Parental investments, socioemotional development and nutritional health in Chile

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Parental investments, socioemotional development and nutritional health in Chile

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Abstract

I use a national administrative dataset covering all children attending public funded pre-schools in Chile to estimate production functions for socioemotional development (SED) and body mass index z-scores (BAZ) as a function of parental time investments, while accounting for endogeneity. Estimates are computed at each decile of the distribution allowing for heterogeneity on factor productivity. Results suggests that accounting for child characteristics and family composition, access to public goods, social support and self-efficacy are important drivers of parental time allocation. In turn, increased frequency of parental time investments can substantially boost socioemotional development and reduce obesity risk, particularly for vulnerable children. Children in the bottom of the SED distribution could gain 0.4 standard deviations for a one standard deviation increase in time investments. A similar increase can lead to a reduction of 0.8 SD in BAZ among severely obese students. Additional analyses indicates that SED can significantly favor the adoption of health behaviors and improved task performance.

Keywords: Health, Socioemotional Development, Nutritional Status, Child Development, Human Capital, Preschool
JEL Codes: I12, J13, J24

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1 Introduction

Socioeconomic vulnerability, inadequate nutrition and psycho-social 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 and behavioral difficulties among children, particularly within resource-constrained households (Popkin 2002; Popkin et al. 2012; Kieling et al. 2011; OECD 2017). Childhood obesity has long-lasting effects in physical, cognitive and socioemotional development (SED) (Ebbeling et al. 2002; Conti et al. 2015; Palermo and Dowd 2012; Wang et al. 2016). Childhood obesity has increased dramatically since 1980 (Ng, Fleming et al. 2014). Nearly one in six children are overweight or obese in the OECD area (OECD 2017). Countries with fast changes in the food supply, disposable income and household time use are particularly exposed. In Chile, 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).

Given the dynamic complementarities between physical, cognitive and socioemotional development, the scientific community has emphasized the importance of strategies to support caregivers in order to address developmental gaps (Alderman and Fernald 2017; Grantham McGregor et al. 2014; Black et al. 2017). Labor market studies had identified that vulnerable households are more time constrained, having an impact in the time allocated to activities that promote human capital accumulation (Cawley and Liu 2012; Brown et al. 2010). Still, beyond labor market participation, there is scarce evidence on the determinants of parental time allocation and its impact on human capital accumulation among pre-school children. Understanding the factors that can contribute to increased quantity and quality of parental time investments is key for policy design. This study contributes new evidence connecting parental behavior, SED and nutritional status in a context of high overweight status prevalence, using rich administrative data from the Chilean National Board of School Aid and Scholarships (JUNAEB, Spanish acronym). The analysis follows a cohort of children that started Pre-Kindergarten in 2015 with repeated measurements at Kindergarten and First grade (nearly 200,000 students across 10,000 schools every year).

[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).

First, I estimate a measurement system to obtain underlying measures of parental time investments, socioemotional development and task performance (i.e. *learning*) for children attending public and subsidized schools, based on near-census data. Second, I use the predicted factors to estimate the determinants of parental time allocation, while accounting for endogeneity due to correlated shocks with the human capital dynamics by introducing information regarding access to public goods as well as quality and tuition costs of nearby schools (relative to schools within the same commune). Based on the approach proposed by Lee and Lemieux (2010), I estimate the production functions of SED and body mass index z-scores (BAZ) at the sample means and each decile using the control function approach in both stages. This strategy allows measurement of the effects of time investments in human capital accumulation along the distributions of baseline SED and BAZ. Finally, I present additional results linking SED, health behaviors and task performance.

The estimated measurement system provides a longitudinal latent SED factor with analogous interpretation to Externalizing Behavior, consistent with one the dimensions of the Big Five Inventory (see Kautz et al. (2014)). When comparing students based on the vulnerability of their schools, the inequality gradient of human capital accumulation increases between grades. Regarding time allocation by the primary caregiver[2], evidence indicates that social support, participation in social organizations and self-efficacy are important determinants of variation in time investments across households (contributing to a total variation of 25% on time investments). Moreover, access to public goods and price and quality of nearby schools contribute to explain parental behavior. The latter suggests potential complementarities between time and material investments. The results also show no differences in time allocation by mother's labor force status, consistent with previous studies (Reynolds et al. 2017). In turn, the impact of parental time investments on SED and BAZ is modest at the sample mean. However, for children with limited SED and high BAZ (obese and severely obese), increasing time investments by one standard deviation can lead to an increase of SED of 0.4 SD and a reduction of BAZ of 0.8 SD. However, for children at the top of the SED distribution, additional time investments can lead to lower SED in the next period. Finally, socioemotional development is strongly linked to increased probability of physical activity outside school and higher *learning* abilities (measured as difficulties in learning or performing tasks).

[2]Time allocation questions in the survey only refers to the primary caregiver. While is possible to identify all the caregivers for a given child, the primary caregiver is not identified. Data analysis shows multiple caregiving arrangements, including parents, grandparents, siblings and other adults, both living in the same household or not. However, in Pre-Kindergarten, for households a single caregiver (57% of all students), two thirds are mothers, 20% are grandmothers, and the remainder is roughly evenly distributed between other adults and siblings. Overall, there are not statistically significant differences in the total time allocation, depending on the relationship of the primary caregiver and the child.

This study connects with seminal work connecting parental investments and early child development (Attanasio 2015; Conti et al. 2015; Cunha et al. 2010). This study has three key contributions based the previous evidence in the literature. First, I analyze human capital accumulation in the context of overnutrition among preschool children, a phenomenon affecting a growing fraction of students in both developed and developing countries. Similar studies (e.g. Attanasio (2015)) have concentrated on the role of material and time interventions in the first years of life, placing focus on early deprivation (i.e. stunting and wasting), highly prevalent in low income countries. In contrast, my analysis focuses on the harms of overnutrition and its connection to parent-child interactions and SED when children reach school age. The potential from interventions targeting parenting SED implied from the estimates in the model is consistent with recent experimental evidence (Carneiro et al. 2019) and follow-up of interventions in adult life (Conti et al. 2015). Secondly, I present a measurement system setup that addresses the nature of the administrative data: Likert-type scales with the presence of extreme response styles. Adequate specification of the measurement system is key to properly identify underlying factors without relying on implausible assumptions. For all latent variables, available measures provide substantial information regarding children's nutritional health and development. Finally, I report potential short term impacts of changes in parental time investments on body mass indeces based on census-type data, providing new estimates that can be used to benchmark programs and policies. Moreover, the rich quality of the data covering all students attending target schools allows exploration of the dynamics of human capital accumulation across the distributions of both SED and BAZ (a similar approach is presented in Majid et al. (2019)). Similarly, this study also contributes additional evidence regarding the impact of scaling-up interventions targeted to caregivers (Murphy et al. 2017; Carneiro et al. 2019). Overall, there is substantial variation in the potential for parental time allocation to enhance socioemotional development and to reduce BAZ.

The paper proceeds as follows. Section 2 describes the data and provides background on obesity among pre-school children and parental time investments. Section 3 introduces the theoretical framework and discusses the estimation approach. In section 4, the main results, secondary analysis and robustness tests are presented. Section 5 concludes.

2 Data and descriptive results

The main dataset follows a cohort of all Chilean children that attended Pre-K in 2015 until 1st grade of primary school, excluding those who attend private schools (less than ten percent of enrollment). JUNAEB collects administrative, individual data each year directly through schools that receive public funding. Teachers measure and collect information on children's height and weight. Parents provide comprehensive household background information regarding family composition, children's health and parenting practices. Schools consolidate and submit the information directly to JUNAEB each year during the school cycle. Appendix A details the information contained in the JUNAEB data. The analytical sample includes only children measured every grade, roughly 60% of all students. The main reasons for incomplete longitudinal links, in order of importance, are: absences during the day of measurement in one or more grades, repeating 1st grade, skipping one year between Kindergarten and 1st grade, and children not attending Kindergarten. I also exclude students that report chronic illness or disabilities and those that have implausible weight and height measurements as they introduce noise to the estimates.[3] The final estimation sample is restricted to students attending urban schools with class size higher than 10 students.[4], in order to recognize the differences in local food systems and school characteristics (84% of longitudinal dataset).

2.1 Early development and excessive weight gain

SED, such as self-regulation, are strong predictors of obesity among children (Graziano et al. 2010). The association between self-regulation, caloric intake and weight gain among children has been substantially documented in observational studies (Francis and Susman 2009). Poor SED can preclude the adoption of other health behaviors, such as physical activity. In turn, 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 (Torres-Fuentes et al. 2017). The latter suggests that energy-dense diets can actually be conducive to depression and stress, limiting the potential for skill accumulation. Moreover, while systematic country-level statistics are rarely available, there is substantial evidence of an increase in the prevalence of both obesity and emotional and behavioral problems among children and adolescents in recent decades (Onis et al. 2010; Tick et al. 2007; Collishaw et al. 2004).

Table 2.1 shows basic descriptive statistics of the analytical sample in contrast with complete cohort data in each grade. There are not significant differences in the anthropometric or household data between the children that have complete data every grade versus those

[3]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 earlier data, relative to previous grades). The total number of excluded observations represents less than 2% of the raw data.

[4]Average class size in 1st grade is 37 students, 39 in urban areas.

