, physical activity and leisure time (Baranowski et al. 2014).

Disentangling the relationship between socioemotional development and weight gain is rather challenging. First, insufficient parental investments can lead to both limited socioemotional development and obesity. Poor households not only have less time and resources to invest in socioemotional skills, but also are more likely to provide meals rich in simple carbohydrates and fats and scarce in key micro-nutrients. Secondly, limited socioemotional skills in the form of poor self-regulation and executive functioning skills can be conducive to increased eating in absence of hunger. The association between self-regulation, caloric intake and weight gain among children has been substantially documented in observational studies (Francis and Susman 2009). In a similar way, poor socioemotional skills can preclude the adoption of other health behaviors, such as physical activity. Third, early evidence on the microbiota-gut-brain axis suggests that the gut modulates the reward system and affects mood, stimulating the intake of calorie-dense foods under emotional distress (Torres-Fuentes et al. 2017). As such, poor diets can actually become an additional stressor to child development. Finally, peers can influence not only socioemotional development (e.g. bullying) but also the adoption of unhealthy behaviors, which is consistent with evidence of behaviors ”spreading” in social networks (Christakis and Fowler 2007; Dishion and Tipsord 2011). Given such complexities, relying on randomized interventions is one promising avenue to understand the complementarities among different dimensions of early childhood development (Heckman et al. 2013; Alderman et al. 2014).

2.2 The Chilean School Meals Program

The SMP was implemented in 1964, as part of the creation of the National Board of School Aid and Scholarships (JUNAEB), an agency within the Ministry of Education, in a coordinated strategy to address the high levels of undernutrition among children in Chile. In 1950, 63% of 0-5 year old children were undernourished; dropping to 0.5% by 2012 (Mönckeberg 2014). However, since 1985 childhood obesity more than doubled in the same age group (Vio and Albala 2000; Atalah 2012). The SMP has responded to the obesity epidemic by continuously improving the nutritional quality of the meals, while increasing the fraction of eligible students (particularly since 2015). Currently, the SMP covers 60% of all students attending public or private subsidized schools (i.e. target schools), and virtually all students in pre-school, with a focus on optimal nutrition and acceptability.[3] Children receive daily meals for more than 200 days a year, covering up to 70% and 33% of daily energy requirements in pre-school and school levels, respectively (Salinas and Correa 2013).

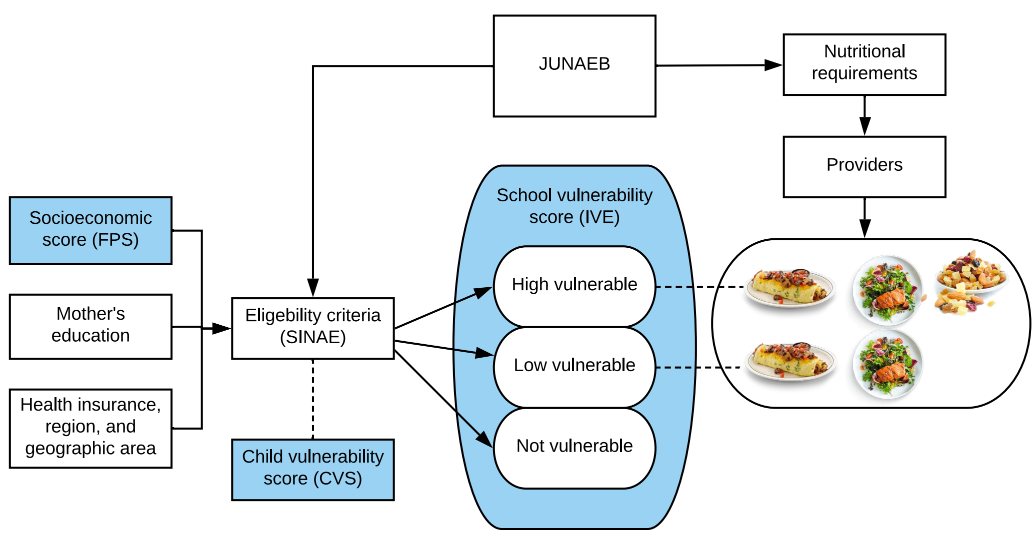
JUNAEB determines program eligibility based on multiple criteria depending on household characteristics (see Figure 2.1). Until 2015, the Household Vulnerability Score (*Ficha de Protecion Social* or FPS, in Spanish), constructed by the Ministry of Social Development (MDS), was a major input to determine program participation. [4] SMP elegibility before 2016 can be described as follows. High-vulnerable beneficiaries were ensured to receive the program fully, accounting for three meals a day (FPS<4,213), while low-vulnerable had a high probability (but not certainty) to be eligible for two meals, breakfast and lunch (4,213<FPS<8,500). While the FPS is not the only information used to determine eligibility, the predetermined cut-offs are linked to strong changes in the probability of being eligible. In principle, the high-vulnerable group are students in extremely poor households, while the low-vulnerable group include individuals within poor households. Lastly, non-beneficiaries had no access to any meals (HVS>8,500) and usually sourced food from home or purchased meals at school kiosks (roughly 25% of 1st grade students attending public or subsidized schools in 2015). Since 2016, JUNAEB considers students eligible for the SMP if they belong to the 60% most vulnerable households, using the Household Social Registry

[3] in 2014, 90% of students attended municipal or private subsidized schools.

[4] The FPS was widely utilized by many public institutions to determine the allocation of subsidies and other social welfare benefits. This score summarizes the self-reported information of households and housing conditions from the Social Protection Registry.

(HSR), a tool developed by the MDS to replace the FPS.[5] Given the multiplicity of factors determining program eligibility and to protect households' private information, JUNAEB also calculates a child vulnerability score (CVS) as the continuous latent variable that arises from the ordered choice model associated with eligibility. [6] Once children's eligibility status is determined, JUNAEB calculates the school vulnerability score (IVE) as the percentage of vulnerable (eligible) students at each school (from 0 to 100). Public and subsidized Chilean schools rarely have private cafeteria services, rather kiosks are available for snacks and light meals to be purchased. SMP services are provided by external companies and a fixed number of servings are cooked at the school based on the number of eligible students. Most schools are equipped with kitchens and dining halls provide meals to students. Meal distribution is assisted by school staff to ensure that only beneficiaries receive meals.

Figure 2.1: The SMP Logic Model



Notes: Blocks in blue represent key variables in the eligibility process.

Due to the centralized nature of the SMP and for administrative purposes, JUNAEB bid

[5]For the small fraction of students without HSR (or FPS before 2016), JUNAEB used other available information to determine participation, such as mother's education, residence and health insurance status.

[6]The CVS preserves the two cut-off points observed in the FPS, and similarly, it has no interpretable scale.

meal services through staggered contracts that cover random, mutually exclusive geographic areas, with a duration of three years. [7] Contracts specify the number of meals to be allocated in each school, the nutritional content of the meals, frequency limits of different food groups, and other characteristics of food processing and meal delivery. Each year JUNAEB auctions one contract, so in any given year there are three different contracts operating simultaneously. Given the constant commitment of JUNAEB to improve SMP nutritional quality, providers operating under newer contracts, particularly from 2015 onwards, incorporated significant changes in the nutritional quality and acceptability of meals, particularly increasing frequency of healthy foods, such as fruits, vegetables and whole grains. [8]

3 Theoretical Framework

The model described below is adapted to incorporate nutritional status into the theory of human capital production in early childhood, drawing substantially from the frameworks discussed in the relevant literature (Cunha et al. 2010; Cunha and Heckman 2007; Attanasio 2015; Conti et al. 2015; Agostinelli and Wiswall 2016). Nutritional status as an input (H_t) can be described by an inverted u-shape, given that both low or excessively high BMI-for-age are related to poor nutritional status. For simplicity, In this model I assume that H_t increases as individuals move from obesity towards normal nutritional status (consistent with a context of high overweight prevalence). There is also a vector of other relevant inputs or *skills* (θ_t), which could include cognition, socioemotional development and other measures of health. All inputs can be determined by parental investments, school and household background, and the past history of nutritional status and socioemotional skills. The model follows (children are not indexed to simplify notation):

[7] Each contract is associated with macro area that contains a pre-fixed subset of geographic units, spread out randomly through the country (Duran and JUNAEB-DII 2006). There are 102 geographic units, each containing several schools.

[8] Overall, JUNAEB enforces a high nutritional standard for the meals offered in the SMP, including mostly traditional (home-style) preparations and low levels of added sugar, fat or salt.

$$H_{t+1} = h_t(\theta_t, H_t, I_t, P_t, X_t, e_t) \tag{1}$$

$$\theta_{t+1} = g_t(\theta_t, H_t, I_t, P_t, X_t, v_t) \tag{2}$$

In the model described above I_t corresponds to parental investments, P_t captures parents stocks of human capital and X_t is a set of covariates that can affect the total factor productivity (Attanasio et al. 2015b). e_t and v_t are random variables that reflect unobserved shocks. $g(.)$ is the high-dimensional skills formation technology, where nutritional status is a direct input in this function, based on the idea that improved nutritional status facilitates skill accumulation. $h(.)$ approximates the metabolic balance equation, where future nutritional status is a function of present choices and previous nutritional background. In this framework, (school) interventions can impact both the stock of inputs and their productivity, as noted by Heckman et al. (2013). In turn, households can change the allocation of resources provided to children in response to external shocks (Todd and Wolpin 2003; Yi et al. 2015; Das et al. 2013; Attanasio 2015). Formally, we can describe the household's demand for parental investments as:

$$I_t = f_t(\theta_t, H_t, P_t, X_t, Z_t, u_t) \tag{3}$$

In this framework, parents make investment choices in each period given childrens socioemotional skills and nutritional status history (Attanasio (2015) formalizes a simple model consistent with this setup). Investments also respond to households characteristics, such as income (included in X_t) and to other variables that measure the market prices and quality of parental inputs, contained in Z_t. Finally, u_t reflects other shocks that might affect investment decisions.

Under this framework, I can empirically test the presence of complementarity between socioemotional skills and nutritional status, and also between school characteristics and parental investments. Moreover, this approach can be used to explore heterogeneity on treatment effects by several household characteristics. However, the simplicity of this model does not allow accounting for other relevant aspects that could influence nutritional status and socioemotional skills such as peer effects, food availability outside the school, and fertility decisions. Moreover, is important to acknowledge that in most empirical applications not all inputs are observed, which can lead to biased estimates. [9]

4 Estimation strategy

4.1 Latent factors and the measurement system

In the SMP data, socioemotional skills are partially captured by many variables that characterize children's behavior (self-reported by caregivers). To avoid model selection over potential proxies and to address measurement error, I obtain latent factors from noisy proxies using a measurement system, that both reduces dimensionality and accounts for measurement error (Gorsuch 2003; Cunha et al. 2010). Methods are discussed in detail in Appendix B. The structure of the measurement system was chosen based on exploratory factor analysis.

While the estimated factors contain (classical) measurement error, is expected to be random at the local cut-off points, thus no adjustment is required. Moreover, given the characteristics of the sample, and the fact that the system is linear, it is not necessary to incorporate adjustments to the standard errors in this step. However, preliminary analysis of the data indicates a strong presence of response styles from parents in the behavioral observation of children's behavior. As such, following Aichholzer (2014), I allow the intercepts to have a common (random) component across measurements for each individual (parent) that is orthogonal to the underlying factors. This random intercept captures the individual preference to report consistently lower (or higher) responses across all measures (see Appendix B for more details). Finally, I choose to estimate separately a measurement system

[9] In this empirical analysis, the absence of cognition measures implies that the moderator effects of socioemotional development could be overestimated due to the (static) positive relationship between inputs.

for skills and investments, in order to use all available data. Results from estimating the system jointly or separately show that there is no significant differences (see Appendix C).

4.2 Identifying average treatment effects

Given the SMP eligibility criteria, local average treatment effects (LATE) can be estimated in a Regression Discontinuity (RD) Framework, with BMI-z as the outcome variable. A natural candidate as running variable is the FPS. While there is no evidence of the FPS being manipulated around the cut-offs, the empirical distribution is largely skewed, over-representing vulnerable households (Larrañaga et al. 2014). Additionally, 16% of students do not have FPS score, affecting external validity of the results. An alternative is to rely on the underlying latent score that arises from the eligibility criteria under a ordered choice model that incorporate all the criteria used by JUNAEB to determine eligibility, previously defined as CVS. The density of CVS replicates the discontinuous changes in probability from the FPS cut-offs, albeit introducing some degree of smoothness given functional form assumptions. More importantly, given that all data are used, it reflects properly the relative vulnerability of children with and without FPS.

The LATE reflects the intent-to-treat impact of the SMP on BMI-z, as CVS does not uniquely determines eligibility (hence a fuzzy design). Students allocated to the low-vulnerable group have a very high probability of receiving meals, but not certainty (mostly due to budget restrictions). In addition, there is scope for non-compliance, i.e. beneficiary students can opt not to consume meals, or alternatively, teachers might allow non-beneficiary children to have meals if there are available after eligible children have been served. There are no available data to measure the degree of non-compliance, although based on interactions with JUNAEB officials, this issue arises among upper middle and high school students. Formally, if we define X_i as the CVS, and c as (one of the two) cut-off, the estimand can be identified as:

$$\tau_{FSD} = E(H_i(1) - H_i(0)|X_i = c, T_i(1) - T_i(0) = 1) \tag{4}$$

Where T_i determines SMP elegibility. Under standard assumptions (Todd and Wolpin 2003; Calonico et al. 2014), the LATE can be estimated as the ratio of two sharp local-linear RD estimators:

$$\hat{\tau}_{FSD}(h_n) = \frac{\hat{\mu}_{Y,+}(h_n) - \hat{\mu}_{T,-}(h_n)}{\hat{\mu}_{Y,+}(h_n) - \hat{\mu}_{T,-}(h_n)} \tag{5}$$

Where $\hat{\mu}_{U,+}(h_n)$ and $\hat{\mu}_{U,-}(h_n)$ are the local-linear estimators for a random variable U_i. As in any RD design, there are several critical considerations: bandwidth selection, functional form (polynomial degree), and construction of robust variance estimators. Recent advances in the statistical properties of the RD estimators allows for a data-driven approach to determine optimal bandwidth selection and functional form, in order to compute covariate-adjusted LATE estimates with robust (bias-corrected) standard errors (Calonico et al. 2014; Calonico et al. 2018; Gelman and Imbens 2018; Bartalotti and Brummet 2017). In this paper, analysis are conducted separately for boys and girls for two important reasons. First, there are significant gender differences in body fat and energy requirements during early childhood (Sweeting 2008). Secondly, several studies have documented important differences in socioemotional development by gender (see Heckman et al. (2013) for a detailed example from the Perry Program).

I extend the fuzzy RD setup to understand heterogeneous effects by segmenting the sample in (binary) sub-groups by parental investments and socioemotional skills, using the method proposed by Carril et al. (2017). As mentioned, this approach is valid under the additional assumptions that treatment is continuous on the running variable over the support of the covariates of interest, and that there are compilers over the conditional distribution of such variables. The method balances the sub-groups in other covariates using an inverse propensity weighting (IPW) approach, in order to avoid bias. A rich set of information on child health and household characteristics are used for balancing the sample across sub-groups. I also explore heterogeneous effects by season (of measurement) and provider contracts in service for a given year. Contracts are bid exogenously (to students) and service areas are pre-defined based on random assignment. If newer contracts have better quality, I expect they might affect the impact of SMP participation, at least for some sub-populations. In terms of peer effects, given that program participation is virtually universal in pre-school, I use the sub-group analysis proposed by Carril et al. (2017) to determine if children with a large fraction of overweight peers in the previous year (Kindergarten) are more (or less) sensitive to program eligibility. An additional concern is that local effects could vary along the distribution of the outcome variable, as noted in previous studies (Frolich and Melly 2010; Hsu and Shen 2016; Frandsen et al. 2012). In particular, children with higher risk of obesity or undernutrition might be more sensitive to the treatment. Hence, I used the quartile treatment effect approach to the RD framework proposed by Frandsen et al. (2012).

In terms of long-exposure effects, eligibility does not change significantly between 1st and 5th grade. The same approaches are used for long and short exposure effects, while accounting for vulnerable children in 5th grade that were not eligible in 1st grade, due to changes in their vulnerability and due to the expansion of the SMP in 2016.

