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Essays on Human Capital and Development

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Essays on Human Capital and Development

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CONTENTS

INTRODUCTION

In this thesis, I use empirical methods to answer questions that can help improve policies' design to reduce inequality. I focus on inequality related to children's and adolescents' skill development and nutrition. Child development is a complex interaction of nutrition, education, and environment, and these factors influence health and cognitive and non-cognitive skills. Understanding the formation of this skill mix is important as it has a crucial impact on later life outcomes such as labor market success and well-being. On the macro level, it also directly impacts a country's economic success and inequality. In my thesis, I combine the different areas of child development to contribute to knowledge that can be used to design effective policies considering inter-dependencies between nutrition, health, and the environment children grew up in to improve future generations' lives.

To do so, I employ various econometric methods to answer each research question. In Chapter 1, I estimate a structural model of skill development with endogenous parental investment decisions. In Chapter 2, I exploit longitudinal panel data using reduced-form methods to estimate the impact of parental style on the non-cognitive and cognitive skill development of children. In Chapter 3, I pool and harmonize data from five randomized control trials on cash transfers to estimate the treatment effects of an income increase on households' food consumption. In the following paragraphs, I shortly summarize the questions studied, applied methods, and findings of each chapter of this thesis.

In chapter 1, *How to Close the Skill Gap? Parental Background and Children's Skill Development in Indonesia*, I analyze the role of parental background and investments (nutrition diversity and schooling expenditure) in cognitive skill development. I estimate a dynamic structural model using longitudinal panel data from Indonesia. I find two main factors contribute to the adult skill gap: household income and parental education, which influences the productivity of investments. Using the model, I simulate three policies: unconditional cash transfers, nutrition, and schooling price subsidies. To compare their long-run effects on adult skills, I account for parents adjusting their investment behavior in response to policies. Given the same cost, a) subsidizing food prices is more effective than subsidizing schooling expenditure, and b) both are more effective than cash transfers. As I find nutrition and schooling to be complements, a price decrease incentivizes parents to increase both inputs. With cash transfers, parents also increase investments but increase consumption relatively more as price incentives do not change. Nutrition subsidies reduce inequality most effectively, as parents with lower education react stronger to food price changes and increase child investments more than parents with higher education. They do so as they spend a larger share of investments on nutrition. Further, nutrition subsidies implemented alone are more cost-effective than any combination of the three policies.

In chapter 2, *Parental Style and Children's Skill Development*, written jointly with Jacek Barszczewski, we analyze how parenting style influences cognitive and non-cognitive skill development in middle childhood and adolescence. Using Australian panel data, we estimate the impact of parenting skill dimensions on skill development, exploiting the panel structure of the data and the rich availability of controls to tackle identification issues. We find that parental hostility (not praising your child, displaying anger during punishments), and inconsistency in enforcing rules negatively impact non-cognitive skills. Reasoning for the implemented rules has a smaller negative effect, while parental warmth has a small positive effect. Magnitudes are substantial; one standard deviation increase in hostility decreases children's non-cognitive skills by 0.12-0.35 standard deviations depending on the econometric specification. For cognitive skills, parenting style has a limited impact. The analysis shows that targeting in particular hostility in parenting skill training is promising to increase children's non-cognitive skills.

In chapter 3, *Income and the Demand for Food*, written jointly with Marc F. Bellemare and Eeshani Kandpal, we study the impact of cash transfers on households' food consumption patterns. Using data from five randomized controlled trials across three continents and four countries, each designed to study the impact of cash transfers, we assess the impact of exogenous income changes on food expenditures, which we use as a proxy for food demand. First, we find that a change in income causes expenditures to increase across all food categories. Second, we find empirical support for Bennett's Law, the empirical regularity whereby consumers first substitute fine grains for coarse grains, and then protein for carbohydrates as incomes increase. Overall, expenditures on protein, primarily animal-sourced, are most responsive to an exogenous change in income, followed by expenditures on staples, while food overall is a necessity. These rigorous estimates of the elasticity of demand for various food items to demand shocks suggest that as households in low-and middle-income countries get wealthier, they will demand substantially more animal-sourced foods, with implications for global poverty measurement and food baskets, social protection policy, and global carbon emission patterns.

1. HOW TO CLOSE THE SKILL GAP? PARENTAL BACKGROUND AND CHILDREN'S SKILL DEVELOPMENT IN INDONESIA

1.1. Introduction

Two-thirds of children globally do not obtain basic skills, and a vast majority of them reside in low- and middle-income countries (Gust, Hanushek and Woessmann, 2022).[1] Within these countries, low cognitive skills are concentrated among children from poorer backgrounds. Early in life, they display lower skill levels than children from wealthier households, which translates into a persistent adult skill gap. This gap results in lower intergenerational mobility and higher inequality (Attanasio, Meghir and Nix (2020)). Simultaneously, there exist significant disparities in parental investments by socioeconomic background. In Indonesia, parents with high school education spend on average more than triple in their child's schooling and invest 15% more in nutrition diversity than parents with no education - who earn less than twice of their income.[2] How much of the adult skill gap is driven by these investment differences compared to parental characteristics? Why does investment behavior vary by socioeconomic status? Are some parents more productive in investing or less resource constrained? Answering these questions is crucial to design effective policies to reduce the gap in adult skills and increase overall skill levels. Different investment behavior by socioeconomic status might lead to parents reacting differently to policies. If so, policies will vary in the degree to which they reduce inequality in skills. Knowing why and when parents invest differently allows to take their response to policies into account and assess the long-run effects of policies on skill levels and inequality.

Therefore, in this paper, I explicitly model parental investment choices and examine how cognitive skill differences transmit from childhood to adulthood outcomes in the setting of Indonesia. Using a dynamic structural model, I quantify the role of parental background and investments (nutrition diversity and schooling expenditure) in skill development. I extend existing frameworks for child development, as Del Boca, Flinn and Wiswall (2014) and Caucutt et al. (2020), by quantifying the impact of parental decisions on nutrition diversity in children's cognitive development. In doing so, I adapt the framework to a low- and middle-income country setting. Here, resources are scarce, and food insecurity plays a prominent role in child development (Aurino, Fledderjohann and Vellakkal (2019), Galasso, Weber and Fernald (2019)). While Attanasio et al. (2020) and Attanasio, Meghir

[1] Basic skills are equivalent to PISA Level 1 skills (able to identify information and carry out routine procedures according to direct instructions in explicit situations).

[2] Author's calculations with data from the Indonesian Family Life Survey (IFLS), supplied by the RAND cooperation. For details, see Frankenberg and Karoly (1995), Frankenberg and Thomas (2000), Strauss et al. (2004), Strauss et al. (2009) and Strauss, Witoelar and Sikoki (2016). Nutrition diversity is measured as the number of food groups consumed.

and Nix (2020) estimate children's skill formation in a low- and middle-income country setting, they do not explicitly model parental choices following Cunha, Heckman and Schennach (2010). By modeling parental choices, I can evaluate policies' long-run effects, carefully controlling for parental responses. I focus on evaluating cash transfers, food and schooling price subsidies, and their joint implementation. For a careful evaluation of these policies, it is crucial that I estimate the substitutability of schooling and nutrition inputs. The degree of substitutability determines how parents increase investment inputs given price subsidies or budget increases and how much cognitive skills increase in the long run.

I employ and estimate a dynamic structural model where parents face a trade-off between consumption, saving, and investing in their child's skills and are constrained by their income and assets.[3] Parents' socioeconomic background shapes their choices via three key mechanisms, and I incorporate them to differ in influence by childhood period. First, preferences for cognitive skills are allowed to vary by parental education. Parents with lower education might value cognitive skills more as they wish their children to have a better life than them. Second, parental choices are constrained by income and assets, which differ by parental education level. Third, I allow for differences in the technology of skill production. Parents with higher education might be more productive in converting the same level of investments into future skills because they can, for instance, encourage learning during playing. They also might be more productive with schooling expenditure by, for example, being able to support their children with homework. These productivity advantages would allow some parents to invest less and yield the same outcome as parents who invest more.

Using this framework, I estimate children's skill formation for each childhood period. I exploit a rich panel data set, the Indonesian Family Life Survey (IFLS). The IFLS follows a large sample of children over time, recording several measures for cognitive skills and parents' investment choices and characteristics. This feature allows me to account for the time-varying impact of parental characteristics and parenting skills and identify production technology and preferences. Further, I identify if parental investments, nutrition diversity, and schooling expenditure are substitutes or complements using available time and regional variation in food prices. If substitutes, parents increase the demand for inputs which drop in price and substitute the other. However, if inputs are complements, a price decrease in food increases both inputs. This mechanism influences how parents react to policies and their effectiveness. Hence, I can use the model in simulations to quantify the drivers of the adult skill gap and the long-run effects of policies.

My analysis reveals that parents' investment choices are constrained by income and assets, and the closing this gap would reduce the adult skill gap of 0.35 standard deviations (SD) by 0.20 SD. In contrast, differences in socioeconomic background by preferences for

[3] Different to Del Boca, Flinn and Wiswall (2014) or Caucutt et al. (2020), I do not model the time parents spend with their children but focus on schooling and introduce nutrition diversity to the model. I focus my analysis on the later periods of childhood as Del Boca, Flinn and Wiswall (2014) find time to matter less than in early childhood. This might be extended for the evaluation of cash transfers as parental time allocation is highly sensitive to participation in transfer programs (Flores, 2021).

children's cognitive skills do not widen the skill gap. Parents with lower education value their children's skills more than their higher-educated peers. Without these differences, the skill gap would be 0.14 SD larger. However, parents, especially mothers, with higher education are more productive in producing cognitive skills.[4] Eliminating these differences would reduce the skill gap by 0.29 SD.

Next, I target the lowest 20% of the income distribution in my policy experiments as income plays a significant role in the skill gap. My simulations show that subsidizing schooling or nutrition prices is more effective than unconditional cash transfers for the same costs.[5] Food price subsidies increase adult skills on average by 0.04 SD and a schooling subsidy by 0.03 SD, while cash transfers have negligible effects. While cash transfers help to lift income constraints, price subsidies change the proportion of investment inputs. As I find nutrition and schooling to be complements, lowering one input price leads to an increase in both inputs.[6] If I compare impacts across the income distribution, cash transfers and nutrition subsidies' impacts decrease with income, while schooling impacts slightly increase. This pattern indicates that parents with low income are significantly more budget constrained and less effective at using schooling investments productively compared to nutrition investments. They spend a higher share of their investment on nutrition resulting in them reacting stronger to nutrition subsidies. Hence, to reduce inequality, nutrition subsidies are the most cost-effective policy. They are also more cost-effective than combining different policies.

Further, I find the complementarity of nutrition and schooling to be stronger in high school, resulting in more significant price reactions by parents in this period and higher investment increases. Additionally, cognitive skills show a low persistence. Thus, the impacts in primary school fade out to some extent until adulthood, leading to interventions in high school being more cost-effective than in earlier ages.[7]

Related Literature I contribute to the literature in a three-fold way. First, I add to the research on nutrition and its importance for child development by modeling nutrition diversity as a separate investment input. Doing so, I compare policies accounting for parental responses and identify changes in nutrition and schooling investments due to food price changes. Interventions like food stamp allocation, nutrition supplementation, and cash transfers reduce stunting (extremely low height-by-age), and early childhood stunting has been shown to decrease cognitive skills (Sánchez (2017), Bailey et al. (2020), Galasso,

[4] Mothers with high school education increase their children's future skills by 20-25% each period compared to mothers with no schooling - holding investment levels and all other factors fixed. Father's education impact equals to a around 10% increase.

[5] Cash transfer size corresponds to 3% of the mean annual income of the lowest 20% of the income distribution.

[6] The percent increase of the targeted input is higher than of the other input. However, the other input increases as well, and therefore total investments.

[7] Note that impacts are only evaluated for cognitive skill outcomes. For example, cash transfers might be invested in consumption or to insure against shocks. In my setting, they seem to be effective in lifting the budget constraint for the ultra-poor, as the effect size is double for the most disadvantaged in the targeted group.

Weber and Fernald (2019), Carneiro et al. (2021)). Nutrition diversity has long run-effects, as early childhood interventions increasing protein intake have been found to result in higher adult cognitive skills (Hoddinott et al. (2008), Behrman, Hoddinott and Maluccio (2020)). However, nutrition affects outcomes not only early in life. School meal programs show significant effects for poorer children on test scores in middle childhood (Aurino et al. (2020), Frisvold (2015)). Impacts increase if school meals are designed to be healthy, emphasizing the importance of diversity (Belot and James, 2011). Further evidence shows that children are negatively affected by higher food prices, especially protein price increases (see Vellakkal et al. (2015), Kandpal et al. (2016), Filmer et al. (2021) and Headey, Hirvonen and Hoddinott (2018)).[8] My results complement these findings as parents increase nutrition diversity with lower food prices leading to higher cognitive skills. However, I depart from the literature by analyzing the co-movement of nutrition and schooling investments. I find schooling expenditure also increases, magnifying food price subsidies' effects.

Second, I contribute to the literature on long-run policy evaluations in developing countries by comparing policies taking into account parental responses. Summarizing the existing evidence, Bouguen et al. (2019) conclude that direct investments in health, cognitive stimulation in early childhood, scholarships, and in some cases, conditional cash transfers have positive effects.[9] My contribution lies in simulating the different combinations and synergies of a collection of policies at different points in childhood. By this, I add to the literature on the use of structural models evaluating child development policies (Todd and Wolpin (2006), Duflo (2012), Daruich (2018), Bobba et al. (2021)). I extend this literature by looking, in particular, at reactions to policies subsidizing investment prices. Food price subsidies have been found to have mixed effects on nutrition diversity. Jensen and Miller (2018) do not find any increases for a staple subsidy in China. In contrast, Kaul (2018) and Krishnamurthy, Pathania and Tandon (2017) find increases in nutritional diversity, especially of young children, for a price subsidy in India. I extend the literature by modeling several dimensions of parental investment responses to price changes. Additionally, I can focus on the long-run effects on cognitive skills as I estimate skill formation up to adulthood. This feature allows me to model the 'missing middle years' of childhood, primary education, a period which is less researched (Almond, Currie and Duque, 2018). How skill changes by policies translate into middle childhood and how these indicators predict adult outcomes would help compare early life interventions with adolescent ones.

[8] Kandpal et al. (2016) and Filmer et al. (2021) show that by a cash transfer in the Philippines stunting decreases via higher protein intake. In comparison, ineligible children are negatively affected in regions with higher protein prices (an association also found by Headey, Hirvonen and Hoddinott (2018) for protein prices and Vellakkal et al. (2015) for food prices in general).

[9] The evidence for the effects of cash transfers on adult outcomes is mixed (see Molina Millán et al. (2019) for a summary). Particularly, for unconditional cash transfers, the long-term evidence is scarce due to fewer trials available (exceptions are Araújo, Bosch and Schady (2018) and Baird, McIntosh and Özler (2019)). For Indonesia, Cahyadi et al. (2020) find long-term effects on schooling by a cash transfer program. My model aligns with this finding, as parents increase schooling investments when receiving cash transfers.

Third, I use data from a lower middle-income country to estimate skill production functions. Parents in low and middle-income countries operate under stronger income constraints, and food scarcity plays a bigger role than in high-income countries. Most of the existing literature on estimating skill production functions uses data from high-income countries (Todd and Wolpin (2007), Bernal (2008), Cunha and Heckman (2008), Cunha, Heckman and Schennach (2010), Del Boca, Flinn and Wiswall (2014), Lee and Seshadri (2019), Caucutt et al. (2020)). Exceptions are, Villa (2017) for the Philippines, Attanasio, Meghir and Nix (2020) for India and Attanasio et al. (2020) for Colombia. However, these studies pool investments and do not model inputs like nutrition separately. Thus, parental choices are not modeled explicitly, and their behavior adaptations to policies cannot be simulated. By modeling nutrition and schooling decisions, I can account for parents' responses to policy changes in the simulations and quantify the impact of nutrition diversity on child development in a low- and middle-income country context. Methodologically related to my work are the papers of Del Boca, Flinn and Wiswall (2014) and Caucutt et al. (2020), as I also explicitly model investment choices. While I use similar methods to estimate parameters, I deviate from their framework by using a different investment input (nutrition), modeling outcomes including adult skills, and using data from a lower-middle income country.

Given the lower-middle income country setting, intra-household allocation and investment trade-offs between siblings can play a role in child development. Calvi (2020) and Brown, Calvi and Penglase (2021) find household poverty to be shared unequally between household members. I control for household size and amount of siblings in the estimation and use food diversity, not quantities, which might be more impacted by unequal sharing. Another potential explanation for the skill gap could be imperfect knowledge of skill formation and the child's current skill level. This imperfect knowledge is unequally distributed across parents via socioeconomic status (see Dizon-Ross (2019) and Cunha, Elo and Culhane (2020)).[10] I argue that in my model's context, these differences would lead to underestimating preferences for lower-educated parents (see section 1.5 for details). Therefore, I treat my estimates as a lower bound. As I estimate lower-educated parents value skills more than higher-educated peers, this gap might be even bigger with knowledge differences. However, extending the framework in this dimension is a promising path for future research.

The rest of the paper is organized as follows. In Section 1.2, I discuss the data used and present facts on the skill gradient in Indonesia. Next, I introduce the theoretical model and describe the estimation procedure in Sections 1.3 and 1.4. In Section 1.5, I discuss results, which are used in the following two sections to quantify the different contributors to the skill gap (Section 1.6) and simulate policy experiments (Section 1.7). I summarize remarks on results, their interpretation, and ideas for future research in Section 1.8.

[10] Parents with lower education are found to overestimate their children's skills and the impact of their investments compared to their peers. They also tend to underestimate the importance of early life investments driven by the persistence of current skills.

1.2. Data and evidence on socioeconomic background and skills

To motivate model assumptions and the empirical analysis, I start by documenting the skill gap by children's socioeconomic background in Indonesia in Subsection 1.2.2. Using data, I will explore the potential drivers of this gap. However, before discussing the facts in detail, I shortly describe the data I use in Section 1.2.1. For further details on the data, see Appendix A.1.

1.2.1. Data

As the main data source, I use the Indonesian Family Life Survey (IFLS)[11]. This survey is a panel dataset from 1993 to 2014, allowing me to observe children from childhood to adulthood. Survey waves are 1993, 1997, 2000, 2007 and 2014. The survey area covered represents 83% of the Indonesian population, which gives me regional variation to exploit. The majority of regions not covered in the survey are in the Eastern provinces, which are very remote and poor. The available sample thus allows me to model choices in a setting where investment choices occur as markets are available and schooling options are not strongly limited by availability.

As I model the skill gap between children from different socioeconomic backgrounds, detailed information on the household and investments in children and their skills is necessary. The data set provides information about investments like schooling and nutrition. It follows children long enough to measure materialized skills in adulthood (low attrition rates around 90% to 95% depending on the survey wave). I use survey waves 1997, 2000, 2007 and 2014. I do not use 1993 due to the lack of availability of food prices. Unfortunately, the gaps between waves do not allow me to model the skill process yearly but only in childhood periods (for details, see Sections 1.3 and 1.4). However, for surveyed years, the panel entails rich information on the household and its members. The household head is the source of the primary data. Interviews also occur with the spouse; more detailed information is collected on 2-3 randomly selected children in the household. My sample for the analysis consists of children for whom information on investments and skills is available. Additionally, they need to have sufficient information on their parents' characteristics. For the estimation, this gives me around 4,563 children in early childhood, 6,329 in primary school and 8,451 in high school (see Table A.1). Investments used are education investments, like schooling fees, exam fees, books, and health investments. For the latter, I take nutrition diversity as a proxy. Food prices vary by municipality level (kabupaten). In the next paragraphs, I will shortly describe the procedure of constructing price and investment data for each investment input. For further details see Section A.1.

For nutrition investments, I use the food consumption information of the household.

[11] IFLS data was supplied by the RAND cooperation, for details see: Frankenberg and Karoly (1995), Frankenberg and Thomas (2000), Strauss et al. (2004), Strauss et al. (2009), Strauss, Witoelar and Sikoki (2016) and `https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html`

With that, I can measure which food groups the family consumes. I assume the child to eat from all parts recorded in household consumption. Following Attanasio, Meghir and Nix (2020), this serves as a proxy for the parents' decisions to invest in the child's health. The food groups counted are vegetables, fruits, dairy, proteins and carbohydrates. Regarding the price of investment for nutrition, I use price data derived from market surveys of the community questionnaires. I use spending reported on schooling fees and materials bought as schooling investments. The price for education, I assume, is one so that the total expenditure on education enters the investments. I only observe schooling investments for primary and high school.

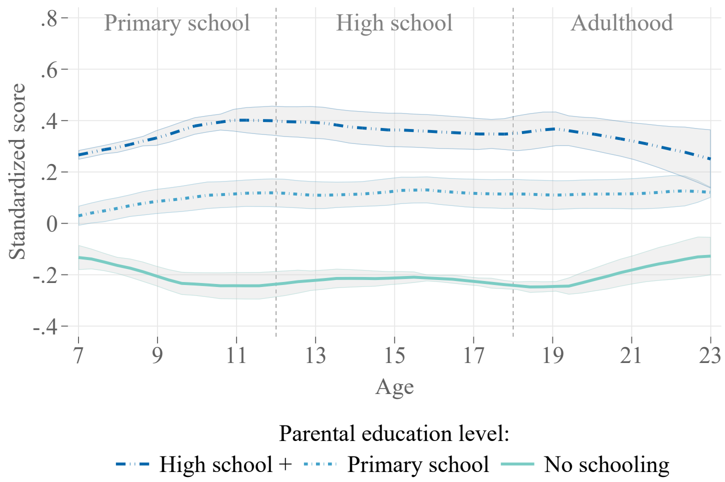
In terms of skill measures, measures for health and cognitive skills are available. For cognitive skills, I use the survey's math, logic or language tests for each child, which I standardize by age and year. In terms of health, I use height and weight, transformed to height/weight-for-age with the help of the WHO Child Growth Standards and WHO Reference 2007 composite data files (Vidmar, Cole and Pan, 2013).