Table 2.1: Descriptive statistics

	Pre-Kinder		Kindergarten		1st Grade	
Anthropometrics and behavior	All	Panel	All	Panel	All	Panel
Age (months)	56.2	56.3	67.5	67.4	77.4	77.7
	4.4	*4.4*	*4.5*	*4.3*	*4.9*	*3.8*
Height-for-age (Z-score)	0.15	0.15	0.16	0.17	0.22	0.24
	1.2	*1.2*	*1.19*	*1.16*	*1.1*	*1.06*
BMI-for-age (Z-score)	0.97	0.96	1.03	1.02	1.00	1.00
	1.46	*1.45*	*1.42*	*1.4*	*1.37*	*1.34*
Fraction overweight	49.0%	48.6%	52.0%	50.5%	50.0%	49.0%
Hard to understand others (%)	16.9%	16.1%	16.9%	16.0%	18.8%	17.0%
Hard to control behavior (%)	40.0%	39.5%	38.5%	37.6%	38.7%	38.9%
Hard to get along with peers (%)	21.2%	20.8%	20.4%	19.5%	21.5%	20.1%
School characteristics						
School vulnerability index (IVE)	69.3	69.4	69.0	69.4	69.2	69.4
	17.4	*17.4*	*17.2*	*17.2*	*16.9*	*16.9*
Public school = 1	0.67	0.66	0.64	0.64	0.43	0.41
Attended daycare = 1	0.71	0.70	0.72	0.70	0.71	0.70
Household characteristics						
Mother's schooling attaintment	12.9	12.6	12.9	12.8	12.9	12.7
	3.0	*3.4*	*3.0*	*3.5*	*3.1*	*3.5*
Father's schooling attaintment	12.8	12.4	12.9	12.5	12.8	12.4
	3.1	*3.8*	*3.1*	*3.8*	*3.2*	*3.9*
Mother's age (years)	31.4	31.4	32.3	32.3	33.1	33.1
	6.8	*6.8*	*6.8*	*6.8*	*6.8*	*6.8*
Household size	4.6	4.6	4.7	4.7	4.7	4.7
	1.7	*1.7*	*1.7*	*1.7*	*1.7*	*1.7*
Mother in labor force = 1	0.54	0.54	0.65	0.67	0.64	0.68
Lives with father = 1	0.68	0.68	0.65	0.66	0.62	0.63
Sample size	153,516	126,738	190,752	126,738	219,518	126,738

Notes: JUNAEB indicates anthropometric data and household survey data from the Nutritional Map. IVE indicates the Spanish acronym for the School Vulnerability Index. Panel indicates children in urban households matched with Kindergarten and Pre-Kinder data. Fraction with behavioral difficulties represent all those parents that indicated any hardship (from mild to extreme). Daycare refers to children 2-4 years old. Standard deviations in italics, if applicable.

that missed school during measurement in at least one grade.[5] Nearly half of children are

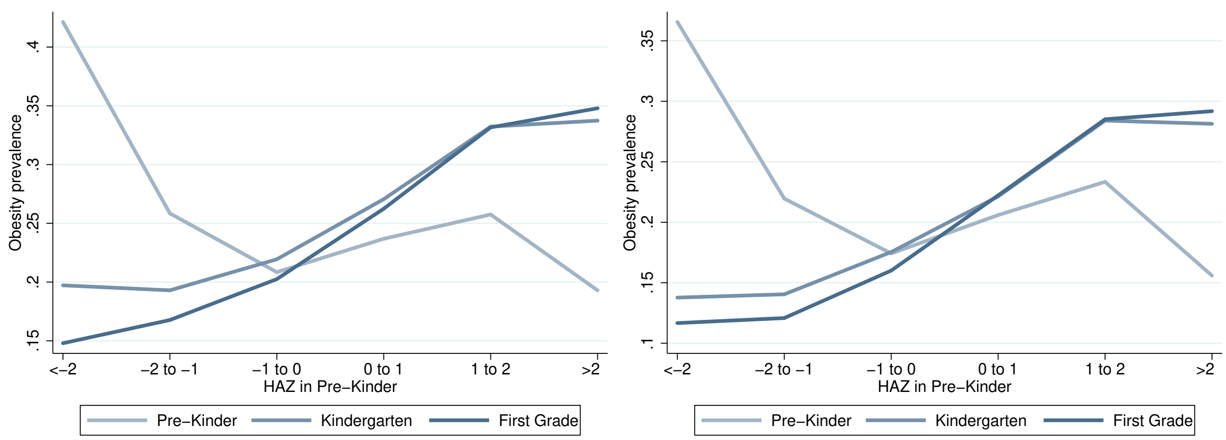
[5]For the remainder of this study, estimates are conducted over complete case analysis. Appendix C contains a sensitivity analysis using Inverse Propensity Weighting (IPW) from a Probit model to predict the probability of attrition between two grades. Observable variables predict only a small fraction of the observed variance on attrition and IPW weighted estimates are fairly similar as unweighted estimates. In First Grade, 18% of students have no previous data. The main reasons for missing data, order of impor-

overweight and their individual and household characteristics are rather stable over time. One exception is labor force participation among mothers, which increases about ten percent points between children' ages 4.5 and 5.5 years old. Relative to behavioral difficulties (proxies for SED), over half of all children report at least some type of hardship, particularly to control behavior.

Figure 2.1: Obesity prevalence by HAZ in Pre-Kinder

(a) Boys

(b) Girls



Notes: Calculations based on the longitudinal matched JUNAEB data.

Figure 2.1 shows the obesity prevalence by grade, based on the HAZ reported in Pre-Kinder, in the analytical sample. Among stunted children in Pre-Kinder, obesity prevalence drops dramatically as children become older. In contrast, for students that are taller for their age, obesity prevalence increase substantially, specially amongst children with HAZ¿2. This pattern has been previously documented in Chile using multiple cohorts (Kain et al. 2005). The prevalence of obesity increased from 15% in 1990 to 35% in 2017 among children with HAZ¿2. The shift in obesity prevalence by HAZ between grades is consistent with earlier BMI rebound among taller children[6], which is a marker of metabolic syndrome in adolescents and adults (Kang 2018; Peneau et al. 2016).

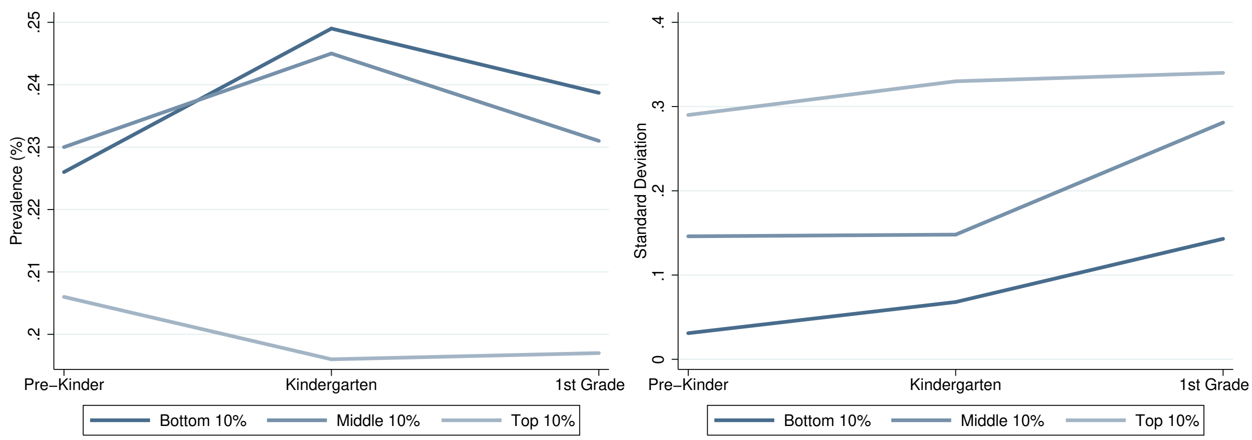
tance, are: (i) absence during measurement day, (ii) repeated 1st grade, (iii) attended preschools part of the INTEGRA/JUNJI network (independently administrated preschools), and (iv) children not attending Kindergarten the previous year. Given that information available, the estimates of time investments and production functions are likely to underestimate the relationships for more vulnerable students, at least to some extent.

[6]BMI or adiposity rebound refers to the age when BAZ increases after reaching its minimal value. From a biological perspective, increased access to energy during the gestational period causes hormonal deregulation increased adiposity which leads to accelerated linear growth (Linares et al. 2016).

Since there is no information about wealth or income data available at the household level, I constructed deciles based on the school vulnerability index calculated by JUNAEB (IVE, Spanish acronym), which measures the fraction of vulnerable children relative to total enrollment. Figure 2.2 shows the obesity prevalence and HAZ by grade and decile of IVE. There is a significant difference in HAZ by decile, however it narrows significantly between grades, particularly for children in the middle of the vulnerability distribution. In contrast, Obesity prevalence is widespread, and only slightly lower at the bottom of the IVE distribution.