5 Data and descriptive statistics

The main dataset follows two cohorts of children that start Pre-K in 2012 and 2013. As an example, in 2015, roughly 230,000 children attend First Grade in over 10,000 public or subsidized schools. JUNAEB collects administrative, individual data each year directly through schools that have at least one student eligible for SMP. Teachers measure and collect information on childrens anthropometrics (e.g. height and weight), constructing the Nutritional Map data. Parents provide comprehensive household background information for children in schools eligible for the SMP, during three consecutive years from Pre-K to First Grade, Fifth Grade (since 2018) and then when students are high school freshmen. This questionnaire is known as the Vulnerability Survey. Schools consolidate and submit the information directly to JUNAEB each year during the the school cycle. The household questionnaire includes background on household characteristics, socioemotional development, health status (including birth weight and premature status), parenting beliefs and parental investments. Appendix A details the information contained in the Vulnerability Survey data.

Table 5.1 shows basic descriptive statistics of the JUNAEB data in contrast with two nationally representative surveys: the 2012 Longitudinal Survey of Early Life (ELPI, Spanish acronym) and the 2015 National Socioeconomic Characterization Survey (CASEN, Spanish acronym). There are not significant differences in the anthropometric data, albeit children in the ELPI data are slightly younger at time of measurement. In terms of household characteristics, we observe that, while eligibility is substantial (almost three of every four children), self-reported participation is lower (66%). Also, 1st grade children in CASEN have mothers that are older and less likely to participate in the labor force. Children in the Vulnerability Survey data are more likely to live without a father (35%) in comparison to the CASEN data (27%).

There are two main estimation samples in this study. First, I analyze the effects on SMP eligibility on all students attending the First Grade in urban schools during 2015 that have a vulnerability measurement (CVS).[10] Given the large variation in local food and schooling systems, rural households are excluded from the primary analysis. I also exclude implausible weight and height measurements.[11] I refer to this sample interchangeably as the First Grade (urban) or overall sample. The second estimation sample includes children that have CVS

[10]Although CVS is calculated for virtually every children in the sample, I restrict the estimation of local treatment effects to children that have FPS scores. The main reason is that I concentrate on the local effects around the eligibility thresholds over the continuous dimension of the CVS. Incorporating the students that do not have FPS introduces lumps in the distribution of the CVS that affect estimation. As shown, there are no major differences between children with and without FPS score.

[11]Measurements are considered implausible if they are 0.5 standard deviations above or below the 1st and 99th percentile of the distribution, respectively. Among the students that are linked longitudinally, I also exclude cases where there are implausible changes in anthropometric measurements as well (e.g. height is lower in First Grade relative to Kindergarten). The total number of excluded observations represents less than 2% of the raw data.

and are linked longitudinally, hereon referred as RD Panel (for more detail see Appendix A).

As noted previously, the main outcome is the z-score of body mass index, calculated by JUNAEB using the WHO reference guide (2007). socioemotional skills are built based on a set of Likert-scale measures that characterize child's health and behavior (see Appendix C for

Table 5.1: Descriptive statistics

	First grade 2015		ELPI 2012	
Anthropometrics	Boys	Girls	Boys	Girls
Age (months)	79.8	79.1	73.2	73.3
	5.6	*5.2*	*3.5*	*3.5*
Height-for-age (Z-score)	0.26	0.32	0.15	0.14
	1.27	*1.15*	*1.13*	*1.08*
BMI-for-age (Z-score)	1.06	0.92	1.05	1.03
	1.49	*1.32*	*1.01*	*1.03*
Fraction overweight	52.7%	49.3%	52.3%	50.3%
Sample size	101,736	98,306	6,031	6,326
	First grade 2015		CASEN 2015	
School characteristics	Boys	Girls	Boys	Girls
SMP participation =1	0.74	0.74	0.66	0.66
School vulnerability index (IVE)	70.3	69.5	72.8	72.4
	17.4	*17.4*	*16.9*	*16.9*
Public school = 1	0.44	0.41	0.42	0.40
Attended Kindergarten = 1	0.98	0.97		
Household characteristics				
Mother's education (years)	12.0	12.0	11.6	11.7
	4.0	*3.9*	3.0	3.4
Mother's age (years)	33.1	33.1	35.8	35.3
	6.9	*6.9*	6.6	6.6
Household size	4.7	4.6	4.9	4.8
	1.7	*1.7*	*1.8*	*1.7*
Mother in labor force = 1	0.61	0.62	0.55	0.53
Lives with father = 1	0.65	0.64	0.73	0.73
Ethnic background = 1	0.13	0.13	0.12	0.13
Sample size	101,736	98,306	1,957	1,844

Notes: First Grade data includes children aged 61-107 months old. ELPI: Early Childhood Longitudinal Survey 2012 (restricted to children between 68-83 months old, weighted values). CASEN: National Survey of Socioeconomic Characterization (restricted to families with children attending 1st grade to public or subsidized schools, weighted values). Mother's age and education in CASEN only available for children living with mother at time of survey. SMP: School Meals Program. Standard deviations in italics, if applicable.

more details). Similarly, parental investments are constructed from questions regarding time inputs (e.g. reading together, play music or sports, and took children to play with others).[12] Based on the results from EFA, the estimated measurement system for behavioral and health measurements elicit three latent socioemotional skills that are consistent with measures of the BFI: Extroversion (θ^E), Openness to Experience (θ^O) and Neuroticism (θ^N) and one learning capacity or process factor (L) [13] (see Appendix B for a discussion on socioemotional skills measurement and latent factors). Results from those measurement systems indicate that deviations from normality are important; the estimated mixing parameter is 0.514 [0.508 , 0.520]. The random intercept allows to remove bias introduced by response styles (small in magnitude). The distribution of response styles and its correlation with parent's education is consistent with social desirability bias. (see Appendix B for additional results). In the case of parental time investments (I), results are remarkably close in terms of model fit and all measures relate to the underlying factor in a similar magnitude.[14]

6 Results

6.1 Short-exposure Intent-to-Treat effects

Figure C.1 shows the discontinuity on eligibility for low vulnerable and high vulnerable groups respectively, using CVS as the running variable. In both cut-off points there is a large change in average probability of being eligible (to either high or low vulnerable). In the case of high vulnerable students, many children on the right of the cut-off are eligible, which is due to the interaction with another important social program, *Chile Solidario* or CHS for short,

[12] The Vulnerability Survey data contains other relevant measures of parental investments, including presence of a father figure (contributing either time or resources) and physical inputs in the household. Secondary analysis reveal no mayor differences in the LATE of the SMP among mutually exclusive groups based on such covariates.

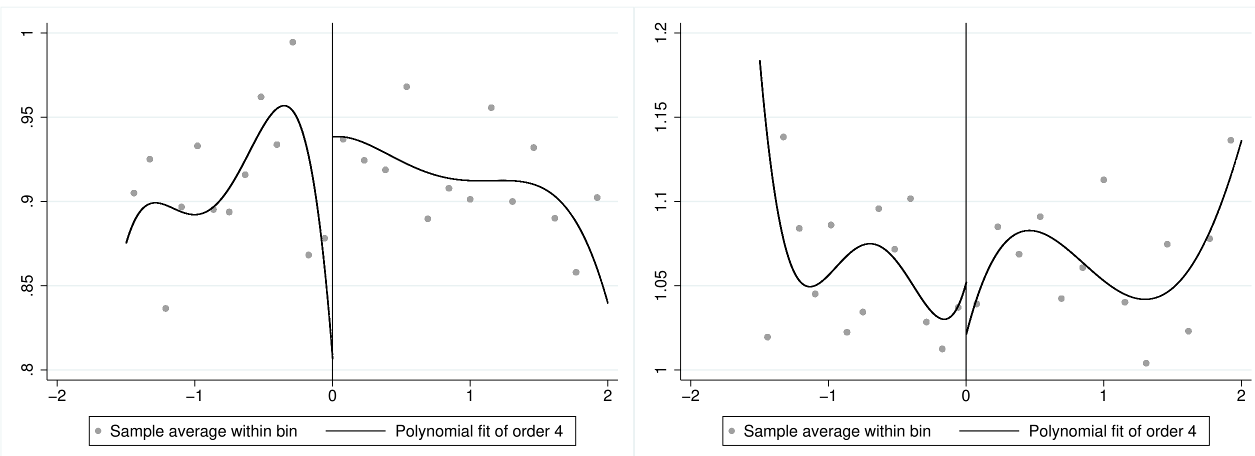
[13] By process, I refer to the extent that socioemotional (and other) skills contribute to the learning capacities of a child, in a similar way that they contribute to other behaviors or abilities

[14] Additional results of the confirmatory factor analysis on parental time investments are available upon request.

which makes children SMP eligible as high vulnerable regardless of their FPS if their families belong to this program. When we exclude that group (about half of the high vulnerable students), both cut-offs have a very similar distribution. Based on the manipulation test proposed by Cattaneo et al. (2018), there is no evidence of potential manipulation of the running variable around the eligibility thresholds, in either case. However, the test is sensitive to the cases of students eligible for CHS, therefore LATE estimates are presented in both cases.

Figure 6.1: Local polynomial fit of BMI-z as a function of CVS (centered)

(a) girls (b) boys



Notes: CVS: child vulnerability score (JUNAEB). Bandwidth on CVS limited avoid overlap with high vulnerable cut-off. Triangular kernel and bin selection based on Integrated Mean Squared Error optimal quantile-spaced method (adjusted to scale for visualization).

Table 6.1 reports the LATE estimates for both cut-off for the 2014 and 2015 cohorts (First grade). Figure 6.1 shows the local polynomial fit of the BMI-z mean at each side of the eligibility cut-off for low vulnerable students (boys and girls) in 2015. The following covariates are included to improve the precision of the estimated standard errors: age, school type (public/subsidized), school size (enrollment), birth weight and z-score of height-for-age. LATE is significant and negative among girls that are eligible as low-vulnerable (compared to non-eligible similar students) in 2015. The average difference in BMI-z between groups is 0.15 SD. Using obesity prevalence as the outcome variable, the effect size is consistent with a reduction of obesity rates of 5 percent points. The LATE estimates between high and low vulnerable students are not significant. The latter is reasonable, given that the additional calories received by low vulnerable students (relative to not eligible) are substantially more relative to the extra calories that the high vulnerable students receive, at the margin.

Table 6.1: SMP local average treatment effects (dependent variable: BMI-z)

Vulnerability	high vs low		high vs low (chs=0)		low vs no	
	Boys	Girls	Boys	Girls	Boys	Girls
Panel a) 2015 cohort						
First Stage	**0.66**	**0.69**	**0.90**	**0.91**	**0.97**	**0.97**
	0.02	*0.015*	*0.011*	*0.008*	*0.005*	*0.005*
LATE	0.016	-0.023	0.007	0.004	0.08	**-0.15**
	0.091	*0.073*	*0.07*	*0.067*	*0.091*	*0.069*
Bandwidth	0.32	0.36	0.39	0.35	0.66	0.67
N	11018	13197	10560	8934	12009	12157
Panel b) 2014 cohort						
First Stage	**0.63**	**0.68**	**0.80**	**0.86**	**0.9**	**0.87**
	0.027	*0.027*	*0.029*	*0.019*	*0.012*	*0.013*
LATE	0.075	-0.067	0.232	0.01	0.029	0.006
	0.183	*0.153*	*0.187*	*0.116*	*0.095*	*0.082*
Bandwidth	0.34	0.31	0.31	0.42	0.86	0.88
N	7125	6341	4607	7177	11741	12546

Notes: significant values in bold ($p<0.1$). Standard errors based on optimal MSE (mean squared error). Standard errors in italics.

Several specification and robustness tests are conducted to determine the validity of the SMP effects on low vulnerable girls and boys (see Appendix Tables C.3 and C.4 and additional figures in Appendix C). Results indicate that the SMP effect on girls is accurately estimated locally, regardless of the functional form, and increasing the bandwidth creates more imprecise estimates. Moreover, estimates are not much changed if I use the RD panel sample instead of the full sample. The results among students in rural schools are somewhat similar but very imprecise (see Table C.4).

6.2 Heterogeneous effects

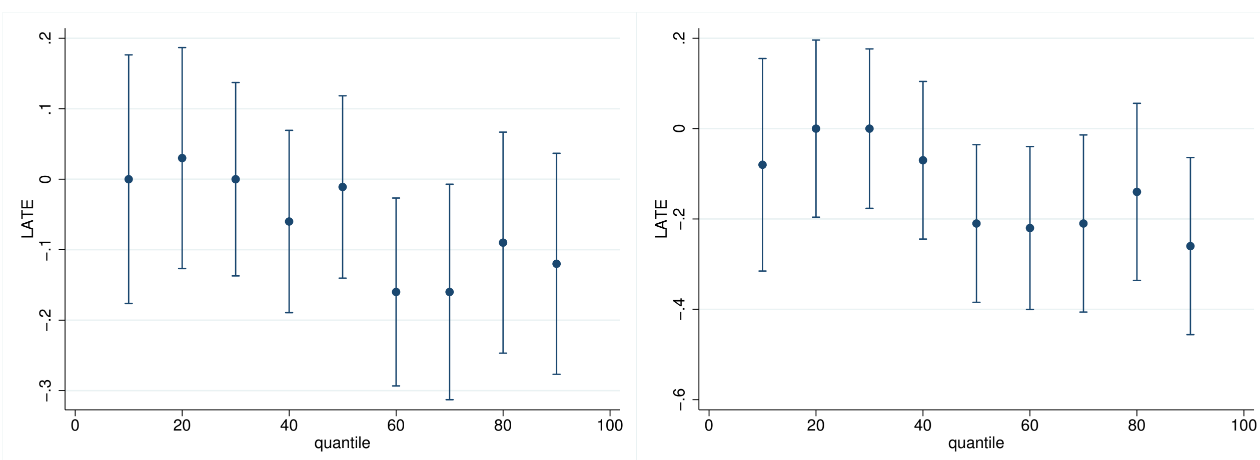
The average estimates suggest that both characteristics of students and the program itself can explain potential differences across sub-groups. To determine potential mechanisms, I explore heterogeneous effects by student's socioemotional skills and nutritional status, parental time investments, and nutritional quality of the meals provided.

6.2.1 Quantile RD

Figure 6.2 shows the local effects of the SMP at different deciles of the BMI-z distribution for girls (between low vulnerable and not eligible). Estimates suggest that the LATE is larger and significant for the top half of the distribution, i.e., for students that are either overweight or obese, but non-significant in the lower half of the distribution. The latter supports the idea that girls with excess weight are benefiting from the SMP, potentially substituting nutrient rich meals offered at school for the energy dense meals offered at home.

Figure 6.2: Average treatment effects by decile of BMI-z for girls

(a) MSE (b) CER



Notes: CI in right panel estimated using bandwidth based on optimal CER (coverage error rate) and in left panel using bandwidth based on optimal MSE (mean squared error). CVS: child vulnerability score (JUNAEB).

6.2.2 Timing and nutritional quality of services provided

Given that children are measured through the school year, I can estimate the LATE of the SMP among students measured during the fall and spring period separately. [15] Estimates in Table 6.2 show that the effect identified among girls occurs mostly during the first part of the school year (after summer vacation), while there is limited effect observed amongst the girls measured in spring. Another important source of variation comes from the quality of the meal services provided. A new bid contract started in 2015, which included more strict nutritional requirements (reduced calories and increased frequency of healthy foods). Differences in the quality of the meals offered could explain the reported differences between the two cohorts. In order to control for potential differences in environmental characteristics, Table 6.3 reports the LATE for each major contract operating in 2014 and 2015, restricting the sample only to students in the Santiago Metropolitan Region (36% of total sample).[16] In schools where there was a change in the contract during 2015, the LATE is large and significant. Conversely, in schools where no change in contract took place, local average effects from the SMP are not significant. Overall, we can conclude that the SMP effects observed in 2015 can be attributed to a short-term reduction in BMI-z on girls, mainly in schools where the nutritional characteristics of the meals improved.

Table 6.2: LATE for low vulnerable versus non eligible students, by semester (dependent variable: BMI-z)

	boys		girls	
	Fall	Spring	Fall	Spring
LATE	0.096	0.072	**-0.361**	0.018
	0.115	*0.134*	*0.148*	*0.091*
Bandwidth	0.84	0.6	0.93	0.68
N	7466	5603	6100	8062

Notes: significant values in bold (p<0.1), adjusted for multiple hypothesis testing using the Sidak method. Bandwidth based on optimal MSE (mean squared error). Robust standard errors, in italics.

[15] Data analysis shows no systematic differences in the timing of measurement based on school and individual characteristics.

[16] The three major contracts in 2015 cover 92% of the total demand for meal services.