The survey also records other observable characteristics such as the number of siblings, household income, assets and wages. As parental education, I use the parents' education level at the start of the child's life. Thus, it does not vary over time. An overview of the descriptives is displayed in Table A.2 for children in the sample. One can observe that a fraction of 0.34 exhibits stunting (extremely low height-for age), and a fraction of 0.09 wasting (extremely low weight-for age). The fraction of stunted children highlights the food security situation in Indonesia. With the above-mentioned WHO scale for z-scores, children below a height-for-age score of -2 are stunted. Wasting is defined by a threshold below a weight-for-height score of -2. Maternal education is, on average lower than paternal education (years of education). Parents' age varies substantially and is likely not always correctly recorded; however, it does not enter the model except for the household income estimation. A fraction of 0.88 of the sample is declaring their religion to be Islam, and the gap in household income is wide. Average households have around four adults and two children.

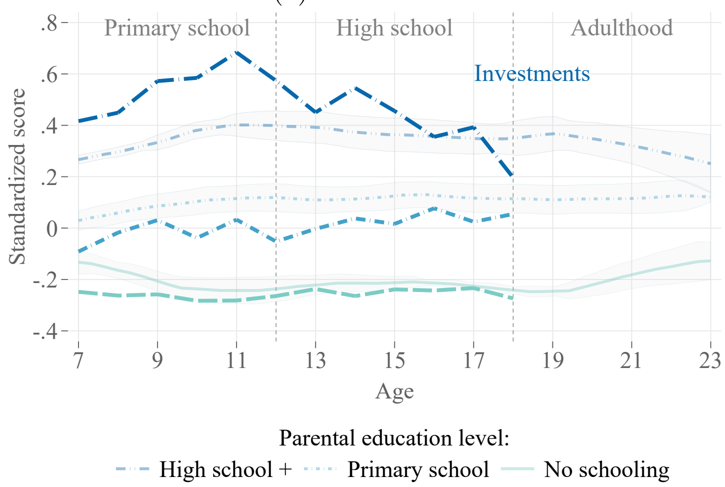
1.2.2. Empirical evidence on socioeconomic background and skills

Firstly, in this section, I document the size of the skill gap for cognitive skills and health by age in Indonesia. Then, I summarize potential drivers for the skill gap and show how these vary for children from different socioeconomic backgrounds in Indonesia. Last, I will show some descriptive evidence to motivate the need for controlling for unobserved parenting skills.

The skill gap in Indonesia is substantial and opens early in life. To show that, I plot averages of skills by parental education group and age in Figure 1.1 and A.1. I use standardized test scores for cognitive skills and height to measure health. Visibly, children with lower educated parents show a lower level of health from the start of life (see Figure A.1a). I only observe test scores from the age of 7, but this initial gap is also large, as shown in Figure 1.1a. For both measures, the gap widens during primary education and closes partly during adolescence. However, it is fairly stable. In adulthood, children from lower educated parents still have substantially lower skills, health and cognitive than their peers.



(a) Test score



(b) Test score and investments

Figure 1.1: Children skills and investments over age by parental education

Note: Skills are fitted with local mean smoothing by age and parental education groups. Parental education groups correspond to the average education of both parents. Confidence intervals displayed are at 95% level. Investments plotted are standardized schooling expenditures. Scores of skills and investments are standardized by age to have a mean of 0 and SD of 1.

Looking at these differences, the question arises of how this gap interplays with parental investments. To answer this, I plot standardized investments for health; food groups consumed onto the skill gap plot with height in Figure A.1b. For cognitive investments, I plot standardized schooling expenditure on the graph with test scores (see Figure 1.1b). We can observe a similar gap for cognitive investments. However, the gap widens more in primary school and closes quicker in high schools than the observed skill gap. In contrast, food investment differences are stable over childhood. Thus, parents with higher education mainly increase investments at the end of primary school, while nutrition differences persist over time.

These investment differences are one potential driver for the skill gap and can be driven by several mechanisms via which parental education influences children's skills. Foremost, parents with lower education have fewer resources to invest in their children. As shown in Table 1.1, lower educated parents have less income available. By that, they can invest less in children, both for nutritional investments and for schooling. Differences in investments are substantial; parents with high school education spend more than triple on education than their counterparts without education.

Table 1.1: Potential sources for the skill gap by maternal education

	Parental education level:					
	None	Primary school	High school	F-test	Mean	Sd
Resources						
HH income	181.02	384.53	522.77	0.00	289.19	479.74
Maternal skill set						
Test score	-0.44	0.24	0.51	0.00	-0.00	1.00
Height	-0.15	0.13	0.31	0.00	0.00	1.00
Initial skill levels						
Test score	-0.23	0.21	0.37	0.00	-0.00	1.00
Height-for-age	-0.17	0.18	0.41	0.00	0.00	1.00
Childhood investments						
Food groups consumed	3.36	3.71	3.85	0.00	3.57	0.91
Education spending	2.30	5.37	7.53	0.00	5.14	10.50

Note: The last column displays p-values for the null hypothesis that means for none and high school education are equal. Skills are normalized to 0 mean, SD of 1. All values are from period 2 (age 6-11), except initial height. Income and education spending expressed in 100,000 rupees.

Income is not the only potential source of the gap between children's skills. Parents with lower income and education might have lower cognitive skills and worse health. On the one hand, this might lead to different initial skills for the children, which I observe in the data. However, their abilities and health might influence their investment productivity. Parents with higher abilities might be more capable of helping children with homework, which makes their schooling investment more productive.

Apart, parents with higher socioeconomic status invest differently. They spend more on education. Figure 1.2 shows that with increasing household income, the share of investments parents spend on nutrition decreases relative to the share spend on education. Despite income differences, this might be driven by differences in productivity, similar to the productivity differences by ability mentioned above. Also, parents' preferences might vary with education. Higher educated parents might differ in valuing skills to their peers. For instance, lower-educated parents might wish for their children to do better off than them and invest more. However, resources might constrain them in doing so. As visualized in Figure 1.2, households in the lower part of the income distribution, spend a significant larger part of their income on investments in their child. This indicates their income constraint but might also be an indicator for stronger preferences for skills.

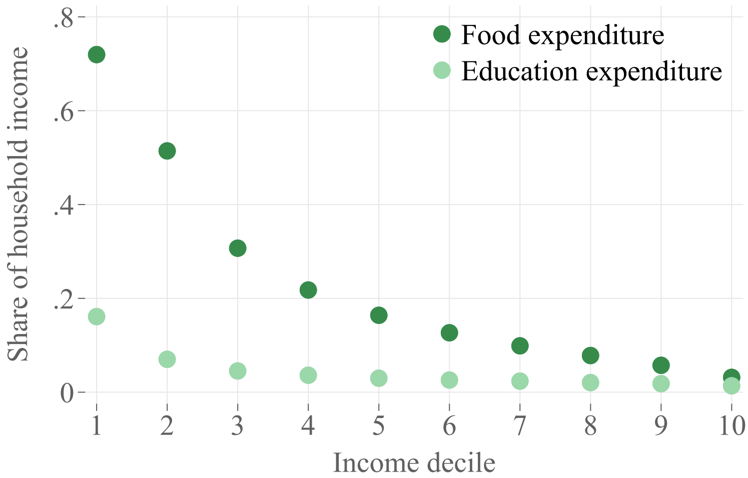


Figure 1.2: Fraction of household income spend on child investments

Note: Expenditures shares are plotted as median fraction of total household income by income decile. Household income is adjusted by household size.

I can only uncover these mechanisms in a structural model, not with the descriptive data available. Therefore, I construct a model where parents decide on different investment inputs, which productivity varies by parental education, among other factors (described in further detail in Section 1.3). These parents face income constraints and value child skills differently by education.

However, controlling only for observable characteristics of the parents might miss an important feature: parenting skills. Some parents could have higher parenting skills, leading them to make better investment decisions due to higher ability. If I omit to control for those that correlate with education, it will lead to biased estimates. To illustrate that they are not aligning with education and income, I plot distribution by parent's income and education groups on Figure A.2. As one can see, the distribution in the lower education and income categories is skewed to the left. However, even in these categories, there is substantial heterogeneity, which parenting skills can drive. The impact of these skills might vary by childhood period, similar to the impact of other potential drivers of the skill gap. Resources might play a more critical role during high school than in early childhood since higher investments are needed to affect future skills.

The potential drivers call for a model-set up where investment effects vary across periods and which includes controls for unobserved parenting skills. Also, the impact of current skills on the following period skills need to change over time. Including these dynamics in a theoretical model might allow policy simulations to mimic the potential fade-out of interventions and to see when and why this happens.

1.3. Model

To capture the empirical facts described in Section 1.2, the theoretical model entails different channels via which socioeconomic background influences skill development. Thus, it captures investment decisions influenced by education and features households' budgets to constrain investment expenditure. Additionally, I will account for parenting skills in the skill production function, and all these influences vary by childhood period.

Regarding modelling choices and functional form assumptions on the skill production function, I follow Del Boca, Flinn and Wiswall (2014) and Caucutt et al. (2020). However, in contrast to both, I focus on nutrition and schooling inputs instead of time inputs. Hence, this model will especially capture later childhood periods, where monetary expenditures become more productive and feature the transition of skills in teenage years to adulthood.

Households represent a parent-child pair. Parents decide on investments into the child each childhood period (early childhood, primary school and high school). In the final period of the model, the child grows up to be an adult, and no further decisions take place. In the decision periods before the child becomes an adult, households derive utility from consumption c_t and current child's skills Ψ_t. In the final period, households only derive utility from the final skills of their child Ψ_{T+1} and assets a_{T+1}. The latter is merely to assure that parents do not deplete assets fully in the high school period to maximize utility in the last period.

To optimize their utility, parents decide to invest their resources into consumption c_t, savings a_{t+1} or investments in the child I_t. Hereby, parents are constrained by their income and their decisions are influenced by the prices of investments. I adjust household income by household size (see Appendix A.1 for details). For the moment, I abstain from further modelling the trade-off in investing between siblings, which would be a potential future extension of this model. Further, as the model only contains monetary investments into children, time does not play a role in the skill production. The trade-off between time at home might only be with consumption and not with spending time and investing it in the child. For this reason, I do not model labor choices as the trade-off between consumption and leisure is not the focus of the model.

Investment decisions are made every period to be able to measure when they matter the most for skill development. Figure 1.3 illustrates a graphic overview of the timeline. Periods are determined by the child's age, following standard definitions in the literature for an early childhood period, primary education and secondary education. In period $t = 0$, the child is born with an initial skill endowment Ψ_1; then, in early childhood, the household decides on nutrition n_t. In later periods, the parents also choose how much to invest in schooling s_t. In $t = 4$, the child is grown up, and final cognitive skills outcomes realized.

Formally, each period the household maximization problem looks like the following:

$$\begin{aligned} V_t(Z_t, a_t, y_t, \Pi_t, \Psi_t) = &\max_{c_t, n_t, s_t, a_{t+1}} u(c_t) + \alpha_e v(\Psi_t) \\ &+ \beta V_{t+1}(Z_{t+1}, a_{t+1}, y_{t+1}, \Pi_{t+1}, \Psi_{T+1}) \\ \text{s.t.} \quad c_t + p_{n,t} n_t + p_{s,t} s_t + a_{t+1} &= (1+r)a_t + y_t \\ a_{t+1} &\geq a_{min,t} \end{aligned} \tag{1.1}$$

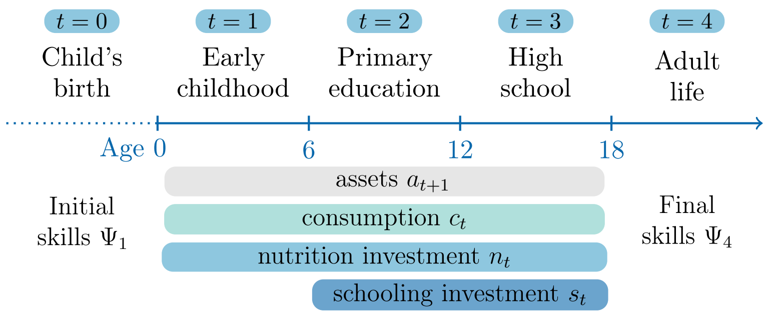


Figure 1.3: Model stages

Households maximize utility with respect to consumption c_t, assets a_{t+1} and investment choices. Investments in the child are investment in nutrition n_t and an schooling investment s_t in period 2 and 3 ($s_t = 0$ in period 1). Nutrition investment can be understood as a proxy for health investments and is measured by the number of food groups a child consumes. Therefore, this measure is a food diversity measure and does not capture food quantity. All investments are associated with their corresponding prices in the budget constraint. The price for nutrition is $p_{n,t}$, and the price for one unit of schooling is $p_{s,t}$. The vector of all prices for investments is denoted by Π_t. The household cannot spend more than their current income y_t and assets a_t. Future utility depends on the evolving state space of future income and prices, as well as future household characteristics Z_{t+1} and future skills Ψ_{t+1}. Households can borrow, but not more than $a_{min,t}$, the maximum amount a household can be in debt.

The current period's utility depends on consumption and skills. The utility functions take the corresponding forms:

$$u(c_t) = \ln(c_t) \tag{1.2}$$

$$v(\Psi_t) = \ln(\Psi_t) \tag{1.3}$$

In the last period of the model, utility exclusively depends on the final skill level of the child Ψ_{T+1} and final assets. By that, a motivation to invest in the child is ensured. Also, not all assets are depleted in the last period:

$$V_{T+1} = u(\Psi_{T+1}) = \alpha_e \gamma_e \ln(\Psi_{T+1}) + \zeta \ln(a_{T+1}) \tag{1.4}$$

Here it is important to note that the altruism factors α_e and γ_e depend on parental education. By this, I allow parents to value their child's skills differently depending on their education. In the adult period, no decisions take place, so the child's skill level is the only variable from which the household derives utility apart from accumulated assets.

What is left to specify is how children's skills evolve. Future skills will depend on current investments I_t, current skills Ψ_t and a total factor productivity $\theta_t(Z_{\theta,t})$:

$$\Psi_{t+1} = \theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}} \tag{1.5}$$

Thus, $\delta_{1,t}$ will describe the impact investments have on future skills, which varies by period. The self-productivity of skills Ψ_t is expressed by $\delta_{2,t}$, also varying by period. I ensure that the estimation is flexible enough to capture that early childhood skills might be not as critical for future skills than skills in high school. Persistence of skills is likely to increase over childhood, and this functional form allows to capture this development flexibly. The total factor productivity depends on observable characteristics $Z_{\theta,t}$. These are parental education and the age of the child.

Total investment are composed of the investment inputs nutrition n_t and schooling s_t:

$$I_t = [n_t^{\rho_t} + a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t}]^{\frac{1}{\rho_t}} \tag{1.6}$$

I assume a CES investment function, following Caucutt et al. (2020). The parameter ρ_t describes the elasticity of substitution between nutrition and schooling. Schooling investments have a relative productivity of $a_{s,t}$, which depends on observable characteristics. These are parental education e, age, number of siblings and the unobserved parenting skills η. Productivity depends on parental education since one could imagine that the investments have differential effects by parents' education. Higher-educated parents might be able to buy books for schooling when the child needs them or to help the child with homework at later levels of schooling. In a similar spirit, unobserved parenting skills η influence productivity. Controlling for the number of siblings allows either siblings to help with homework or reduce the time parents can spend with the child on homework, thus reducing the productivity of schooling. An assumption is that $a_n = 1$, thus the productivity of nutrition investments is normalized for identification. In early childhood $I_t = n_t$.

The elasticity of substitution each period ϵ_t is measured by ρ_t with $\epsilon_t = \frac{1}{1-\rho_t}$. Thus, if $\epsilon_t < 1$ the investments are complements, if $\epsilon_t \geq 1$ they are substitutes. The elasticity will drive price reactions. Suppose goods are substitutes and the price of one rises. In that case, it will be substituted by the other one to some degree. If they are complements, this substitution will not happen, and overall investment might be decreased depending on the degree of complementarity.

Depending on the productivity of each investment, price increases will have different impacts on investments varying by parental education and other observable factors. For instance, if food prices increase and the goods are substitutes, investments might shift to more schooling expenditure. However, if schooling investments are more productive for high-educated mothers, they might have to buy less quantity to substitute for the loss in nutrition than mothers with lower education. In terms of complements, the substitution would not take place. However, if schooling is more productive for high-educated parents, changes in food prices might impact them less than low-educated parents. This interplay shows why it is essential to know if investments are substitutes or complements. This knowledge can help to design suitable policies. In the case of substitutes, a price subsidy on one product might lead to less investment in another. In case of complements, this might lead to an increase in all types of investment.

As Caucutt et al. (2020), Moschini (2019) and Molnar (2018), I exploit the fact that the maximization problem can be separated into an inter-temporal and an intra-temporal problem. The intra-temporal problem minimizes the costs for investments for a given amount of total investments I_t. The inter-temporal problem will then maximize utility with respect to total investments and consumption. The minimization problem takes the following form:

$$\begin{aligned} \min_{n_t, s_t} \quad & p_{n,t} n_t + p_{s,t} s_t \\ \text{s.t.} \; It &= [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}} \end{aligned} \tag{1.7}$$

I can derive solutions for each investment input given the total investment level. With having derived equations for the investment inputs n_t and s_t given I_t, I can reduce the maximization problem to maximizing with respect to I_t, simplifying derivations (see Appendix A.5). Then, the inter-temporal problem can be characterized by:

$$\begin{aligned} V_t(Z_t, a_t, y_t, \Pi_t, \Psi_t) = & \max_{c_t, I_t, a_{t+1}} u(c_t) + \alpha_e v(\Psi_t) \\ & + \beta V_{t+1}(Z_{t+1}, a_{t+1}, y_{t+1}, \Pi_{t+1}, \Psi_{T+1}) \\ \text{s.t.} \quad c_t + \Lambda_t I_t + a_{t+1} & = (1+r)a_t + y_t \\ a_{t+1} & \geq a_{min,t} \end{aligned} \tag{1.8}$$

Λ_t will describe the price for one unit of total investment, which arises from the results of the cost minimization (see Appendix A.5). Given the results, investment input prices will determine the amount of each investment input and the price for one unit of total investment.

Hence, the model captures investment decisions in children influenced by investment prices and parental preferences, differences in investment productivities and parenting skills. I allow for the interplay of the budget constraint, preference parameters and productivity of skill formation differing by education and observables. This way, I can quantify how and when income and parental education influence children's skill development most. Further, it allows me to distinguish between the influence of nutrition and schooling as inputs and when they have the highest impact on skill development.

1.4. Estimation and calibration

To estimate the model, I take the following steps:

1. Estimation of types of parenting skills by k-means algorithm
2. Estimation and prediction of household income by OLS
3. Estimation of skill formation parameters by joint Generalized Method of Moments (GMM) for:
   - Investment parameter: using relative demand ratio moments
   - Human capital parameters: using skill moments and factor loading moments
4. Estimation of preference parameters by simulated methods of moments (SMM)

In the following paragraphs, I describe each step in the listed order in detail. For further details, see Appendix A.3. In step 1, I start the estimation procedure by determining the unobserved parenting skill types. Since all equations depend on the types $k = \{1, ..., K\}$ of unobserved parenting skills η, these need to be estimated first. To do so, I use the k-means algorithm in the spirit of Bonhomme, Lamadon and Manresa (2022) to control for unobserved heterogeneity. The advantage of this method is that it allows for types whose impacts vary over childhood periods. Additionally, estimating the types outside the model is less computationally intensive, and the strategy uses empirically relevant data to determine the types. For identification, I can exploit the fact that I observe parents over time and across children (siblings) in terms of their investments. Assuming that the impact of parenting skills is the same for each child, I can use this additional data to identify the skill type for each pair of parents.

To perform the k-means algorithm, data moments must be chosen, which are influenced by the types. In my case, these are household income, schooling expenditure and nutrition investments. I assume investments to be partly driven by unobserved parenting skills and that these skills can translate into higher productivity in the labor market resulting in higher income. The moments I calculate are lifetime averages of parental investment decisions and income across childhood periods and their children. I calculate lifetime moments because an assumption of the k-means algorithm is that parents of the same type would converge over the life cycle to have the same moments with $T \to \infty$ (for details, see Appendix A.3).

Thus, I can use the variation in lifetime moments in the data to determine types. To do so, the algorithm minimizes the within-cluster (type) variance. The state-space is split into clusters, so that parents within a cluster are as similar as possible:

$$\min_{k \in \{1,..,K\}^N} \sum_{t=1}^{N} \sum_{c=1}^{C} ||\boldsymbol{m_{t,c}} - \boldsymbol{\overline{m}_k}||^2 \tag{1.9}$$

where $\overline{m}_k$ is the average of the moment vector m of parenting skill type k, t stands for time and c indexes each child the parents have. Moments are standardized to have mean zero and variance one. To run the minimization, the researcher needs to determine the total number of clusters K. With the help of the elbow and silhouette criteria, I determine the optimal amount of types K, as plotted in Figure A.3. These two criteria determine the number of clusters at which variation within cluster decreases and variation between clusters increases without adding significant computing time. The optimal number is $K = 4$. A detailed discussion of robustness checks including different numbers is in the Appendix A.3. Using the optimal number of clusters, I can determine for each parent pair the unobserved parenting skill type they have according to the algorithm.

Moving on to step 2, having estimated parenting skills, I use these as inputs to estimate household income with a standard Mincer equation since I abstract from modeling labor choices. Household income depends on parental education, number of household members, rurality, age of the household head, and parenting skills. The parameters for these characteristics will then be used to predict household income for the calibration and simulations. For these predictions, I assume the income shocks to be i.i.d. normally distributed. Thus $\epsilon \overset{i.i.d}{\sim} N(0, \sigma_y)$.