Figure 2.2: BAZ and obesity prevalence by school vulnerability status

(a) Obesity (b) HAZ



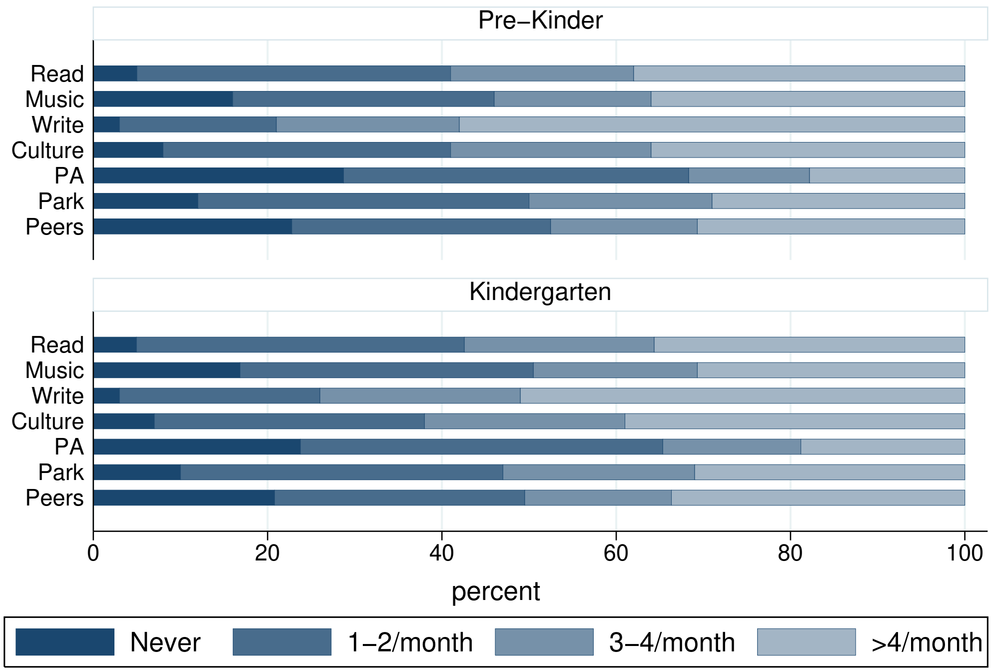
Notes: Vulnerability deciles are constructed based on the school vulnerability index (IVE). Calculations based on the longitudinal matched JUNAEB data.

2.2 Parental time investments

Vulnerable households have less resources and disposable time to allocate on SED, but also are more likely to have access to cheaper meals, often rich in simple carbohydrates and fats while scarce in key micro-nutrients. Low parental investments to promote socioemotional development and nutritional health create a vicious circle: limited SED promote unhealthy behaviors that lead to obesity. In turn, overweight children are more likely to be marginalized and bullied, stunting their socioemotional development (Strauss and Pollack 2003; Cornette 2011). Care-giving activities incorporate both a quantity and quality component, driven largely by parents' own human capital and beliefs about the nature of the skills accumulation process (Sylvia et al. 2018; Guryan et al. 2008; Attanasio et al. 2015b). Campaña et al.

(2017) shows that parents in Latin America, devote (on average) about the same time to cover children's basic needs as to invest in human capital.[7]

Figure 2.3: Distribution of responses for time investments by grade and activity



Notes: Culture indicates cultural activities, including going to museums or to watch a movie. Write includes writing or painting with the child. PA indicates physical activity, while peers refer to activities including similar-age children. Calculations based on the longitudinal matched JUNAEB data.

Figure 2.3 shows the distribution of frequency of parental time investments for each activity included in the survey data for Pre-Kinder and Kindergarten, based on the longitudinal data. While there is remarkable differences between activities, on average, only a third of all parents spend time in each activity at least once per week. Physical activity outside school is the least frequent activity, while writing (or painting) is the most frequent activity (nearly all parents engage at least once a month). Remarkably, more than 20% of caregivers declare to never engage in physical activity or socialization with peers with their children in the last month.

[7]Note that in this study, the authors do not consider meal preparing time as an investment in child's human capital. Similarly, in the JUNAEB data it is not possible to infer time (or monetary) investments towards nutritional health.

3 Conceptual framework and methods

The framework in this study builds the idea of nutritional health into the model of early human capital accumulation, drawing substantially from the basic setup discussed in the relevant literature (Cunha et al. 2010; Attanasio 2015; Conti et al. 2015; Agostinelli and Wiswall 2016). I focus on nutritional health and socioemotional development since both are malleable and responsive to parental behaviors at pre-school ages. In addition, as discussed previously, theory suggests the potential complementarities between SED measures (such as Externalizing Behavior) and nutritional status. Based on previous work, I describe the dynamics of SED (θ_t) and nutritional health (H_t) on a given period, indexed by t, using a sequence of dynamic production functions that depend on parental behaviors (i.e. investments), initial conditions and household characteristics.

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

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

where I_t denote parental time investment, P corresponds to parents' schooling attainment, vector X_t includes parental background and household characteristics, and e_t and v_t are idiosyncratic shocks. Parental time investments are assumed to be the optimal allocation of time on human capital enhancing activities based on the intrahousehold trade-offs with labor supply, leisure and basic child care.[8] Time investments depend on its marginal productivity at each stage, price and quality of investment goods (e.g. schooling) and available household resources. In this study, the objective is to characterize the role of time investments on SED and nutritional health, as well as the complementary between both forms of human capital along their own conditional distribution in the population.

3.1 Production functions

The production functions recognize the evolution of SED and nutritional health in two stages: Pre-Kinder to Kindergarten and Kindergarten to 1st Grade. In contrast with most developing countries where stunting and wasting coexist for a large part of vulnerable children, many middle- and high-income countries exhibit large obesity prevalence and near-zero stunting prevalence. As such, I characterize the path of nutritional health (H) using a linear-log function, while keeping BAZ in its own metric. In turn, I model socioemotional development using a Cobb-Douglas function with an exponential link to BAZ. In every period, future

[8]Based on previous work, basic care can be defined as any repetitive activity such as feeding, dressing, medical care, etcetera.

stock H_{t+1}, θ_{t+1} is a function of previous period stock, parental time investments and the evolution of total factor productivity A_t (which includes a random shock).

$$H_{t+1} = \delta_\theta ln\theta_t + \delta_H H_t + \delta_I lnI_t + \delta_P lnA_{Ht} \tag{3}$$

$$ln\theta_{t+1} = \alpha_\theta ln\theta_t + \alpha_H H_t + \delta_I lnI_t + lnA_{\theta t} \tag{4}$$

Where $A_{Ht} = exp(\delta_{0t} + \delta_{Xt} X_t + e_t)$ and $A_{\theta t} = exp(\alpha_{0t} + \alpha_{Xt} X_t + v_t)$. Unobserved random shocks are captured by e_t and v_t. Variables in X_t include family background (parental education, ethnic background, mother's age at birth, presence of a father figure[9], birth order and number of siblings) and individual characteristics (age, HAZ, birth weight and exclusive breastfeeding for six months). While family composition captures heterogeneity in parenting practices, individual data allows to account for variation in growth patterns within the cohort as well as early life investments.

3.2 Parental time investments

Caregivers choose the allocation of time investments towards children's human capital based on individual preferences, time and resource constraints, and their prior on the production technology (Todd and Wolpin 2003; Yi et al. 2015; Das et al. 2013; Attanasio 2015). As noted in previous work (Attanasio 2015), without explicit information on parental beliefs, estimating the structural model behind the dynamic optimization process impose strong assumptions that are contrary to recent evidence. In this analysis, the reduced form of the supply for time investments is log-linear, consistent with an approximation to the solution of a simple structural model (for example, see Attanasio (2015)).

$$lnI_t = \gamma_0 + \gamma_\theta ln\theta_t + \gamma_H H_t + \gamma_X X_t + \gamma_Z Z_t + u_t \tag{5}$$

In this study, time allocation depends on observed human capital stock, household characteristics, family composition and parental background (e.g. education, employment status and resources).[10] In particular, self-reported measures of parental social support and self-efficacy are included. Moreover, I assume that at pre-school age, parents choose time investments also based on the price and quality of investment goods available in the market.

[9] In the survey, respondents indicate whether the father figure is present always, sometimes or never, while also indicating the relationship to the child. In 87% of cases when a father figure is present it corresponds to the biological father or the mother's partner. Grandfathers are father figures in 8% of the analytical sample.

[10] Resources are approximated using the Household Social Registry data (more information can be found at http://desarrollosocialyfamilia.gob.cl. In particular, dummy varies are included to reflect in which decile on the HSR distribution each household is located.

The relationship between time investment and investment goods (and services) is ambiguous; parents might consider them either substitutes or complements. In particular, vector Z_t includes the relative difference in standardized test scores (reading and math) for elementary school children (grades 2 and 4 respectively) in 2014, comparing the closest ten schools versus all the schools in the same commune. Also, school monthly tuition in the year prior to the cohort data is included, in bins ($2-$50, $50-$100, $100 or more). In order to incorporate monthly tuition as instruments, I set tuition-free schools as the base group and then create on indicator variable per bin that are set to one if there is at least one school with tuition cost in that bin, for the ten closest schools.[11]

An important issue to consider is the bias on the production function estimates that comes from endogeneity of parental time investments. Endogeneity can arise from unobserved inputs and correlated shocks between the supply of time investment and the production functions. Given a set of instruments, the control function approach is a natural strategy to test and account for potential endogeneity. If we assume linear conditional dependence between e_t, v_t and u_t, we can include the estimated residual of the investment equation as an additional variable in the TFP. The estimated parameters of the residual allow for a direct test of endogeneity. The choice of the instruments must ensure that they are not correlated with the production function error term. From a theoretical perspective, variables included in the time and budget constraints are key candidates, such as observed relative price and qualities of nearby schools, access to health services, and parental labor supply (included in vector Z_t). Previous studies have documented that parental time investments are not strongly correlated with prices of investment goods for mothers with young children (Attanasio 2015). However, recent experimental evidence from Chile shows that parents with pre-school age children are likely to complement investment goods (school choice) with parental time investments (Allende et al. 2019). As such, information regarding schools quality and prices, as well as access to other goods and services (e.g. parks, healthcare) can influence parents to substitute between leisure and time investments (conditional on resources and location choice).[12]

3.3 Latent factors and the measurement system

In the dataset, SED and time investments are partially captured by many categorical 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

[11] Georeferenced school data is available at http://www.ide.cl/

[12] between every year, less than 5% of all households move to a different commune.

from noisy proxies using a measurement system, that both reduces dimensionality and accounts for measurement error (Gorsuch 2003; Cunha et al. 2010). Explicitly, I define θ_t as the vector of all latent factors in the period t, where for a given j factor, there are k measurements. The measurement system then can be defined as:

$$M^j_{kt} = a^j_{kt} + \lambda^j_{kt} ln\theta^j_t + \eta^j_{kt} \tag{6}$$

$$\text{Factor Means: } E(ln\theta^j_t) = \mu^j_t \tag{7}$$

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

Where a denotes factor intercepts, λ indicates factor loadings, and η are independent Gaussian measurement 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 (see Appendix B for an extensive discussion of the estimation of underlying factors from data).