Table 6.3: LATE for low vulnerable versus non eligible girls in the Metropolitan Region by contract during Fall semester (dependent variable: z-BMI)

	2014			2015		
Contract	16LP12	35LP11	35LP11*	16LP12	35LP11	10LP14
LATE	0.146	-0.42	**0.548**	-0.381	-0.077	**-1.06**
	0.322	*0.27*	*0.237*	*0.543*	*0.384*	*0.362*
Bandwidth	0.93	0.72	0.84	0.57	0.68	0.48
N	814	1105	1342	303	683	447

Notes: significant values in bold (p<0.1), adjusted for multiple hypothesis testing using the Sidak method. Bandwidth based on optimal MSE (mean squared error). Standard errors in italics. *Indicates schools in 2014 that switched to contract 10LP14 in 2015.

6.2.3 The role of skills, paternal investment and physical activity

Table 6.4 summarizes the LATE for girls, between low vulnerable and not eligible, for several different sub-groups of interest. There are small differences by parental time investments (in the previous year), but they are not significant.[17] However, socioemotional skills are a meaningful moderator for the SMP local effects. Between girls that are in the top quartile of Neuroticism and Openness to Experience, the effects are quite large and more significant than in the rest of the distribution. An important concern with this results is potential spillover effects of the SMP on socioemotional skills that could bias the results. Results in Appendix C show no effect of program eligibility on the measures of socioemotional development.

In addition, there is suggestive evidence of complementarity of the SMP with a large mental health intervention, the Abilities for Life Program, which covers a third of schools, based on vulnerability. Table C.5 shows that among children in AfLP participating schools, the SMP local effect is significantly larger, compared to children attending equivalent non-participant schools. [18]

Finally, given the importance that sedentarism and diet have on energy balance, I com-

[17] Note that, in scale, time investments in the bottom half are associated with a frequency of 0-1 times a month, and in the top half to 1-2 times a month or more. Results are also estimated in the top quartile, without meaningful differences.

[18] School eligibility for the AfLP is loosely related to school vulnerability. To compare across similar schools, the analysis was conducted balancing schools on their IVE, and restricting the sample only to schools with an IVE higher than 60.

Table 6.4: LATE for low vulnerable versus non eligible girls, by sub-group (dependent variable: BMI-z)

Sample	Parental investment		Neuroticism		Openness		Physical activity	
	$< p(50)$	$> p(50)$	$< p(75)$	$> p(75)$	$< p(75)$	$> p(75)$	none	some
LATE	-0.116	-0.182	-0.088	**-0.289**	-0.068	**-0.32**	-0.046	**-0.166**
	0.105	*0.115*	*0.089*	*0.148*	*0.089*	*0.141*	*0.170*	*0.084*
Bandwidth	0.65		0.65		0.65		0.65	
N	11464		11215		11463		11470	

Notes: significant values in bold (p<0.1), adjusted for multiple hypothesis testing using the Sidak method. Bandwidth based on optimal MSE (mean squared error). Robust standard errors, in italics.

pared children that engage in some type of physical activity outside the Physical Education versus those who do not. Results suggests that children that engage in physical activity benefit more from SMP eligibility, while girls that are sedentary do not. The latter can be interpreted in, at least, two different ways: sedentary children might also be more likely to consume more snacks and junk foods, and/or active children might be more likely to avoid weight gain if the majority of their meals come from sources low in added sugars and fats.[19]

6.3 Long-exposure effects and policy changes

In 2016, three major policy changes were introduced, impacting SMP eligibility criteria and availability of food in schools. The extension in coverage allows estimation of the LATE on children that were not eligible for the program before 2016. In addition, the introduction of the RSH as eligibility measure changed a continuity feature of the SMP until 2015. Before 2016, children classified as vulnerable remained in the program for at least three consecutive years, while from 2016 onward, children have a probability of changing eligibility status every year. Finally, in the context of the Food Labelling and Regulation Act of 2012, foods classified as "unhealthy" according to the new regulation standards were banned from schools (and 100 meters around them) since June 2016. As such, food availability for students inside

[19]The SMP guidelines not only restrict the total amount of calories in the meals that are delivered but also enforces the frequency of specific foods, reducing the availability of added sugars or fats.

schools changed dramatically.

In this section I present estimates for different sub-samples to understand both the potential long exposure effects of the SMP (by 5th grade), as well as the effects that might arise from policy changes, summarized on Table 6.5. The first two columns give estimates of the LATE between students that participated in the SMP continuously until Fifth grade versus those who never participate in the program, or ”continuity”. Columns 3 and 4 estimates the effect of being continuously eligible in the program until Fifth grade versus those that”dropout” from the program based on their RSH assessment. Finally, columns 5 and 6 compare the effect of students that were eligible for the program only during Fourth and Fifth grade, relative to students that never participated in the SMP, due to the program ”extension” in coverage.

Table 6.5: LATE for boys and girls, 2014 cohort by sub-group (dependent variable: BMI-z in 5th grade)

	Continuity		Dropouts		Extension	
	Boys	Girls	Boys	Girls	Boys	Girls
LATE	0.033	**0.094**	0.053	0.007	-0.009	0.042
	0.031	*0.031*	*0.046*	*0.041*	*0.028*	*0.028*
LATE (weighted)	0.036	**0.076**	0.03	0.016	-0.001	0.042
	0.032	*0.033*	*0.048*	*0.042*	*0.029*	*0.028*
LATE (RDD)	**-0.342**	0.219				
	0.152	*0.184*				
Mean CVS treated	0.54	0.55	0.54	0.55	-0.96	-0.96
Mean CVS untreated	-0.96	-0.96	0.39	0.37	-0.69	-0.71
Bandwidth	0.65	0.57				
N	5,383	5,414	3,841	4,007	5,986	6,050

Notes: HSR cut-off since 2016 is percentile 60. Sample restricted to students between 40 and 80 percentile on the HSR (low vulnerable and no eligible students only). Significant values in bold (p<0.1). Robust standard errors in italics. LATE weighted estimates based on the inverse of absolute distance from CVS low-vulnerable cutoff. RDD indicate fuzzy regression discontinuity estimates. Optimal bandwidth based on optimal MSE in the full sample.

In the 2014 cohort, girls with continuous participation in the SMP until Fifth grade had higher BMI-z relative to students that were never eligible. However, treatment and control groups are remarkably different in their vulnerability, hence direct estimates introduce bias. While accounting for the discontinuity on eligibility in 1st grade, LATE estimates for the same group show that locally, continuous participation in the SMP significantly reduces average BMI-z in boys but not girls, relative to never participants. [20] Additional analysis reveals that reductions for boys occur in the upper half of the BMI-z distribution, i.e. among overweight students (see Appendix C).

For those children who were eligible to the SMP continuously, average BMI-z is not different from those students that dropped out from the program due to a change in their household vulnerability status. Students who only recently participated in the program due to the extension of the SMP coverage have similar average BMI-z relative to students who never participated in the program. Overall, the evidence suggests that within this cohort, short-term effects are not apparent for Fifth grade BMI-z on boys or girls, however sustained effects in 5th grade indicate that overweight boys who continuously participated in the SMP had lower BMI-z relative to non-participants. Similarly, the latter suggests that program exposure in early years (ages 5-9) could carry persistent effects on BMI-z, at least for some students.

6.4 Discussion

Evidence from the Chilean school meal program suggests that eligible (low vulnerable) overweight girls have lower average body mass index during 1st grade, relative to non-eligible in 2015. There does not seem to be a meaningful difference between low and high vulnerable students in the same period. The short-term effects seem to be driven by improved nutritional quality in 2015. International evidence indicates that students have the largest weight gain during the summer (particularly those who are overweight or obese), hence it is

[20] Regression discontinuity estimates at 5th grade for all students (including SMP movers between Fourth and Fifth grade) are similar. To understand the results it is important to note the variations in program participation due to the SMP expansion and change of eligibility criteria of 2016. There is significantly limited overlap in CVS across never participants and always participants. However, movers are distributed across all the distribution of the CVS.

expected that major effects appear during the first months of the school year (Baranowski et al. 2014; Moreno et al. 2013; Kobayashi and Kobayashi 2006). Additional evidence is needed to understand whether significant differences persist during summertime. [21]

When conducting sub-group analysis, evidence suggests that Neuroticism and Openness to Experience are important moderators of the SMP effects, consistent with previous literature. Given the attributes of personality associated with both skills, it seems plausible that self-control is limited among children that are more prone to stress and negative feelings, while students that show curiosity and intellectual vocation are more likely to develop more in their executive functioning skills.[22] Evidence from observational studies support the premise that young children that are less neurotic and open to experience are also more likely to eat fewer fruits and vegetables, while increasing the consumption of sweet drinks (Vollrath et al. 2012a; Vollrath et al. 2012b). Regarding potential bidirectional effects, results suggests that differences in consumed meals to not affect socioemotional development at this age. Similarly, parental time investments in the previous year do not directly act as moderator of the program. Rather, parental investments can contribute through increased socioemotional skills accumulation. The latter might reflect a divergence between parental behaviors regarding stimulation and feeding practices. Unfortunately, the available data does not provide additional information on other types of parental behaviors that might be conducive to healthier diets. Finally, there is important evidence of complementarity between the SMP and a large, community-based mental health program (AfLP), consistent with previous evidence.

Why are there no short term SMP effects on boys in the First grade? First, boys consistently have lower socioemotional skills, compared to girls. [23] Observational evidence from Chile suggests that boys from similar age are more likely to snack and eat foods richer in

[21] Data analysis shows that the BMI-z diminishes through the school year, however results suggests that the BMI-z decrease is larger among SMP participants during the first months of the school year.

[22] Results for extroversion and learning as moderators for girls are not significant. Results for boys are not significant using skills as moderators. Results are available upon request.

[23] Results from the measurement system show that differences by gender are related to differences in the estimated latent factors and not to differences in the factor loadings.

sugars and fats, which are the main contributors to weight gain, which is consistent with the overall differences in BMI-z (Correa-Burrows et al. 2015; Jensen et al. 2019). In addition, evidence suggest that the influence of different (and multiple) caregivers vary by gender (of both the student and caregiver). Preliminary evidence from the Vulnerability Survey data suggests that the presence of a father (or a grandparent) as caretaker can significantly reduce the effects of the SMP among girls. Similarly, the absence of a grandmother as caretaker is associated with a large SMP effect on boys in the First grade, while the presence of a grandmother, all else equal, drives the effect to zero.[24] These estimates are consistent with previous evidence that Chilean children living with grandmothers are at a higher risk of being obese (Marshall 2015). Additional information is needed to understand whether specific caregiver arrangements promote excess weight gain among boys, for example, by repeating meals at home and school. This is particularly relevant in the Chilean context, as grandmothers are the second most important caregiver for these children. Only 14% of fathers report taking care of the child outside school, while the same response from grandmothers and mothers are 24% and 68% respectively.

In terms of long-run effects and policy changes introduced to the SMP, early continuous exposure to the program has significant effects on BMI-z for boys, relative to students that never participated in the SMP by Fifth grade. Lack of effects from continuous exposure for girls in 5th grade could be linked to female students reaching the growth spur associated with puberty at this age, while it occurs later for boys. It is important to recall that there are no apparent short term effects in this cohort. Still, by 2018 all children are receiving meals with improved nutritional quality, due to the changes introduced since 2015. Finally, there is no evidence short-term effects due to the expansion of the program in 2016, relative to (locally) comparable students. Lack of short-term effects in 4th and 5th grade could be explained due to the ban on "unhealthy foods" from schools introduced in 2016. Additional evidence is needed to understand if long term effects are consistent across cohorts and meal

[24]Results available upon request.

contract characteristics.

7 Conclusion

School meal programs have been subject to extensive controversy, particularly for countries undergoing a nutritional transition. In the case of Chile, the SMP is contributing to mitigate the obesity epidemic, mostly impacting overweight and obese students attending public and subsidized schools. Children with higher socioemotional development are the ones largely benefiting from meals with high nutritional quality. This can introduce a significant gradient of inequality, as children with lower socioemotional skills are also those living in more vulnerable households, thus more likely to be exposed to unhealthy diets. Based on this study, integration of stimulation and nutritional support through the school system is key to prevent such disparities early in life.

While producing novel evidence of the effect of school meal programs on nutritional status and its connection to socioemotional development, this analysis leaves many open questions to be addressed in future studies. First, parental investments are treated as exogenous. While differences might be random in an RD study, there is still scope for sorting on unobserved characteristics. Hence, studying the production functions of nutritional health and socioemotional development, while accounting for endogenous parental investments is a next logic step. Second, I have been silent about the scope for peer effects. Available data indicates that there is no tracking on Chilean schools at this grade, however there is important scope for parental choice and sorting. Incorporating peer effects in regression discontinuity designs is a challenging but promising area of study.[25] Third, there is scope to take advantage of other sources of exogenous variation to understand the evolution of early human capital. The sixth largest earthquake recorded in history impacted the coast of the central part of Chile in 2010. High quality geo-referenced data can be useful to study early

[25]Preliminary analysis using the proportion of obese peers in the previous year shows no significant differences in the LATE among students exposed to a higher or lower proportion of obese classmates.

life shocks, mitigation and human capital accumulation in this context. Fourth, the data on this analysis only partially accounts for the important changes introduced by the Food Labelling and Regulation Act of 2012, which prohibits the sale of junk foods inside schools since July of 2016. Studying more closely the interaction between the SMP and changes in the food environment by relying on compliance data from schools is a promising avenue to understand the effects of regulations that target obesogenic environments. Finally, while I account for physical activity in this study, body mass is only a proxy to understand how socioemotional skills influence behavior. In the following years, additional data from JUNAEB will be available to directly explore the link between early development and eating behaviors.

Many countries are concentrating their efforts on enacting strict regulations to shape their food systems in order to mitigate the obesity epidemic, with limited success. However, results from this study contribute to the recent RCT evidence that investing in children's socioemotional development and optimal nutrition through pre-school and beyond can be extremely effective to prevent obesity among children in the short term, but also to avoid excess weight over the life-cycle.

References

Abarca-Gómez, Leandra et al. (2017). "Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128Δ 9 million children, adolescents, and adults". In: *The Lancet* 390.10113, pp. 2627–2642.

Agostinelli, Francesco and Matthew Wiswall (2016). *Estimating the Technology of Children's Skill Formation*. Report. National Bureau of Economic Research.

Aichholzer, Julian (2014). "Random intercept EFA of personality scales". In: *Journal of Research in Personality* 53, pp. 1–4.

Alderman, H., J. R. Behrman, S. Grantham-McGregor, F. Lopez-Boo, and S. Urzua (2014). "Economic perspectives on integrating early child stimulation with nutritional interventions". In: *Annals of the New York Academy of Sciences* 1308, pp. 129–38. DOI: 10.1111/nyas.12331.

Alderman, Harold and Donald Bundy (2011). "School feeding programs and development: are we framing the question correctly?" In: *The World Bank Research Observer* 27.2, pp. 204–221.

Alderman, Harold and Lia Fernald (2017). "The nexus between nutrition and early childhood development". In: *Annual review of nutrition* 37, pp. 447–476.

Almlund, M., A. L. Duckworth, J. Heckman, and T. Kautz (2011). "Personality Psychology and Economics". In: *Handbook of the Economics of Education, Vol 4* 4, pp. 1–181. ISSN: 0169-7218.

Amigo, Hugo, Marcia Erazo, Patricia Bustos, Carolina Aguilar, and Marcela Taibo (2008). "Vigilancia nutricional en escolares chilenos: validez de la información". In: *Revista médica de Chile* 136.8, pp. 989–995.

Anderson, Patricia M and Kristin F Butcher (2006). "Childhood obesity: trends and potential causes". In: *The Future of children*, pp. 19–45. ISSN: 1054-8289.

Anderson, Patricia M, Kristin F Butcher, and Diane Whitmore Schanzenbach (2019). "Understanding recent trends in childhood obesity in the United States". In: *Economics & Human Biology*.

Atalah, S Eduardo (2012). "Epidemiología de la obesidad en Chile". In: *Revista Médica Clínica Las Condes* 23.2, pp. 117–123.

Attanasio, Orazio P (2015). "The determinants of human capital formation during the early years of life: Theory, measurement, and policies". In: *Journal of the European Economic Association* 13.6, pp. 949–997. ISSN: 1542-4766.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina (2015a). *Estimating the production function for human capital: Results from a randomized control trial in Colombia*. Report. National Bureau of Economic Research.

Attanasio, Orazio, Costas Meghir, and Emily Nix (2015b). *Human capital development and parental investment in india*. Report. National Bureau of Economic Research.