In step 3 follows the estimation of the human capital and investment parameters consisting of a joint GMM estimation. For this estimation, I derive a set of moments for the investment function parameters in Equation 1.6 and another for the human capital parameters in Equation 1.5. To do so, for the investment parameter moments, I start by deriving and rearranging the first-order conditions of the cost-minimization problem to formulate the following linear relative demand equations, which I can estimate for periods 2 and 3 (for derivations, see Appendix A.5):

$$\ln\left(\frac{p_{n,t}n_t}{p_{s,t}s_t}\right) = \frac{1}{\rho_t - 1} Z_t'\phi_{s,t} + \frac{\rho_t}{\rho_t - 1}\ln\left(\frac{p_{n,t}}{p_{s,t}}\right) - \frac{1}{1-\rho_t}\eta + \epsilon_{ns,t} \tag{1.10}$$

The relative demand ratio between nutrition and schooling quantities will depend on observable characteristics $Z_{s,t}$. These form, following Caucutt et al. (2020) assumptions, the relative schooling productivity $a_{s,t}(Z_{s,t}, \eta) = exp(Z_{s,t}'\phi_s + \eta)$. Note, as mentioned in Section 1.3, I normalize $a_{n,t}(Z_{n,t}) = 1, \phi_{n,t} = 0$ to identify all parameters. Thus, I will only be able to have results on the relative magnitude in terms of their impact on the productivity of investments. The characteristics $Z_{s,t}$ include paternal and maternal education and other observable characteristics such as religion, age of the child, rural area, siblings in the household, and gender. Additionally, the productivity will depend on η, the unobserved parenting skill type, as one can see in Equation 1.10. $Z_{s,t}$ here is a matrix of variables as parental education. As one can see ρ_t, the substitution parameter for nutrition and schooling is identified with the price ratio of these inputs. As schooling prices are assumed to be 1, this parameter will be identified by variation in the food price.

As instruments $Z_{t,ns}$ for the GMM moments displayed in Equation 1.10, I use the observable characteristics $Z_{s,t}$, the price of inputs and parenting skill types k. Thus I assume the moments to be orthogonal:

$$\mathrm{E}\left(\left[\ln\left(\frac{p_{n,t}n_t}{p_{s,t}s_t}\right) - \frac{1}{\rho_t - 1}Z_t'\phi_{s,t} + \frac{\rho_t}{\rho_t - 1}\ln\left(\frac{p_{n,t}}{p_{s,t}}\right) - \frac{1}{1-\rho_t}\eta\right] Z_{t,ns}\right) = 0 \tag{1.11}$$

For this equation to be accurate, I need to assume that the measurement error in Equation 1.10 is independently distributed across individuals, and no variables in the error term influence the demand ratio and instruments used for the moment equations. For this not to be true, a variable would need to influence schooling and nutrition inputs differently, as influences of the same magnitude factor out by the ratio. For example, not controlling for parenting skills η might bias the results as it could influence schooling differently from nutrition but be correlated with parental education. It might be driven by ability which influences education and via parenting skills, also the ratio of investments.

To control for this potential bias, I use the estimated types from step 1. As these estimated types do not correlate strongly with education, I assume that education is not working solely through parenting skills in influencing the ratio of nutrition versus schooling parents spend. I understand the influence of education, to be for example, knowing to help your child with homework. In contrast, unobserved parenting skills capture, e.g., parents' empathy to react to their children's problems at school and spend more time with them, which then increases their productivity in school as it might mitigate behaviors that hinder learning.

Note that the identification of the substitution parameter ρ_t depends on food prices, whose variation I assume to be exogenous. Parents' choices might influence food prices or schooling fees, which would break this assumption. For instance Bold et al. (2015) find that providing free public primary education shifted parents demands to private education and increased prices for these schools in Kenya. I do not model differences in public and private education provision and the supply side for simplicity, a caveat to keep in mind for interpreting the results. Regarding food prices, Filmer et al. (2021) find that cash transfers lead to higher food prices for proteins by increased demand of recipients having negative effects on ineligible children. However, these results are mainly found in remote areas or when a large proportion of the village received treatment. In this context, this is unlikely to be the case, as I look at only a subpopulation, relatively urban areas, and not extremely remote villages. Thus, for simplicity, I abstract from modeling prices, but this could be a future extension of the model. Nonetheless, it is vital to keep this simplification in mind when evaluating the outcomes of the policy experiments.

Turning to the human capital parameter moments, I will mainly use Equation 1.5 which describes how current investments and skills translate into future skills. However, one must consider how skills are measured in this context before estimating these parameters. I use logic (raven) and math test scores in the later periods of the model for cognitive skills and height and weight in early childhood as a proxy. These measures, however, only proxy the latent skills and are measured with error. To account for this, I follow Cunha, Heckman and Schennach (2010) and assume a measurement system for the latent skills

Ψ_t. The system looks like the following:

$$S_{ts_1,t} = \lambda_{ts_1,t} \ln(\Psi_t) + \epsilon_{ts_1,t} \tag{1.12}$$

and:

$$S_{ts_2,t} = \lambda_{ts_2,t} \ln(\Psi_t) + \epsilon_{ts_2,t} \tag{1.13}$$

where ts stands for test scores I use in the corresponding period. Following Caucutt et al. (2020), I normalize one factor loading $\lambda_{ts_1} = 1$ each period.

Combining the measurement system Equations 1.12 and 1.13 with Equation 1.5 for the skill formation process,I derive additional moments for the GMM estimation (for details see Appendix A.5):

$$\frac{1}{\lambda_{ts,t+1}} S_{ts,t+1} = \phi_{\theta,t} Z_{\theta,t} + \delta_{1,t} \ln(I_t) + \delta_{2,t} \frac{1}{\lambda_{ts,t}} S_{ts} + \epsilon_{\Psi,t} \tag{1.14}$$

Moreover, to identify the factor shares:

$$0 = \mathrm{E}[(S_{ts_1,t+1} - \lambda_{ts_2,t+1} S_{ts_2,t+1}) S_{ts_1,t}] \tag{1.15}$$

and:

$$0 = \mathrm{E}[(S_{ts_1,t} S - \lambda_{ts_2,t} S_{ts_2,t}) S_{ts_1,t+1}] \tag{1.16}$$

In this context, $Z_{\theta,t}$ entails parental education and the child's age. Again, I assume these factors to map into the total factor productivity $\theta_t(Z_{\theta,t})$. As instruments Z_{t,Ψ_t} for the skill moments I use the characteristics in $Z_{\theta,t}$ and investment inputs schooling s_t and n_t. Thus:

$$\mathrm{E}\left(\left[\frac{1}{\lambda_{ts,t+1}} S_{ts,t+1} - \phi_{\theta,t} Z_{\theta,t} + \delta_{1,t} \ln(I_t) + \delta_{2,t} \frac{1}{\lambda_{ts,t}} S_{ts}\right] Z_{t,\Psi_t}\right) = 0 \tag{1.17}$$

I abstract for modeling investments between the points of time I observe the children in the data. I do not have enough information on investments or income to impute those. Another shortcoming is that while I control for measurement error in skills, I do not do so for investments, which could lead to biased results, and therefore the results have to be taken with caution. However, as I do instead treat investments in nutrition as a proxy for health investments and schooling for education investments, these inputs are not supposed to be understood as precisely modeled. In general, measurement error in investments is likely to decrease the coefficient of investments, thus underestimating the impact (Cunha, Nielsen and Williams, 2021).

After this estimation procedure, I move to step 4 and estimate the preference parameters γ_e, α_e and ζ. To do so, I use the optimal solution for total investments and assets (see Appendix A.5 for details) in the simulated method of moments. I set the discount factor β to 0.98, following calibrations in the literature on Indonesia (Dutu, 2016). I match mean investments by childhood periods and parental education level and assets by period to their data counterparts (see Appendix A.3 for details). For the simulated method of moments and simulations, I assume wages and prices change over time. However, for simplicity, for the transition of state variables, I assume all other household characteristics to be fixed. Thus, households do not move from rural to urban areas, and the number of siblings does not change. This process could also be enriched in future research.

1.5. Results

I will discuss the results in order of the estimation strategy described in Section 1.4. Thus, I start with the parenting skills types. Remember that in the model, parenting skill types capture unobserved heterogeneity among parents, influencing their investment behavior. I assume there are parents who, independent of income or education, might be more effective in investing in schooling. If these types are more effective in schooling, they will shift their investments to schooling rather than nutrition, which influences schooling and nutrition investment levels. I assume these parenting skills also influence income. A parent with certain parenting skills might be better at communication, increasing their income. I determine types by using the variance in investments and income with the help of the k-means algorithm. The outcomes of the k-means algorithm suggest that there are four types. These types are different in investment levels and income, driven by the identification method. In the upper graph of Figure 1.4 I show the types' distribution and their characteristics in terms of income and investments. The two most often occurring parenting skill types, 0 and 1, have low income and schooling investments compared to the other types. Additionally, type 1 also has low food investments. In contrast, type 2 has higher income but also very high education expenditure. Type 3 seems to have mainly very high income and modestly increased investments. Types could be, in general, correlated with education. If they are correlated strongly, this will cast doubts on their identification. To check, I show the education distribution in the bottom part of Figure 1.4. Types are partly correlated with education, but there is still substantial variation within education groups. The share of mothers with no schooling is higher for the low-income and low-investment types 0 and 1, while the share of high school mothers is higher for types 2 and 3. The share of mothers with primary education is similar for all types. Hence, while there is some correlation between education and types, there is still some variation regarding unobserved parenting skills within education groups.

Turning to the results on household income, one can observe that these parenting skill types matter. In Table A.3, one can see that types 2 and 3, which are associated with higher income, also tend to have higher productivity of income in the household income estimation. Especially type 3 has high productivity, which is the one with the highest observed income, while type 1, the lowest, is associated with a negative coefficient. In terms of magnitude, being of type 2 corresponds to an increase in household income of having a mother with a high school education. Furthermore, being of type 3 exceeds this by influencing a third more than both parents' high school education. Unobserved parenting types are likely to contribute to the gap by socioeconomic status. They are

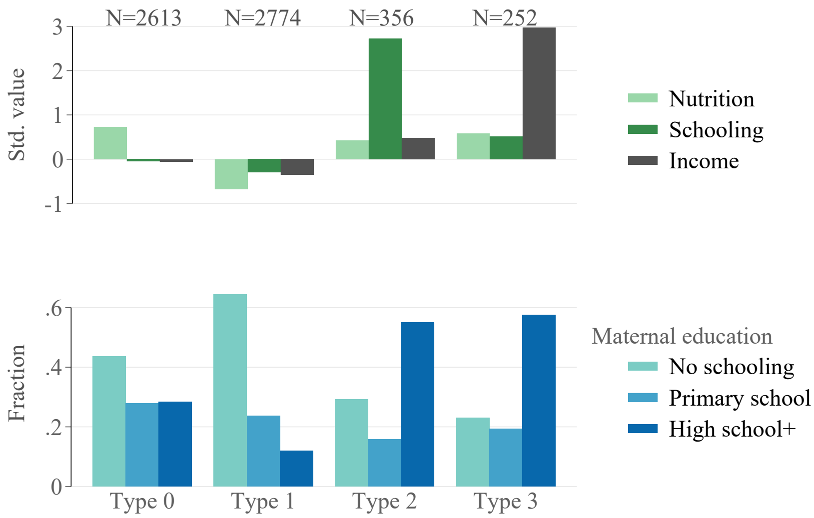


Figure 1.4: Characteristics of parenting types η (investments/resources and education)

Note: Nutrition is food groups consumed, schooling describes schooling expenditure, and income annual household income (lifetime averages by parenting pair).

driving part of the income differences between parents. The other coefficients from the household income estimation show the expected signs and magnitudes; education and age increase income, while living in a rural area decreases it.

The GMM estimation results for investment parameters using Equation 1.10 reveal the degree of complementarity for investment inputs and their productivity by period (see Table 1.2 and for further parameters A.4). Nutrition is complementary to schooling in both periods, primary and high school. Consequently, if prices for nutrition increase, parents decrease their investments in nutrition and schooling. Worth to note that the complementarity increases in high school with a higher substitution parameter ρ_t of -11.38 versus -3.75 in primary school. The complementarity is stronger than what Caucutt et al. (2020) find for time and goods investments ranging around -1 for the US.

The higher degree of complementarity in high school leads to parents responding to price changes of one input with decreasing demand for the other one stronger than in primary school. A reason for this reaction might be that in primary school, schooling is mandatory, making the demand for it less elastic. However, in high school, parents reduce investments more in their children if food prices increase as securing the households food consumption is a priority and schooling is not mandatory for the full period. For parents, it is not efficient to reallocate investments to the relatively cheaper input schooling. Reallocation does not happen because strong complementarity means that if both investment inputs increase simultaneously, this yields the highest total investment. Increasing only one is not efficient.

Considering policies, this is an essential result since decreasing nutrition prices might increase food diversity and schooling expenditure. However, this depends on how parents react to price changes (e.g., if they reallocate money to another input or spend the money for consumption). For this question, policy counterfactuals are necessary. In general, the

Table 1.2: Estimation results for investment parameters

	Primary school		High school	
Investment elasticity:				
ρ_t	-3.75	(0.86)***	-11.38	(5.11)**
Implied elasticity	0.21		0.08	
Schooling investment productivity $\phi_{s,t}$:				
Constant	-3.68	(0.51)***	-42.17	(16.55)**
Mother primary	1.10	(0.25)***	3.06	(1.32)**
Mother high	1.87	(0.39)***	5.04	(2.15)**
Father primary	0.09	(0.16)	0.63	(0.47)
Father high	-0.08	(0.19)	0.51	(0.50)
Parenting type 1	-0.24	(0.14)*	0.06	(0.34)
Parenting type 2	4.74	(0.97)***	9.62	(4.10)**
Parenting type 3	1.64	(0.50)***	2.47	(1.29)*
Observations 27,366				

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

complementarity of schooling and nutrition is in line with findings that children's test scores increase with the availability of school meals (see Alderman and Bundy (2012), Chakraborty and Jayaraman (2019) and Aurino et al. (2020)). Nutrition increases learning ability; and further increasing both inputs yields higher skills than increasing only one.

Additionally, schooling productivity differences might affect how parents react to price changes. Regarding productivities, Table 1.2 shows how these vary with parenting type and education and Table A.4 for other characteristics. The relative productivity of schooling increases with maternal education, especially in the last childhood period. Thus, schooling is more productive for children with mothers with high school education. Similarly, parenting types 2 and 3 are more productive in schooling. Living in a rural area decreases the productivity of schooling, especially in high school. This magnitude offsets the productivity increase of having a mother with a high school education. Having siblings negatively influences schooling productivity, more so in high school, while not being Muslim increases productivity. By similar magnitude, productivity increases for female children, both are only significant in the high school period. Parents with high productivity will invest a higher share in schooling than parents with lower productivity. Other estimation and calibration results are needed to interpret the results on productivities for policy implications because these enter several spots in total investment prices and investment choices.

These parameters mentioned above describe the total investments parents will supply. To link parental investments to skill, Table 1.3 displays estimation results from the key parameters in Equation 1.5 which quantifies the impact of parental investments and current skills on future skills. The human capital parameter δ_1 describes the impact current investments have on future skills, δ_2 characterizes the impact of current skills.

They are multiplied by the total factor productivity of parents, which varies by their education and the child's age and is characterized by $\phi_{\theta,t}$.

Table 1.3: Estimation results for human capital parameters

	Early childhood		Primary school		High school	
Human capital parameters:						
$\delta_{1,t}$ (investment)	0.28	(0.06)***	0.16	(0.05)***	0.18	(0.03)***
$\delta_{2,t}$ (skills)	0.10	(0.02)***	0.19	(0.02)***	0.22	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.73	(0.08)***	-0.02	(0.12)	-0.22	(0.09)**
Mother primary	0.02	(0.04)	0.06	(0.04)	0.05	(0.02)**
Mother high	0.22	(0.03)***	0.25	(0.04)***	0.16	(0.03)***
Father primary	0.02	(0.04)	0.13	(0.04)***	0.03	(0.03)
Father high	0.11	(0.03)***	0.07	(0.04)*	0.11	(0.03)***
Observations	27,366					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

The human capital parameters, δ_1, δ_2, and the factor productivity vary by period. Looking at magnitudes, investments have a higher impact early in life, with a coefficient size of 0.28, and similar impacts in primary and high school with sizes 0.16 and 0.18. These magnitudes can be interpreted as the fraction of a standard deviation increase in test scores if investments increase by one log point. Thus, investments impact the next period's skills more in early childhood than in other periods. Looking at the impact of current skills δ_2, skill persistence increases over life. In the first period, the current skills have a lower impact on future skills (0.1 in magnitude). However, in the first period, I only used a proxy for cognitive skills, which are health measurements. These parameters are not directly comparable and just indicative in their compared magnitudes. In later periods the persistence of skills ranges around 0.2. This persistence is relatively low compared to other findings in the literature. Cunha, Heckman and Schennach (2010) find a very high persistence of cognitive skills using US data. However, in India Attanasio, Meghir and Nix (2020) find a similar low persistence for cognitive skills at age 8 as I do. They find a higher one at age 12. Indicated by the lower persistence in India and Indonesia than in the US, noisier skills measures might also drive this. The US data uses age-adjusted test scores, which are comparable between waves. They might more accurately display skills. I account for this measurement error but assume that errors are not correlated. Therefore, future work is needed to account for measurement error under weaker assumptions and using data with more precise measures to support the analysis in this paper. In terms of investments, I find higher impacts than Caucutt et al. (2020) and Attanasio, Meghir and Nix (2020). However, these coefficients are harder to compare due to different investment inputs and functional form assumptions. Nonetheless, the findings of Bailey et al. (2017) speak for a lower persistence of cognitive skills, at least when measured in test scores and not underlying intelligence. In the meta-analysis of early childhood interventions, a significant amount of interventions display fading out effects on cognitive skills.

To illustrate the magnitudes, I compute the effect of rising current skills and investments by one unit on future skills. The calculations are visualized in Figure 1.5 for each childhood period. I take average skills and investments as base comparisons for the main calculation. To illustrate what increases of one unit mean for children with low investments, I also calculate the percentage increase for base investments of one. This increase in comparison to current investments of one is higher than in the case of three, leading to a higher growth rate. This is relevant for policies, as it means that for the same costs of one unit of investments, increasing them for the children with low investments will lead to large increases. Adding one unit of investments increases future skills by around 9% in period one and around 5% in later childhood periods. In comparison, from a lower level of investments, adding one unit induces an increase of 20% in the first period and around 12% afterward. In contrast, adding one unit of skills to the current skills in early childhood leads to 6% higher skills in primary skills. Later, the effect of increasing skills by one unit is higher than that of investments, increasing to around 12-15%. Thus, investing early to increase current skills in the next period leads to higher adult skills with lower costs.

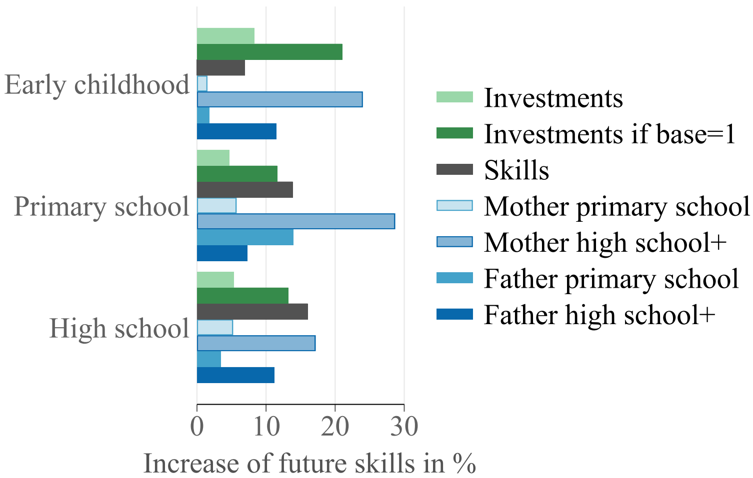


Figure 1.5: Increase of future skills if characteristic/input increases by one unit

Note: Percent increase of future skills if investment or skills increase by one unit. Increases calculated with sample means as base skills (1.01) and base investments (3) if not otherwise indicated. For parental education, the base category for calculation of changes are parents with no schooling.

The total factor productivity (TFP) increases the impact skills, and investments have, as it multiplies with these values. This productivity might vary with parental education. Results in Table 1.3 show that in early childhood, only parents with high school education have a higher TFP, whereas, in later periods, also parents with primary school education do so. While maternal education's impact decreases over childhood, paternal education seems to stay the same in magnitude. The impact of age is negligible. The coefficient sizes translate into percentage differences in the following period skills as depicted in Figure 1.5. Having a mother with a high school education leads to around 25% higher next-period skills in early childhood and primary school and 18% in adulthood. Father's education, in contrast, has a lower impact, around 10%. These differences also magnify investment or skill input changes as they multiply with skills and investments in the skill formation equation (see Equation 1.5). A reason for these high magnitudes could be neighborhood effects, as I only control for rural areas but not more nuanced units (see Chetty and Hendren (2018*a*), Chetty and Hendren (2018*b*)). Parents with high school education might live in districts with better amenities or schools. Similarly, they might send their children to different schools. If the qualities of these schools are not reflected in the differences in fees, I do not capture them separately but with the productivity differences by education. Another explanation might be that higher educated parents play with their children and might have access to toys that encourage learning. Therefore, their children are more efficient in accumulating human capital. Further, this might also be an inherited ability. More nuanced and detailed analyses and a different model are needed to disentangle these potential effects further. Hence, I abstain from framing these further and leave this to future research. In general, the magnitudes of technological differences highlight that even if parents with less education invest the same in their child as a parent with high education, their returns will be lower.

In terms of preference parameters parents vary by education (see Table 1.4). Parents with higher education value cognitive skills less than their lower-educated peers compared to consumption. This is the case for the utility of current skills. Regarding future skills, parents with high education have a slightly higher valuation. In the last period, the total valuation is $\alpha_e \gamma_e$, both parameters multiplied. Given that, the valuation for skills also in the last period of childhood is higher for parents with no schooling than the ones with high school education. Thus, parents with lower education invest less in their children is not driven by their preferences. The preference for assets, ζ, after the child becomes an adult indicates that parents value assets. This parameter is not allowed to vary by education and, therefore, is the same for all groups.