Given that all measures are categorical, I follow the framework in Liu et al. (2017) to account for longitudinal measurement invariance, in order to properly examine changes over time. The intuition is that repeated measures should capture the same latent factor (i.e. construct) in the same metric over time. If measurements for a given factor have C response categories, latent measurement M^*_{kt} is linked to the observed measurement M_{kt} such that

$$M_{kt} = \text{c if } \tau_{c,jt} \leq M^*_{kt} < \tau_{c+1,jt} \tag{9}$$

Where $c = 0, 1, ..., C$ and $\tau_{c,jt}$ are threshold parameters to be estimated. In this case, I restrict thresholds for each measure to be the same over time, while allowing for variance of each measure to be unrestricted over time (i.e. threshold invariance model). This model guarantees that mean changes in the latent measurement over time are solely identified by changes in the latent factor. The latter condition is sufficient to characterize the dynamic nature of each latent factor from categorical indicators.

In addition, preliminary analysis of the data indicates a strong presence of response styles from parents in the behavioral observation of children's behavior (but not on parental time investments). Response styles can lead to extreme values across all measurements, affecting the quality of the estimated latent factors. As such, following Aichholzer (2014), I allow the intercepts to have a common (random) component across measurements and periods for each individual (parent) that is orthogonal to the underlying factors: $a^j_{ikt} = a_{it} + a^j_{kt}$. This random intercept captures the individual preference to report consistently lower (or higher) responses across all measures (see Appendix B for more details). With this additional structure, equation (6) can be redefined as

$$M_{ikt}^{j*} = a_i + a_{kt}^j + \lambda_{kt}^j ln\theta_i^j t + \eta_{ikt}^j \tag{10}$$

The measurement system is identified if the means of log factors and measurement errors are set to zero and the factor loading for the first measurement associated with each factor is fixed as one. In addition, to conduct valid inference, in each period the latent factor is normalized to the same measurement, which determines scale.[13]

3.4 Estimation

The estimation is conducted in three steps. First, the joint distribution of the measurement system is estimated from all observed measures and variables that enter the production functions and investment equations. The system is estimated by Means and Variance Adjusted Weighted Least Squares (WLSMV). The WLSMV estimator is robust to deviations from normality, common in ordinal data, such as Likert-type scales. Latent factors are estimated for each individual and period based on the linear prediction (Barlett scores). In the second step, time investment equations are estimated separately for each year, and the corresponding residuals are predicted. Finally, production functions are jointly estimated for each period, separately for boys and girls, using the control function approach. Following Lee and Lemieux (2010), both time investment supply and production functions are estimated at the sample means as well as at every decile of the distribution, in order to estimate the marginal productivity of investments along the empirical distribution of human capital. Standard errors are estimated using nonparametric bootstrap procedures with 100 repetitions.

4 Results

First, I present the results from the measurement system and descriptive characteristics of the estimated latent factors. Secondly, I discuss the determinants of parental time investments and the impact of parental engagement on the production of SED and the dynamics of BAZ. Finally, I conclude with a brief discussion on the potential of interventions on human capital accumulation and the impact of SED on health behaviors and learning.

[13] In this case, all measurements have the same domain, since they are all based on Likert-type scales or ordinal variables with equal numbers of potential responses.

4.1 SED and parental investments

Given the measurement system, it is possible to evaluate the quality of the estimated latent variables based on how much each set of measures contain a common signal captured by each factor. First, there is substantial evidence of response styles, measured as a random intercept across respondents, accounting for roughly 20% of the variance across measures (See Appendix B for more details). The estimated response styles correlate inversely with parental investments, mother's age and parental schooling attainment, consistent with previous studies (Meisenberg and Williams 2008). The associations suggest that more educated, older caregivers are more likely to identify children's behavioral difficulties.

Table 4.1 reports the variables allocated to each factor in the dedicated measurement system and the signal-to-noise ratios, i.e. the information content of each measure given the model specification. The formula for a given measure is

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

Questions regarding behavioral difficulties provide consistent information of a single latent factor over time, defined as socioemotional skill, suggesting a single latent proxy of behavioral issues (the normalizing measure). The assessment of parental time investments also indicates consistency across periods. Finally, using questions regarding behavioral difficulties it is also possible to construct a process measure, defined as *learning*, reflecting difficulties with task performance at school or home. Since all variables are categorical, each factor is scaled based on the empirical distribution of the latent measurements. However, given the longitudinal threshold invariance assumption, changes in the latent scale are associated with the probability of belonging to a given response category. Moreover, results suggests that the variance of each measure does not significantly vary over time, which allows to standardize the variance of the latent normalizing measure for each factor. This permits the prediction of each log-factor in the metric of a standardized z-score, in order to be comparable to the measure of nutritional health.

Figure 4.1 shows the average levels of SED and time investments for each period by decile of school vulnerability, as described in the Data section. In contrast with HAZ, the vulnerability gradient in SED widens over time. In relative terms, skill accumulation processes in children attending the less vulnerable schools are remarkably different from the bottom half of the IVE distribution. In contrast, the vulnerability gradient in parental time investments seems almost unchanged between grades.

Table 4.1: Signal-to-noise ratios

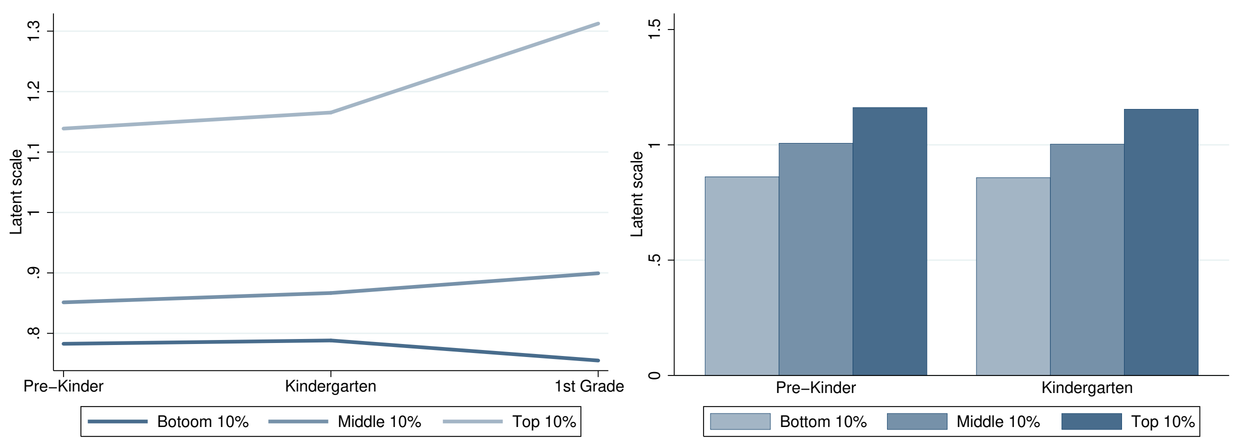
Socioemotional skills			
	Pre-K	Kinder	1st Grade
Hard to understand others	39.8%	39.2%	42.9%
Hard to control behavior	54.2%	58.5%	62.9%
Hard to get along with peers	59.3%	60.2%	64.6%
Learning			
Hard to learn			71.0%
Hard to perform a task			72.9%
Hard to complete homework			62.9%
Parental time investment			
Read to child	45.4%	41.7%	
Plays music	33.1%	34.7%	
Writes or paints	45.0%	46.7%	
Cultural activities	32.8%	34.4%	
Physical activity	52.6%	54.4%	
Goes to park	53.9%	55.7%	
Socializes with peers	27.4%	28.8%	

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

Figure 4.1: SED and parental investments by vulnerability status

(a) SED

(b) Time investment



Notes: Vulnerability deciles are constructed based on the school vulnerability index (IVE). Calculations based on the longitudinal matched JUNAEB data. Latent scales are constructed so log means are zero.

4.2 Determinants of parental time investments

In order to comprehend the role of time investments in the production of human capital, it is key to understand the role of environmental and household characteristics in parental behavior. While the production functions provide an order of magnitude to the role of parental engagement, understanding the investment process is key for policy design. Table 4.2 report the estimated parameters for the investment equations as well as the estimated standard errors via bootstrap (clustered the commune level). All variables are expressed in logs except for binary indicators. While BAZ does not seem to provide relevant information, parents seem to reinforce time investments to the observed SED. Regarding children charateristics, while age, gender and HAZ provide little information, parents invest more time with children that are first born and those with fewer siblings, specially if they invested more early in life (exclusive breastfeeding over 6 months). While parental education (and labor market attachment, not reported) contribute little to local variation in time investment, the permanent presence of a father figure (father or other), as well as social support for parenting and participation in social organizations contribute significantly. Similarly, self-efficacy seems to be quite important. Parents that indicate having challenges raising their children also spend over 10% less time in human capital enhancing activities.