Baranowski, Tom, Teresia O'Connor, Craig Johnston, Sheryl Hughes, Jennette Moreno, Tzu-An Chen, Lisa Meltzer, and Janice Baranowski (2014). "School year versus summer differences in child weight gain: a narrative review". In: *Childhood Obesity* 10.1, pp. 18–24.

Bartalotti, Otavio and Quentin Brummet (2017). "Regression discontinuity designs with clustered data". In: *Regression Discontinuity Designs: Theory and Applications*. Emerald Publishing Limited, pp. 383–420. ISBN: 0731-9053.

Behrman, Jere R (1996). "The impact of health and nutrition on education". In: *The World Bank Research Observer* 11.1, pp. 23–37.

Behrman, Jere R, Yingmei Cheng, and Petra E Todd (2004). "Evaluating preschool programs when length of exposure to the program varies: A nonparametric approach". In: *Review of economics and statistics* 86.1, pp. 108–132.

Bhatia, Rajiv, Paula Jones, and Zetta Reicker (2011). "Competitive foods, discrimination, and participation in the National School Lunch Program". In: *American Journal of Public Health* 101.8, pp. 1380–1386.

Bhattacharya, Jayanta, Janet Currie, and Steven J Haider (2006). "Breakfast of champions? The School Breakfast Program and the nutrition of children and families". In: *Journal of Human Resources* 41.3, pp. 445–466.

Birch, L. L. (1999). "Development of food preferences". In: *Annu Rev Nutr* 19, pp. 41–62. ISSN: 0199-9885 (Print) 0199-9885 (Linking). DOI: 10.1146/annurev.nutr.19.1.41.

Birch, Leann L and Stephanie L Anzman (2010). "Learning to eat in an obesogenic environment: a developmental systems perspective on childhood obesity". In: *Child Development Perspectives* 4.2, pp. 138–143. ISSN: 1750-8592.

Black, Maureen M et al. (2017). "Early childhood development coming of age: science through the life course". In: *The Lancet* 389.10064, pp. 77–90.

Calonico, Sebastian, Matias D Cattaneo, Max H Farrell, and Rocio Titiunik (2018). "Regression discontinuity designs using covariates". In: *Review of Economics and Statistics*. ISSN: 0034-6535.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik (2014). "Robust nonparametric confidence intervals for regression discontinuity designs". In: *Econometrica* 82.6, pp. 2295–2326. ISSN: 0012-9682.

Campbell, F., G. Conti, J. J. Heckman, S. H. Moon, R. Pinto, E. Pungello, and Y. Pan (2014). "Early childhood investments substantially boost adult health". In: *Science* 343.6178, pp. 1478–85.

Carril, Alvaro, Andre Cazor, Maria Paula Gerardino, Stephan Litschig, and Dina Pomeranz (2017). *RDDSGA: Stata module to conduct subgroup analysis for regression discontinuity designs*. Statistical Software Components, Boston College Department of Economics. URL: https://ideas.repec.org/c/boc/bocode/s458429.html.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma (2018). "Manipulation testing based on density discontinuity". In: *The Stata Journal 18.1 (2018): 234-261.*

Christakis, Nicholas A and James H Fowler (2007). "The spread of obesity in a large social network over 32 years". In: *New England journal of medicine* 357.4, pp. 370–379. ISSN: 0028-4793.

Collishaw, Stephan, Barbara Maughan, Robert Goodman, and Andrew Pickles (2004). "Time trends in adolescent mental health". In: *Journal of Child Psychology and psychiatry* 45.8, pp. 1350–1362.

Conti, Gabriella, James J. Heckman, Rodrigo Pinto, and National Bureau of Economic Research. (2015). *The Effects of Two Influential Early Childhood Interventions on Health and Healthy Behaviors*. Electronic Book.

Cornette, Robert E (2011). "The emotional impact of obesity on children". In: *Global Perspectives on Childhood Obesity*. Elsevier, pp. 257–264.

Correa-Burrows, P., R. Burrows, Y. Orellana, and D. Ivanovic (2015). "The relationship between unhealthy snacking at school and academic outcomes: a population study in Chilean schoolchildren". In: *Public health nutrition, 18(11), 2022-2030.*

Cunha, Flavio and James Heckman (2007). *The technology of skill formation*. Report. National Bureau of Economic Research.

Cunha, Flavio, James J Heckman, and Susanne M Schennach (2010). "Estimating the technology of cognitive and noncognitive skill formation". In: *Econometrica* 78.3, pp. 883–931. ISSN: 0012-9682.

Das, Jishnu, Stefan Dercon, James Habyarimana, Pramila Krishnan, Karthik Muralidharan, and Venkatesh Sundararaman (2013). "School inputs, household substitution, and test scores". In: *American Economic Journal: Applied Economics* 5.2, pp. 29–57. ISSN: 1945-7782.

Dee, Anne, Karen Kearns, Ciaran ONeill, Linda Sharp, Anthony Staines, Victoria ODwyer, Sarah Fitzgerald, and Ivan J Perry (2014). "The direct and indirect costs of both overweight and obesity: a systematic review". In: *BMC research notes* 7.1, p. 242. ISSN: 1756-0500.

Dishion, Thomas J and Jessica M Tipsord (2011). “Peer contagion in child and adolescent social and emotional development”. In: *Annual review of psychology* 62, pp. 189–214.

Donnellan, M Brent and Richard E Lucas (2008). “Age differences in the big five across the life span: evidence from two national samples.” In: *Psychology and aging* 23.3, p. 558.

Duran, Guillermo and Seminario JUNAEB-DII (2006). “Investigacion de operaciones, modelos matematicos y optimizacion”. In: *Santiago de Chile: Seminario JUNAEB-DII*.

Ebbeling, Cara B, Dorota B Pawlak, and David S Ludwig (2002). “Childhood obesity: public-health crisis, common sense cure”. In: *The lancet* 360.9331, pp. 473–482.

Ehrler, David J, J Gary Evans, and Ron L McGhee (1999). “Extending Big-Five theory into childhood: A preliminary investigation into the relationship between Big-Five personality traits and behavior problems in children”. In: *Psychology in the Schools* 36.6, pp. 451–458.

Fleeson, William and Erik Noftle (2008). “The end of the person–situation debate: An emerging synthesis in the answer to the consistency question”. In: *Social and Personality Psychology Compass* 2.4, pp. 1667–1684.

Francis, Lori A and Elizabeth J Susman (2009). “Self-regulation and rapid weight gain in children from age 3 to 12 years”. In: *Archives of pediatrics adolescent medicine* 163.4, pp. 297–302. ISSN: 1072-4710.

Frandsen, Brigham R, Markus Frolich, and Blaise Melly (2012). “Quantile treatment effects in the regression discontinuity design”. In: *Journal of Econometrics* 168.2, pp. 382–395. ISSN: 0304-4076.

Frolich, Markus and Blaise Melly (2010). “Quantile treatment effects in the regression discontinuity design: process results and gini coefficient”. In:

Fung, Christina, Jessie-Lee D McIsaac, Stefan Kuhle, Sara FL Kirk, and Paul J Veugelers (2013). “The impact of a population-level school food and nutrition policy on dietary intake and body weights of Canadian children”. In: *Preventive medicine* 57.6, pp. 934–940.

Gelman, Andrew and Guido Imbens (2018). “Why high-order polynomials should not be used in regression discontinuity designs”. In: *Journal of Business Economic Statistics*, pp. 1–10. ISSN: 0735-0015.

Gorsuch, Richard L (2003). “Handbook of psychology: Vol 2. Research methods in psychology”. In: *ed. JA Schinka and WF Velicer, Chapter Factor Analysis*, pp. 143–164.

Grantham McGregor, Sally, Lia CH Fernald, Rose Kagawa, and Susan Walker (2014). “Effects of integrated child development and nutrition interventions on child development and nutritional status”. In: *Annals of the New York Academy of Sciences* 1308.1, pp. 11–32. ISSN: 1749-6632.

Grantham McGregor, Sally, Yin Bun Cheung, Santiago Cueto, Paul Glewwe, Linda Richter, Barbara Strupp, International Child Development Steering Group, et al. (2007). "Developmental potential in the first 5 years for children in developing countries". In: *The lancet* 369.9555, pp. 60–70.

Graziano, Paulo A, Susan D Calkins, and Susan P Keane (2010). "Toddler self-regulation skills predict risk for pediatric obesity". In: *International Journal of Obesity* 34.4, p. 633.

Gundersen, Craig, Brent Kreider, and John Pepper (2012). "The impact of the National School Lunch Program on child health: A nonparametric bounds analysis". In: *Journal of Econometrics* 166.1, pp. 79–91.

He, Jia, Dave Bartram, Ilke Inceoglu, and Fons JR Van de Vijver (2014). "Response styles and personality traits: A multilevel analysis". In: *Journal of Cross-Cultural Psychology* 45.7, pp. 1028–1045.

Heckman, J., R. Pinto, and P. Savelyev (2013). "Understanding the Mechanisms Through Which an Influential Early Childhood Program Boosted Adult Outcomes". In: *Am Econ Rev* 103.6, pp. 2052–2086. DOI: 10.1257/aer.103.6.2052.

Heckman, James J (2007). "The economics, technology, and neuroscience of human capability formation". In: *Proceedings of the national Academy of Sciences* 104.33, pp. 13250–13255.

Heckman, James J and Rodrigo Pinto (2015). "Econometric mediation analyses: Identifying the sources of treatment effects from experimentally estimated production technologies with unmeasured and mismeasured inputs". In: *Econometric reviews* 34.1-2, pp. 6–31. ISSN: 0747-4938.

Hsu, Yu-Chin and Shu Shen (2016). *Testing for treatment effect heterogeneity in regression discontinuity design*. Report. Institute of Economics, Academia Sinica, Taipei, Taiwan.

Jensen, M. L., C. Corvalfffdfffdn, M. Reyes, B. M. Popkin, and L. S. Taillie (2019). "Snacking patterns among Chilean children and adolescents: is there potential for improvement?" In: *Public Health Nutrition, 1-10.*

John, O. P. and S. Srivastava (1999). "Big Five Trait taxonomy: History, measurement, and theoretical perspectives". In: *Handbook of personality: Theory and research (pp. 102-138). New York, NY, US: Guilford Press.*

JUNAEB (2017). *Mapa Nutricional*. Web Page. URL: http://bpt.junaeb.cl:8080/MapaNutricionalGx/.

Kain, Juliana, Marcos Galván, Marcela Taibo, Camila Corvalán, Lydia Lera, and Ricardo Uauy (2010). "Evolución del estado nutricional de niños chilenos desde la etapa preescolar a la escolar: resultados antropométricos según procedencia de las mediciones". In: *Archivos Latinoamericanos de Nutrición* 60.2, pp. 155–159.

Kautz, Tim, James J. Heckman, Ron Diris, Bas Ter Weel, L. Borghans, and National Bureau of Economic Research. (2014). *Fostering and Measuring Skills Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success*. Electronic Book.

Kobayashi, Masako and Maiko Kobayashi (2006). "The relationship between obesity and seasonal variation in body weight among elementary school children in Tokyo". In: *Economics & Human Biology* 4.2, pp. 253–261.

Larrañaga, Osvaldo, Denise Falck, Rodrigo Herrera, and Amanda Telias (2014). "De la Ficha de Protección Social a la Reforma de la Focalización". In: *Santiago: Programa de las Naciones Unidas para el Desarrollo*.

Lillycrop, Karen A and Graham C Burdge (2011). "Epigenetic changes in early life and future risk of obesity". In: *International journal of obesity* 35.1, p. 72. ISSN: 1476-5497.

Marshall, Daniela (2015). "Family determinants of early childhood well-being: Three studies from Chile". In: *Dissertations available from ProQuest. AAI3709514.* URL: https://repository.upenn.edu/dissertations/AAI3709514.

McEwan, Patrick J (2013). "The impact of Chile's school feeding program on education outcomes". In: *Economics of Education Review* 32, pp. 122–139.

Millimet, Daniel L and Rusty Tchernis (2013). "Estimation of treatment effects without an exclusion restriction: with an application to the analysis of the School Breakfast Program". In: *Journal of Applied Econometrics* 28.6, pp. 982–1017. ISSN: 0883-7252.

Miyawaki, A, JS Lee, and Y Kobayashi (2018). "Impact of the school lunch program on overweight and obesity among junior high school students: a nationwide study in Japan". In: *J Public Health*.

Mizala, Alejandra and Florencia Torche (2012). "Bringing the schools back in: the stratification of educational achievement in the Chilean voucher system". In: *International Journal of Educational Development* 32.1, pp. 132–144.

Mönckeberg, Fernando (2014). "Desnutrición infantil y daño del capital humano: damage to the human capital". In: *Revista chilena de nutrición* 41.2, pp. 173–180.

Moreno, Jennette P, Craig A Johnston, and Deborah Woehler (2013). "Changes in weight over the school year and summer vacation: results of a 5-year longitudinal study". In: *Journal of School Health* 83.7, pp. 473–477.

Murphy, J Michael, Madelaine R Abel, Sharon Hoover, Michael Jellinek, and Mina Fazel (2017). "Scope, Scale, and Dose of the World's Largest School-Based Mental Health Programs". In: *Harvard review of psychiatry* 25.5, pp. 218–228. ISSN: 1067-3229.

OECD (2019). *The Heavy Burden of Obesity*, p. 240. DOI: https://doi.org/https://doi.org/10.1787/67450d67-en. URL: https://www.oecd-ilibrary.org/content/publication/67450d67-en.

Palermo, Tia M and Jennifer B Dowd (2012). “Childhood obesity and human capital accumulation”. In: *Social science & medicine* 75.11, pp. 1989–1998.

Popkin, Barry M (2002). “An overview of the nutrition transition and its health implications: the Bellagio meeting”. In: *Public Health Nutr* 5, pp. 93–103.

Popkin, Barry M, Linda S Adair, and Shu Wen Ng (2012). “Global nutrition transition and the pandemic of obesity in developing countries”. In: *Nutrition reviews* 70.1, pp. 3–21.

Puhl, Rebecca M and Kelly D Brownell (2006). “Confronting and coping with weight stigma: an investigation of overweight and obese adults”. In: *Obesity* 14.10, pp. 1802–1815. ISSN: 1930-7381.

Salinas, Judith and Felipe Correa (2013). “Marco normativo para promover una alimentacifffdfffdn saludable en escuelas bfffdfffdsicas de Chile”. In: *Revista chilena de nutricifffdfffdn* 40.3, pp. 274–282. ISSN: 0717-7518.

Schanzenbach, Diane Whitmore (2009). “Do school lunches contribute to childhood obesity?” In: *Journal of Human Resources* 44.3, pp. 684–709. ISSN: 0022-166X.

Schwartz, Marlene B, Kathryn E Henderson, Margaret Read, Nicole Danna, and Jeannette R Ickovics (2015). “New school meal regulations increase fruit consumption and do not increase total plate waste”. In: *Childhood Obesity* 11.3, pp. 242–247.

Specht, Jule, Boris Egloff, and Stefan C Schmukle (2011). “Stability and change of personality across the life course: The impact of age and major life events on mean-level and rank-order stability of the Big Five.” In: *Journal of personality and social psychology* 101.4, p. 862.

Strauss, Richard S and Harold A Pollack (2003). “Social marginalization of overweight children”. In: *Archives of pediatrics & adolescent medicine* 157.8, pp. 746–752.

Sweeting, Helen N (2008). “Gendered dimensions of obesity in childhood and adolescence”. In: *Nutrition journal* 7.1, p. 1.

Swinburn, Boyd A, Gary Sacks, Kevin D Hall, Klim McPherson, Diane T Finegood, Marjory L Moodie, and Steven L Gortmaker (2011). “The global obesity pandemic: shaped by global drivers and local environments”. In: *The Lancet* 378.9793, pp. 804–814. ISSN: 0140-6736.

Taber, Daniel R, Jamie F Chriqui, Lisa Powell, and Frank J Chaloupka (2013). “Association between state laws governing school meal nutrition content and student weight status: implications for new USDA school meal standards”. In: *JAMA pediatrics* 167.6, pp. 513–519.

Tick, NT, J Van der Ende, and FC Verhulst (2007). “Twenty-year trends in emotional and behavioral problems in Dutch children in a changing society”. In: *Acta Psychiatrica Scandinavica* 116.6, pp. 473–482.

Todd, Petra E and Kenneth I Wolpin (2003). "On the specification and estimation of the production function for cognitive achievement". In: *The Economic Journal* 113.485. ISSN: 1468-0297.