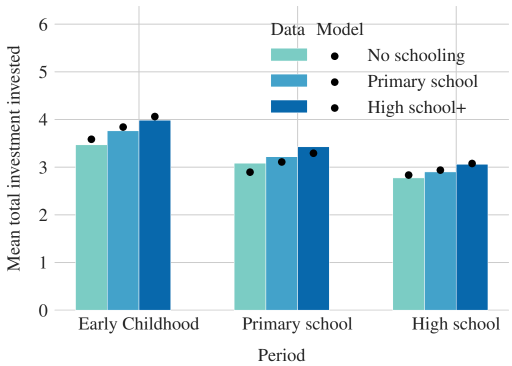
Table 1.4: Calibrated preference parameters

	Parental education:		
	No schooling	Primary school	High school+
For current skills:			
α_e	2.39	1.65	0.98
For final skills:			
γ_e	1.39	1.37	1.46
For final assets:			
ζ	9.99	9.99	9.99

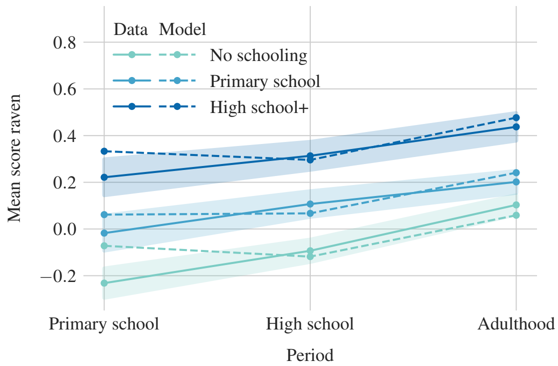
Note: Calibration method used: simulated methods of moments. Moments targeted were investments by parental education and by childhood period.

Regarding their children's skills, if anything, parent's budget constraint or their productivities keep them from investing more in their children. These utility parameters are derived assuming that parents fully know the skill formation process. Dizon-Ross (2019) and Cunha, Elo and Culhane (2020) find that parents with lower education overestimate the impact of their skills and underestimate the persistence of current skills. Thus, they invest less than optimal in this scenario and should invest more. As I do not account for this type of imperfect knowledge in the model, the optimal value is the one observed. Hence, preference parameters are derived for these values indicating the utility derived in contrast to the one from consumption. These parents would invest more without the knowledge barrier, lowering their consumption, and the value for preferences would be even higher. Therefore, the values found here are instead the lower bound of parameters.

Regarding the model fit, I will display first the targeted moments, thus, the moments I match in the simulated methods and moments. Second, I will display untargeted moments, which are not matched in the estimation procedure. Here, I chose the skill formation by parental education group, as these outcome and process is important for policy analysis. Comparing the targeted moments of the model with the data shows that the model does reasonably well (see Table A.5). The model fits the data well regarding investments and untargeted moments for skills, as shown in Figure 1.6. If anything, total investments in the early and primary school periods seem slightly off in the model simulations. Regarding the untargeted moments of nutrition and schooling, Figure A.5 shows the fit. The model fits schooling investment in primary school well and tends to simulate too high levels of schooling expenditure in high school and generally too low nutrition investments in both periods. The gap between parents of different education is fitted well, however. Looking at untargeted moments on raven test scores, I match well the horizontal gap between parents from different education backgrounds. I also fit the gap vertically well between high school and adult skills. In primary school, the levels of skills are slightly off. In Figure A.4, displaying the result for math test scores, the curvature of the skill gap is better captured, but the level for low-educated parents in primary school is still off. As the model's focus is not on early childhood, I concentrate the analysis on policy experiments in primary and high school.



(a) Targeted moments: investments



(b) Untargeted moments: skills

Figure 1.6: Model fit for investment choices and skills by period and parental education
Note: Investment and skill means plotted by parental education and childhood periods.

As these parameters are modeling the skill formation process well, I can now use them to simulate the skill gap by socioeconomic status and for policy experiments. For these, it is vital to keep in mind that they will only use the estimated parameters, thus not capturing behavioral responses which are not modeled. Thus, I will not be able to account for differences in, e.g., school quality or network effects, other than the parts captured by parental education productivities or parenting skill types.

Because of data limitations, I also cannot model time investments - the time parents spend actively with their children - well. In general, Del Boca, Flinn and Wiswall (2014) find parental time to matter most in early childhood and monetary investments in later childhood. Hence, later periods should be less impacted by this modeling choice. My focus is on modeling the whole childhood period, not only early childhood. Thus, more insights on monetary investments can complement the literature by adding results on other investment inputs and the transformation to adult skill outcomes.

Also, I do not observe children in between periods and do not impose assumptions on the inputs in between periods. Therefore, I only model skill development by period and control for the age I observe the child. I abstract from modeling intra-household allocation and investment trade-offs between siblings due to data constraints and complexity, although household poverty might be shared unequally (Calvi (2020)). I account for the number of siblings in the schooling productivity and for the number of children and adult household members in the income estimation. Further, I adjust household consumption with equivalence scales (for details, see Appendix A.3). To limit the impact on the results, I control for household size and amount of siblings in the estimation and calibration. Additionally, I only use food diversity as a measure, not quantity, which is more likely to be impacted by disproportionate sharing.

In this context, gender and ethnic group investment differences might also play a role, as Ashraf et al. (2020) find that Indonesian parents who have the tradition of bride prices invest more in a girl's education after an education policy. I control for gender in the investment function estimations but not in overall levels of investments. I did not find significant differences in education expenditure by gender for groups with bride prize traditions in general. The sample size might drive this null result. In my sample, the share of children who grew up in families with a bride price tradition is not high at 17%. In general, Maccini and Yang (2009) find evidence for investment differences by gender in nutrition allocation in times of hardship in Indonesia. However, these findings are in the context of in utero exposure, a period which I do not model. Nonetheless, future work might extend the analysis and model on this notion to lead to more detailed results.

1.6. Decomposing the skill gap

Using the models, I can quantify how parental socioeconomic background drives the skill gap. To do so, I shut down potential channels one by one in the model and report simulated results in Table 1.5. For simplicity, I compare parents with high school education and parents without schooling. For the drivers, I will start with differences in preferences.

Then I will close technology differences in the skill production function by education. Lastly, I will account for the different levels of income and assets. To do so I will assign parents with no education the parameter values or income of parents with high school education and simulate their choices in this setting

Table 1.5: Skill gap decomposition

	Investment gap (%)	Adult skill gap (std.)
Baseline gap	10.61	0.35
Closing the gap by:		
Preferences	88.94	0.49
+ Investment productivities	103.55	0.53
+ Skill productivities	103.55	0.20
+ Income	15.79	0.05
+ Assets	-0.29	0.00

Note: Gaps indicated are between high school parents and parents with no schooling. Rest of the gap derives from differences in initial skills and prices and survey year.

Preferences for skills are lower for parents with high school education. When I close this gap, parents with no schooling have the same value for cognitive skills as parents with high school education. Given their smaller budget, they will invest less in their children than they do in the status quo. Therefore the investment gap increases to 88.94%. This increase translates into a skill gap of 0.49 SD. If parents with lower levels of education did not value their children's skills more than parents with high school education do, the gap in cognitive skills would be 0.14 SD larger.

The next step is to close the gap in the productivity of schooling. Parents with high school education have higher productivity of schooling than parents without schooling. This productivity leads them to shift inputs toward schooling expenditures away from nutrition, given the same total investment level. Given this shift, their total price of investments increases. This price increase happens because goods are complementary, and increasing one nutrition unit is cheaper than the same amount in expenditure units. This relation is reflected in the total price of investments, which varies for each parent (see Equation A.12). Closing these differences leads to higher prices for parents without schooling, resulting in a bigger investment gap. This gap increases the adult skill gap to 0.53 SD. However, the increase is small compared to one of the other drivers. Another difference is the difference in total factor productivity. This productivity describes the ability to transform current skills and investment into future skills. The higher the productivity, the higher future skills for the same level of investments and current skills (see Section 1.5 for details). Parents without schooling have lower productivity than parents with high school education. Therefore, assigning them the productivity values of the parents with a high school education closes the skill gap to 0.2 SD. It does not change the investment gap, as this productivity does not influence investment levels.

Remaining sources of the socioeconomic skill gap are differences in income and assets. Closing income differences reduces the investment gap to 15.79% and the adult skill gap to 0.05 SD. As this decrease is large, income constraints play a significant role in forming the adult skill gap, which means closing income differences can also have significant effects on future generations. Differences in assets constitute most of the rest of the gap. Leftover differences are marginal and mainly steam from differences in initial skill levels, prices by region of residence, and survey year.

To understand further the dynamics of skill development, I plot in Figure 1.7 changes in the skill gap over childhood periods. In early childhood and high school, income and preference differences contribute more to the gap than in primary school. In contrast, in primary school, differences in productivity are more critical. Herefore, lifting income constraints in early childhood and high school is more effective than in primary school.

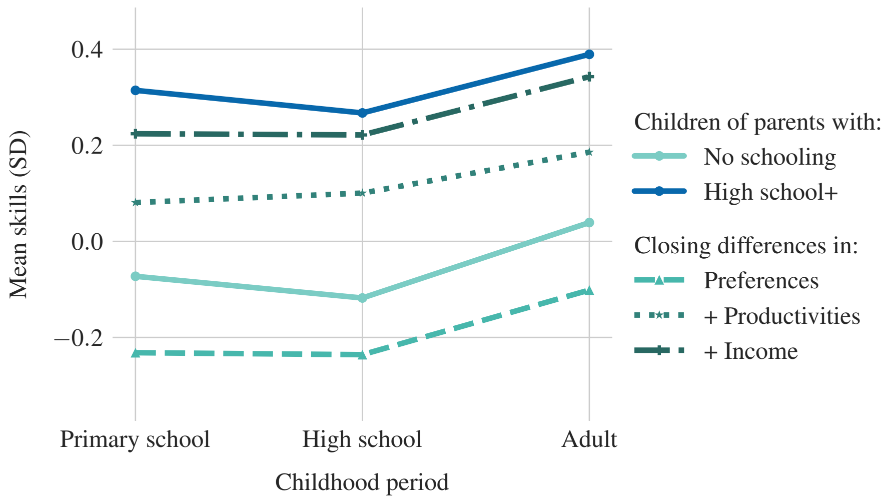


Figure 1.7: Skill gap decomposition

Note: Solid lines represent the existing skill gap between children of parents with no schooling and parents with high school education. Non-solid lines are indicating the skill level of children of parents with no schooling when closing differences in: preferences, productivities and income. To do so, parameters of parents with high school education are assigned to parents with no schooling and skill outcomes simulated.

To compare this with investment gap changes by period, see Table A.7. For investment differences, income plays a significant role in all periods but most in the high school period. This significance for the high school period could be driven by the fact that monetary investments become more critical with time, and schooling gets more expensive in high school. Preference differences magnify in high school, same for differences driven by investment productivities, although those are small in comparison.

Income, preferences, and differences in skill production technology are the main drivers for the skill gag. For policies, closing income differences would have significant effects. Targeting the total factor productivity is more challenging. Increasing parents' education would increase productivity and lead to a smaller skill gap. Doing so would also mitigate large parts of the income differences. Due to model constraints, I cannot speak on targeting differences in total factor productivity apart from increasing parental education.

Changes in these children's environment might mitigate low productivity. As these are not explicitly modeled here, further extensions of this work are needed to give more clear policy implications.

1.7. Policy experiments

I simulate three policies, a nutrition price subsidy, a schooling price subsidy, and an unconditional cash transfer. With these policies, I target the children with parents who are in the 20% lowest part of the income distribution. I first simulate the impact of each of these policies on adult skill outcomes. Second, I simulate the impact of combining them. This means for example, allocating money to a cash transfer and one of the price subsidies. I focus on the last two periods of childhood, thus do not simulate the policies for early childhood as I do not model this period in detail. To ease the comparison of policies, I simulate them to have the same costs.

Given the same costs, the cash transfer has a size of 3% of the mean average income of the lowest 20% of the income distribution. The food price subsidy is around 20%. This subsidy could be implemented using vouchers, which allow parents from the lower part of the income distribution to shop at lower prices. The schooling expenditure subsidy is 99%. This high percentage means that the program pays nearly all the schooling expenditure of the household. One could treat that as a tuition waiver. For costs, I only use the costs I can identify with my simulations. Thus, the monetary amount supplied to households is part of the program's costs but not the implementation costs. This shortcoming needs to be considered to interpret effects. The lack of implementation costs could be especially relevant for the last two policies, as subsidies need a distribution system of vouchers in place and shops which accept them. Further, I do not simulate any other impacts than on cognitive skills and cannot simulate general equilibrium effects. The simulations' results are displayed in Table 1.6.

Table 1.6: Policy counterfactuals - investment and skill change

	Cash transfer	Nutrition subsidy	Schooling subsidy
Change in mean adult skills (SD):			
All targeted	0.00	0.04	0.03
Change in mean investments (%):			
Investments	1.65	16.29	8.87
Nutrition	1.57	15.92	6.80
Schooling	1.46	18.44	90.54
Costs in 100,000 rupees per child:			
Per 0.01 SD increase	1676.02	210.28	288.96
Total amount	7.60	7.60	7.60

Note: Policies are designed to have the same costs (in 100,000 rupees $\sim$ \$7), resulting in a 3% cash transfer, 20% nutrition subsidy and 99% schooling subsidy.

As one can see, the cash transfer has little impact, supporting the conclusion of limited effects of cash transfers on cognitive skills summarized by Molina Millán et al. (2019) and Baird, McIntosh and Özler (2019). A food price subsidy is most effective for the same costs, with an average increase in adult skills of 0.04 SD. A school price subsidy is slightly less effective than a food subsidy, with an increase of 0.03 SD. This result reflects that it is cost-effective to target parental investment behavior via price incentives. By decreasing one input price, both inputs increase in quantity. This behavior is a direct consequence of the complementarity of nutrition and schooling expenditure. The increase in investments is higher than in the case of unconditional cash transfers. Therefore, skill outcomes increase. In general, the input with the price decrease increases more as optimal shares of inputs change due to different prices. Regarding prior findings in the literature, the increase in food diversity with price subsidies complements findings of Kaul (2018) and Krishnamurthy, Pathania and Tandon (2017). These evaluations find a price subsidy in India to increase households food diversity. In contrast Jensen and Miller (2018) do not find any increases in nutrition diversity for a staple subsidy in China. Apart, the evidence on school meals supports my findings. Provision of school meals has been found to increase cognitive skills in several context (see Alderman and Bundy (2012), Frisvold (2015), Chakraborty and Jayaraman (2019) and Aurino et al. (2020)). Additionally, if the healthiness of school meals increases, they yield higher impacts, as found in an intervention in the United Kingdom (Belot and James, 2011). Extending these findings, I further find parents to increase also schooling expenditure, which additionally increases child outcomes.

A detail to note is that total investments into schooling increase little in the schooling subsidy scenario compared to the food subsidy. This behavior is partly driven by period effects. It is most effective for parents to increase investments in high school and less in primary school (see Table A.8). In contrast, with the food subsidy, parents increase mean investments in both periods. The increase in skills in the high school period translates into adult skills with more persistence than in primary school. Therefore, the schooling subsidy is nearly as effective as nutrition, even if investment levels change less on average. In general, the high degree of complementarity between nutrition and schooling investments leads to strong reactions of parents to price changes.

Combining the policies shows that the interventions have no additional increase in skills when jointly implemented (see Table 1.7). Hence, there are no significant dynamic complementarities between these two policies when one considers parental responses. However, parents increase their investments, which leads to bigger costs. The increase in skills is effectively lower though, which which is why jointly implemented policies are not cost-effective even if they maximize impact on investments. It is more cost-effective to implement the nutrition subsidy alone.

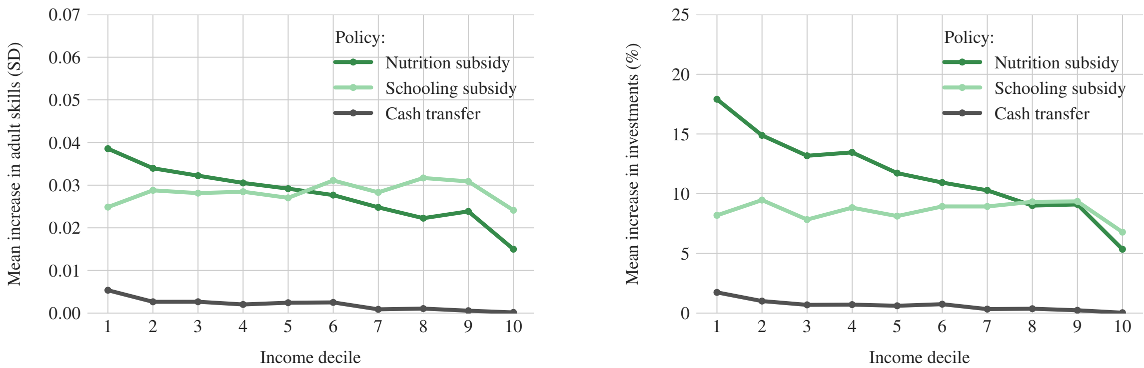
As these policies are targeted toward the lowest 20% of the income distribution, I now extend the analysis to the entire population to see if there are differential effects. To do so, I simulate the described policies for the full sample, and then plot mean effects by income

Table 1.7: Policy combination counterfactuals - investment and skill change

	Cash+ nutrition	Cash+ schooling	Nutrition+ schooling	Nutrition subsidy
Change in mean adult skills (SD):				
All targeted	0.04	0.03	0.06	0.10
Change in mean investments (%):				
Investments	17.55	10.51	26.49	48.17
Nutrition	17.09	8.37	23.94	47.26
Schooling	20.16	93.30	131.66	63.61
Costs in 100,000 rupees per child:				
Per 0.01 SD increase	387.52	483.49	267.80	157.45
Total amount	15.25	15.31	17.31	15.25

Note: Costs are expressed in 100,000 rupees (∼ \$7), combined policies are a 3% cash transfer, 20% nutrition subsidy and 99% schooling subsidy. The nutrition subsidy is 51% to be cost-equivalent to the cheapest combination.

decile (see Figure 1.8). Overall, I find that nutrition subsidies and cash transfer impacts decrease with income. In contrast, schooling subsidy effects slightly increase. In support of the stronger impact of nutrition subsidies on children from poorer households, Aurino et al. (2020) find poorer children to significantly stronger profit from the proposition of school meals in Ghana.



(a) Increase in skills (SD) (b) Increase in investments (%)

Figure 1.8: Policy impacts by income decile

Note: Plotted are mean increases in cognitive skills and investment changes in percent from baseline by income decile for each policy.

Nutrition price subsidies incentivize parents in the lower part of the income distribution to invest more in nutrition. In contrast, parents in the upper part of the distribution react to a lesser extent in increasing their investments. The opposite is true for schooling subsidies. Parents in the lower part of the income distribution are more effective at producing investments with increased nutrition investments and less effective regarding schooling. Consequently, they spend a higher share of investments on nutrition which leads to them reacting stronger to nutrition price changes and a schooling price reduction has smaller effects on children in this part of the income distribution. Additionally, one can observe that unconditional cash transfers mainly increase investments for the lowest part of the income distribution, while later, parents react only marginally in their investments. This pattern indicates that cash transfers can help lift the budget constraint of the ultra-poor. The top parts of the income distribution are not as budget-constrained leading to negligible effects on cognitive skills. Regarding cost-effectiveness, nutrition subsidies still outperform other policies (see Table A.9). Given the differential reaction of parents by socioeconomic status, nutrition subsidies reduce inequality in skills most.

Note, that the average increase of investments for schooling are lower than for nutrition in most cases. However, especially for the top part of the income distribution effects are higher. This is driven by the unequal increase of investments by period. The schooling price subsidy mainly increases investments in high school not in primary school. Skills and therefore also earlier investments have a low persistence, which is why increases in nutrition investments in primary school fade out to some extend until adulthood. Regarding the most disadvantaged, the lowest decile in the income distribution, decreasing costs for nutrition is very effective. Further, for this part of the population, cash transfers have an effect of 0.01 SD on skill development (see Table A.9, rounded to the second decimal). This indicates the stringent budget constraint under which these parents operate.

1.8. Concluding remarks

This paper documents the skill gap for children from different socioeconomic backgrounds in Indonesia. I quantify which drivers contribute to the skill gap in each childhood period: early childhood, primary school, and high school. To do so, I estimate a dynamic structural model of children's skill formation and parental investment decisions on nutrition and schooling. Results show that investments matter, especially in early childhood, and skills become more persistent in later childhood. Nutrition and schooling are complements and more complementary in high school than in primary school.

I explicitly model and quantify drivers of the socioeconomic skill gap among adults and find that parental income and assets contribute to 0.2 SD of the adult skill gap. Mainly, the skill gap is driven by differences in skill production technology by parental education (0.29 SD). These differences are particularly evident in primary school. Importantly, I also find that parental preferences differ across education groups: parents with lower education value their children's skills more than parents with high school education in Indonesia. Thus, the differences in skills are not driven by preferences but mainly by income and skill production productivity. If parents without schooling valued skills like parents with high school education, the skill gap would be 0.14 SD larger than the status quo.

Policies such as nutrition and price subsidies can partly close the skill gap. A nutrition price subsidy targeted to parents in the lowest 20% of the income distribution increases adult skills by 0.04 SD, and a schooling subsidy by 0.03 SD. In contrast, cash transfers have a negligible impact on cognitive skills. If anything, they support the most income-constrained parents investing more in their children. Combining these different policies is not cost-effective. Regarding impacts across the income distribution, the nutrition subsidy increases skills most for the bottom part of the distribution reducing inequality. Similarly, the effects of cash transfers, albeit already small, decline further with income. For the upper part of the income distribution, the effect of subsidizing schooling is higher than the impact of nutrition subsidies. This pattern indicates the stringent budget constraints for the bottom part of the distribution but also that the top part is more effective in utilizing schooling to increase cognitive skills.