In terms of instruments, the relative quality of nearby schools (measured by average test-scores) are positively related to time investments, suggesting potential complementarities between time and resources devoted to preschool children, as noted in previous studies in developing and developed countries. However, while parents that enroll their children in public, tuition-free schools seem to devote less investment time, on average, amongst those children enrolled on voucher schools, the price of tuition does not seem to be strongly related to parental time investments. The latter suggest the coexistence of binding time and resource constraints among vulnerable households. Similarly, households that report having access to health services and recreation areas also allocate more time in investment activities. Given the evidence of limited inter generational mobility in Chile (Celhay et al. 2010), these results confirm that family stability and wealth are key for time investments.

Interestingly, while most determinants of parental time investments remain stable between grades, the salience of SED (Externalizing Behavior) increases significantly between Pre-Kinder and Kindergarten. Similarly, the constant presence of a father figure becomes more relevant for older children. This is quite relevant as one third of all children lives without a father and 7% have no father figure by the time they enter elementary school.

Table 4.2: Parental time investments

	Pre-Kinder		Kindergarten	
Skills (log)	**0.07**	*0.003*	**0.10**	*0.003*
BAZ	0.00	*0.001*	**0.00**	*0.001*
School tuition (monthly USD)				
$2 to $50	**0.05**	*0.009*	**0.07**	*0.008*
$50 to $100	**0.07**	*0.008*	**0.08**	*0.008*
$100 or more	**0.08**	*0.009*	**0.07**	*0.009*
School math z-score (grade 4)	**0.01**	*0.003*	**0.01**	*0.003*
School reading z-score (grade 2)	**0.01**	*0.003*	**0.01**	*0.003*
Age (log)	0.00	*0.034*	0.00	*0.034*
HAZ	**0.01**	*0.003*	**0.01**	*0.001*
Gender (male=1)	**0.01**	*0.003*	**0.01**	*0.003*
First born	**0.05**	*0.004*	**0.05**	*0.004*
Exclusive breastfeeding	**0.04**	*0.003*	**0.04**	*0.003*
Number of siblings	**-0.04**	*0.002*	**-0.04**	*0.002*
Caretakers (number)	**0.03**	*0.002*	**0.03**	*0.002*
Etnic background = 1	**-0.05**	*0.007*	**-0.03**	*0.007*
Mother age at birth (log)	**-0.02**	*0.009*	**-0.04**	*0.010*
Mother education (log years)	**0.01**	*0.004*	**0.02**	*0.003*
Father education (log years)	**0.02**	*0.002*	**0.02**	*0.002*
Father figure present (Never)				
Sometimes	**0.01**	*0.007*	**0.02**	*0.008*
Always	**0.10**	*0.007*	**0.14**	*0.008*
Pareting this child is (Easy)				
Not easy nor hard	**-0.05**	0.003	**-0.05**	0.003
Hard	**-0.11**	0.007	**-0.12**	0.009
Pareting support (Always)				
Sometimes	**-0.05**	0.003	**-0.05**	0.003
Never	**-0.06**	0.006	**-0.06**	0.006
Participation in social org.	**0.11**	*0.003*	**0.11**	*0.003*
Home close to recreation area	**0.14**	*0.004*	**0.15**	*0.005*
Home close to health services	**0.05**	*0.006*	**0.05**	*0.006*
Instruments F-stat (p-value)	**67.46**	*0.00*	**70.56**	*0.00*
N	97,049		96,028	

Notes: significant values in bold ($p<0.1$). In the school tuition categories, the excluded group is public, tuition-free schools. Based on information from the Ministry of Education, no schools have tuition prices between $0-\$2$ dollars. Standard errors in italics.

4.3 Production function estimates

Table 4.3 shows the estimates of the production functions of SED and BAZ for each year and gender, accounting for endogeneity on parental time allocation. Parental investment elasticity is roughly 0.1 and rather constant between grades. The persistence in SED is large and increasing from Kindergarten to First Grade, consistent with previous evidence for non-cognitive abilities in the literature (Cunha et al. 2010). Nutritional health and SED are weak complements; children with higher BAZ have lower SED in the next period, however the magnitude is quite small, on average. While parental education is significantly related to skill production, the magnitude is negligible. However, mother's age is strongly related to higher SED. The constant presence of a father figure has a remarkable effect on SED, after accounting for time investments, which might suggest an unobserved channel not captured in the time investments. Interestingly, children's age is strongly associated with SED in 1st Grade but not in Kindergarten. Given the longitudinal balance of the analytical sample, the latter estimate reflects age differences within year, i.e. older children because of a longer period between measurements (since schools report data throughout the year). Relatively older children are more exposed to socialization through school, which can facilitate skill accumulation, particularly in elementary school.[14]

For nutritional health, parental time investments have a significant effect on BAZ, but its importance decreases over time, as persistence increases. There also evidence of complementarity between dimensions of human capital, increased SED leads, to some extent, to lower BAZ in the next period. As expected, after accounting for seasonal patterns, age and HAZ explain a signficant part of the BAZ in a given year, taller and older children within the cohort are more likely to be overweight and obese, consistent with previous longitudinal evidence (Freedman et al. 2005). Weight at birth also contributes substantially, in the line with emerging evidence on the importance of managing weight at birth. Vehapoglu et al. (2017) shows that Turkish children with weight higher than 3.8 kilos have greater risk of being overweight or obese during early childhood, after controlling for feeding practices and parental characteristics. Finally, there is strong evidence of endogeneity in both SED and HAZ (Table D.3 in Appendix C shows the estimates of the production functions without using the control function approach).

[14]In Pre-K and Kindergarten most measures occur in the middle of the year, while in 1st Grade most schools report their data at the beginning of the school year.

Table 4.3: SED and nutritional health production technology

	Socioemotional (t+1)				BAZ (t+1)			
	Kindergarten		1st grade		Kindergarten		1st grade	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Investment	**0.10**	**0.08**	**0.10**	**0.08**	**-0.15**	**-0.10**	**-0.07**	**-0.08**
	0.02	*0.02*	*0.03*	*0.02*	*0.08*	*0.04*	*0.04*	*0.05*
BAZ	**-0.01**	**0.00**	**-0.01**	**-0.01**	**0.40**	**0.40**	**0.48**	**0.49**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Socioemotional	**0.68**	**0.67**	**0.79**	**0.77**	**-0.02**	-0.01	**-0.02**	**-0.02**
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Mother education	**0.01**	0.00	**0.02**	**0.02**	-0.01	-0.02	-0.03	-0.02
	0.00	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Father education	**0.01**	0.01	**0.01**	0.00	0.00	-0.01	-0.01	-0.01
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Mother's age at birth	**0.12**	**0.12**	**0.15**	**0.13**	**0.06**	**0.07**	0.01	**0.07**
	0.01	*0.02*	*0.01*	*0.01*	*0.03*	*0.03*	*0.03*	*0.03*
Father figure (Never)								
Sometimes	0.00	0.00	0.00	0.00	0.02	-0.03	-0.01	0.04
	0.01	*0.01*	*0.01*	*0.01*	*0.03*	*0.03*	*0.02*	*0.01*
Always	**0.07**	**0.06**	**0.13**	**0.10**	-0.01	-0.01	-0.01	**0.04**
	0.01	*0.01*	*0.02*	*0.01*	*0.03*	*0.04*	*0.03*	*0.02*
Age	0.03	0.00	**0.20**	**0.14**	**0.27**	**0.30**	**0.58**	**0.35**
	0.02	*0.02*	*0.05*	*0.04*	*0.09*	*0.08*	*0.03*	*0.07*
HAZ	0.00	**0.00**	0.00	0.00	**0.20**	**0.20**	**0.26**	**0.25**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Weight at birth	0.01	-0.02	0.01	0.01	**0.40**	**0.35**	**0.35**	**0.36**
	0.01	*0.01*	*0.01*	*0.02*	*0.04*	*0.03*	*0.03*	*0.03*
Exclusive breastfeeding	**0.01**	0.00	**0.01**	**0.01**	**0.03**	0.01	**0.03**	**0.02**
	0.00	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
First born	**-0.01**	0.00	**0.02**	**0.02**	0.01	-0.01	-0.01	0.01
	0.00	*0.00*	*0.01*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Number of siblings	**-0.01**	**-0.01**	**-0.02**	**-0.01**	**-0.05**	**-0.04**	**-0.04**	**-0.03**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Etnic background	0.00	0.00	**0.02**	**-0.02**	**0.11**	**0.04**	**0.10**	**0.07**
	0.01	*0.01*	*0.01*	*0.01*	*0.02*	*0.02*	*0.02*	*0.02*
Investment Res.	**-0.08**	**-0.06**	**-0.01**	**-0.06**	**0.17**	**0.08**	**0.08**	**0.07**
	0.02	*0.02*	*0.03*	*0.03*	*0.06*	*0.02*	*0.04*	*0.03*
N	45,661	46,680	45,522	48,572	42,161	43,330	40,860	42,231