Torres-Fuentes, Cristina, Harriët Schellekens, Timothy G Dinan, and John F Cryan (2017). "The microbiota–gut–brain axis in obesity". In: *The lancet Gastroenterology & hepatology* 2.10, pp. 747–756.

Vandevijvere, Stefanie et al. (2019). "An 11-country study to benchmark the implementation of recommended nutrition policies by national governments using the Healthy Food Environment Policy Index, 2015-2018". In: *Obesity Reviews*.

Vio, FERNANDO and CECILLA Albala (2000). "Obesidad en Chile: una mirada epidemiológica". In: *Obesidad un desafío pendiente. Santiago: Editorial Universitaria*, pp. 31–43.

Vollrath, M. E., S. E. Hampson, and P. B. Juliusson (2012a). "Personality and gender are associated with obesogenic food consumption and overweight in 6-to 12-year-olds." In: *Appetite, 58(3), 1113-1117.*

Vollrath, M. E., S. E. Hampson, K. Stene-Larsen, S. Tonstad, and M. K. Rothbart (2012b). "Associations between temperament at age 1.5 years and obesogenic diet at ages 3 and 7 years." In: *Journal of developmental and behavioral pediatrics: JDBP, 33(9), 721.*

Wang, Chuanming, John SY Chan, Lijie Ren, and Jin H Yan (2016). "Obesity reduces cognitive and motor functions across the lifespan". In: *Neural plasticity* 2016.

WHO (2016). "Consideration of the evidence on childhood obesity for the Commission on Ending Childhood Obesity: report of the ad hoc working group on science and evidence for ending childhood obesity, Geneva, Switzerland". In:

Withrow, D. and D. A. Alter (2011). "The economic burden of obesity worldwide: a systematic review of the direct costs of obesity". In: *Obesity Reviews* 12.2, pp. 131–141. DOI: 10.1111/j.1467-789X.2009.00712.x.

Woodward-Lopez, Gail, Wendi Gosliner, Sarah E Samuels, Lisa Craypo, Janice Kao, and Patricia B Crawford (2010). "Lessons learned from evaluations of California's statewide school nutrition standards". In: *American Journal of Public Health* 100.11, pp. 2137–2145.

Wyatt, Sharon B, Karen P Winters, and Patricia M Dubbert (2006). "Overweight and obesity: prevalence, consequences, and causes of a growing public health problem". In: *The American journal of the medical sciences* 331.4, pp. 166–174. ISSN: 0002-9629.

Yi, Junjian, James J Heckman, Junsen Zhang, and Gabriella Conti (2015). "Early Health Shocks, Intrahousehold Resource Allocation and Child Outcomes". In: *The Economic Journal* 125.588, F347–F371. ISSN: 0013-0133.

A The Chilean National Board of School Aid and Scholarships

Chile has several long-standing social programs directed to children and their families in the school context. Since 1964, the National Board of School Aid and Scholarships (JUNAEB, Spanish acronym), an agency part of the Ministry of Education, has been responsible for assessing students' needs and allocating resources through different programs. Their mission statement follows[26]:

> *To support all students in a condition of social, economic, psychological and/or biological disadvantage, by providing quality, comprehensive products and services, that contribute to the realization of equal opportunities, human development and social mobility.*

JUNAEB manages programs and services covering all educational levels from pre-school to college. The range of programs includes: medical and dental services, nutrition, stimulation and mental health, scholarships, transport, housing and school supplies. The two largest programs within JUNAEB are the School Meals Program (since 1964) and the Abilities for Life Program, AfLP, (since 1999). Both programs are considered large relative to the served population (as a fraction of target students), in comparison to similar programs in other countries (McEwan 2013; Murphy et al. 2017). Since 2016, the SMP covers the 60% of students based on vulnerability at the individual level.[27] As of 2018, AfLP provided services to 30% of public and subsidized schools, targeted by the proportion of vulnerable students attending each school. Given eligibility, participation in the AfLP for schools (and their communities) is voluntary(Murphy et al. 2017). During the last decades, both programs have provided support to hundreds of thousands of families with adequate nutrition and mental health services.

[26]Translated from JUNAEB website

[27]Vulnerability and eligibility criteria is defined and measured as explained in Section 2.

As discussed in the Introduction, countries during and post nutritional transition face a particular challenges when it comes to nutrition and stimulation during childhood. After toddlerhood, rapid weight gain among children can be a cause and consequence of insufficient socioemotional stimulation. As noted by Alderman and Bundy (2011), SMPs can provide significant support to low income students and their families, promoting parental investments. In obesogenic environments, SMPs with high nutritional value and adequate energy contribution can help to protect children from obesity risk induced by less nutritional food options outside the school. Moreover, integrated interventions such as the SMP and AfLP have a substantial potential to impact students' development over the life-cycle.

While identifying and estimating the effects of the AfLP on children's development is outside the scope of this paper, I do report differential effects of the SMP across schools participating and not participating in the AfLP (Appendix Table C.5). Given the scope and size of the AfLP, it seems reasonable to expect differential effects of the SMP across schools. Preliminary results suggest that after balancing the sample by eligibility criteria for the AfLP and other relevant characteristics of students, for girls that attend schools participating on the AfLP, the protective effect of the SMP is much larger and significant. Results for boys show a similar direction but with a substantial variation. Overall, given the limited evidence from large scale nutrition or stimulation programs (Kautz et al. 2014), together, the SMP and AfLP constitute an unique starting point to contextualize the potential effects of RCT-based interventions when they are scaled up to population level using mean-tested eligibility criteria.

A.1 The Nutritional Map

Every year, JUNAEB requires the assistance of all schools participating in the SMP to collect a census of anthropometric measurements and household characteristics. The anthropometric information is officially known as the Nutritional Map. In 2015, 742,489 children had both instruments applied, this is 90% of all students attending public or private subsidised schools.[28] The coverage of the instruments is remarkable, considering that average daily attendance rates in Chile, as well as many developed countries, is close to 90%. Annual reports from JUNAEB show that coverage rates for the instruments has not changed significantly over time.[29] As noted in section 3, I refer to SMP data as the dataset for the sub-sample of students with valid instruments. Appendix Table A.2 summarizes a comparison between official enrollment data and the population with SMP data in the 2014-2015 cohort.[30] Compared to Kindergarten, SMP data coverage is lower in first grade, which can be explained by two factors. First, While SMP in pre-school is virtually universal, several subsidized schools have no participation in the program, hence SMP data is not collected. Secondly, average daily attendance decreases as children move through the educational system.[31]

The Nutritional Map is conducted by the class professor (or the professor designated by the school) through direct measurement of children's weight and height, as well as presence of cavities. While there is significant variation in the methods and instruments used for the measurements, the distribution of data is consistent across sub-populations and over time. Studies conducted in random samples of Chilean students show that while the distribution of measurements from teachers are not substantially different than trained professionals, there is room for missclassification of nutritional status due to noise introduced by variation in the methods and instruments used by teachersKain et al. 2010; Amigo et al. 2008. Evidence suggests that teachers are more likely than trained professionals to heap (round) weight and height measures, which create important discrepancies in the BMI-z averages. Appendix Figures A.1 and A.2 show heaping in height and weight in the SMP data for children in the 2014-2015 cohort when attending first grade. Average BMI-z is significantly lower in the observations with heaped weight data, which represent three quarters of the sample (.96 versus 1.12 in the non-heaped weight observations). Differences between heaped and non-heaped height data are not significant. However, heaping does not appear to be statistically

[28]For further information on the Chilean voucher system, see Mizala and Torche (2012).

[29]For more see JUNAEB Nutritional Map.

[30]Similar calculations for the 2012-2018 cohort are available upon request.

[31]For an example with U.S. data visit the following link.

related to school or other student level characteristics.

A.2 The Vulnerability Survey

The Vulnerability Survey contains rich information at the household level to characterize vulnerability along with several dimensions of child's health and development. The instrument presents some differences between each educational level. The common information is: household composition and interactions with index child, geographic location and cultural background, educational attainment and occupation of caregivers, physical resources for learning/development, children's health status and educational attainment. Also in all years there are questions regarding birth and breastfeeding frequency. There are two sections that are different between pre-school and the school years. The first one relates to paternal time investments (only available in pre-school) and the second one relates to social and emotional aspects the child (only available in school grades, with slight variation across grades).[32] Vulnerability Survey data has been consistently collected and coded since 2007 (including the generation of standarized anthropometric measurements from the Nutritional Map using 2007 WHO reference guide). However, there are two important caveats to constructing longitudinal information at the household level. First, the quality of the data in the year 2013 is limited due to changes in the questionnaire recording format, affecting all grades. Secondly, the surveys before and after 2015 contain slight variations in the context of the questionnaire. For example, a section on children health difficulties is only introduced from year 2014. As a result, for the 2014-2015 cohort, it is not possible to construct latent factors in both periods. Information on the effect that variation in the sections of the Vulnerability Survey questionnaire affects the model specification in each cohort is explained in Appendix B.

[32]A version of the Vulnerability Survey questionnaires (in Spanish) can be acquired from JUNAEB, upon request.

A.3 Estimation sample

Table B.2 shows descriptive information on the estimation samples, including the sample of all children linked longitudinally (Panel sample). There are not significant differences across estimation samples, however the sample size decreases significantly when data is linked longitudinally. The main reasons for the loss of data are: random absences, repeating grades, postponing entry to First Grade, and children not attending Kindergarten.

Table A.1: Descriptive statistics

	1st grade 2015		1st grade 2015 (urban)		Panel (2014-2015)		RD Panel (2014-2015)	
Anthropometrics	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Age (months)	79.8	79.1	79.8	79.1	79.0	78.6	79.0	78.6
	5.6	*5.2*	*5.5*	*5.2*	*4.6*	*4.5*	*4.6*	*4.5*
Height-for-age (Z-score)	0.26	0.32	0.27	0.33	0.31	0.37	0.30	0.35
	1.2	*1.16*	*1.19*	*1.16*	*1.16*	*1.14*	*1.16*	*1.14*
BMI-for-age (Z-score)	1.06	0.92	1.05	0.91	1.04	0.92	1.05	0.93
	1.49	*1.32*	*1.48*	*1.31*	*1.46*	*1.31*	*1.46*	*1.31*
Fraction overweight	52.7%	49.3%	49.8%	46.0%	49.7%	46.4%	50.0%	46.8%
School characteristics								
SMP participation =1	0.74	0.74	0.72	0.72	0.72	0.72	0.78	0.78
School vulnerability index (IVE)	70.3	69.5	68.3	67.5	68.3	67.7	70.5	69.8
	17.4	*17.4*	*17.2*	*17.2*	*16.9*	*16.9*	*15.5*	*15.5*
Public school = 1	0.44	0.41	0.39	0.37	0.38	0.37	0.41	0.39
Attended Kindergarten = 1	0.98	0.97	0.98	0.98	0.99	0.99	0.99	0.99
Household characteristics								
Mother's education (years)	12.0	12.0	12.2	12.2	12.3	12.3	12.1	12.1
	4.0	*3.9*	*4.0*	*3.9*	*3.8*	*3.8*	*3.6*	*3.6*
Mother's age (years)	33.1	33.1	33.2	33.2	33.1	33.2	32.7	32.8
	6.9	*6.9*	*6.9*	*6.9*	*6.8*	*6.9*	*6.8*	*6.9*
Household size	4.7	4.6	4.7	4.7	4.6	4.6	4.7	4.7
	1.7	*1.7*	*1.7*	*1.7*	*1.7*	*1.7*	*1.7*	*1.7*
Mother in labor force = 1	0.61	0.62	0.62	0.61	0.63	0.64	0.61	0.62
Lives with father = 1	0.65	0.64	0.65	0.64	0.65	0.65	0.63	0.63
Ethnic background = 1	0.13	0.13	0.13	0.13	0.12	0.12	0.13	0.13
Sample size	101,736	98,306	89,781	87,120	70,681	72,421	58,941	60,342

Notes: Panel indicates children in urban households matched with Kindergarten data. RD Panel indicates children in urban households matched with Kindergarden data and Household Vulnerability Score (FPS). Standard deviations in italics, if applicable.

Table A.2: School enrollment and SMP data

	Kindergarten 2014			1st Grade 2015		
	MINEDUC	JUNAEB		MINEDUC	JUNAEB	
Public and subsidized	193,713	188,512	97%	236,201	200,063	85%
Public	74,098	70,067	95%	94,152	85,082	90%
Subsidized	119,615	118,445	99%	142,049	114,965	81%

SMP: School Meal Program (JUNAEB).

Figure A.1: Weight distribution for children in first grade during 2015 (kgs.)

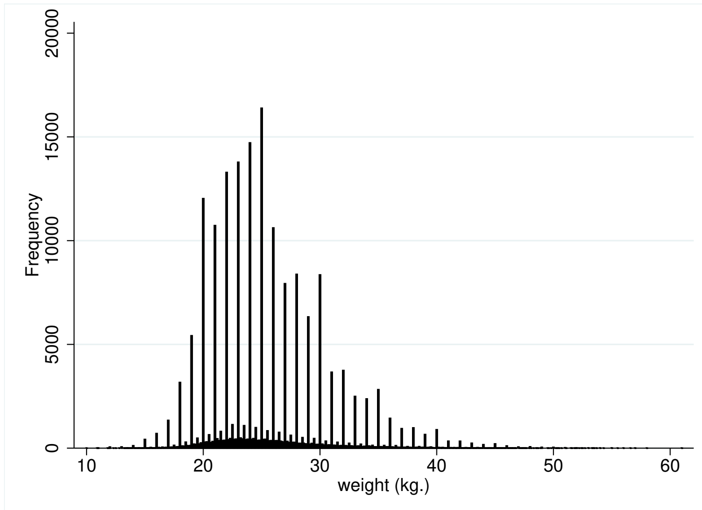
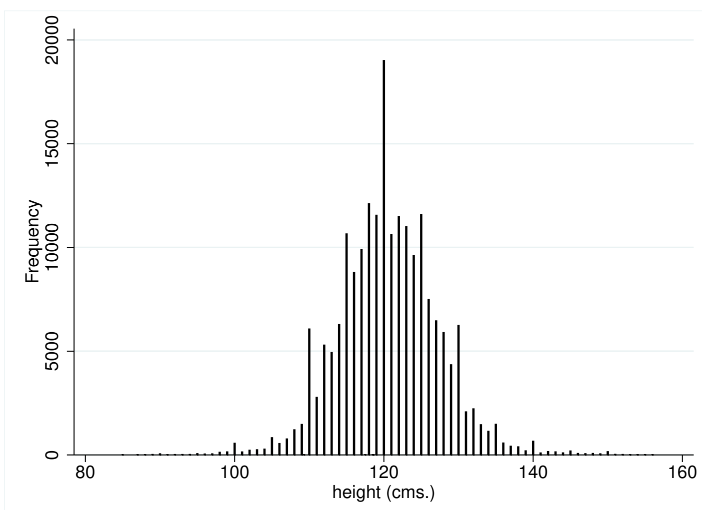


Figure A.2: Height distribution for children in first grade during 2015 (cms.)



B Measuring socioemotional skills and parental investments

In the last decade, several economists have provided a strong framework to incorporate psychological constructs into economic models (Almlund et al. 2011; Alderman et al. 2014; Attanasio 2015; Heckman et al. 2013; Cunha et al. 2010). This framework is often referred as the production technology of early human capital (or skills). Alderman et al. (2014) does an excellent job of characterizing the types of human capital inputs in three groups: cognitive skills, socioemotional skills and physical health. Although measuring cognition and physical development has been widely studied, less consensus exists on characterizing and measuring socioemotional skills (Kautz et al. 2014). A main issue is that socioemotional skills can only be proxied. Psychology, neuroscience and similar fields provide strong theoretical background and extensive evidence on survey items and inventories that consistently identify a given personality (or character) construct. As noted by Kautz et al. (2014), personality constructs contain a mixture of two components: the part that is malleable over time and the portion that is mostly inheritable and stable in the life-cycle. Throughout this paper, I refer to socioemotional skills as those that, at least to some extent, can be shaped during developmental stages. These skills can be considered equivalent to character constructs discussed in the psychology literature, such as personality traits.[33]

A prominent theoretical model in psychology is the Big Five Inventory (BFI), developed by [cite]. The BFI consists in 44 items that are rated in a 1-5 Likert scale (e.g. strongly agree to strongly dissagree). The BFI questionnaire aims to elicit five key dimensions of personality: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness. Statistical analysis from several sources confirms the existence of personality traits that are consistent with this model and stable across different populations, although not necessarily fixed over time (Donnellan and Lucas 2008; Specht et al. 2011). However, the extent that

[33]Some studies refer to these traits as the stable, inheritable part of personality. However, I avoid such distinction in order to remain consistent with the language used in economics and psychology

personality traits relate to behavior is part of a larger and complex system (Almlund et al. 2011). As such, for any given level of personality traits, these can be interpreted as the anchor from which behavior varies depending on the situation (Fleeson and Noftle 2008). In the economic and psychology literature, several authors have model socioemotional development among children using these personality traits and other measures of behavioral performance (e.g. inhibitory control, executive functioning, resilience), as they are consistent with the definition of skills: malleable over time and predict relevant economic and social outcomes in the short and long term (Ehrler et al. 1999; Heckman et al. 2013).