Future research could focus on extending the framework used in several dimensions. First, by accounting for information disparities between parents from different socioeconomic statuses and addressing how they influence parents' responses to policies is a potential enrichment of this model. Recent work by Dizon-Ross (2019) and Cunha, Elo and Culhane (2020) shows that parents with lower education are found to overestimate their children's skills and the impact of their investments compared to their peers. They also tend to underestimate the importance of early life investments driven by the persistence of current skills. Closing these information differences could lead to a smaller skill gap. Second, the interplay between time investments and a more detailed modeled first period of childhood and prenatal investment could lead to additional insights into the skill formation process.

Another avenue could be to model intra-household allocation among siblings and the effects older siblings have on the development of cognitive skills of younger ones. Calvi (2020) and Brown, Calvi and Penglase (2021) find household poverty to be shared unequally between household members. Knowing if and which children of the household are most impacted by this and in which setting could have implications for the targeting of policies. With richer data on all household members, dynamics might be uncovered. These dynamics could also play a role in the analysis and targeting of policies.

2. PARENTAL STYLE AND CHILDREN'S SKILL DEVELOPMENT

written jointly with Jacek Barszczewski

2.1. Introduction

Parenting decisions, including parenting style, shape children's skills early on in life and influence their long-run accumulation of human capital. Human capital, represented by cognitive and non-cognitive skills, is a crucial determinant of individuals' well-being, wages, and health (Conti, Mason and Poupakis (2019), Hanushek and Woessmann (2008)). Children from lower socioeconomic backgrounds start to display lower skill levels than their peers early in life, which is widely documented across contexts (Cunha et al. (2006), Heckman and Mosso (2014), Attanasio, de Paula and Toppeta (2020)). The gap emerges in cognitive skills like mathematical reasoning, logical thinking, or language skills, and non-cognitive or socio-emotional skills, which influence how individuals interact with others and navigate social situations. In the long run, these differential development patterns result in lower intergenerational mobility and higher inequality (Attanasio, Meghir and Nix (2020)).

Numerous policies aim to close the skill gap, but to do so, the main drivers behind the skill gap need to be identified. To design effective policies to close the gap, it is crucial to understand when it emerges and in which behaviors and conditions it originates. While factors such as lower investments, initial skills, and, e.g., peers are well documented (see Heckman and Mosso (2014) and Almond, Currie and Duque (2018) for an overview), less is known about the impact of parenting style. Parents' overall approach and pattern of behaviors when interacting with their children can influence their skill development (Doepke and Zilibotti (2017)). How parents establish rules, offer guidance, and respond to their children's needs, behaviors, and emotions might influence children's cognitive and non-cognitive skill development. Child development policies like parenting training interventions have been increasingly used to improve parenting skills. They aim to enhance skill development and close the skill gap between children from different socioeconomic backgrounds. However, to design these interventions more effectively, decision-makers need to know which parenting styles positively impact skill development, which parenting behaviors to target, and at which stages of childhood they are most important.

Answering these questions is challenging, as parents' parenting style might correlate with other characteristics, e.g., initial ability, which influence children's skill development. Additionally, identifying the impact of parenting skills on a child's skill development requires a long-run panel data structure. Surveys collecting detailed data on parenting style dimensions, capturing, e.g., how consistent parents are and how much they explain rules to the children, are rare. In general, the literature has focused so far mainly on other parental investments, such as time or monetary investments (Cunha, Heckman and Schennach (2010), Del Boca, Flinn and Wiswall (2014), Caucutt et al. (2020)). Some papers include parenting style as a factor in skill development but focus on a particular dimension, e.g., if parents interfere with the choice of friends of their children (Agostinelli et al. (2023)). Others like Del Bono et al. (2016), Del Boca, Flinn and Wiswall (2016), Fiorini and Keane (2014), Le Forner (2021) do include broader definitions of parenting style in their estimations of skill production functions. However, they focus on other factors like time investments in the analysis. Therefore, they use a reduced number of parenting dimensions and, due to that, do not explore its multi-dimensionality. However, the effective design of policy interventions requires a better understanding of which parenting dimensions are most influential. If parental warmth is a key determinant, interventions should aim to increase warm behaviours of parents, as hugs for example. Additionally, to model parenting style in skill development, one needs to know if it enters the production function as an input itself or if it rather enhances the productivity of other investments. Finally, extreme parenting styles might disproportionately impact the children's skills, which would suggest a non-linear relationship between those two factors.

Therefore, in this paper we investigate how parenting style influences human capital development in middle childhood and adolescence. We estimate the impact of different parenting dimensions on cognitive and non-cognitive skill development of children. Doing so, we study how parenting style influences skill development and which dimensions of parenting style influence skill development most. Further, we investigate if these relationships are non-linear and test if parenting style influences the productivity of other inputs as time investments (time spend with the child by parents). The analysis provided can help to design parenting training interventions more effectively and be informative for design of models for children's skill formation.

In order to accomplish this, we use data from Australia, the Longitudinal Study of Australian Children (LSAC), supplied by the Australian Government Department of Social Services in collaboration with the Australian Institute of Family Studies. This panel dataset contains observations of approximately 10,000 children from two birth cohorts: one followed from age 0-1 to 14-15 (younger cohort) and the other from age 4-5 to 18-19 (older cohort). The LSAC dataset offers comprehensive longitudinal information on parenting styles and other relevant factors such as time investments and measures of children's skills. Given data availability, we focus on the age range of 8-15.

To measure parenting style, we employ a factor analysis on various survey modules targeting parenting. This approach yields five distinct dimensions of parenting style. Firstly, parental warmth captures how much affection parents express to their children. Secondly, parental reasoning assesses how parents explain rules and consequences to their children. The third dimension, parental hostility, captures how often parents praise the child for positive behavior or react angrily in response to negative behavior. The fourth dimension attempted consistency, evaluates how often parents attempt to reinforce the completion of requests and punishments for non-compliance. Lastly, the fifth dimension, inconsistency, measures how often the child gets out of such punishment. We use Matrix Reasoning (MRT) and Peabody Picture Vocabulary (PPTV) tests to measure cognitive skills. Strength and Difficulties Questionnaires (SDQ) measure non-cognitive skills, which record behavioral, emotional, and conduct-related problems.

To estimate the influence of parenting dimensions on skill development, we exploit the panel structure of the LSAC dataset and the comprehensive range of controls. This approach allows us to tackle potential issues such as unobserved ability and endogeneity. However, it is important to acknowledge that none of the employed models can entirely eliminate all potential biases, given the absence of exogenous variation. Therefore, we carefully analyze the outcomes of each econometric specification to assess if they consistently indicate a significant impact of parenting style on skill development.

In addition, we run several robustness checks to account for different ways of creating parenting style measures and include varying sets of controls. These checks serve to assess the stability and reliability of our estimates. Thanks to that, our analysis can enrich the existing literature and offer valuable insights for future policy interventions or randomized control trials to test these findings further. They might also inform modeling choices for skill formation.

We find a significant negative impact of parental hostility on the development of non-cognitive skills. Specifically, a one standard deviation increase in hostility corresponds to a decrease in non-cognitive skills ranging from 0.12 to 0.35 standard deviations. This finding is consistent across age groups, with increasing magnitudes as children grow older. We observe a comparatively weaker but still negative influence of inconsistency and parental reasoning on non-cognitive skill development. On the other hand, parental warmth leads to small increases in non-cognitive skills. Interestingly, our results indicate that high levels of hostility exert an even greater negative impact on skills, suggesting a non-linear relationship. Notably, we do not find parenting style to influence the productivity of time investments in skills formation. Thus, we can conclude that incorporating parenting style as an additional input in the skill production function is a more accurate modeling approach.

Our study indicates that the connection between authoritative parenting (low hostility, high warmth, consistency, and reasoning) and non-cognitive skill development, as documented in previous research (see Spera (2005) and Doepke and Zilibotti (2019) for an overview), is primarily influenced by low levels of hostility and inconsistency. Parenting warmth and reasoning have only a minor impact. In contrast, for authoritarian parents, the beneficial effect of consistency is outweighed by the negative impact of higher levels of hostility. We additionally document, that parents with lower income display higher levels of hostile and inconsistent parenting, which may contribute to the skills gap between children from different socioeconomic backgrounds in the case of non-cognitive skills. For example, hostile and inconsistent parenting can arise from stress (Sanders and Woolley

(2005), Bloomfield and Kendall (2012) and Hutchison et al. (2016)), which parents with lower income experience to a higher level. As we do not find a parental style to influence cognitive skills, other factors like time investments or school environment might play a bigger role in the development process of these skills.

Our findings show that parental training programs aimed at reducing hostility might be more effective than programs targeting other dimensions of parenting, assuming that parental behavior is equally amenable across dimensions. The results indicate a progressively stronger negative effect on non-cognitive skills with increasing levels of hostility. Therefore, focusing on households where hostile parenting is prevalent may be the most efficient approach to increasing non-cognitive skills. In contrast, we do not find consistent impacts of any parenting dimension on cognitive skills. These findings suggest that if the goal is to increase cognitive skills solely, policy interventions should consider targeting other factors beyond parenting. However, a combined approach may be necessary to increase the overall skill level.

Related literature: As we look at human capital development and how to improve it, our paper links to the literature on skill development. Models as Cunha and Heckman (2008), Cunha, Heckman and Schennach (2010), Attanasio, Meghir and Nix (2020) Attanasio et al. (2020) study how children's skills dynamically accumulate over time along the dimension of health, cognition, and socio-emotional (non-cognitive) skills. Enriching this process with endogenous parental investment choices, Todd and Wolpin (2007), Del Boca, Flinn and Wiswall (2014), Lee and Seshadri (2019), Caucutt et al. (2020), Wiswall and Agostinelli (2020) model how parents decisions influence their children's outcomes. In this context, the listed models abstract from modeling the influence of parenting style and proxy it by parental background characteristics or modeling it as unobserved heterogeneity.

Human capital development models, including parenting style as an additional input in skill formation, are, for instance, Lizzeri and Siniscalchi (2008), Cunha (2015), Del Boca, Flinn and Wiswall (2016), Cobb-Clark, Salamanca and Zhu (2019), Kim (2019) and Falk et al. (2021). These papers build a theoretical framework for including parenting style in the process and empirically support underlying assumptions. They propose to include parenting style as an additional input in the production function, as Dooley and Stewart (2007), Fiorini and Keane (2014), Del Boca, Flinn and Wiswall (2016), Kim (2019) and Falk et al. (2021) empirically show that different styles can have impacts on skill development (mainly non-cognitive skills, but also to some extend educational achievement). Related to Dooley and Stewart (2007) and Kim (2019), we, in particular, analyze the negative effects of hostile parenting/punishment (e.g., angrily shouting), but take a step further and look at these factors in interaction with other parental investments and at different ages to get a better understanding of the skill production function.

Regarding the increasing use of parenting training in combination with early childhood interventions, a deeper understanding of how parental style dimensions influence investment decisions and skill development could give insights into how intervention can be designed more effectively. If a particular dimension of parenting style has a large impact on skill development, it might be most effective to target that dimension if it is malleable. Our analysis aims to enrich the literature by giving new insights on how to model parenting style in children's skill formation process and potentially design interventions more effectively.

Doing so, we link to the literature on parenting style in economics and developmental psychology. In economics, the literature has focused on the impact of different parenting styles following Baumrind (1967) and Maccoby and Martin (1983) like permissive, neglecting, authoritarian, and authoritative style on skill development (see Doepke, Sorrenti and Zilibotti (2019) for an overview). The styles summarize the extent to which parents choose to intervene in their children's behavior. For instance, see Doepke and Zilibotti (2017) who define the following: parents exert a permissive style when they leave children their independence and are supportive but not strict. This is contrasted by an authoritarian style, where parents impose their will through coercion strictly and are not supportive. Parents can instead also be authoritative; which is when they aim to affect the child's choice using persuasion and are strict but supportive. Another category are neglectful parents who are neither strict nor supportive.

Doepke and Zilibotti (2017) find an association between higher educational outcomes and authoritative and, somewhat less extent, permissive parenting compared to neglecting and authoritarian parenting using US data. Distinguishing between authoritarian and non-authoritarian styles of intervening with peer interactions of adolescence, Agostinelli et al. (2023) find that positive impacts of interventions like moving children to better neighborhood are smaller as parents push back on children's new peer groups (if they have an authoritarian styles). This result highlights the importance of investigating the interaction between parenting style and investments of parents as well as children's environment. In contrast to these papers, we do not focus on parenting style as a choice to which extent parents influence children's behaviors. Instead, we would like to determine the components of parenting styles that influence skill development most and should be the target of parenting training. Thus, we study separately parenting dimensions such as parental warmth, reasoning, consistency, and hostility.

This strategy links us to the literature on developmental psychology, which studies parenting styles and their impact on skill development. Also, this literature defines styles using Baumrind (1967)'s categories. However, following Spera (2005) and McWhirter et al. (2023) styles vary in definition slightly from the economics literature. Authoritarian style is described as low in warmth and responsiveness; parents are strict and demanding, expecting obedience, and do not reason for rules. They assert power and use punishment if a child misbehaves and score high on control. The authoritative style is characterized by warmth, responsiveness, high reasoning, demandingness, and scoring high on control. In contrast, neglecting/indulgent parents score low on responsiveness, warmth, and control, and permissive ones moderately in responsiveness, low on control, and high on warmth while they are not demanding.

The literature finds authoritarian and neglecting styles negatively associated with non-cognitive skills. In contrast, the authoritative style has a positive association, confirming Doepke and Zilibotti (2017)'s results (see Spera (2005), Fletcher et al. (2008), García and Gracia (2009), Luyckx et al. (2011), Howenstein et al. (2015) and McWhirter et al. (2023)). However, most papers suffer from small sample sizes and do not use panel data. By exploiting a large longitudinal survey, we can leverage the panel data structure to provide a more structured analysis of different components of parenting style. Doing so allows us to correct for unobserved factors which could confound the analysis, like a parents' selection of a certain parenting style due to their initial ability, which also impacts children's skill outcomes. To enrich the existing literature, we also look at the interaction of parental investments with parenting styles and the potentially non-linear relationship between parenting styles and children's skills.

Looking at the context of Australia, we analyze the impact of different dimensions of parenting style and their interaction with investments in children's skill development in high-income countries. Other papers have studied skill development in this context using the LSAC data[12]. Fiorini and Keane (2014) and Le Forner (2021) focus on the impact of time investments on children's skills, similar to the analysis of Del Bono et al. (2016) for the UK. Summarizing different parenting style components using principal component analysis, they find parental warmth and authoritarian style to influence non-cognitive skills, while time investments do not. Building on their results, we complement the literature by analyzing different components of parenting style, the interaction with investments, and a larger sample. Additionally, we extend the analysis by looking at a longer period, spanning middle childhood, an often understudied period in child development (see Almond, Currie and Duque (2018)). This could give additional insights on when to best implement parenting training interventions and when their impact is best measured.

The rest of the paper is organized as follows. In Section 2.2, we describe the data used and present relevant empirical facts on parenting skills and skill development in Australia. Next, we introduce the empirical framework in Section 2.3. In Section 2.4, we discuss results, followed by concluding remarks and ideas for future research in Section 2.5.

2.2. Data

2.2.1. Data sources and construction

The Longitudinal Study of Australian Children (LSAC) is a biannual survey following two cohorts of Australian children since 2004. The older cohort ("K cohort") was born between March 1999 and February 2000 (4,983 children), and is followed from age 4-5 to

[12]Australian data in child development, as the LSAC and LSIC (Longitudinal study of Indigenous children) data sets have been used to study in particular non-cognitive skill development due to the richness of their measures. For instance, Guy et al. (2016) and Twizeyemariya et al. (2017) study the occurrence of mental health risks for Australian children, while Christensen et al. (2017) study the impact of these risk factors on non-cognitive skills over time.

18-19. The younger cohort ("B cohort") is born between March 2003 and February 2004 (5,107 children) and followed from age 0-1 to 14-15. Both cohorts were surveyed biannually from 2004 to 2020. The survey collects information about the children and their parents, along with measures of child development, including cognitive and non-cognitive skills. The advantage of the LSAC data set is that it combines detailed information on parenting styles with time-use diaries and children's skills and demographics. This feature allows a rigorous analysis of the impact of parental styles on children's skill outcomes taking into account other parental investments like time spent with the child. Additionally, interactions between parenting styles and time investments can be investigated, and the impact on different types of non-cognitive skills can be compared across different ages. In particular, the richness of the parenting style questions allows us to explore different dimensions of parenting style and their impact.

For the analysis, we pool both cohorts together and compare their outcomes at the same ages. Therefore, we estimate impacts in age groups consisting of two years: ages 8-9, 10-11, 12-13, 14-15, and 16-17. As the survey is conducted biannually, this is the most granular level possible. In our main analysis, we exclude outliers and restrict the sample to observations with available skill measures, parenting style, time investments, and necessary control variables.

Non-cognitive skills

The LSAC measures non-cognitive skills by a strength and difficulties questionnaire (SDQ) filled out by parents for children aged 6-15.[13] The SDQ consists of 25 questions covering five subjects: emotional health, behavioral problems (conduct), hyperactivity issues, peer problems, and pro-social behavior. Following Goodman, Lamping and Ploubidis (2010) and Le Forner (2021), one can summarize these subjects into four broader indexes. The indexes are emotional skills (internalizing SDQ), behavioral skills (externalizing SDQ), and pro-social skills (social SDQ). Behavioral skills capture behavioral problems and hyperactivity issues. In contrast, emotional skills entail questions about emotional health and peer problems. Finally, pro-social skills are the index for pro-social behavior. Behavioral and emotional skills can be summarized to the total SDQ as an index.

To keep results tractable, we restrict our analysis for now to one index and follow Le Forner (2021) in using the total SDQ, which is the sum of behavioral and emotional skills. By doing so, we intend to capture non-cognitive skills in their various dimensions in one index. We standardize this measure by age group to facilitate the interpretation of estimated coefficients and comparability across different age groups.

[13] The survey also collect information from teachers. We use only the parental assessments in the analysis. The teacher questionnaires suffer from missing information, which is why we abstract from using them.

Cognitive skills

We use two measures for cognitive skills which are available in the LSAC. Firstly, the Peabody Picture Vocabulary Test (PPVT) which measures children's knowledge of the meaning of spoken words and their receptive vocabulary. The PPVT is adjusted to age in terms of difficulty and administered in the survey for children aged 4-5 years, 6-7 years, and 8-9 years. To conduct the test, children are shown 40 plates of pictures in a PPVT stimuli book and told a word to which they were required to choose the picture which best represents the meaning of the word. They could do so by pointing a picture or saying the number of a picture. Test scores are calculated using Rasch Modelling to ensure changes in scores relate to real changes in knowledge not changes in position relative to peers. As the test is only administered up to age 9, we cannot compare the outcomes to older age groups.

The second measure available in the LSAC is a Matrix Reasoning Test (MRT). This test was administered to children at ages 6-7 years, 8-9 years and 10-11 years. The test is a nonverbal intelligence test consisting of 35 items of increasing complexity. Each item is an incomplete set of diagrams, and the child is required to complete the set from five different options. The test score is the number of correct responses, the child gave, scaled based on age norms (determined in the WISC-IV manual). As the test is only administered up to age 11, we cannot compare the outcomes to older age groups. Therefore, we mainly focus on non-cognitive skills when comparing coefficients over childhood. As there are no measures in the survey beyond age 11, we have to restrict the analysis to that age group for cognitive skills. We standardize both cognitive measures by age for comparability and interpretation facility.

Parenting style

The survey collects information on both parents and their behaviour towards the child. Parenting questions are consistently asked across waves in four different areas: hostile parenting, parental warmth, consistent parenting and inductive reasoning (see appendix Table B.1 for a more detailed description of each subgroup). We abstract from using other available information, which is not consistently available across waves to avoid not comparable measures and use the information available for the principal care giver. Following Fiorini and Keane (2014), Del Bono et al. (2016) and Le Forner (2021), we use factor analysis to derive dimensions of parenting style using the survey information. Given, that we conduct a detailed analysis of parenting style, we keep as many dimensions as possible. In contrast to Fiorini and Keane (2014) and Le Forner (2021), who also use the LSAC data, we do not pool parenting questions together to get as least factors as possible. As our paper focuses on the impact of parenting style on skill development and not on time investments, we investigate how the different components influence skill development to isolate which dimension to target in parenting training. Therefore, we conduct a separate factor analysis for each of the four areas as we would like to analyse each dimension of parenting style. We conduct this analysis wave by wave. We retain factors with eigenvalues larger than 1 and factors are rotated. As for inductive reasoning, at age 4-5 and age 6-7 only 2 respectively 3 of the 5 questions asked in other waves are included, we use only those available in those waves.

Table B.2 shows the rotated factor loading coefficients of the principal component analysis for each measure and each wave. Factor loadings which are larger than 0.25 in absolute value are displayed in bold. The principal component analysis for each measure leads to one factor pooling all sub questions (eigenvalues>1). Only for the measure consistency two factors are needed to summarize the variation. The first factor can be described as inconsistent parenting style, the child gets out of punishment or ignores it. The second factor captures if parents attempt to make the child fulfill requests and attempt to punish it if not. We will call this factor: attempted consistency. Factor loadings are stable across waves, except for parental consistency in wave 3, here only one factor is needed to describe the variation (inconsistency). Hence, we conclude that measures are comparable across waves despite for consistency in wave 3.

Later in the analysis, we interact parenting style with investments to determine if parenting style influences the impact of investments and if there is a quality-quantity trade-off. To do so, we summarize the variation in dimensions of parenting style in additional factor analysis in the style of Diamond (2016). We do so to minimize the number of necessary interactions. Doing so, we proceed as before; results of the factor analysis are displayed in Table B.3. We find that two factors are needed to summarize the variation in parenting styles (except for wave 3 with one). Factor one can be described as loading on parental warmth, reasoning, and attempted consistency. Factor two loads on hostility and inconsistency. From wave 6, the assignment of these factors switches, so factor two loads on parental warmth, reasoning, and attempted consistency, and factor one on hostility and inconsistency. To keep consistency across waves, we frame factor 1 for the age group younger than 14 and factor 2 for the age group older than 14 as an empathetic parenting style (warm, reasoning, and attempted consistency). Factor 2 for the age group younger than 14 and factor 1 for the age group older than 14 are framed as harsh parenting (hostile and inconsistent). Similarly to the dimensions of parenting styles, the loadings for parenting styles are fairly consistent across waves except for wave 3.