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

4.4 The potential of interventions

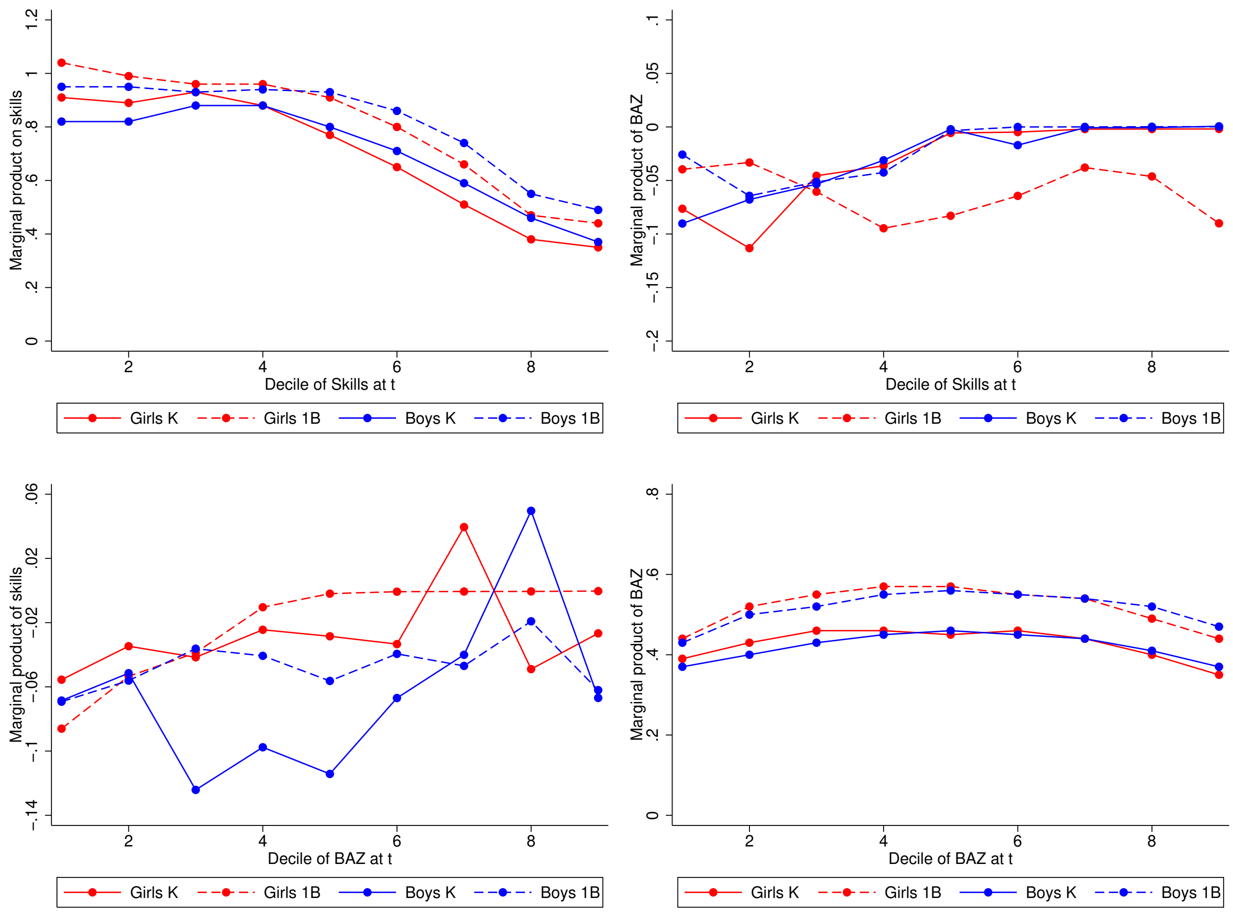
In order to understand the magnitude of the estimated effects across the population, I estimate the marginal product of SED, BAZ and investments at each decile of the distribution of both measures of human capital, allowing for both marginal productivity and baseline level of inputs to vary (implicitly allowing for average households characteristics to vary along with BAZ and SED in the first period). Figure 4.2 shows the effects on future human capital, in standard deviations, from increasing BAZ or SED one standard deviation, at each decile of the baseline distribution of SED. The top-left graph shows the large persistence of SED, higher at lower levels, consistent with previous evidence for non-cognitive and cognitive SED (Attanasio et al. 2015b).

Similarly, the prevalence of BAZ is substantial and increasing between grades along the distribution (bottom-right panel). The inverted U-shape is consistent with larger yearly variation in BAZ among underweight and obese children. Consistent with evidence of developing and developed countries, higher persistence in 1st grade can be largely attributed to natural physiological change around age 6 know as adiposity rebound. Children who rebound younger are also more likely to be obese, which also explains the larger effect of age on BAZ in 1st grade, where is more likely for a larger proportion of children to experience the inflection point in the BAZ age trend.

Evidence of complementarities between SED and BAZ are relatively stable over the distribution of each factor. In the bottom-left panel, there is weak evidence that children with lower BAZ are more likely to experience a small BAZ decrease from increasing SED by one standard deviation (less than 0.1 SD, on average). In turn, for overweight and obese children, there does not seem to be any significant association either in a given year or by gender. The effect of BAZ on SED is presented in the top-right panel. During Kindergarten, there is an positive effect of roughly 0.1 SD in SED from reducing BAZ by one standard deviation for children in the bottom of the socioemotional development distribution. Given the relative distance between children with normal weight and those who are severely obese, gains in SED from a large reduction in BAZ among severely obese children (roughly 6% of all students) could be approximately 0.3 SD in a year. While this association remains for boys in 1st grade, for girls, even increases in socioemotional development at the top of the distribution can have positive effects on health (by reducing BAZ).

Now, I turn to the extent to which parental time investments could affect socioemotional development and BAZ, in Figure 4.3. As before, the results are presented as the effect (in SD) from one standard deviation increase in parental time investments, given the distribution of human capital at baseline. Interestingly, evidence suggests that the marginal productivity of time investments on socioemotional development is larger for children with lower SED at baseline (up to 0.4 SD) and decreasing across the distribution. Children with lower SED in the initial period benefit significantly more from parent-child activities. However, increasing time investments could harm children at the top of the distribution. As discussed previ-

Figure 4.2: Marginal product of SED and nutritional health

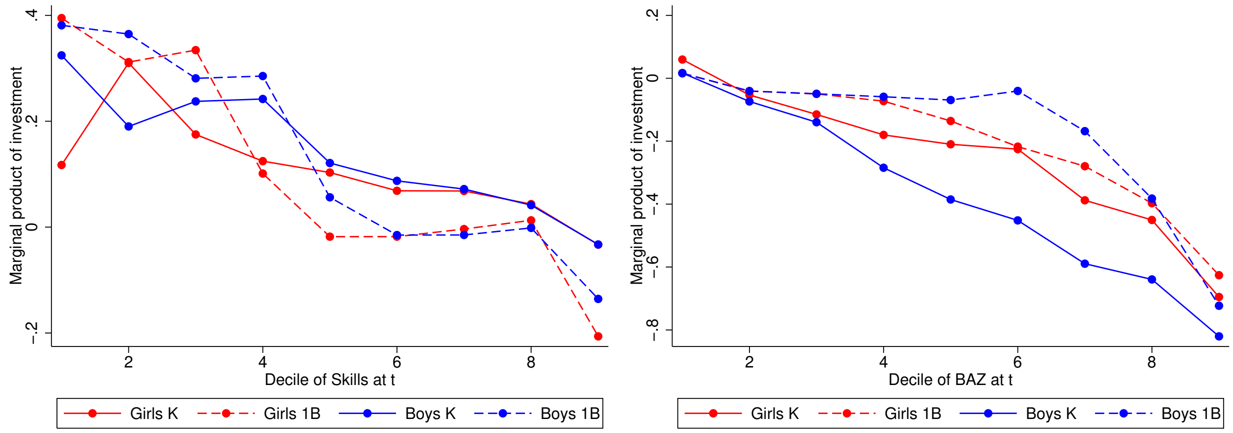


Notes: Vulnerability deciles are constructed based on the school vulnerability index (IVE). Calculations based on the longitudinal matched JUNAEB data. Latent scales are constructed so log means are zero.

ously, since investments are measured based on the frequency of parent-child interactions on different activities, it is not possible to separate quality from quantity of time investments. For example, cultural activities, the second most frequent interaction after reading, could capture inattentive parenting which can negatively impact behavioral control among high-skilled children. The latter could also be possible for unsupervised peer socialization. Another potential explanation is related to the concept of *intensive parenting*, this is the idea that parents introduce excessive structured activities leading to overcrowding, which could decrease (or at least not improve) developmental outcomes (Schiffrin et al. 2015). Unfortunately, without strong (unlikely plausible) assumptions it is not possible to disentangle the effects.

The results for BAZ are also remarkably interesting. The impact of time investments is inversely related to BAZ at baseline, and the impact could be up to 0.8 SD reduction among

Figure 4.3: Marginal product of parental time investments



Notes: Vulnerability deciles are constructed based on the school vulnerability index (IVE). Calculations based on the longitudinal matched JUNAEB data. Latent scales are constructed so log means are zero.

severely obese children. While the effects are higher for boys than girls in Kindergarten, the effects are quite similar for both genders in 1st Grade, being only significant for overweight and obese children. Evidence from labor studies in United States and other developed countries indicate that lower time in home child care due to labor supply variation can substantially increase children's obesity risk at school age (Campaña et al. 2017; Benson and Mokhtari 2011; Anderson 2012). Given the diverse tasks included in the time investments, there are two mechanisms that could explain the results. First, at least two of the tasks included in the measures involve some form of physical (recreational) activity, which directly impacts BAZ, all else constant. Secondly, given time restrictions, it is likely that available time for educational tasks could be positively correlated with other activities that could reduce BAZ: home cooking, purchasing fresh produce, family meals, etcetera.

Overall, the results suggest that time (and potentially resource) constrained caregivers could largely benefit from adopting strategies that could allow them to be more effective using their time allocated for child development (by task switching for example), although is unclear to which extent there is scope for trade-offs with leisure and other time costs (e.g. time allocated to child basic care or transport if recreation areas are far from home). In this analysis, mother's labor force participation and employment status are not linked with differences in time investments (households with full time employed fathers spend overall marginally less time investments).

In addition, there might be other important factors limiting time investments such as self-efficacy and social support. After accounting for family composition, child human capital and resources, caregivers invest 12% less time if they perceive parenting as *hard*, compared to those that consider it *easy*. Similarly, parenting support from an stable father figure presence, as well as from a social support network, are a key to increase time investments. Results are consistent with short term evidence from a randomized intervention in Chile, *Nadie es Perfecto*, a 6-session workshop design to improve self-efficacy and social support for caregivers with children 0-5 years old (Carneiro et al. 2019).