Current evidence from several programs and interventions at different ages elucidates a joint production of cognition, physical health and socioemotional skills during early childhood (Attanasio et al. 2015b; Heckman and Pinto 2015; Kautz et al. 2014; Alderman et al. 2014; Behrman et al. 2004). The link between physical health and cognition has been widely studied (see Heckman (2007) and Behrman (1996)). The connection between socioemotional development and mental health in children (and adults) is less understood. While some personality traits have been associated with higher likelihood of mental disorders (depression, ADHD, addiction), neuroscience scholars are only beginning to study the biological basis of how cognition, personality, values, identity and memory direct behavior. Nevertheless, personality traits are consistent predictors of behavior and can be fostered during early childhood, thus being a policy-relevant starting point to study the connection between socioemotional development and specific health behaviors.

From an empirical perspective, consistently measuring socioemotional skills relies in the psychometric properties of the questionnaires that are developed to elicit specific constructs. There is a myriad of different inventories and scales that capture different dimensions of personality, development and behavior. Some of this off-the-shelf questionnaires have been extensively studied in terms of their construct validity. However, in many cases, instead of relying on off-the-shelf surveys, programs and interventions develop their own ad-hoc questionnaires (e.g. Perry Program). Regardless, the same principles and methods for analysis of construct validity can be applied, in order to develop consistent measures of skills. In the remainder of this section I further describe the steps to obtain socioemotional skills and parental investment factors from the items in the Vulnerability Survey data.

B.1 Measures available in the Vulnerability Survey data

Here I discuss the model implemented to estimate short-term SMP effects in the 2014-2015 cohort, however the procedures are similar in other reported analyses with slight differences due to small changes in the questions over time. The Vulnerability Survey in first grade has two sections where aspects of socioemotional and cognitive development arise. The first set of questions document health-related behavioral difficulties, including motor, visual/hearing, self-control, learning and task performance (items D1-D9). The second set measures aspects of affection, social interactions and curiosity (items S1-S13). Appendix Table B.3 lists the Vulnerability Survey items used to construct socioemotional skills and the questions used to measure parental time investments in Kindergarten (which are not available in first grade), items I1-I7.

An important feature of the proxy measures in the Vulnerability Survey is the emergence of response styles, i.e., consistent patterns of response across items for each individual(He et al. 2014). In this case, a large fraction of parents have a tendency of consistently report "desirable" behavior from their children, alongside with minimal behavioral difficulties (13% of parents respond the lowest value on the scale to 20/22 items). Extensive literature proposed methods to address the presence of response styles when measuring personality constructs. Following Aichholzer (2014), I model response styles as individual (random) intercepts that are common across all measures. Another feature of the survey items on the Vulnerability Survey data is how questions are framed to elicit a given response. All but one of the questions are phrased such that lower values are associated with desirable/healthy behavior. Question S7 is inverted relative to the rest of survey items, eliciting a different response pattern. This introduced an additional challenge to identification.

B.2 Exploratory factor analysis

A starting point to characterize skill constructs is to conduct Exploratory Factor Analysis (EFA), to unveil the potential structure of the measurement system (Gorsuch 2003). In contrast to Attanasio et al. (2015b), in the analysis of the 2014-2015 cohort, I separately estimate the measurement system for skills and investments, for two reasons. First, a large fraction of students are not linked longitudinally, and excluding them from analysis can affect the underlying distribution of underlying factors. Secondly, while response styles are observed when parents respond to child's behavior, answers directed towards time investments do not present similar skewness. Thus, imposing a random intercept across all survey items would not be recommended. In Appendix Table C.2, I report the differences between the estimated correlations between investment and skills when the measurement system is estimated jointly versus separated within the same sample. Estimates suggest that estimating factors separately does not introduce significant changes in the underlying distribution.

Apppendix B.4 reports the (quartimin) rotated factor loadings from EFA with random intercepts. Most questions load into one factor, consistent with previous studies that propose a dedicated measurement system, i.e. each measurement loads into one factor. Many criteria have been proposed to determine the number of factors. In this analysis, based on the Kaiser's eigenvalue rule and the Cattrell's scree plot criteria (Figure B.2, data suggests that after accounting for response styles, four factors can be identified. Based on the questions' content and structure, as well as the rotated factor loadings, I consider three of the factors to be consistent with dimensions of the BFI (extroversion, openess, neuroticism) and one factor that represents a process measure (dubbed as "learning" skill).

B.3 Confirmatory factor analysis

The next step is to estimate the dedicated measurement system, as presented in Methods section. The scale in all questions used to elicit socioemotional skill factors are inverted to facilitate interpretation. As discussed, I follow standard normalization of loadings and mean factors for identification, while introducing a random intercept across measurements to capture response styles. Based on Cunha et al. (2010) and Attanasio et al. (2015b), the measurement system is estimated by approximating the distribution of latent factors by mixture or joint normal distributions and allowing the error terms to be independent and normally distributed.

I define θ as the vector of all unobserved factors (skills and investments, to simplify notation). For each j factor, I have k measurements ($\mathbf{M}$). The measurement system can be defined as:

$$\text{Measures:} M_{kt}^{j} = a_{kt}^{j} + \lambda_{kt}^{j} ln\theta_{t}^{j} + \eta_{kt}^{j} \tag{6}$$

$$\text{Factor Means: } E(ln\theta_{t}^{j}) = \mu_{t}^{j} \tag{7}$$

$$\text{Factor Covariance: } Var(\Theta) = \Omega_{\theta} \tag{8}$$

Where a denotes factor intercepts, λ indicates factor loadings, and η are independent gaussian errors. This is a dedicated system, where each measure can only be associated with one factor. The structure of the measurement system was chosen based on exploratory factor analysis, or EFA for short. To recognize the deviations from multivariate normality in the distribution of the data, I approximate the joint distribution of latent factors as a mixture of two gaussians: $F_{\theta} = \pi\phi(\mu_A, \Omega_A) + (1-\pi)\phi(\mu_B, \Omega_B)$. where π is the mixing factor. In matrix form, the measurement system can be represented as $M = \Lambda ln\theta + \Sigma\eta$, where Λ is a matrix that incorporates the normalizations required for the dedicated measurement system, and Σ is a diagonal variance-covariance matrix. As such, the mixture factor model to be estimated from data is:

$$F_M = \pi\phi(\Pi_A, \Gamma_A) + (1-\pi)\phi(\Pi_B, \Gamma_B) \tag{9}$$

Where $\Pi = \Lambda\mu$ and $\Gamma = \Lambda\Omega_{\theta}\Lambda + \Sigma$, and the normalization $\pi\mu_A + (1-\pi)\mu_B = 0$ is imposed for identification. Given the restrictions between measurement and underlying factors described above, we can identify all the parameters in the system with one additional normalization: the factor loading for the first measurement associated with each factor is fixed as one, which determines the scale of the factor.[34] The joint distribution of the measurement system can be estimated by maximum likelihood. With the estimated parameters, we can predict the factor (Barlett) scores for each individual with the following formula:

$$\hat{\theta}_t = (\Psi'\Sigma^{-1}\Psi)^{-1}\Psi'\Sigma^{-1}M_t \tag{10}$$

Given the potential for response sytles across measurements, I allow the intercepts to have a common (random) component across measurements for each individual (parent) that is orthogonal to the underlying factors: $a^j_{ikt} = a_{it} + a^j_{kt}$.

Initially, the system was estimated allowing for different loading for each SMP eligibility group, however there are not statistically significant differences between eligibility groups and the factor loadings or mixture weights. Therefore, the final system is estimated assuming equal factor loadings across eligibility groups. Appendix Figure B.1 shows the density of the estimated random intercept. Most parents in the data express a significant response style that correlates positively with parent's education and expectations regarding their children's human capital attainment, which suggests social desirability bias. Appendix Table B.5 shows the estimated factor loadings in each measurement equation. Appendix B.6 summarizes the correlation among all factors. As expected, all factors have a positive relationship with time investments, although of different magnitudes.

A common way to understand the importance of the measurement system is to analyze the signal to noise ratios, which captures the information content of each measure to the common factor.

[34] In this case, all measurements have the same domain, since they are all based on Likert-type scales.

$$s_j^{ln\theta_{kt}} = \frac{(\lambda_{kt}^j)^2 Var(ln\theta_{kt})}{(\lambda_{kt}^j)^2 Var(ln\theta_{kt}) + Var(\eta_{kt}^j)} \tag{11}$$

Table B.1 shows the structure of the measurement system for skills and investments as well as the signal to noise ratios. The results are very similar to comparable studies (Attanasio et al. 2015b; Attanasio et al. 2015a), confirming the importance of using multiple measures to mitigate measurement error. Extroversion indicates high energy levels, sociability and emotional expressiveness. Neuroticism refers to emotional instability, anxiety, sadness and irritability (scale is reverse so all the scale of the factor reflects absence of the trait, i.e., emotional stability). Openness characterizes curiosity, independent-minded, intellectual and imaginative (John and Srivastava 1999). An additional confirmation of the statistical characteristics of the obtained factors comes from comparing the results from the measurement system against the simple averages of BFI measurements on a sub-sample of young caregivers (20 years of younger) in the ELPI data. Table B.2 shows correlation among the estimated socioemotionalskills from the Vulnerability Survey and those in the ELPI sample. The similarities in the relative relationships among factors is remarkable, as extroversion and openness are closely related, while neuroticism seems to relate to the other two skills to a similar degree. Moreover, in terms of the learning factor, it seems that neuroticism correlates, to a great extent, with learning skills, followed by openness, while extroversion is less meaningful.[35]

As expected, we noted important differences in socioemotional skills by gender. Figures B.3 and B.4 show the kernel density for skills and parental time investments by gender. In a similar way, there are also meaningful differences in the accumulation of socioemotionalskills and parental time investment by years of education and the presence of a father figure.[36] Overall, at the same age (on average), girls have significantly lower BMI-z and higher socioemotional development. In particular, differences in neuroticism are important as they

[35]Note that in part this can be due to the timing in which data is collected, therefore interpretation should proceed with caution.

[36]Detailed results are available upon request.

Table B.1: Signal to noise ratios

θ^E		L	
affection to family	39.6%	difficult to learn	46.1%
affection to peers	45.0%	difficult to perform a task	84.5%
express feelings	40.9%	difficult to complete homework	85.3%
shows feelings physically	50.4%	θ^N	
plays with peers	31.5%	difficult to understand others	33.2%
shares with peers	24.5%	explosive/aggressive	11.6%
θ^O		difficult to control behavior	61.9%
ask adults	38.3%	difficult to get along with peers	40.6%
interested in books	36.8%	I	
interested in environment	54.0%	reads to child	39.3%
plays to (dis)assemble	30.8%	plays music with child	34.2%
shows artistic interest	28.3%	paints or writes with child	36.3%
		cultural activities with child	47.5%
		goes to parks with child	32.7%
		plays outside with child	41.8%
		takes child to play with peers	26.1%

Questions refer to index child in each case. Calculations done to the skills and investments in log scale.

Table B.2: Correlations among socioemotional factors

ELPI Big Five Inventory, (unadjusted average scores, n = 2,842)			
	θ^E	θ^N	θ^O
θ^E	1		
θ^N	0.191	1	
θ^O	0.368	0.197	1
VS (random intercept CFA, n = 193,539)			
	θ^E	θ^N	θ^O
θ^E	1		
θ^N	0.276	1	
θ^O	0.753	0.335	1
L	0.158	0.752	0.341

ELPI: 2012 Longitudinal Survey of Early Life (Big Five Inventory applied to primary caregivers younger than 20 years). Calculations done to the skills and investments in log scale.

have been previously associated to adoption of healthy behaviors (Heckman et al. 2013).

B.4 Available measures across cohorts

Following the same approach presented here, Appendix Table B.7 shows the availability of measures to characterize different constructs in every year of data available for each cohort. Although in the analysis of the 2014-2015 cohort there is only one observation of each factor per child, the study of long term effects (cohort 2012-2018) includes measures of socioemotional skills in more than one time period. In the latter case, the model is estimated in the panel sample, this is the students that are linked longitudinally. The main reason to favor estimating the dynamic measurement system while losing a large fraction of the sample, is to maintain the scale of factors over time. As noted in Agostinelli and Wiswall (2016), re-normalizing the data in each time period can introduce bias and obscures the interpretation of within child variation in skills over time.

Table B.3: Vulnerability Survey questions used in measurement system

Item	Question	Item	Question
	How often does the child:		*How difficult is for the child to:*
S1	show affection to family	D1	perform a task
S2	show affection to peers	D2	complete homework
S3	express feelings	D3	see without glasses
S4	shows feeligs phisically	D4	hear without aid
S5	plays with peers	D5	walk without assistance
S6	shares with peers	D6	understand others
S7	is explosive/aggressive with others	D7	learn
S8	participates actively in games	D8	control behavior
S9	ask questions to adults	D9	get along with peers
S10	is interested in books		
S11	is interested in his/her environment		*With the child, how often:*
S12	plays to (dis)assemble objects	I1	read or tell stories
S13	shows artistic interest	I2	sing or play an instrument
		I3	paint or write
		I4	participate in cultural activity
		I5	participate in sports
		I6	play in a public park or square
		I7	took to play with peers

Vulnerability Survey: Vulnerability Survey (JUNAEB).

Table B.4: Quatimin-rotated factor loadings (random intercept EFA, standarized values)

Measurements	Factors θ^O		θ^E		θ^N		L	
difficult to perform a task	-0.014	*0.001*	0.028	*0.001*	-0.014	*0.002*	**0.920**	*0.002*
difficult to complete homework	-0.008	*0.001*	0.026	*0.001*	0.007	*0.002*	**0.904**	*0.002*
difficult to understand others	0.125	*0.006*	-0.096	*0.006*	**0.313**	*0.007*	0.255	*0.006*
difficult to learn	0.161	*0.005*	-0.108	*0.005*	0.212	*0.006*	**0.495**	*0.006*
difficult to control behavior	0.027	*0.003*	-0.052	*0.003*	**0.678**	*0.007*	0.127	*0.007*
difficult to get along with peers	-0.041	*0.003*	0.108	*0.005*	**0.686**	*0.004*	-0.058	*0.002*
affection to family	0.034	*0.005*	**0.580**	*0.006*	-0.005	*0.004*	0.022	*0.003*
affection to peers	-0.012	*0.005*	**0.632**	*0.006*	0.132	*0.005*	-0.002	*0.003*
express feelings	0.025	*0.005*	**0.638**	*0.006*	-0.081	*0.003*	0.059	*0.003*
shows feeligs phisically	0.030	*0.005*	**0.687**	*0.006*	-0.043	*0.003*	0.042	*0.002*
plays with peers	0.102	*0.008*	**0.458**	*0.009*	0.147	*0.007*	-0.056	*0.005*
shares with peers	0.116	*0.007*	**0.353**	*0.008*	0.208	*0.006*	-0.052	*0.004*
explosive/aggressive	-0.036	*0.004*	0.021	*0.005*	0.342	*0.004*	-0.002	*0.004*
participates actively	0.267	*0.008*	0.224	*0.008*	0.077	*0.006*	-0.045	*0.004*
ask adults	**0.522**	*0.005*	0.152	*0.005*	-0.056	*0.003*	-0.003	*0.003*
interested in books	**0.604**	*0.004*	-0.076	*0.003*	0.025	*0.004*	0.146	*0.004*
interested in environment	**0.712**	*0.004*	0.040	*0.004*	-0.006	*0.002*	-0.046	*0.002*
plays to (dis)assemble	**0.569**	*0.005*	0.025	*0.004*	-0.035	*0.003*	-0.049	*0.003*
shows artistic interest	**0.519**	*0.005*	0.027	*0.004*	0.017	*0.004*	-0.021	*0.003*

Notes: RI-EFA estimates by maximum likelihood on panel data sample. Variables representing dedicated system in bold, standard error in italics.