Time investments

In the LSAC dataset, Time Use Diaries (TUD) are utilized to gather data on children's activities. The data collection process involves two methods. For cohort K, spanning three waves (ages 4-9), and cohort B, also across three waves (ages 0-5), data is collected over two 24-hour periods, typically one on a weekday and another on a weekend day. The information is recorded on paper diaries, divided into 96 15-minute intervals, which parents fill out. Parents select the activity, location, and individuals involved from a predefined set of options.

For cohort K, spanning three waves (ages 10-15), and cohort B, also across three waves (ages 10-15), children themselves become the informants (with support from the interviewer). Furthermore, the Time Use Diaries undergo significant changes. Instead of paper diaries, data is now collected using a computer instrument. Additionally, the time span of activities is not limited to 15-minute intervals. Moreover, activities are recorded only on a single day of the week, either a weekday or a weekend day. However, similar to the previous version, children complete the diary by selecting the activity, location, and individuals involved from a predetermined set of options.

To analyze the effect of parental time investment on children's cognitive and non-cognitive skills, we aggregate the recorded activities into five main groups:

1. Educational activities with parents
2. Educational activities with adults other than parents
3. General care with parents
4. General care with adults other than parents
5. Other time

Since time investments are not the focus of our analysis, we follow the aggregation rules established by Fiorini and Keane (2014) and Le Forner (2021) to group activities. It is important to note that the set of alternatives may change over time, but the primary divisions between educational, general care, and other activities remain consistent across different survey waves. In cases where multiple activities are reported simultaneously, we prioritize the primary activity. If information about the activity is missing, we assign it to the category other time. This ensures that the total time spent on activities always sums up to 24 hours. Regarding time spent with adults other than parents, we only consider it if the activity was conducted with adults while parents were not participating. If parents were involved in the activity, it is classified as time spent with parents.

The two methods of TUD collection differ in terms of the days of collection. For these waves, when TUDs were collected on both weekdays and weekends, we calculate a weighted average for each time input. Weekdays are assigned a weight of 5, while weekend days are assigned a weight of 2. However, for the remaining waves, data collection was conducted on a single day only. As a result, in all regressions, we include dummy variables to indicate whether the record was on a weekday, weekend day, or an average of both diaries.

2.2.2. Demographics

Table 2.1 shows statistics for main descriptive characteristics of the sample population across different age groups. The age groups range from 4-5 years to 14-15 years. In terms of child characteristics, the table shows that approximately half of the children are female. The percentage of indigenous children is relatively low and stays constant across age groups. The percentage of children living with both parents decreases with age, because parents may separate or divorce as the child grows older, leading to the child living with only one parent or transitioning between households. Additionally, around half of the children belong to cohort K.

The proportion of primary caregivers with a college education increases slightly over time, which suggest that parents with higher education tend to drop less from the sample. However, it might be also that some parents acquire higher education in the process. The household characteristics indicate that the average number of children under 18 in the household ranges from 1.51 to 1.66. The vast majority of households lives in urban areas.

Table 2.1: Demographic characteristics of the sample

	Age					
	4-5	6-7	8-9	10-11	12-13	14-15
Child:						
Gender	0.49	0.49	0.49	0.49	0.48	0.49
Age	4.22	6.32	8.34	10.38	12.45	14.38
Indigenous	0.04	0.04	0.04	0.04	0.03	0.03
Living with both parents	0.82	0.79	0.76	0.73	0.72	0.69
Born early	0.07	0.07	0.07	0.07	0.07	0.07
Older cohort (K)	0.51	0.51	0.51	0.51	0.51	0.51
Primary caregiver:						
Age	34.83	36.95	39.04	41.10	43.27	45.31
College education	0.27	0.27	0.27	0.27	0.29	0.29
Household:						
Number of children	1.51	1.61	1.66	1.65	1.63	1.55
Weekly income (in AUD)	1,486	1,667	1,918	2,027	2,214	2,257
Urban	0.87	0.87	0.86	0.86	0.86	0.87
Observations	9,285	8,632	8,343	7,858	7,215	6,607

Note: All means calculated using population weights.

2.2.3. Facts on parenting styles and income

Composition of parenting styles and their association with skills

Given the survey information and results of the principal component analysis, we can look at several dimensions of parenting: parental warmth, hostility, attempted consistency, actual inconsistency and reasoning. Parenting warmth expresses how much parents hug their child, show affection and feel close to the child. Parental hostility describes if the parents rarely praise the child and often disapprove their behaviour, react angry while punishing them. Parents scoring high on attempted consistency often make sure the child completes their requests and punish the child if they do not. Inconsistency then describes, how effective parents are in punishing, thus, if the child gets away from punishment. High values mean parents are not often enforcing their punishments. Lastly, reasoning captures how often parents explain rules and the consequences of the child's behaviour (see Table B.1 for details).

As the literature tends to summarize these dimensions into parenting styles (patterns occurring across parents), we look at their correlation in Table 2.2. Parental warmth and parental hostility are negatively correlated, while warmth positively correlates with reasoning. Attempted consistency is also positively correlated with reasoning, but the magnitude of the correlation coefficient is smaller. In contrast, hostility is positively correlated with inconsistency. Other correlation coefficients are relatively small. By construction, attempted consistency and inconsistency are not correlated, as they originate from the same factor analysis. Overall, the correlations are not very high, suggesting the multi-dimensional character of parenting styles.

Table 2.2: Correlation between parenting dimensions

	Parental warmth	Parental reasoning	Hostile parenting	Attempted consistency	Inconsistent parenting
Parental warmth	1.000				
Parental reasoning	**0.492**	1.000			
Hostile parenting	**-0.385**	-0.047	1.000		
Attempted consistency	0.128	**0.310**	0.036	1.000	
Inconsistent parenting	-0.134	-0.031	**0.442**	0.000	1.000

Note: Displayed are correlation between different dimensions of parenting styles in the data (exemplary for age group 8-9). Statistics are calculated using population weights.

To compare these dimensions and their correlations with the parenting styles in the literature, we classify the dimensions into styles following Baumrind (1967) and Maccoby and Martin (1983) (see Spera (2005) and McWhirter et al. (2023) for an overview). This classification encompasses four styles:

1. Authoritarian: low warmth and reasoning, high consistency and hostility
2. Authoritative: high warmth, reasoning, and consistency, low hostility
3. Permissive: high warmth, low consistency, and hostility
4. Neglecting: low warmth, reasoning, consistency, and hostility

Regarding the described correlations, the positive association of parental warmth and reasoning indicates patterns of an authoritative parenting style. High hostility would indicate an authoritarian parenting style; however, low consistency does not apply to that and could rather speak of a neglecting style. Let us compare these to the factor analysis summarizing dimensions into parenting styles. We mainly find the variation to describe an authoritative parenting style for the first factor (see Table B.3). Values are high for parents loading on warmth, reasoning, and attempted consistency. Parents scoring low on this factor could be described as neglecting. In contrast, the second-factor loads on hostility and actual inconsistency, which could speak for an authoritarian style. Permissive would be described by loading on the first and second factors jointly, offsetting the hostility in the second factor.

We investigate parenting style dimensions since they are associated with skill outcomes. In our data, this association mainly holds for non-cognitive skills rather than for cognitive ones. We present scatter plots with fitted lines for non-cognitive skills and each dimension of parenting style in Figure 2.1 and for cognitive skills in Figure B.1. Visibly, non-cognitive skills positively correlate with parental warmth and negatively with hostility and inconsistency. For cognitive skills, there is a weak negative correlation with inconsistency. These patterns hint at which factors might parenting training should particularly target.

However, it is important to consider that other factors may also drive these associations. Therefore, our empirical strategy aims to establish a more structured and informative relationship. For instance, the income and education levels of the parents could influence their parenting style. Financial stress, for example, may lead to increased hostility or inconsistency as parents may lack the time, patience, or capacity to enforce rules in a non-angry manner. Additionally, the number of siblings or the gender of the child could act as confounding factors. By accounting for these potential confounders and employing a rigorous empirical approach, we can better understand the nuanced relationship between parenting style dimensions and skill outcomes.

Parenting styles and income

Children from lower socioeconomic backgrounds display lower skill levels than their peers (Cunha et al. (2006), Heckman and Mosso (2014), Attanasio, de Paula and Toppeta (2020)). This skill gap is widely documented across contexts and applies to cognitive and non-cognitive skills. Numerous policies aim to close it, but to do so the main drivers behind this gaps need to be identified. To design effective policies to close the gap, it is crucial to understand when it emerges and in which behaviours and conditions it originates in. While factors as lower investments, initial skills and e.g. peers are well documented (see Heckman and Mosso (2014) and Almond, Currie and Duque (2018) for an overview), less is known on the impact of parenting style. For instance, Cobb-Clark, Salamanca and Zhu (2019) find a monitoring parenting style, so for instance knowing where the child goes after school, to be negatively correlated with socioeconomic disadvantage. If parenting styles vary systematically by income or education, it might contribute to the skill gap and be a driver for inequality in children's skills. For example, hostile and inconsistent parenting can arise from stress (Sanders and Woolley (2005), Bloomfield and Kendall (2012) and Hutchison et al. (2016)), which parents with lower income experience to a higher level. Therefore, they might have an on average higher score on hostility, which is negatively associated with non-cognitive skills.

We examine if the distribution of parenting styles in Australia varies by income and

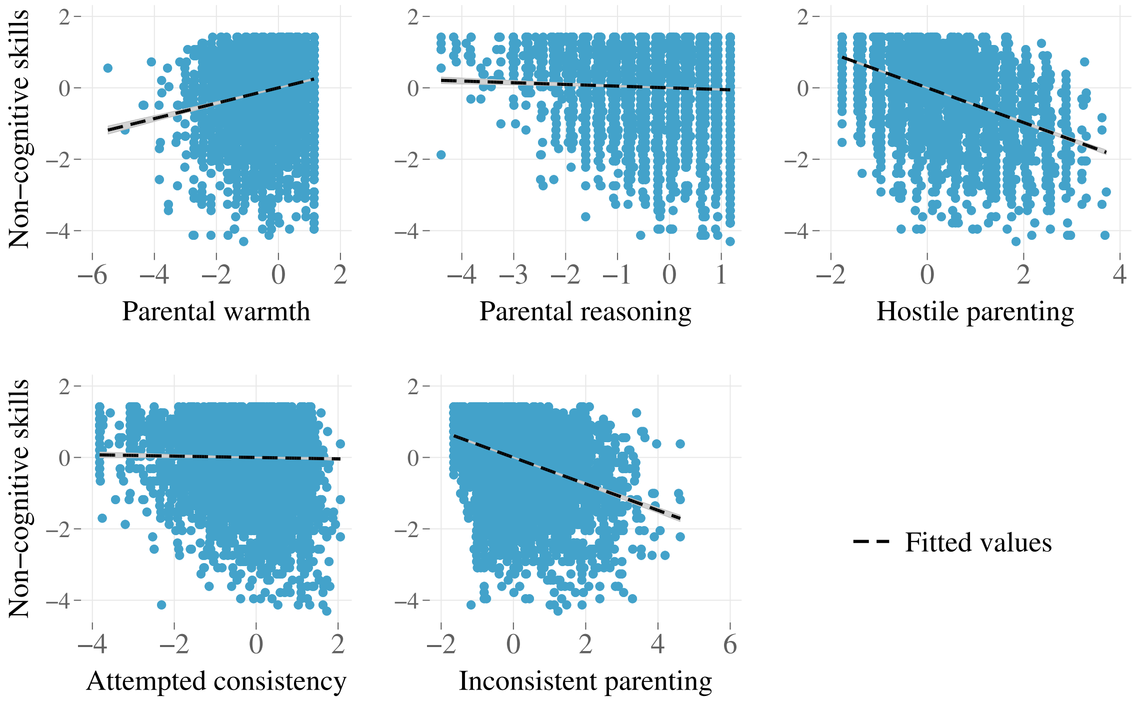


Figure 2.1: Correlation of parenting dimensions with non-cognitive skills

Note: The figure displays the relationship between non-cognitive skills (measured by the SDQ test) and different parenting styles. Each data point represents a child from the 8-9 age group. In addition to the data points, a line is plotted on the graph, which represents the fitted values based on a linear regression analysis. The line slope is estimated using population weights.

education. To do so, we estimate the kernel density of parenting dimensions for different household income groups (the 1st, 3rd, and 5th quintiles) and the primary care gives education level (college and non-college). Figures 2.2 and B.2 illustrate these distributions. Regarding Figure 2.2, our analysis reveals notable differences in parenting styles across income quintiles. Parents in the lower segment of the income distribution are more likely to display high hostility and inconsistency compared to their counterparts in higher income quintiles. Simultaneously, parents with lower income on average show lower warmth, reasoning, and attempted consistency levels. Furthermore, the distributions of parenting dimensions for parents in the 3rd and 5th income quintiles are pretty similar. However, parents in the 3rd quintile demonstrate a slightly lower tendency to persist in establishing consistency. They also have a higher likelihood of exhibiting inconsistency.

Based on Figure 2.1, hostility and inconsistency are associated negatively with non-cognitive skills. Moreover, parenting styles are correlated with income. Thus, the difference in parenting styles might drive a part of the skill gap between children from different socioeconomic backgrounds. As the distribution of parental consistency measures varies the most by income, these might be a parenting dimension that mainly contributes to the observed skill gap between the bottom and the top parts of the income distribution.

To investigate this, one needs to control for selection into parenting style and other confounding factors such as parental investment decisions.

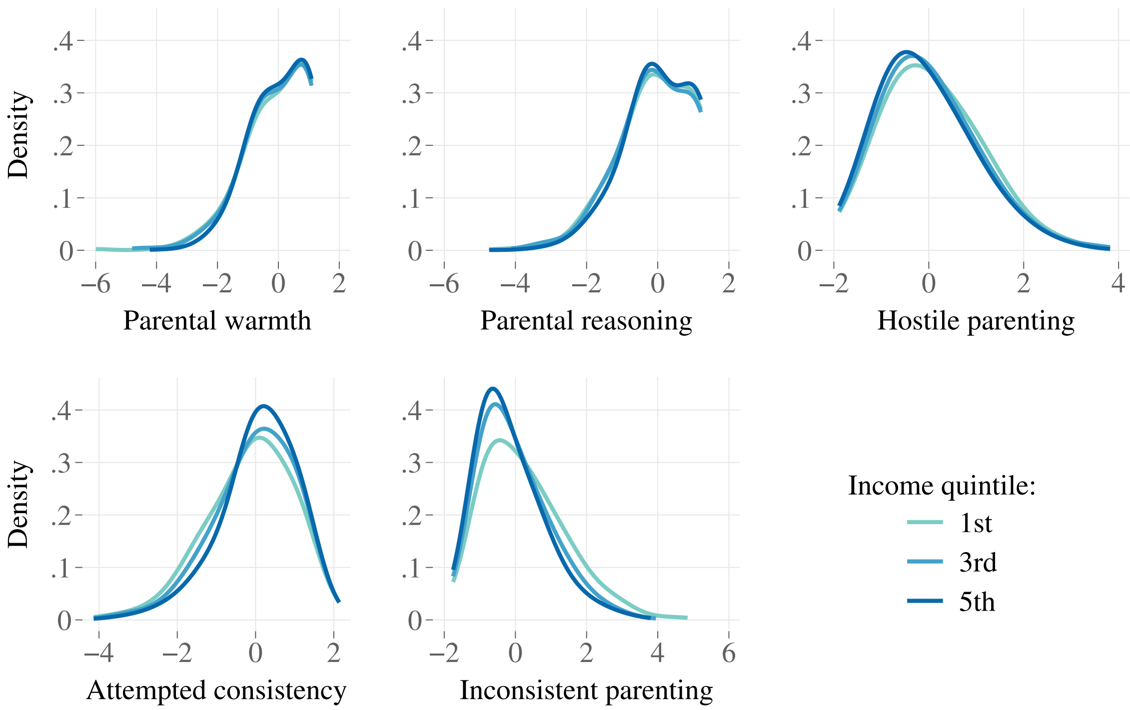


Figure 2.2: Distribution of parenting dimensions by household income

Note: The figure displays the empirical distribution (smoothed using the kernel function approach with population weights) of different parenting styles by income quintile for children aged 8-9.

Turning to another socioeconomic status factor, primary caregivers' education, the variation in parenting skills is lower. Parents mainly vary in their level of consistency by education (see Figure B.2). Primary caregivers with college degrees are likelier to have consistent parenting levels than those without college. College-educated parents tend to display higher warmth and reasoning. Differences in hostility are minimal. These factors could contribute to children with lower socioeconomic status lagging in skills to their peers, especially regarding non-cognitive skills. Nonetheless, these are pure correlations, and we will use our estimation strategy to disentangle the effects.

2.3. Empirical framework

In this section, we outline the empirical strategy employed to estimate the impact of parenting styles on cognitive and non-cognitive skills. First, we assume the production function of children's skills to take the following form:

$$Y_{ia} = F_a(Z_{ia}, Y_{i0}) + \epsilon_{ia} \tag{2.1}$$

where Y_{ia} is a skill measure for child i at age a, and F_a if an age-specific function transforming production inputs Z_{ia} and the measure of child's initial skills edowement Y_{ia} into the skill level at age a. Production inputs Z_{ia} entail a vector describing past and current parenting style dimensions PS, time investments TI (educational and care time spent with parents and others, and another time spent (i.e., on sleep or socializing), and other parental and household characteristics X up to age a which influence skill development.

To estimate the production function expressed in Equation 2.1 we use the approach of Todd and Wolpin (2003, 2007), applied by Aurino, Fledderjohann and Vellakkal (2019), Fiorini and Keane (2014), Del Bono et al. (2016) and Le Forner (2021). In contrast to these papers, we focus on the impact of parenting style dimensions, rather than time investments or food insecurity, to determine the impact on skill development. Estimating Equation 2.1 without controlling for all inputs and initial endowment can lead to biased estimates due to endogeneity and selection. There are three sources of bias. Firstly, omitted variables can lead to biased estimates if correlated with independent variables. An example could be omitting past investments, which could be related to current ones, and both matter for skill development. Additionally, parents might select into certain parenting style (e.g., driven by education), which directly influences the child's skills and the choice of parenting style. Then, without controlling for education, the coefficient of parenting styles might be biased. Secondly, reversed causality might play a role. Parents might adjust their investments due to skill outcomes, compensating, for example, low skills with higher investments. Thirdly, measurement errors in skills and investments can bias results.

Each of the specifications we employ deals with some of these biases. While presenting different specifications, we thoroughly discuss their results and limitations to draw conclusions on underlying relationships. However, given data constraints, none of the estimation strategies can solve all estimation issues. As a result, in the absence of a dominating specification, we use a set of strategies to establish an estimator-robust direction of parenting skills and time input impacts on a child's skill development. To do so, we proceed with the following:

1. Estimate the impact of different parenting dimensions on skill development
2. Identify if there is a quantity-quality trade-off between time investments and parenting style
3. Estimate if time investments have differential impacts depending on parenting style
4. Estimate if parenting style impacts skills in a non-linear way

In the next paragraphs we detail on each step of the estimation strategy. For the first step, we are going to use the set of six econometric models to estimate the impact of parenting dimensions for which we are going to discuss identifying assumptions. Our main specification takes the following form:

$$Y_{ia} = \alpha_a + PS'_{ia}\delta_a + TI'_{ia}\gamma_a + R'_{ia}\rho_a + \epsilon_{ia} \tag{2.2}$$

where current skills Y_{ia} depend on current parenting style PS_{ia} and time investments TI_{ia}. Further, R_{ia} describes all other relevant inputs, not including current parenting style and time investments. This term could entail initial endowment, past investments, and other observable characteristics.

In terms of econometric models, we start with the most simple model, the contemporaneous linear model (OLS):

$$Y_{ia} = \alpha_a + PS'_{ia}\delta_a + TI'_{ia}\gamma_a + X'_{ia}\beta_a + \epsilon_{ia} \tag{2.3}$$

where current skills only depend on current parenting style PS_{ia}, time investments TI_{ia}, and characteristics X_{ia}. Household characteristics in our base specification are the age of the primary caregiver, the number of siblings, the log of family income and dummies for college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the child, the study child's cohort, and the day of data collection. This specification is only unbiased if production inputs are constant over time. Then, the current values can summarize the whole history of production inputs. Further, the current inputs are uncorrelated with, for instance, the permanent unobserved ability of parents, or temporary shocks, which would be captured by the error term ϵ_{ia}. Additionally, current characteristics X_{ia} need to proxy well for the innate ability Y_{i0} in Equation 2.1.

To control for innate ability and past investments we add lagged skill measures to the estimation, employing a Value Added model (VA) as a second model:

$$Y_{ia} = \alpha_a + PS'_{ia}\delta_a + \lambda_a + TI'_{ia}\gamma_a + X'_{ia}\beta_a + Y_{ia-1} + \epsilon_{ia} \tag{2.4}$$

This model is based on the assumption that the past period's skill outcomes Y_{ia-1} capture the impact of past investments and innate ability with rate λ_a. Additionally, to be unbiased, all current investments that respond to past skills must be part of the estimation. Further, if Y_{ia-1} is measured with a measurement error correlated with the one of Y_{ia}, this might exacerbate measurement error bias.

Another way to control for unobserved ability is using fixed effects (FE), our third model:

$$Y_{ia} = \alpha_i + PS'_{ia}\delta + TI'_{ia}\gamma + X'_{ia}\beta + \epsilon_{ia} \tag{2.5}$$

where α_i is a child-fixed effect. This approach assumes that the fixed effect captures the child's innate ability and other time-invariant influences as parents' ability. However, this estimation strategy only leads to unbiased estimates if the impact of these time-invariant factors is constant across ages. Additionally, past investments do not influence current skills after controlling for innate ability or do not correlate with current investments like parenting style or innate ability. Another assumption is strict exogeneity: past, current, and future inputs are not correlated with past, current, and future errors.