While the complementary between SED and BAZ are low, the effects of interventions boosting parental time investments are quite promising. In particular, given that the co-existence of excess weight and limited behavioral control SED among vulnerable students. For example, in the longitudinal sample, obesity prevalence in children in the bottom of the SED distribution is 45% higher (26 percent points) compared to children with high socioemotional development. Early interventions, such as *Nadie es Perfecto*, can boost both quality and quantity of parental time investments up to 25% on average. Similarly, urban planning policies that ensure access to health services and green spaces could potentially boost utilization, and thus time investments.

4.5 Human capital and child behavior

Until now, the measure of SED has not been connected with specific behaviors or task performance. I consider two measures of child behavior in this analysis. First, I consider the effect of socioemotional development in Kindergarten of the probability of engaging in physical activities outside school in First Grade using an ordered probit model. Secondly, I use the *learning* process measure to understand the link between SED and task performance between the same grades. Table 4.4 shows the marginal effects of socioemotional development on physical activity and learning based on regressions adjusted by parental education, parental time investments, BAZ, gender and other child and household characteristics included in the estimation of production functions to account for other potential channels.

Based on the information in 1st Grade, a 10% increase on socioemotional development (roughly 0.15 SD at the mean) is associated with reduced probability of sedentary behavior by 11%, while increasing the likelihood of physical activity 2-3 times a week by 9%. The results are robust to the inclusion of parental time investments in the previous period.[15] Similarly, increasing SED by one standard deviation is linked to 0.24 SD rise in task performance, on average. Past time investments do not seem to meaningfully impact learning, once accounting for the indirect channel though enhanced human capital. Moreover, there

[15] By construction, is expected that time investments increase the frequency of children's physical activity outside school. The difference in time investments between active and sedentary students is roughly 0.5 SD.

Table 4.4: SED in Kindergarten and child behavior in First Grade

Physical activity (times per week)				
	Mean probability		Marginal effect	
Never	**0.15**	*0.002*	**-0.011**	*0.001*
Once	**0.36**	*0.003*	**-0.080**	*0.001*
2-3 times	**0.37**	*0.003*	**0.009**	*0.001*
4 times	**0.05**	*0.001*	**0.003**	*0.000*
5+ times	**0.07**	*0.002*	**0.006**	*0.001*
Learning (standarized, by decile)				
	Estimated coefficient		Standarized effect	
1st	**0.21**	*0.004*	**0.32**	*0.07*
Median	**0.16**	*0.003*	**0.24**	*0.04*
9th	**-0.002**	*0.003*	**-0.003**	*0.03*

Notes: significant values in bold (p<0.1). Standard errors estimated by bootstrap with 100 repetitions.

is significant variation along the distribution of learning. Among children with low levels of task performance, one standard deviation increase in SED is associated to 0.32 SD higher learning, while the relationship at the top of the distribution is not significant.

5 Conclusion

Recent evidence suggests that the quality and quantity of time investments devoted by caregivers has a significant effect on health and socioemotional development in the first years of life (Sylvia et al. 2018; Attanasio 2015). In the case of Chile, this study presents evidence from a complete cohort of all students starting Pre-Kinder in public or subsidized schools in 2015, identifying the potential that parental time allocation have on both obesity risk and socioemotional development. First, following the framework discussed in Cunha et al. (2010) and Attanasio et al. (2015b), I estimate measures of parental time investments and developmental SED using a measurement system that accounts for the categorical nature of the data and extreme response styles. Secondly, using the latent factors I estimate the parent's time investment schedule and obtain the residuals in order to account for endogeneity in the estimation of the production functions.

Results from the investment equations reveal that caregivers time allocation is only connected with children's SED but not with body mass index z-scores. Interestingly, social support and self-efficacy are important determinants of variation in time investments. Moreover, access to public goods and price and quality of nearby schools contribute to explain parental behavior. The latter suggests potential complementarities between time and material investments. Results also indicate that vulnerable households are bounded by time and resource constrains in order to optimally provide stimulation and nutrition at pre-school age. Still, given the results it is possible that caregivers can also benefit from behavior change interventions aimed to provide self-efficacy and support networks. In this context, extending universal coverage to successful, ongoing programs provided through the health and education systems, such as *Nadie es Perfecto* and *Habilidades para la Vida*, could substantially benefit the development of young vulnerable children. Turning to the production functions, time investments have a significant impact on both future SED and BAZ. The effects are quite substantial for vulnerable children, consistent with experimental evidence from randomized interventions. However, results also offer a word of caution: measures of time investments could also capture how unresponsive or intensive parenting could harm the socioemotional development of children at the top of the distribution.

The effects of additional parenting time on body mass reduction are quite substantial. In perspective, recent evidence of the structural policies targeted to the food environment in Chile shows that changes in the total energy intake are significant but not meaningful to significantly impact body mass indices among children (only a few calories per day). In contrast, increasing parental activities from 1-2 to 3-4 times per month for a year can reduce BAZ up to 0.8 SD among severely obese children.[16] Given that more than 20% of caregivers do not engage on physical activities or peer socialization with their children, there is substantial scope to shape policies in order to favor not only access to recreational areas and information, but also promote self-efficacy and social support through interpersonal communication through social organizations.

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, significant evidence from observational studies, RCTs and large interventions indicate that providing support to parents can have a substantial effect in the quality and quantity of material and time investments towards children's development and optimal nutrition at pre-school and beyond. Such programs can be extremely successful (and cost-effective) not only to prevent obesity among children in the short term, but also to avoid excess weight over the life-cycle by fostering SED that promote the adoption of healthy behaviors.

[16] A recent evaluation of the Chilean School Meals Program shows that is conducive to a (local) reduction on BAZ of 0.3 SD among obese girls in 1st Grade (**caro2019**)

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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[17]:

> *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.[18] 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.

[17]Translated from JUNAEB website

[18]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 **??**). 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 JUNAEB administrative data

Every year, JUNAEB requires the assistance of all schools participating in the SMP to collect a census on the health and vulnerability of children attending such schools (regardless of SMP eligibility). Children from pre-school, first, fifth and ninth grade participate in anthropometric measurements and their parents complete an extensive household and child survey.

These two components form the Nutritional Map (NM) the Vulnerability Survey (VS). In 2015, 742,489 children had both instruments applied, this is 90% of all students attending public or private subsidised schools.[19] 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.[20] As noted in section 3, I refer to SMP data as the dataset for the sub-sample of students with valid NP and VS instruments. Appendix Table **??** summarizes a comparison between official enrollment data and the population with SMP data in the 2014-2015 cohort.[21] 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.[22]

The NM 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 **??** and **??** 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 ob-

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

[20]For more see JUNAEB Nutritional Map.

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

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

servations 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 related to school or other student level characteristics.

The VS 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).[23] VS data has been consistently collected and coded since 2007 (including the generation of standarized anthropometric measurements from the MN 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 VS questionnaire affects the model specification in each cohort is explained in Appendix B.

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

B Measuring socioemotional development 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 SED). Alderman et al. (2014) does an excellent job of characterizing the types of human capital inputs in three groups: cognitive, socioemotional and physical health. Although measuring cognition and physical development has been widely studied, less consensus exists on characterizing and measuring SED (Kautz et al. 2014). A main issue is that SED 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 SED as those that, at least to some extent, can be shaped during developmental stages. These SED can be considered equivalent to character constructs discussed in the psychology literature, such as personality traits.[24]

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 personality traits relate to behavior is part of a larger and complex system (Almlund et al.

[24]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

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 SED: 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 SED 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 SED 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 SED. In the remainder of this section I further describe the steps to obtain SED and parental investment factors from the items in the VS data.

B.1 Measures available in the dataset

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 VS 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 **??** lists the VS items used to construct SED 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 VS 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 VS 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 SED 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 D.2, I report the differences between the estimated correlations between investment and SED 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.1 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. 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 analysis: Externalizing Behavior, parental time investment and a process measure of learning.

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. 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.

As reported in previous studies, I noted important differences in SED by gender. Figures B.3 and B.4 show the kernel density for SED and parental time investments by gender. In a similar way, there are also meaningful differences in the accumulation of SESK and parental time investment by years of education and the presence of a father figure.[25] Overall, at the same age (on average), girls have significantly lower BAZ and higher socioemotional development. In particular, differences in neuroticism are important as they 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 **??** 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 SED 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

[25] Detailed results are available upon request.

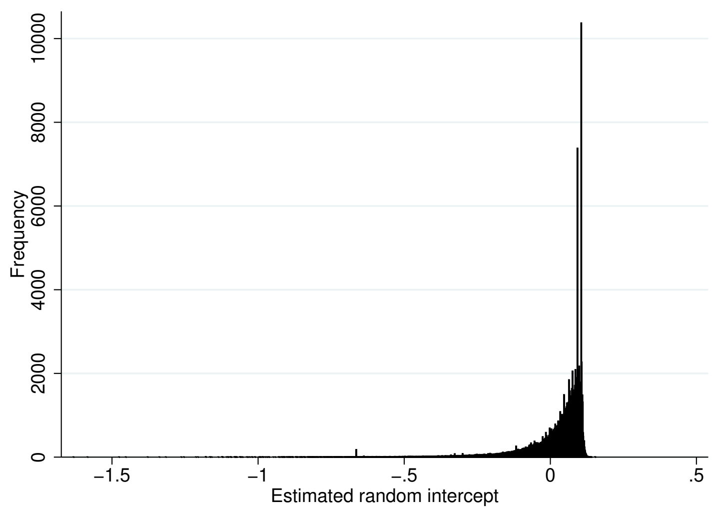
data in each time period can introduce bias and obscures the interpretation of within child variation in SED over time.