Table B.5: Factor loadings (random intercept CFA)

	Factor			
Measurements	θ^O	θ^E	θ^N	L
difficult to complete homework	0	0	0	1.000
difficult to perform a task	0	0	0	0.981
difficult to learn	0	0	0	0.592
difficult to understand others	0	0	0.444	0
difficult to control behavior	0	0	1.000	0
difficult to get along with peers	0	0	0.556	0
affection to family	0	0.756	0	0
affection to peers	0	0.123	0	0
express feelings	0	1.110	0	0
shows feeligs phisically	0	1.212	0	0
plays with peers	0	0.889	0	0
shares with peers	0	1.000	0	0
ask adults	0.733	0	0	0
interested in books	1.000	0	0	0
interested in environment	0.899	0	0	0
plays to (dis)assemble	0.816	0	0	0
shows artistic interest	0.956	0	0	0

Notes: RI-CFA estimates by maximum likelihood on panel data sample.

Table B.6: Estimated correlation among predicted factors

	Unadjusted average scores		
	θ^E	θ^N	θ^O
θ^E	1		
θ^N	0.258	1	
θ^O	0.539	0.199	1
L	0.272	0.751	0.413
	Confirmatory factor analysis		
	θ^E	θ^N	θ^O
θ^E	1		
θ^N	0.475	1	
θ^O	0.823	0.393	1
L	0.284	0.768	0.422
	Random intercept confirmatory factor analysis		
	θ^E	θ^N	θ^O
θ^E	1		
θ^N	0.258	1	
θ^O	0.748	0.314	1
L	0.141	0.739	0.320

Vulnerability Survey: Vulnerability Survey (JUNAEB). CFA: Confirmatory Factor Analysis.

Table B.7: Latent factors based on available EVS data

	Pre-school			
	2012	2014	2015	2016
θ^E				
θ^N			X	X
θ^O				
L			X	X
I	X	X	X	X
	Elementary school			
	2014	2015	2017	2018
θ^E	X	X	X	X
θ^N		X	X	X
θ^O	X	X	X	X
L b		X	X	X

Vulnerability Survey: Vulnerability Survey (JUNAEB).

Figure B.1: Distribution of random intercept in the measurement system

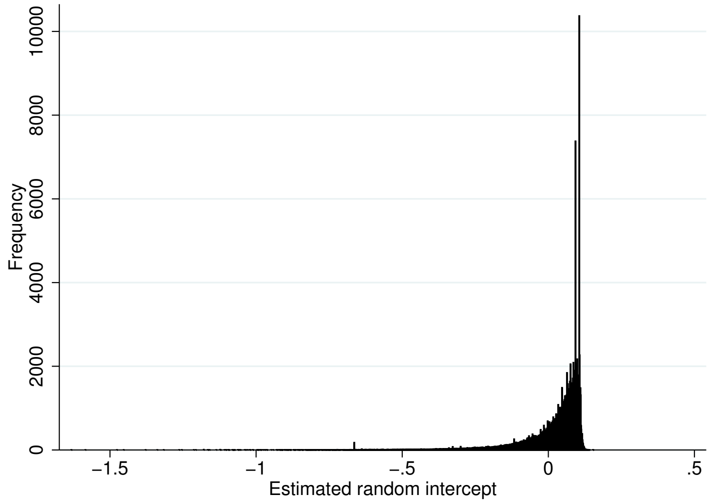


Figure B.2: Scree plot for Exploratory Factor Analysis (skills)

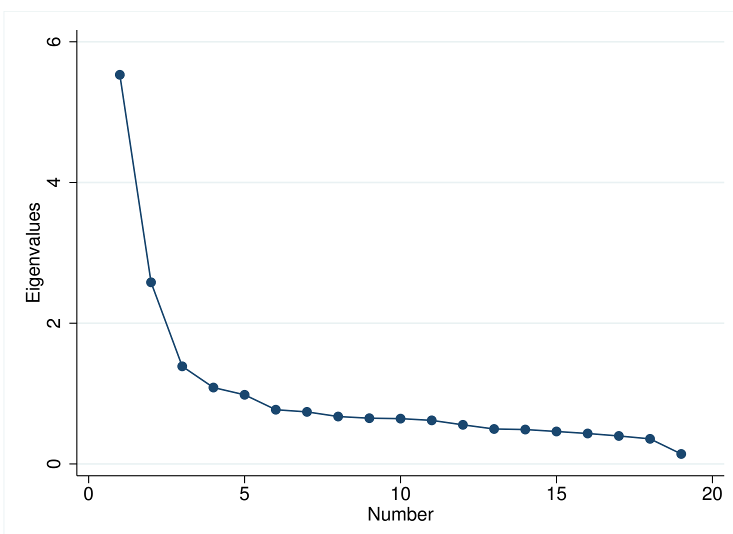


Figure B.3: socioemotionalskills by gender

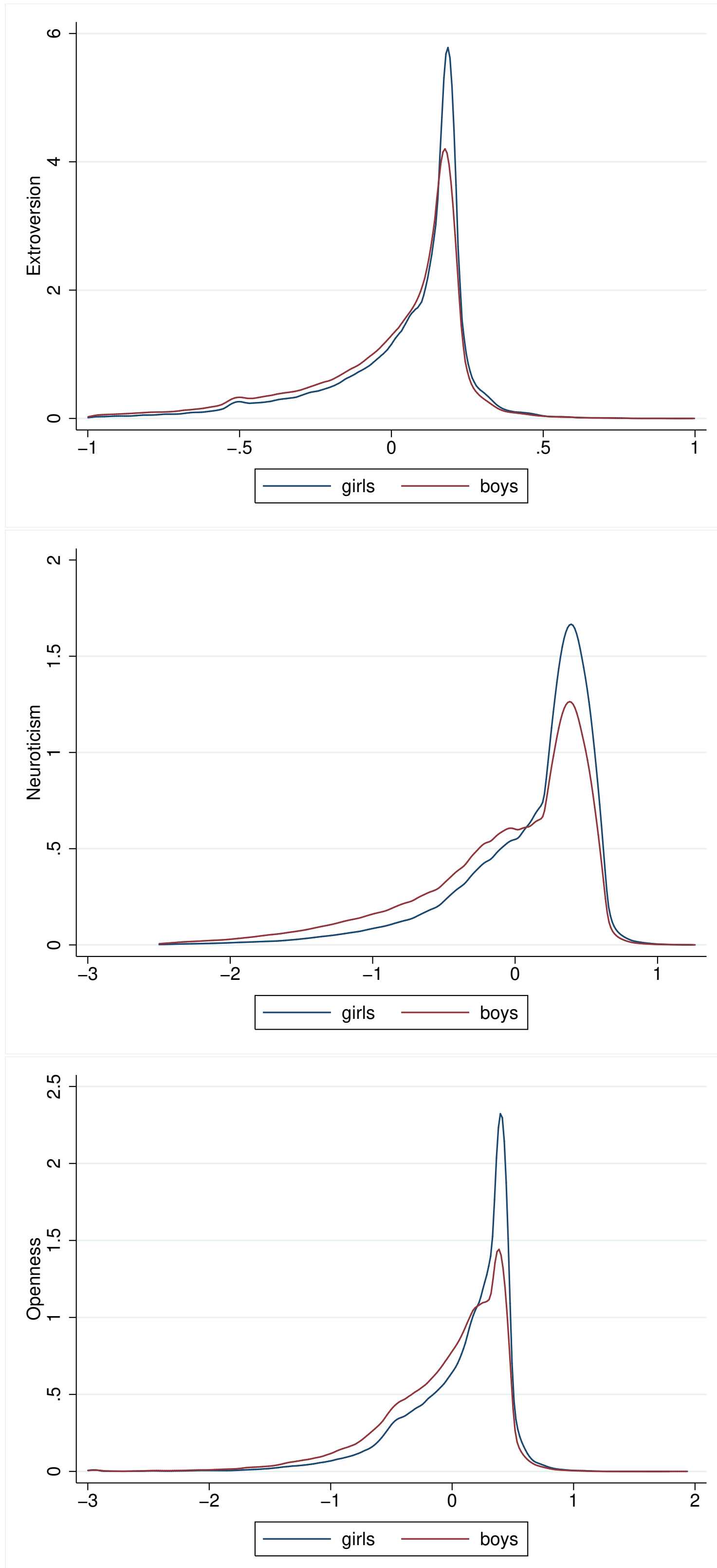
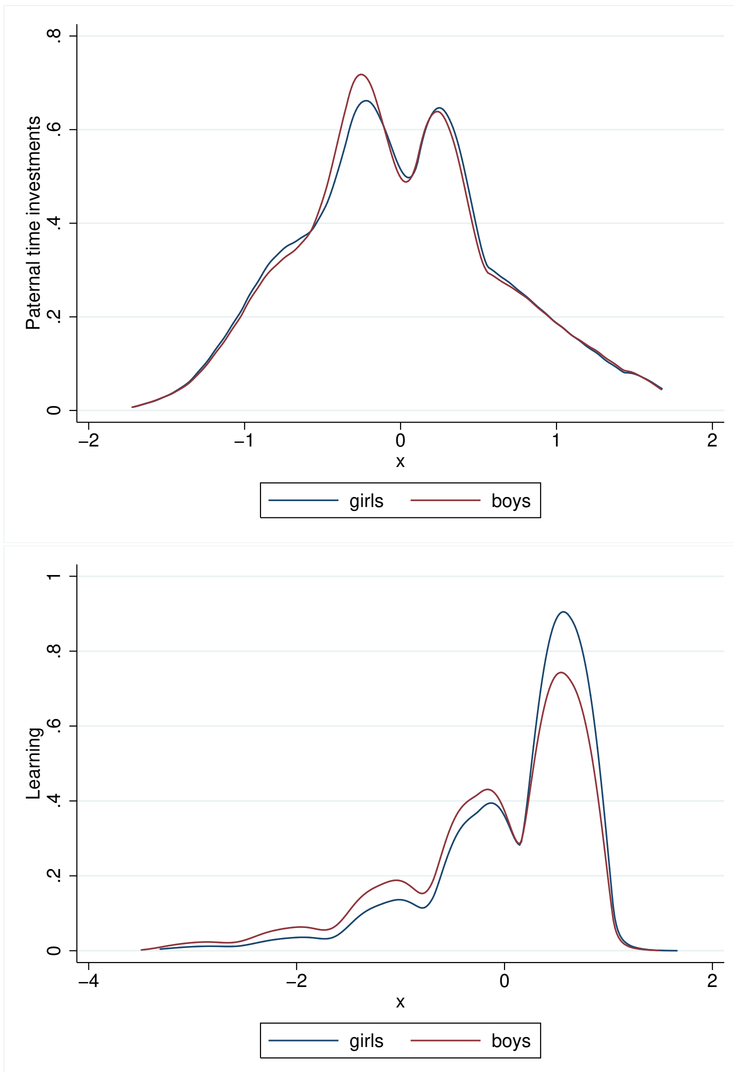


Figure B.4: Parental time investments and learning skills by gender



C Specification analysis and robustness checks

C.1 Factor analysis

Results from Confirmatory Factor Analysis suggests that there are no major differences in the relationship between different factors when investments and skills are estimated jointly or as independent measurement systems. Appendix Table C.1 reports the variances of the estimated skill factors in the overall sample versus the Panel sample for the 2014-2015 cohort. Appendix Table C.2 shows the correlations between in the skill and investment factors when measurement system is estimated jointly versus separated, using the Panel sample for the 2014-2015 cohort.[37]

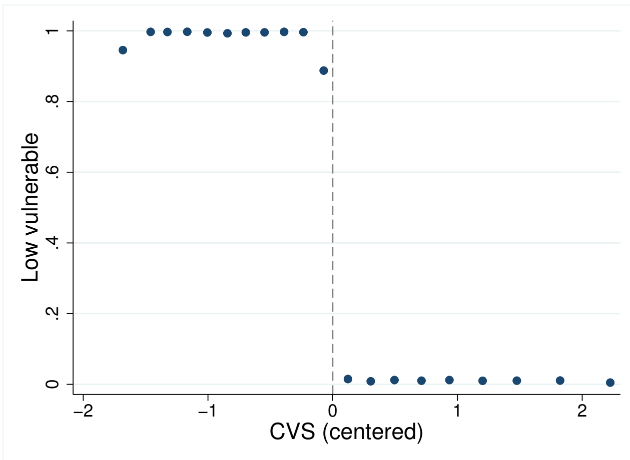
C.2 Local average treatment effects

This section reports different complementary analysis to understand the validity of the SMP local average treatment effects. Appendix Figure C.1 shows the elibility to the program for the different cut-offs. Appendix Table C.3 reports standard specification tests to the regression discontinuity LATE estimates. I include the impact on the LATE estimates for boys and girls from the following changes on specification: functional form (linear versus quadratic), placebo test (age) and bandwidth selection . Appendix Table C.4 shows further robustness checks due to different characteristics of the data. I report sensitivity of LATE estimates that might arise from estimating the LATE using the RD Panel data only. Similarly, I show the estimated LATE on rural schools. Figures C.2 andC.3 show placebo tests on other variables as well as the potential LATE of the SMP on socioemotional skills. Finally, Figure C.4 presents the quantile estimates for the long-run exposure effects of the SMP in 5th grade.

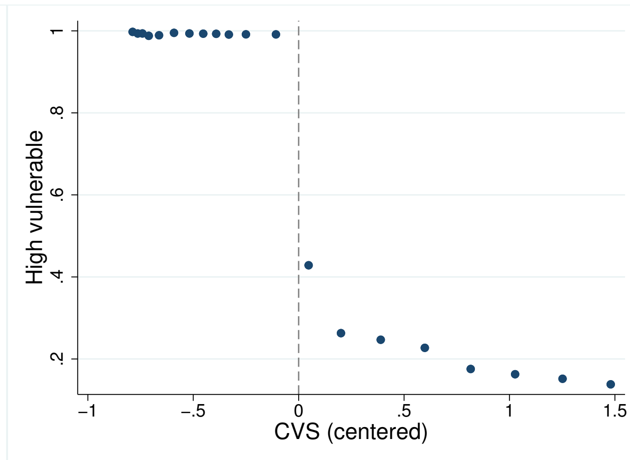
[37] Additional specification checks for different cohort years are available upon request.

Figure C.1: Program eligibility by CVS

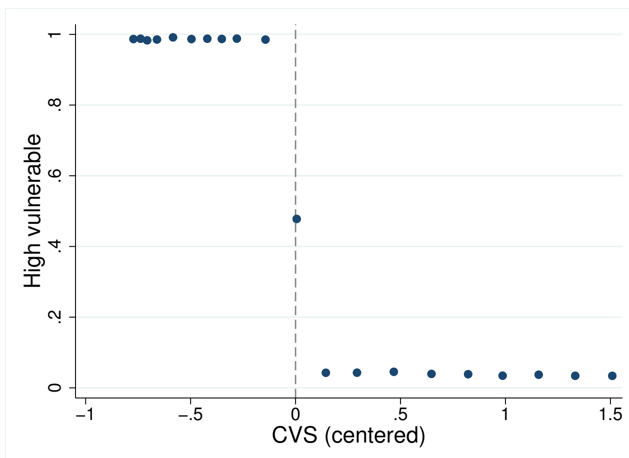
(a)



(b)



(c)



Notes: Panel (a) indicates change in probability between low vulnerable and no vulnerable children. Panels (b) and (c) indicates change in probability between low and high vulnerable. Panel (c) excludes children in families participating on *Chile Solidario*, a comprehensive program that makes children automatically high vulnerable, regardless of their FPS score. Each point represents one percentile of the data. Excludes students without a FPS score. CVS: child vulnerability score (JUNAEB).