To allow for influence of past investments on current skills, we extend the FE framework by controlling for lagged skills. This gives us the fourth model (AB):

$$Y_{ia} = \alpha_i + PS'_{ia}\delta + TI'_{ia}\gamma + X'_{ia}\beta + \lambda Y_{ia-1} + \epsilon_{ia} \tag{2.6}$$

We estimate this model using a GMM estimation that uses all available exogenous variation in estimation proposed in the seminal paper of Arellano and Bond (1991). This allows us to relax the strict exogeneity assumption required for the fixed effects model. The Arellano-Bond estimator introduces a weaker assumption, the orthogonality condition, which states that the lagged skill measure is uncorrelated with the error term after controlling for the lagged production inputs. This means that the lagged skills can be used as an instrumental variable to address the endogeneity issue caused by the presence of lagged skills in the model.

Another approach is to control for all past inputs, which gives us the fifth estimation strategy, the cumulative model (CU):

$$Y_{ia} = \alpha_a + \sum_{t=0}^{a} PS'_{ia-t}\delta_{at} + \sum_{t=0}^{a} TI'_{ia-t}\gamma_{at} + X'_{ia}\beta_a + \epsilon_{ia} \tag{2.7}$$

This specification controls for all available past inputs, however, not for innate ability. Therefore, the assumption is that either innate ability is uncorrelated with past and current inputs or captured well by past investments. To control for innate ability in the sixth and last specification, we again add lagged skill outcomes. This gives us the cumulative model with lagged inputs and skills (CV):

$$Y_{ia} = \alpha_a + \sum_{t=0}^{a} PS'_{ia-t}\delta_{at} + \sum_{t=0}^{a} TI'_{ia-t}\gamma_{at} + X'_{ia}\beta_a + \lambda_a Y_{ia-1} + \epsilon_{ia} \tag{2.8}$$

This model relies on the assumption, that all investments are controlled for as otherwise they might be in the error term and bias coefficients of interest. Additionally, measurement error in skills, might effect results and the assumption is that innate ability influences skills at rate λ_a.

After running these models for the main specification in Equation 2.2, we proceed by the following specifications with the same subset of econometric models. Firstly, that is the main specification but only with time investments, to see if they alone can explain skill development and how magnitudes change with adding parenting style to the equation to see if results are robust:

$$Y_{ia} = \alpha_a + TI'_{ia}\gamma_a + R'_{ia}\rho_a + \epsilon_{ia} \tag{2.9}$$

Secondly, we run a specification including interaction terms between current time investments and parenting style, to see if time investments have differential impacts depending on parenting style and if there is a quantity-quality trade-off:

$$Y_{ia} = \alpha_a + PS'_{ia}\delta_a \times TI'_{ia}\gamma_a + +R'_{ia}\rho_a + \epsilon_{ia} \tag{2.10}$$

Using interactions between five initially defined parenting styles and four time investments would result in many interaction terms (20 in total). It can lead to statistical inefficiency and potential collinearity issues. Further, the high dimensionality can make the interpretation and estimation of the model more complex and challenging. Instead, we aggregate the parenting styles into two broader dimensions. Section 2.2.1 describes the construction of these parenting styles, and Table B.3 displays the result of the factor analysis used to derive them. Then, we use aggregated parenting styles to create interactions with time investments. This approach simplifies the model by reducing the number of interaction terms to only eight (2 parenting dimensions multiplied by 4 time investments). It reduces the risk of multicollinearity and makes the estimation more manageable.

Last but not least, we test for non-linearities in the impact of parenting style dimensions on skills:

$$Y_{ia} = \alpha_a + PS'_{q2,a}\delta_{q2,a} + PS'_{q3,a}\delta_{q3,a} + PS'_{q4,a}\delta_{q4,a} + TI'_{ia}\gamma_a + R'_{ia}\rho_a + \epsilon_{ia} \tag{2.11}$$

To do so, we devide the sample of parents into quartiles ($PS_{q1,a}, PS_{q2,a}, PS_{q3,a}, PS_{q4,a}$) to determine if extreme forms of parenting have a particularly strong impact on skill development. We include the 2nd to 4th quartile dummy in the estimation and keep the 1st quartile as base category.

2.4. Results and Discussion

We now discuss the estimation results obtained following the strategy discussed in Section 2.3. We start with the results for non-cognitive skills, followed by those for cognitive skills, and briefly discuss the outcomes of the conducted robustness checks. For both types of skills, we first present the results of the main specification in Equation 2.2, and the implications of estimating this equation using different econometric models (see Equations 2.3 - 2.6). We also compare these results to those obtained from estimating the skill development process only with time investments as inputs, without considering parenting style (see Equation 2.9). Second, we highlight the outcomes of interacting parenting styles with parenting time, as described in Equation 2.10. Thirdly, we discuss the results of testing for non-linearities (Equation 2.11).

Non-cognitive skills

We start by describing results for non-cognitive skills using the main specification in Equation 2.2. Tables 2.3 and B.10 - B.12 summarize the different econometric models for each age group at which the skill development process is estimated. To facilitate interpretation, we will use a specific age group as the benchmark and then compare the outcomes to other age groups. Specifically, we examplary choose to present mainly estimation results for the age group 8-9, as shown in Table 2.3 (arbitrarily chosen as the first wave with data available for all specifications). Later we will relate them to other age groups.

Table 2.3: Estimated parameters of production function for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.065***	0.020	0.048**	0.011	0.050*	0.042**
	(0.022)	(0.017)	(0.020)	(0.017)	(0.027)	(0.020)
Parental reasoning	-0.084***	-0.043***	-0.025*	-0.013	-0.056***	-0.031*
	(0.019)	(0.014)	(0.015)	(0.015)	(0.021)	(0.016)
Hostile parenting	-0.352***	-0.163***	-0.162***	-0.117***	-0.295***	-0.188***
	(0.023)	(0.018)	(0.016)	(0.017)	(0.026)	(0.020)
Inconsistent parenting	-0.153***	-0.060***	-0.061***	-0.044**	-0.108***	-0.074***
	(0.023)	(0.018)	(0.018)	(0.018)	(0.028)	(0.021)
Attempted consistency	0.003	-0.011	-0.017	-0.010	-0.010	-0.007
	(0.018)	(0.015)	(0.015)	(0.014)	(0.021)	(0.016)
Educational time parents	-0.002	-0.000	0.001	0.003	-0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Educational time others	0.006	0.000	-0.013	-0.012	0.010	0.001
	(0.014)	(0.012)	(0.010)	(0.010)	(0.015)	(0.012)
Care time parents	-0.002	-0.001	-0.001	-0.000	-0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.004	-0.001	-0.000	-0.003	0.004	-0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)
Lagged test outcome		0.637***		0.253***		0.635***
		(0.020)		(0.019)		(0.020)
Observations	2,780	2,667	6,599	6,463	2,419	2,417
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table 2.3 shows that hostile parenting is consistently negative and significant at conventional levels across different econometric models. Similarly, parental reasoning and inconsistent parenting negatively influence skill development (parental reasoning becomes insignificant in the Arellano-Bond model). The magnitudes vary, with hostile parenting having the biggest impact on non-cognitive skills, followed by inconsistency and a lower impact on reasoning. Increasing hostility by one standard deviation (SD) leads to a decrease in non-cognitive skills by 0.12-0.35 SD, depending on the model employed. Inconsistency, increased in the same magnitude, decreases skills by 0.04-0.15 SD, and reasoning by 0.01-0.08 SD. Parental warmth has a small positive impact across models, varying in significance. Attempted consistency seems not to affect skill outcomes, indicating that what matters is the enforced consistency, summarized under the factor named inconsistent parenting. Regarding the self-productivity of skills, we find evidence for it for non-cognitive skills. We find estimates for the impact of last periods test outcome to be between 0.25 and 0.64 SD, indicating that high levels of non-cognitive skills in earlier ages persist to some extend independent of current investments and parenting style. These results are consistent across age-groups.

The literature suggests that children of authoritative parents tend to have higher non-cognitive skills (Spera (2005), Luyckx et al. (2011), Delvecchio et al. (2020), McWhirter et al. (2023)). The authoritative parenting style is characterized by high warmth, reasoning, and consistency, and low hostility. Our results support these findings, with warmth having a tentative positive effect and hostility and inconsistency having negative effects. Moreover, our analysis enables us to identify which dimensions of the authoritative parenting style are associated with higher non-cognitive skills. Our findings suggest that low hostility is the primary driver of the positive impact of this style, followed by high consistency. In contrast, warmth appears to have a limited role, while reasoning may have a negative effect.

The literature has also found negative associations between non-cognitive skills and authoritarian and neglectful parenting styles (Fiorini and Keane (2014), Le Forner (2021), Spera (2005), Fletcher et al. (2008), Heberle, Briggs-Gowan and Carter (2015), McWhirter et al. (2023)). Our results suggest that this negative association might be due to high hostility levels, offsetting the positive impact of consistency for authoritarian parenting. For neglectful parenting, low consistency and warmth might contribute to the negative association with skills.

Permissive parenting is associated with more externalizing problems and antisocial behavior (see McWhirter et al. (2023) for an overview). Regarding our findings with regard to non-cognitive skills, in the case of permissive parenting, the negative impact of inconsistency might be offset by low levels of hostility and higher warmth, depending on the magnitude of these dimensions. In general, it seems promising to target parental behaviors that lead to hostility and inconsistency in parenting training to increase the effectiveness of these interventions.

Figure 2.3 shows how different parenting styles affect the non-cognitive skills of children in different age groups. The graph shows the predicted values of non-cognitive skills at the 25th, 50th, and 75th percentiles of parenting styles, using coefficients from a fixed effects model with lagged values (Arellano-Bond). Generally the skill gap is the widest across at all ages within the hostile parenting group. While analysing the different age groups, the gap in skills between children with hostile parents (75th percentile) and those with non-hostile parents (25th percentile) is smallest among the youngest age group and increases slightly over time. At the age of 14-15, the difference in non-cognitive skills between children with hostile parents in the 25th percentile and those in the 75th percentile is about 0.2 standard deviations. The impact of parental warmth, reasoning, and inconsistent parenting on non-cognitive skills also increases with age. However, the difference in non-cognitive skills between children in the 25th and 75th percentiles of these parenting styles is much smaller than in the case of hostile parenting, and in some cases, it is insignificant. Lastly, attempted consistency in parenting does not appear to affect non-cognitive skills in every age group. To sum up, these graphs illustrate that, in particular, hostile parenting has a negative impact on non-cognitive skills, especially at later ages.

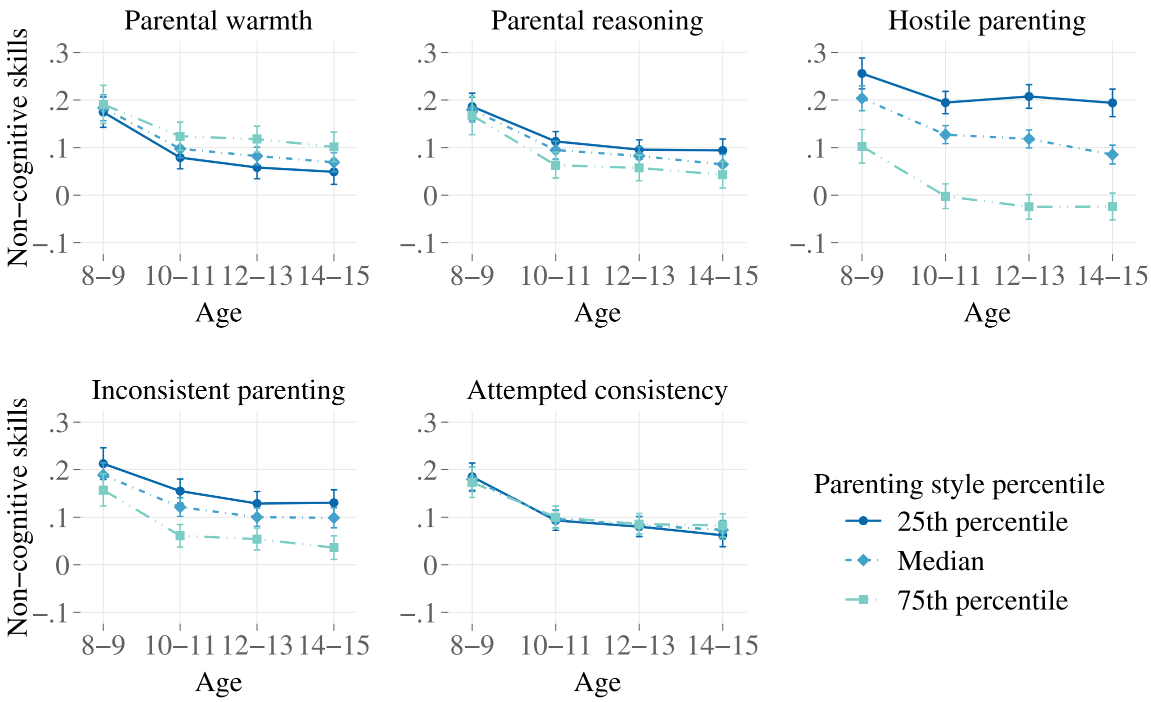


Figure 2.3: Change in the impact of parenting dimensions over age

Note: The figure presents predicted values of standardized non-cognitive skills for the 25th, 50th, and 75th percentile of the different parenting styles. The rest of the production inputs are at the sample mean. The range bars correspond to a 95% confidence interval for the point prediction.

Table B.13 presents our estimation results for Equation 2.9 using only time investments as inputs for the age group 8-9 to see if estimates of time investments are robust to including parenting style. The coefficients for all time investments remain insignificant, indicating no significant differences in the impact of different types of time spent with the child compared to other time investments. Additionally, the coefficients do not vary much in magnitude, indicating they are robust to including parenting dimensions in the specification. These findings are consistent across age groups (see Tables B.14 - B.16) and align with previous studies by Fiorini and Keane (2014) and Le Forner (2021), who also did not find significant impacts of time investments on non-cognitive skills on younger children (age 4-11). We extend this analysis to older children (middle childhood/teenage years), and our results align with the literature. Del Boca, Flinn and Wiswall (2014) find a decreasing productivity of active time spent with children by age in the UK, further supporting our findings.

Next, we investigate the interaction of time investments with parenting style. Table B.21 displays the estimates of this specification (Equation 2.10) for age group 8-9 (for estimates for other groups, see Tables B.22 - B.24). Note that here we use the parenting styles to summarize parenting dimensions. We also run the main specification, Equation 2.2, using summarizing styles instead of the parenting dimensions. Using the summarizing styles leads to similar conclusions as the styles originating from the single factor analysis. Therefore, the summarizing scores seem to reflect the findings for the parenting dimensions well (see Tables B.17 - B.20 for details). Turning to the interactions, we do not find any additional effect of parenting style with increasing time investments at any age. This is the case for an empathetic style (capturing high reasoning, warmth, and attempted consistency) and a harsh style (capturing hostility and inconsistency). This shows that including parenting style as an additional input independent of time investments would better mimic the skill development process.

To test for non-linearities, we estimate Equation 2.11. Using dummies for each quartile of parenting style, we can explore if extreme values disproportionally impact skills. Figure 2.4 presents estimated coefficients of dummies for belonging to the quartiles of different parenting dimensions (with the 1st quartile as a baseline category) for four age groups (for estimates, see Table B.25 - B.28). It allows us to analyze the potentially non-linear relationship between parenting dimensions and non-cognitive skills. The results suggest a non-linear relationship between some parenting styles and non-cognitive skills. In general, the non-linearity is stronger for older age groups. However, the nature of this relationship varies by the dimension of the parenting style. Regarding parental warmth, dummies for the quartiles are mostly insignificant, which aligns with findings from the estimation with the linear specification. Moving from one quartile to another has a decreasingly negative impact on non-cognitive skills in the case of parenting reasoning. In contrast, for hostile and inconsistent parenting, moving to a higher quartile has an increasingly negative impact on non-cognitive skills, indicating that parents with high hostility and inconsistency have an especially detrimental impact on their child's non-cognitive skills. In the case of attempted consistency, most of the coefficients are insignificant, which confirms the findings drawn from the linear specification.

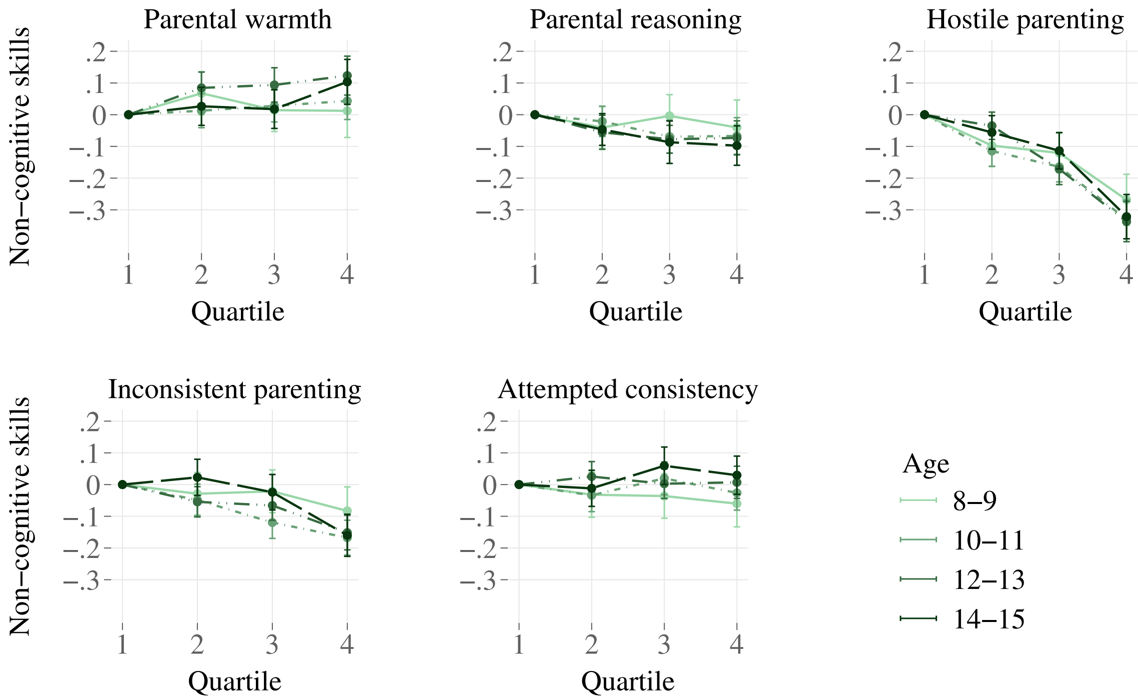


Figure 2.4: Non-linear impact of parenting style on non-cognitive skills

Note: The figure presents estimated coefficients of dummies for belonging to the 2nd, 3rd, and 4th quartile of parenting styles (the 1st quartile serves as baseline category) for four age groups: 8-9, 10-11, 12-13, and 14-15. The range bars correspond to a 95% confidence interval for the estimated coefficients.

Cognitive skills

Tables 2.4 and 2.5 present the estimation results for the cognitive skills production function at age group 8-9 (see Table B.29 for estimation results for age group 10-11). Tables 2.4 display the results for MRT scores, while Table 2.4 shows the results for PPVT scores. Most of the coefficients for parenting dimensions are insignificant, except for inconsistency and warmth in some specifications. The magnitudes of the coefficients are small, and the standard errors indicate that the impact is likely to be zero rather than noisy estimates. Inconsistency and warmth have negative coefficients, suggesting they are associated with a decrease in cognitive skills. However, overall, parenting style does not seem to substantially impact cognitive skill development. In contrast, educational time spent with parents positively affects skills in most econometric models, particularly for the younger age group (8-9). The coefficients are not significant in the estimations using the fixed effect and Arellano-Bond approach. It might suggest that the effect of educational time with parents disappears when one controls for the child's innate ability. Excluding parenting style from the estimation does not significantly alter the coefficients for time investments (see Tables B.30 - B.32), and results are similar for all age groups. Regarding the self-productivity of skills, we also find evidence for it for cognitive skills. Estimates for the impact of last periods test outcome are between 0.18 and 0.46 SD for the MRT and 0.15 and 0.49 SD for the PPTV. These values are slightly lower than in the case of non-cognitive skills, suggesting a stronger persistence of non-cognitive skills.

Table 2.4: Estimated parameters of production function for cognitive skills (MRT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.040	-0.036	-0.034	-0.017	-0.033	-0.035
	(0.027)	(0.025)	(0.024)	(0.033)	(0.034)	(0.031)
Parental reasoning	-0.002	-0.003	-0.005	-0.007	-0.017	-0.016
	(0.024)	(0.021)	(0.021)	(0.028)	(0.027)	(0.025)
Hostile parenting	0.004	0.014	0.014	-0.002	0.008	0.018
	(0.026)	(0.023)	(0.023)	(0.030)	(0.032)	(0.028)
Inconsistent parenting	-0.068***	-0.052**	-0.027	0.003	-0.037	-0.027
	(0.026)	(0.023)	(0.024)	(0.031)	(0.031)	(0.026)
Attempted consistency	0.002	-0.015	-0.032*	-0.029	-0.032	-0.050**
	(0.022)	(0.019)	(0.019)	(0.025)	(0.027)	(0.023)
Educational time parents	0.014***	0.007*	-0.000	0.003	0.014***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Educational time others	0.017	0.013	0.012	0.007	0.001	0.001
	(0.017)	(0.016)	(0.015)	(0.016)	(0.017)	(0.015)
Care time parents	-0.000	0.000	0.002	0.003	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.005	0.003	0.002	0.009	0.012*	0.006
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Lagged test outcome		0.457***		0.179***		0.455***
		(0.019)		(0.039)		(0.021)
Observations	2,753	2,690	7,428	2,504	2,399	2,392
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

These results align with Fiorini and Keane (2014) and Le Forner (2021), who do not find evidence for the impact of an authoritarian or warm parenting style on cognitive skills. Similar to their analysis, we find evidence for the impact of educational time spent with parents on cognitive skills. In general, our evidence of the impact of different types of time investments is weaker than the one found by Fiorini and Keane (2014) and Le Forner

Table 2.5: Estimated parameters of production function for cognitive skills (PPVT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.050**	-0.048**	-0.070***	-0.055*	-0.030	-0.037
	(0.024)	(0.021)	(0.026)	(0.028)	(0.031)	(0.026)
Parental reasoning	0.019	0.016	-0.001	-0.002	-0.003	-0.017
	(0.024)	(0.020)	(0.025)	(0.026)	(0.027)	(0.023)
Hostile parenting	-0.001	-0.014	-0.039	-0.035	0.020	0.002
	(0.023)	(0.020)	(0.025)	(0.027)	(0.028)	(0.025)
Inconsistent parenting	-0.091***	-0.035*	0.014	0.020	-0.053*	-0.025
	(0.023)	(0.021)	(0.026)	(0.026)	(0.028)	(0.026)
Attempted consistency	0.025	-0.004	-0.011	0.004	0.004	0.001
	(0.021)	(0.018)	(0.021)	(0.023)	(0.024)	(0.021)
Educational time parents	0.017***	0.010***	0.001	-0.004	0.015***	0.008**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Educational time others	0.013	0.001	-0.016	0.002	0.003	-0.007
	(0.015)	(0.015)	(0.025)	(0.025)	(0.016)	(0.016)
Care time parents	0.002	0.000	-0.001	-0.002	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	-0.001	-0.003	-0.004	0.003	0.006	0.001
	(0.005)	(0.005)	(0.010)	(0.011)	(0.006)	(0.006)
Lagged test outcome		0.494***		0.150***		0.488***
		(0.019)		(0.044)		(0.020)
Observations	2,755	2,633	3,437	2,156	2,401	2,343
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Peabody Picture Vocabulary Test (PPVT) outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

(2021). However, we look partly at older cohorts, where time investments matter less (see Del Boca, Flinn and Wiswall (2014)). Additionally, time investment measures vary across ages due to the survey collection method, which could drive these results to some extent.