Table B.1: Quatimin-rotated factor loadings (random intercept EFA, standarized values)

	Factors							
Measurements	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.

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



C A simple model of parental input allocation

Based on the previous literature, I motivate parental investment decisions with a simple model.[26] Households derive utility from own consumption $u_t = u(c_t)$, in each period. The utility of the child given their human capital accumulated through adulthood is defined as $v(H_a, \theta_a)$. The sub-index a indicates the time period in which an individual becomes an adult. Human capital accumulation of inputs follows equations (1) and (2). The present value of the parent household utility over the lifecycle can be described as

$$U = \sigma_{t=1}^{T} \beta^t u(c_t) + \beta^a \mu v(H_a, \theta_a) \tag{12}$$

where, as noted by Attanasio et al. (2015a), μ is a parameter that reflects how parents value the utility of their offspring in adult life[27], and β is a discount factor. This model assumes that parents do not derive utility from their children's human capital when $t > a$. Parents can invest in children in each period of childhood ($t < a$) to boost $H_{t+1,t+1}$ in order to maximize human capital in adulthood (given equations 1 and 2). To simplify, parents can buy I_t in the market at a fixed price p_t^I. As such, the household inter-temporal budget constrain is:

$$A_{t+1} = (1 + r)(A_t - c_t - p_t^I I_t + y_t) \tag{13}$$

Where A_t represents net wealth (given the opportunity to borrow or save), and y_t is the income in the period. The household's problem is to maximize lifetime utility subject to the budget constrain and the production functions of human capital. The problem can be described by the corresponding Bellman equation for each relevant period and the solution of the investment time supply can be consistently approximated by equation (5).

[26] For a more complete framework which includes labor supply and time investments see Del Boca et al. (2013).

[27] Previous models of parental investments assume that parents derive utility directly from the enjoyment of children's human capital in each period (Aizer and Cunha 2012; Del Boca et al. 2013). Here, I assume that parents value the expected wellbeing of their adult child, as in Attanasio et al. (2015b)

D Specification and robustness checks

D.1 Investment equation and production functions

This section reports different complementary analysis to understand the validity of the SMP local average treatment effects. Appendix Table D.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 **??** 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.

Table D.1: Correlations between investment and socioemotional factors (Panel 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

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

Table D.2: Time investment equation: different specifications

	OLS (PA)		FE		Mixed		Hybrid (CRE)	
Skills	**0.08**	*0.002*	**0.12**	*0.006*	**0.09**	*0.001*	**0.08**	*0.003*
Skills SE					**0.11**	*0.006*	**0.11**	*0.009*
BAZ	0.00	*0.001*	0.00	*0.010*	**0.00**	*0.001*	0.00	*0.010*
BAZ SE					**0.02**	*0.002*	0.00	*0.012*
School tuition (No pay)								
$2 to $50	**0.06**	*0.009*			**0.06**	*0.002*	**0.06**	*0.002*
$50 to $100	**0.08**	*0.008*			**0.08**	*0.002*	**0.09**	*0.002*
$100 or more	**0.08**	*0.009*			**0.08**	*0.002*	**0.11**	*0.002*
School math z-score (grade 4)	**0.01**	*0.003*			**0.01**	*0.002*	**0.01**	*0.002*
School reading z-score (grade 2)	**0.01**	*0.003*			**0.01**	*0.008*	**0.02**	*0.008*
Age (log)	0.01	*0.034*	**0.03**	*0.011*	**0.03**	*0.000*	0.01	*0.000*
HAZ	**0.01**	*0.003*	**0.00**	*0.001*	**0.00**	*0.000*	**0.01**	*0.000*
Gender (male=1)	**0.01**	*0.003*	**0.01**	*0.005*	**0.01**	*0.003*	**0.01**	*0.004*
First born	**0.05**	*0.004*	-0.01	*0.004*	**0.03**	*0.002*	**0.04**	*0.003*
Exclusive breastfeeding ¿6mo	**0.04**	*0.003*	**0.04**	*0.004*	**0.04**	*0.000*	**0.04**	*0.000*
Number of siblings	**-0.04**	*0.002*	**-0.01**	*0.002*	**-0.04**	*0.001*	**-0.04**	*0.001*
Caretakers (number)	**0.03**	*0.002*	**0.01**	*0.002*	**0.02**	*0.000*	**0.02**	*0.000*
Etnic background	**-0.03**	*0.007*			**-0.02**	*0.009*	**-0.03**	*0.007*
Mother age at birth (log)	**-0.07**	*0.009*	**-0.02**	*0.019*	**-0.08**	*0.000*	**-0.08**	*0.000*
Mother education (log years)	**0.04**	*0.004*	**0.01**	*0.004*	**0.03**	*0.001*	**0.03**	*0.001*
Father education (log years)	**0.03**	*0.002*	**0.01**	*0.002*	**0.02**	*0.000*	**0.02**	*0.001*
Father figure present (Never)								
Sometimes	**0.01**	*0.011*	0.00	*0.005*	**0.01**	*0.005*	**0.01**	*0.004*
Always	**0.08**	*0.005*	**0.04**	*0.004*	**0.08**	*0.005*	**0.09**	*0.004*
Pareting this child is (Easy)								
Not easy nor hard	**-0.03**	0.002	**-0.01**	0.003	**-0.03**	0.002	**-0.03**	0.002
Hard	**-0.08**	0.005	**-0.03**	0.006	**-0.08**	0.005	**-0.08**	0.005
Pareting support (Always)								
Sometimes	**-0.04**	0.002	**-0.02**	0.003	**-0.04**	0.002	**-0.04**	0.002
Never	**-0.05**	0.004	**-0.03**	0.005	**-0.05**	0.004	**-0.05**	0.004
Participation in social org.	**0.09**	*0.003*	**0.06**	*0.003*	**0.09**	*0.009*	**0.09**	*0.009*
Home close to recreation area	**0.15**	*0.004*	**0.06**	*0.005*	**0.11**	*0.020*	**0.11**	*0.004*
Home close to public services	**0.05**	*0.006*	**0.03**	*0.005*	**0.04**	*0.011*	**0.04**	*0.000*
Instruments (p-value)	0.00				0.00		0.00	
N	160,345		160,345		187,556		187,556	

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

Table D.3: Production functions (exogenous time investments)

	Socioemotional (t+1)				BMI (t+1)			
	Kindergarten		1st grade		Kindergarten		1st grade	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Investment	**0.02**	**0.02**	0.01	**0.01**	0.01	**-0.02**	-0.01	**-0.02**
	0.00	*0.00*	*0.03*	*0.02*	*0.01*	*0.01*	*0.01*	*0.01*
BAZ	**-0.01**	**0.00**	**-0.01**	**-0.01**	**0.40**	**0.41**	**0.50**	**0.51**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Socioemotional	**0.66**	**0.67**	**0.79**	**0.77**	**-0.04**	**-0.02**	**-0.03**	**-0.03**
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.02*	*0.01*	*0.01*
Mother education	**0.01**	-0.01	**0.02**	**0.02**	-0.02	**-0.03**	**-0.02**	0.00
	0.00	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Father education	**0.01**	**0.01**	**0.01**	0.00	0.00	-0.02	**-0.01**	0.00
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Mother's age at birth	**0.12**	**0.12**	**0.15**	**0.12**	**0.08**	**0.07**	0.03	**0.06**
	0.02	*0.02*	*0.01*	*0.01*	*0.03*	*0.03*	*0.03*	*0.03*
Father figure present (Never=0)								
Sometimes	-0.01	0.01	0.01	0.01	0.00	-0.02	-0.03	-0.01
	0.01	*0.01*	*0.01*	*0.02*	*0.02*	*0.02*	*0.05*	*0.02*
Always	**0.07**	**0.05**	**0.14**	0.01	-0.04	-0.01	0.00	-0.01
	0.01	*0.01*	*0.02*	*0.02*	*0.02*	*0.02*	*0.05*	*0.02*
Age	0.01	0.01	**0.18**	**0.16**	**0.26**	**0.30**	**0.57**	**0.31**
	0.02	*0.02*	*0.05*	*0.04*	*0.09*	*0.08*	*0.03*	*0.07*
HAZ	0.00	0.00	0.00	0.00	**0.20**	**0.20**	**0.26**	**0.24**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Weight at birth	0.00	0.00	0.02	0.01	**0.41**	**0.34**	**0.36**	**0.37**
	0.01	*0.01*	*0.01*	*0.02*	*0.04*	*0.03*	*0.03*	*0.03*
Exclusive breastfeeding ¿6mo	**0.01**	0.00	**0.01**	**0.01**	**0.04**	0.01	**0.03**	**0.02**
	0.00	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
First born	**-0.01**	0.00	**0.04**	**0.03**	-0.01	-0.02	0.01	0.00
	0.00	*0.00*	*0.01*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Number of siblings	**-0.01**	0.00	**-0.02**	**-0.01**	**-0.04**	**-0.04**	**-0.03**	**-0.02**
	0.00	*0.00*	*0.00*	*0.00*	*0.01*	*0.01*	*0.01*	*0.01*
Etnic background	0.00	0.00	**0.02**	**-0.02**	**0.11**	**0.04**	**0.10**	**0.07**
	0.01	*0.01*	*0.01*	*0.01*	*0.02*	*0.02*	*0.02*	*0.02*
N	45,661	46,680	45,522	48,572	42,161	43,330	40,860	42,231

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.