Table C.1: Standard deviation of socioemotional skills and investment factors, cohort 2014-2015

	θ^E	θ^N	θ^O	L	I
Full sample	0.309	0.541	0.481	0.784	0.699
Panel sample	0.398	0.578	0.544	0.802	0.697

Skills notation as follows; E: extroversion, N: neuroticism, O: openness, L: learning

Table C.2: Correlations between investment and socioemotional factors (Panel 2014-2015)

	θ^E	θ^N	θ^O	L
Investment (separated)	0.087	0.108	0.136	0.114
Investment (joint)	0.097	0.123	0.175	0.144

Skills notation as follows; E: extroversion, N: neuroticism, O: openness, L: learning

Table C.3: Local average treatment effects: specification tests (dep var: BMI-z)

	linear polynomial		placebo test (age)		twice optimal bandwidth	
	Boys	Girls	Boys	Girls	Boys	Girls
First Stage	**-0.97**	**-0.97**	**-0.98**	**-0.97**	**-0.97**	**-0.97**
	0.005	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*
LATE	0.059	**-0.128**	-0.187	0.129	-0.006	-0.069
	0.079	*0.071*	*0.271*	*0.282*	*0.057*	*0.055*
Cut-off	1.59	1.59	1.59	1.59	3.2	3.2
Bandwidth	0.4	0.4	0.41	0.37	1.60	1.40
N	7374	7134	7480	6198	14742	16477

Notes: significant values in bold (p<0.1) Bandwidth based on optimal MSE (mean squared error). Standard errors in italics.

Table C.4: Further specification tests (dep var: BMI-z)

	rural schools		RD panel	
	Boys	Girls	Boys	Girls
First Stage	**-**	**-**	**-0.98**	**-0.98**
	-	-	*0.005*	*0.005*
LATE	0.3	-0.234	0.109	**-0.133**
	0.274	*0.213*	*0.096*	*0.079*
Cut-off	1.59	1.59	1.59	1.59
Bandwidth	0.638	0.634	0.714	0.77
N	3760	1410	1471	11750

Notes: significant values in bold (p<0.1 based on optimal MSE). Standard errors in italics. First stage not available for rural schools due to perfect compliance for low vulnerable students.

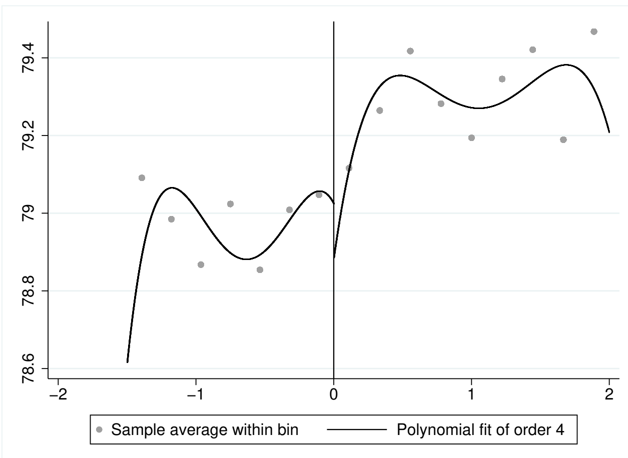
Table C.5: LATE by school participation in the Abilities for Life Program (AfLP)

	boys		girls	
	no AfLP	AfLP	no AfLP	AfLP
LATE	0.026	-0.101	-0.178	**-0.361**
	0.135	*0.206*	*0.115*	*0.199*
Bandwidth	0.59		0.59	
N	10753		10442	

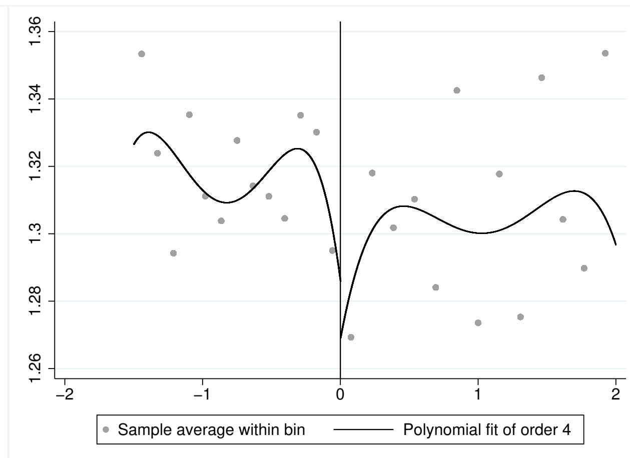
Notes: significant values in bold (p<0.1) Bandwidth based on optimal MSE (mean squared error). Standard errors in italics.

Figure C.2: Placebo tests (low vulnerable girls in 1st grade 2015)

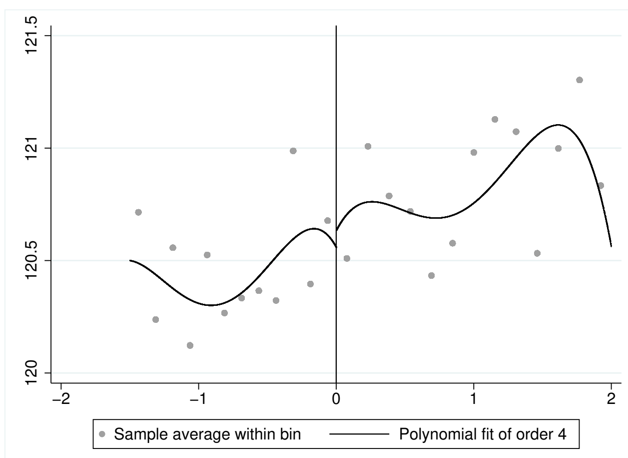
(a)



(b)



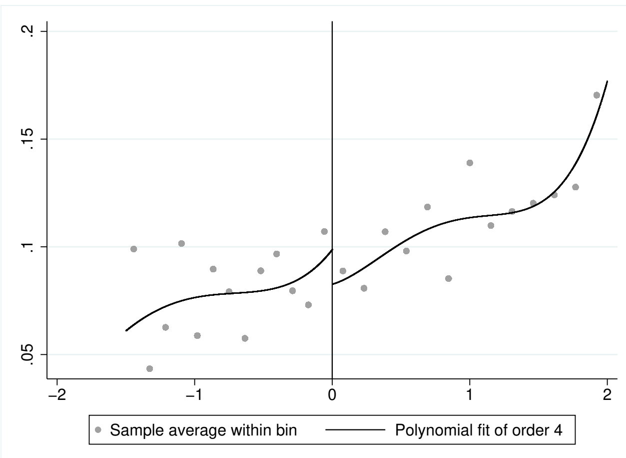
(c)



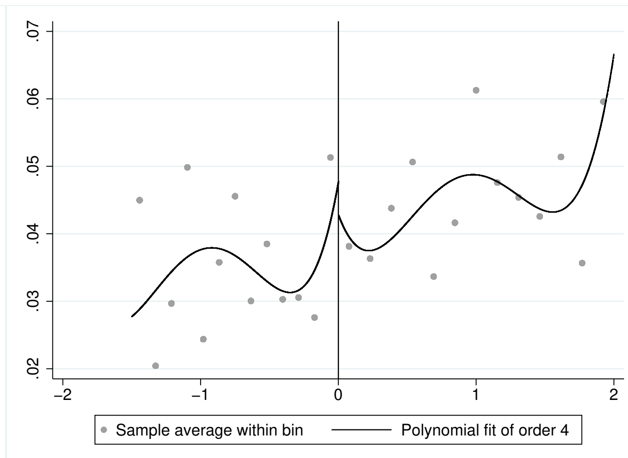
Notes: Panels: (a) Age (months), (b) Visual problems (1-5), (c) Height (cm). Excludes students without a FPS score. CVS: child vulnerability score (JUNAEB).

Figure C.3: Local polynomial fit for socioemotionalskills (low vulnerable girls in 1st grade 2015)

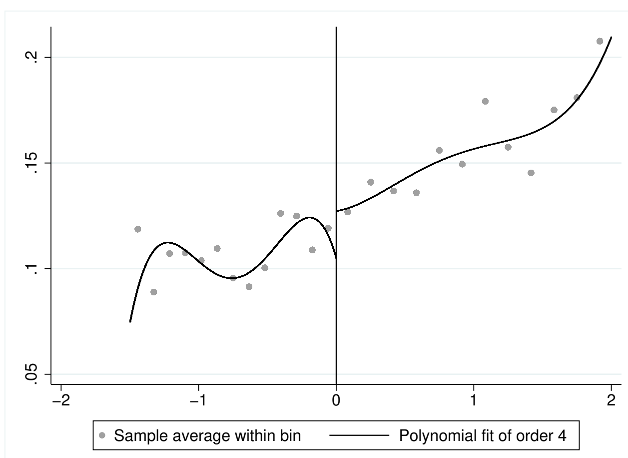
(a)



(b)



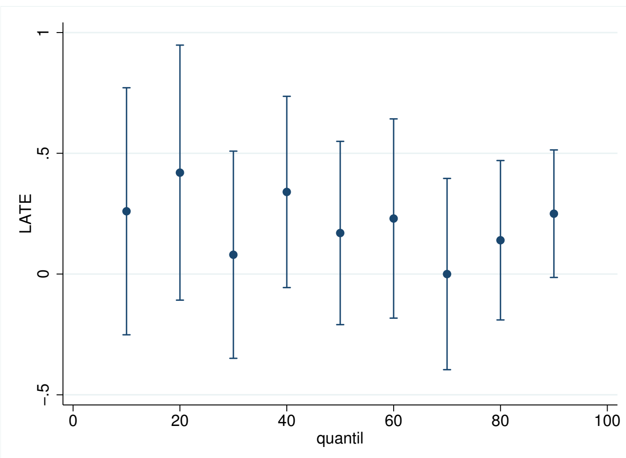
(c)



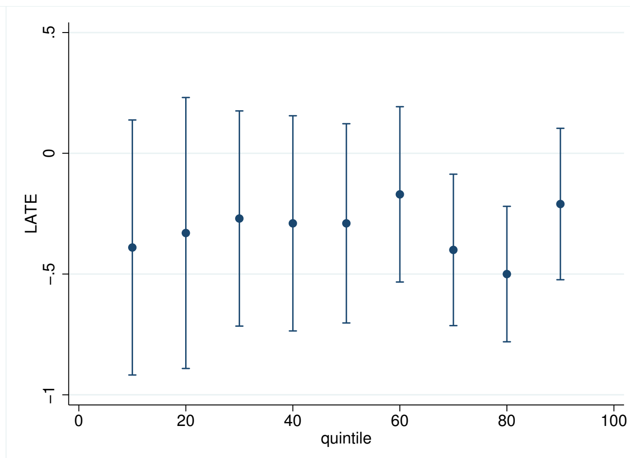
Notes: Panels: (a) Openness, (b) Extroversion, (c) Externalizing behavior. Excludes students without a FPS score. CVS: child vulnerability score (JUNAEB).

Figure C.4: Average treatment effects by decile of BMI-z for boys and girls in 5th grade

(a) girls



(b) boys

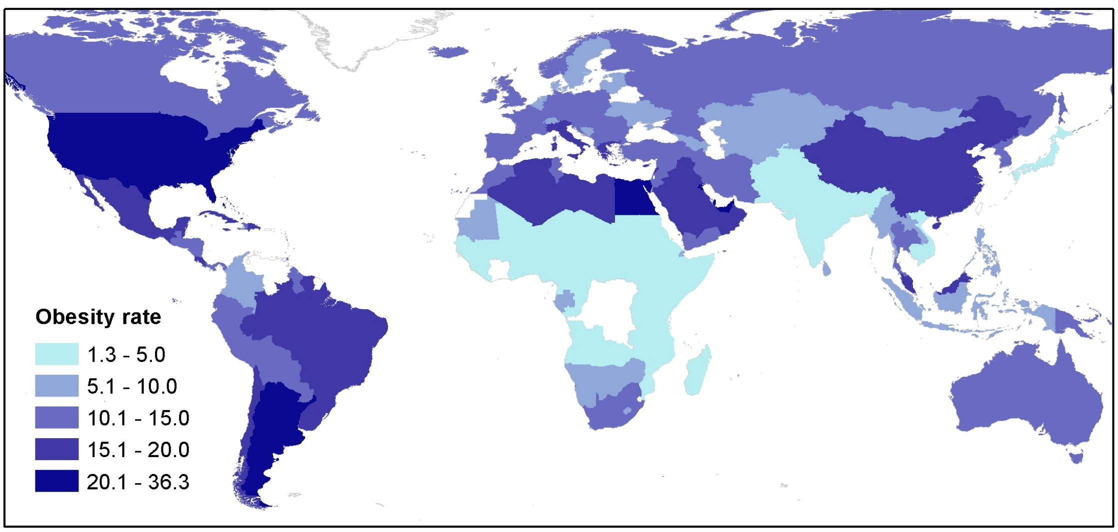


Notes: Estimates for boys and girls using bandwidth based on optimal mean squared error. CVS: child vulnerability score (JUNAEB).

D Additional figures and tables

This section includes additional statistics to contextualize the findings. Figure D.1 is a country-level map of child obesity prevalence, based on the calculations done by the NCD Risk Factor Collaboration in 2017 (estimated and projected data). Figure D.2 shows obesity prevalence by parental education (years) in the Nutritional Map data for 1st grade in 2015. Similar gradients between parental education and obesity prevalence are observed in other year cohorts and grades (results available upon request). The differences between maternal and parental education are consistent with higher obesity risk for children in households with lower income (a third of the mothers are not attached to the labor force).

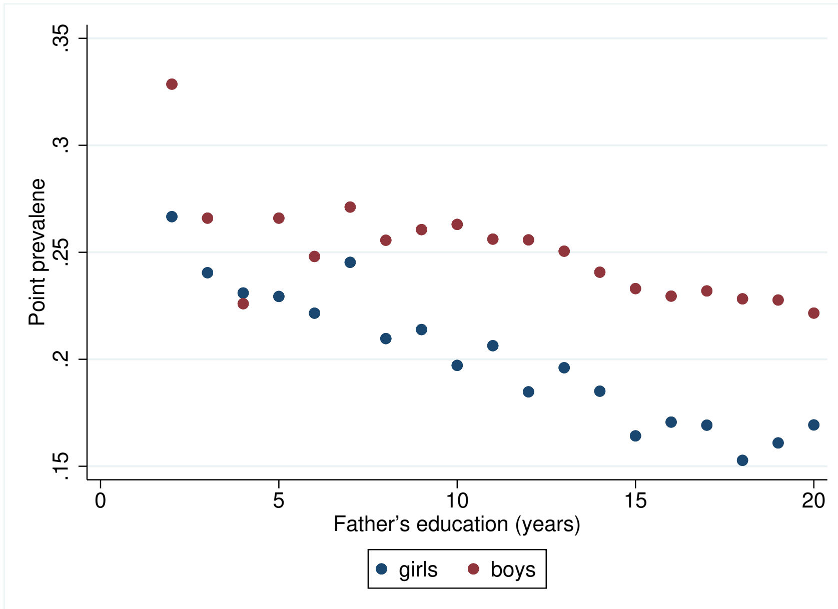
Figure D.1: Obesity rates among children 5-9 years by year (crude estimates)



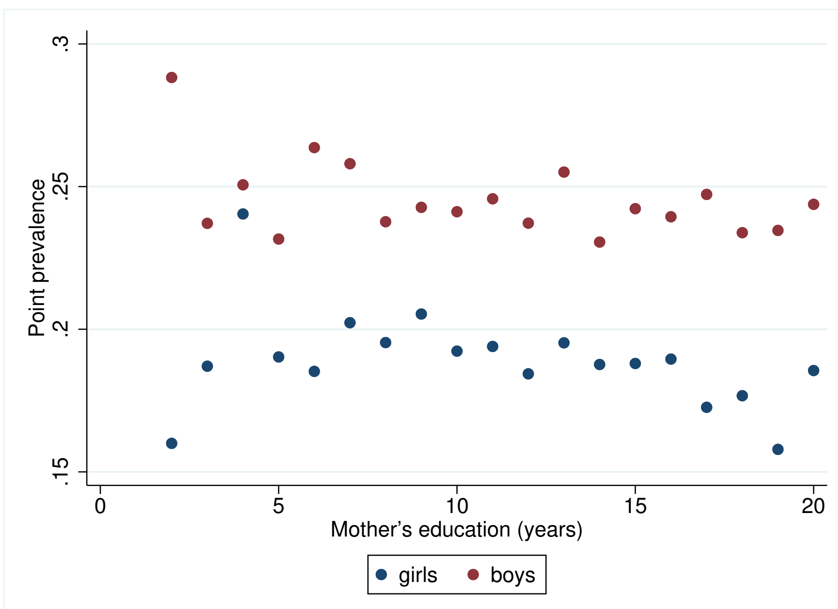
Prepared with data provided by WHO from the NCD Risk Factor Collaboration (Abarca-Gómez et al. 2017).

Figure D.2: Obesity prevalence and parent's education (1st grade students in 2015)

(a)



(b)



Notes: Nutritional map data. Crude means for each year, only students living in urban areas. Sample sizes differ due to students living with one parent only (17% lives without their father and 4% lives without their mother).