We further test for the effect of parenting style on additional time spent with the child. Results for the interaction of parenting styles with time investments are displayed in Tables B.33 - B.35. We do not find consistent effects of the interaction between parenting style and time investments. Hence, for the skill formation of cognitive skills, skill production functions without parenting style are likely to capture the skill process well in contrast to non-cognitive skills. Similar conclusions hold for non-linearity. Tables B.36 - B.38 show the estimation results for testing for non-linearity in the impact of parenting styles. We do not see strong evidence for non-linearity.

These results indicate that parenting training targeting parenting style might be particularly effective in increasing non-cognitive skills but not cognitive ones. Depending on which improvements policymakers aim for, different intervention designs are needed. However, it is important to keep in mind that severe behavioral problems can impact grade progression and school outcomes which in return might affect cognitive skill development in the long run and that there are increasing returns from non-cognitive skills for wages later in life (see Carneiro, Crawford and Goodman (2007), Deming (2017) and Edin et al. (2022)).

Robustness checks

In this section, we examine the robustness of our findings on the relationship between parenting style and non-cognitive and cognitive skills. We analyse the sensitivity of our results to various econometric specifications. By conducting these additional analyses, we aim to ensure that our conclusions are robust to model specification.

First, we examine how our results are affected by the way we define parenting styles. In the main specification, we conducted a factor analysis on selected subgroups of questions related to parental behavior, resulting in five different dimensions of parenting styles. Alternatively, we can pool all the questions together and obtain four factors in a joint factor analysis. Based on the reported loadings (see Tables B.4 - B.9), we labeled the factors as warm style, reasoning style, hostile and inconsistent style, and consistent style. Depending on wave, the described factors load differently, so we assign the factors produced to the fitting variable (see table notes for details). We then run our main specification with the jointly estimated factors.

Tables B.39 - B.42 present the estimated parameters of the production function with the jointly estimated factors for non-cognitive skills. On average, warm style and consistent style have a positive influence on children's non-cognitive skills. However, the impact of the latter one is insignificant in the specifications with fixed effects and becomes negative for the age group 14-15. In contrast, reasoning style and hostile and inconsistent style have a negative impact on non-cognitive skills. These findings are consistent with the previous results. The main difference is that the jointly estimated warm style has a consistently significant impact, which is not the case in the main specification. The reason for this might be that in the joint factor case, warmth indicates among others how much parents praise their child. In the case of the main specification with parenting dimensions, praise is classified under hostility given the survey module. This indicates that praising positively affects the development of non-cognitive skills. Additionally, in the jointly estimated model, the consistent style has an impact and is significant in some model specifications. This could additionally support the conclusion that implemented consistency matters and not attempted one, which is mainly insignificant in the main specification.

Tables B.47 - B.49 present the estimated production function parameters with jointly estimated factors for cognitive skills. The effect of parenting style is, on average, small and mostly insignificant. This confirms previous findings that parenting style does not strongly impact a child's cognitive skill development.

As a second robustness check, we include an extended set of controls in the main model specification. The additional controls consist of dummies for urban areas and Australian states, aimed at capturing the effect of geographical factors on the development of non-cognitive and cognitive skills. They may also account for differences in school quality and public services between rural and urban areas and across states. The second control group consists of the Socio-Economic Indexes for Areas (SEIFA), which measure four aspects of socio-economic advantage and disadvantage. These indexes are constructed based on Australian census data. They are created for each statistical area, allowing us to control the economic situation of the local region in which the child is growing up. Finally, we also include controls for birth weight and early birth as proxies for innate ability.

The addition of a new set of controls only marginally changes the estimated coefficients associated with parenting styles and time investments in the production function of non-cognitive skills (see Tables B.43 - B.46). Similar conclusions can be drawn from the analysis of the same coefficients in the production function of cognitive skills (see Tables B.50 - B.52). This indicates that the omitted controls in the main specification are uncorrelated with the parenting style inputs and do not represent a source of endogeneity bias.

Despite these robustness checks, certain limitations of our approach remain. Firstly given that we use time-invariant fixed effects, we do not control for time-varying selection. Therefore, estimates could be biased if, for example, financial shocks influence skills directly and indirectly via increasing parenting hostility due to stress. Another limitation is the measurement of parenting skills and non-cognitive skills. Firstly, there might be measurement errors. Measurement error might be tackled using the latent factor modeling approach of Cunha and Heckman (2008) and Cunha, Heckman and Schennach (2010) in future extensions of this work. Further, we use measures of cognitive skills and parenting style, which are self-reports by parents. García-Miralles and Gensowski (2023) point out that parental health shocks influencing their children's health might change parents' perception of their child's behavior at the same time. A similar endogeneity might occur in our case. Hostile parents could perceive their children as more hyperactive than others because they might value obedience higher than permissive parents and notice it more. One could extend this work in the future by using teacher reports to validate parents' reporting in a robustness check. Further, our measures of time investments are not consistent over waves as the method of reporting changes, as well as the responding person. This could drive the results of the interaction of time investments with skills to some extent. If the varying measures do not capture time investments well, measurement error might bias results.

2.5. Summary and Concluding Remarks

In this paper, we investigate the impact of different parenting dimensions on cognitive and non-cognitive skill development. Additionally, we provide empirical facts showing the association between income and parenting dimensions. To do so, we use the Longitudinal Survey of Australian Children to estimate the impact of parental warmth, reasoning, hostility, and consistency on skills. We exploit the panel structure of the data and the availability of rich demographic and investment variables to control for potential endogeneity issues. These include controlling for unobservable time-invariant characteristics, past investments, and skill outcomes. Doing so, we enrich the existing literature by providing a structured analysis of the impact of parenting dimensions on skills testing for interactions with time investments and non-linearities.

We find that non-cognitive skills decrease with higher parenting hostility and inconsistency and to a lesser extent with higher reasoning. Parenting warmth positively influences non-cognitive skills, however, with low magnitude and not consistently significant across the employed econometric models. We show that the positive association between authoritative parenting and skill development found in the literature seems to be driven by low levels of hostility and inconsistency. Parenting warmth and reasoning play a limited role. In contrast, for authoritarian parents, the higher level of hostility seems to offset the positive effect of consistency. We find hostility impacts skill development in higher magnitudes than inconsistency and that the impact increases with age. As parents from the bottom of the income distribution tend to have higher levels of hostile and inconsistent parenting, these factors might be an additional driver for the skill gap between children from different socioeconomic backgrounds (at least for non-cognitive skills).

Regarding how to model parenting style in skill formation, we do not find evidence for parenting styles influencing the impact of time investments, e.g., increasing their productivity. Therefore, parenting style should be modeled as additional investment input in skill production functions. Further, hostile parenting is the only parenting dimension displaying a strong non-linear relationship in impact on non-cognitive skills. Hence, our analysis indicates that linear modeling of the impact of parenting styles captures the skill formation process well (except for hostility). We do not find consistent evidence for the influence of parenting styles on cognitive skills. For the development of cognitive skills, other factors seem to be more important, like as the literature suggest, time investments or monetary investments (see Del Boca, Flinn and Wiswall (2014)). This highlights the importance of modeling non-cognitive and cognitive skill development with different functional form assumptions and inputs.

These results indicate that for non-cognitive skill development, it is particularly important to have parents with a low level of hostility and inconsistency. This finding is informative for the design of child development policies. For instance, targeting these two parenting behaviors might be particularly efficient regarding parenting training. Given the non-linearity of the impact of hostility, it might be particularly important to target parents who display a high level of hostility or are likely to do so. Given that we find the impact of hostility to increase with age, targeting adolescence seems important. Nonetheless, given that skills are self-productive, starting at earlier ages could be beneficial, in particular as we find non-cognitive skills to display more persistence than cognitive skills. More research is needed to determine the trade-off between periods. Hostile and inconsistent parenting is often associated with increased stress levels in parents. Therefore, another promising approach might be to combine parenting training with stress management training to maximize the impact. Nonetheless, more research is needed on the amenability of these behaviors to determine the efficiency of this approach, and our results indicate that focusing, in particular, on hostility and inconsistency in doing so is promising.

3. INCOME AND THE DEMAND FOR FOOD

written jointly with Marc F. Bellemare and Eeshani Kandpal

3.1. Introduction

On the basis of a handful of uncontroversial assumptions, microeconomic theory makes unambiguous predictions about the effects of income changes on the demand for food. Denoting a consumer's demand for a vector x of food items as a function of the prices p that this consumer faces and their income w, microeconomic theory predicts that while food overall x is a normal good (i.e., $\frac{\partial x}{\partial w} > 0$), specific foods i may be luxuries (i.e., $\frac{\partial x}{\partial w} > 1$) while other foods j may be inferior goods (i.e., $\frac{\partial x}{\partial w} < 0$).

But while microeconomic theory makes predictions about the effects of changes in income on the demand for food, either for food overall or for specific categories of food, empirical estimates of these effects typically suffer from important shortcomings. These shortcomings can generally be classified under the broad headings of limits to internal validity and limits to external validity. The former is threatening the causal identification of estimates of the effect of a change in income on the demand for food and the latter the generalizability of those same estimates. On the internal validity front, extant estimates of the effect of a change in income on the demand for food are typically plagued by endogeneity issues that are usually only resolved by making strong assumptions. On the external validity front, those same estimates typically focus on a handful of commodities or on consumers in a narrow context.[14]

What is the effect of a change in income on the demand for various types of food? Is Bennett's Law—the empirical regularity whereby poor households seem to respond to increases in income by (i) spending more on fine staples than they do relative to coarse staples, or (ii) spending more on protein relative to staples (Bennett, 1941)—indeed a law, or is it just the result of mere correlations? And what is the income elasticity of specific types of food? We answer these questions by analyzing aggregate data from five randomized controlled trials (RCTs) in which recipient households were selected at random to receive cash transfers across four countries spanning three continents: two in Mexico (Hoddinott and Skoufias, 2004; Cunha, De Giorgi and Jayachandran, 2019; Attanasio and Pastorino, 2020) and one in each of Nicaragua (Adato and Roopnaraine, 2004), the Philippines (Filmer et al., 2023), and Uganda (Gilligan and Roy, 2013). We exploit the

[14] Another shortcoming can also arise on the construct validity front, when different estimates measure food demand in different ways. For instance, Behrman and Deolalikar (1987) looked at the relationship between income and food demand as measured in terms of nutrients, whereas Bouis and Haddad (1992) look at the same relationship but for food demand as measured in terms of calories. We abstract from construct validity considerations by focusing here on studies measuring food demand in terms of expenditures.

treatment of receiving a cash transfers as an exogenous increase in income. We analyze the impact of an income increase on staples, protein and vegetable and fruit expenditures across countries. Further, we exploit the increase to estimate income elasticities for the respective food groups.

A central contribution of this paper is to provide causal estimates of the income elasticity for food from five settings around the world. By aggregating data from five RCTs, we bring internally *and* externally valid evidence to the well-established question in economics of whether the poor spend additional income on food. Our results show that food is both a normal good and a necessity (i.e., as income increases, food expenditures increase, but at a lesser rate than the rate at which income increases) across all the categories we consider, viz. protein, staples (both coarse or fine, and with or without tubers), as well as fruits and vegetables. We further find that, with an exogenous increase in income, the average household spends more on fine staples than it does on coarse staples, and it spends more on protein than it on coarse staples. This is broadly consistent with Bennett's Law (Bennett, 1941). We provide causal income elasticities quantifying the effect of income on food expenditure as well as the shifts in allocation across food groups.

Our work is related to a nascent literature on the impacts of exogenous changes in income on food demand. Angelucci and Attanasio (2013), Attanasio, Battistin and Mesnard (2012), Attanasio and Lechene (2010), Hoddinott and Skoufias (2004) and Hoddinott and Wiesmann (2008) estimate the impact of conditional cash transfers on the food share of expenditures using cross-sectional variation. More recently, Almås, Haushofer and Shapiro (2019) estimate the impacts of a change in income on the food share of expenditures and calorie consumption by exploiting an unconditional cash transfer in rural Kenya. While Hoddinott and Wiesmann (2008) compare the estimates for the impact of cash transfers for Honduras, Mexico, and Nicaragua, the other paper focus on evaluating one program each. Our contribution lays in pooling and harmonizing available data across three continents to provide empirical evidence for Bennett's Law.

Almås, Haushofer and Shapiro (2019) estimate income elasticities for nutrition in response to a very large income shock– approximately 18 months' of beneficiary consumption in one lump-sum transfer provided by Give Directly. As income elasticities are locally estimated, it is perhaps unsurprising that their estimated elasticities are large. For instance, their estimated income elasticity for protein consumption is 1.29. Using smaller, but also exogenous, changes in income (between 10 and 25 percent increases), our estimated income elasticity for protein is 0.33. Other reasons may also explain the difference: the income levels prior to the transfer may be different between their setting and the five contexts we studied. Finally, we study the impacts of routine (monthly to quarterly) transfer whereas the GiveDirectly transfer is a one time transfer (and known to be as such). While both estimates are useful for policy making, we believe that our estimate is more likely observed in real world setting than the much larger income shock provided by GiveDirectly.

The remainder of this paper is organized as follows. In Section 2, we briefly discuss the data we use for our analysis. Section 3 presents our empirical framework. In Section 4, we present and discuss our estimation results. Section 5 concludes.

3.2. Data

We use publicly available data from impact evaluations of five cash or in-kind support programs. Three of those programs are conditional cash transfer programs: the Mexican *Progresa* program (Attanasio and Lechene, 2010), the Nicaraguan *Red de Protección Social* (Macours, Schady and Vakis, 2012) program, and the Philippine *Pantawid* program (Filmer et al., 2023). Two of these programs deliver both cash and in-kind support: the Ugandan World Food Program Cash and Food transfer program (Gilligan and Roy, 2013) and the *Programa Apoyo Alimentario* (PAL; Cunha, De Giorgi and Jayachandran, 2019), which compared to *Progresa* is allocated to more remote and poor areas of Mexico (Progresa and Pal barely overlap). For comparability, we only use data on the cash transfer arms of these programs. In this section, we first describe the variables we construct and the harmonization process undertaken for our analysis. We next briefly describe each data set, the identification strategy leveraged in the underlying evaluations, and the harmonization process undertaken to construct the indicators used in our analysis. Finally, we briefly present descriptive statistics.

Variable construction and harmonization for analysis

To assess the impacts of income shocks on poor households' food consumption choices and estimate the underlying elasticities for various food groups, the analysis requires a measure of the income shock and budget shares of the relevant food groups. As Bennett's law pertains to dietary or nutritional upgrading from staples to proteins, and from coarse to fine staples, we define the following eligible food groups: coarse grains, fine grains, tubers, animal-sourced proteins, vegetables and fruits, processed foods, and all other food items. The surveys all report quantities purchased of each food item in kilograms and weekly expenditures. We use it to construct unit prices for each food group using reported weekly expenditures for each food item. For consistency, we only use expenditures on purchased items and not estimated values of home production. Expenditures are calculated in nominal terms, deflated using the country-specific consumer price index and then adjusted by purchasing power parity (PPP) with base year 2011 to harmonize the data across RCTs.

As the contexts from which we draw data vary greatly, so do the specific food items in each category for each country. Indeed, there is even some within-country variation. For instance, in the Mexican *Progresa* data, the only coarse grain is corn, whereas in the PAL data, coarse grains include oats. In Nicaragua, coarse grains include oats, corn, and grained corn. Table C.1 details the individual food items in each of the food groups in the data sets we use.

Mexico's *Progresa*

The Mexican *Progresa* conditional cash transfer has an established evaluative sample dating back to the initial program roll-out in 1998 (Skoufias, Davis and Behrman, 1999; Gertler, 2004). Treatment assignment was randomized at the community level across 506 localities in 7 states, to yield 320 treated and 186 control units. Household eligibility was defined using a proxy means test (PMT) score. Households with a PMT score below a certain threshold were deemed eligible to receive the transfer if they lived in a treated locality.[15] In treated localities, eligible households started receiving the transfer in August or September of 1998. In control localities, none of the households received the transfer. The program made transfers conditional on school attendance as well as visiting health centers for curative and preventive care-seeking for children younger than five, and antenatal care use by pregnant women. The transfer amounted to USD 66 (2011 PPP) each month and represented about 20 percent of baseline consumption in beneficiary households.

We use data publicly released for the replication package of Attanasio and Pastorino (2020). These data provide us the necessary information on food groups (i.e., coarse grains, fine grains, tubers, proteins, vegetables, fruits, processed foods, and other food items).

The Nicaraguan *Red de Protección* program

We use data collected for the experimental evaluation of the program during its pilot stage (Macours, Schady and Vakis, 2012). During this stage, the government targeted two departments (out of 17 departments nationally) chosen on purpose for their elevated and worsening poverty levels, but also for having minimum capacity to deliver the program. Specifically, this meant that treated municipalities had received investments in their schools and health clinics from a national participatory development program. Eligible households are poor households identified using a PMT. The program provided USD 87 (2011 PPP) in monthly transfers, representing about 20 percent of beneficiary household consumption. Program conditions were similar to those used for Progresa, with grants tied to children's school attendance, and curative and preventive health care usage by young children. Treatment assignment was randomized at the community level to yield 21 treated and 21 control units.

[15] Initially, the definition of poor included 52 percent of households; this was revised to include 78 percent of households before treatment started (Gertler, 2004). We use the broader definition of eligibility in our analysis.

The Philippine *Pantawid* program

The *Pantawid* program was evaluated in its pilot stage, and we use these data in our analysis (Filmer et al., 2023). The pilot stage was implemented in 130 randomly selected villages representing each of the four macro-regions of the country. Of these 130 villages, 65 were randomly assigned to treatment and 65 to control. Households were eligible if identified as poor by a PMT and if they had school-aged or younger children. The program provided USD 78 (2011 PPP) in monthly transfers, representing 23 percent of beneficiary household consumption. The program conditions monitored school attendance and enrollment, as well as pregnancy-related care seeking. We use the data from the endline survey which was conducted in 2011.

Mexico's *Programa de Apoyo Alimentario* (PAL)

The PAL provides unconditional in-kind or cash transfers to poor households. The transfer size is USD 26 (in 2011 PPP terms) a month, representing about 11.5 percent beneficiary household consumption. This program supplements *Progresa* in remote and poor areas. Villages are eligible for PAL if they have fewer than 2,500 inhabitants, are highly marginalized (as classified by the Mexican Census Bureau), and do not receive aid from *Liconsa*, a Mexican milk subsidy program, or *Progresa*. The PAL villages tend to be poorer and more rural than *Progresa* villages (Cunha, De Giorgi and Jayachandran, 2019). In 2003, 208 localities were randomized into 156 treated units, 104 of which received the in-kind transfer and 52 received the cash transfer. There were 38 control localities and 14 excluded localities. Eligible households were surveyed in cash-transfer and control communities for a baseline in 2003 and an endline in 2005. We use data from the publicly available replication package of Cunha, De Giorgi and Jayachandran (2019).

The World Food Program's Cash and Food transfer in Uganda

The World Food Program, in collaboration with other development agencies, implemented a cash and food transfer in Uganda between 2010 and 2011 (Gilligan and Roy (2013)). For the program, 99 localities were randomized into 66 treated units, each with equal probability assignment to the food or cash arms, and 33 control units. Households that were enrolled in public early childhood development (ECD) centers in these localities were deemed eligible. Within these localities, eligible households were surveyed in cash and control localities. The program provided USD 35 (in 2011 PPP terms) every six weeks if the index child attended the ECD at least 80 percent of the time over the previous six week period. The transfer amounts to approximately 13 percent of beneficiary household consumption.

Table 3.1: Mean weekly consumption expenditure of the control group by RCT

	Mean expenditures of control group					
	Food	Staples	Tubers	Protein	Veg+ fruits	Other
Mexico PAL	52.30	5.52	0.72	15.55	5.66	21.56
Mexico Progresa	31.35	4.61	0.89	5.99	3.13	18.45
Nicaragua RSP	47.81	15.73	0.84	6.12	1.67	23.23
Philippines PPPP	48.63	21.61	0.67	14.39	2.18	9.79
Uganda WFP	17.41	5.60	0.66	3.53	0.86	6.56
Observations	22,232	22,232	21,986	22,231	22,232	19,513

Note: All expenditures are expressed in USD (2011 PPP terms).

Descriptive Statistics

Table C.2 summarizes the foregoing discussion of the five RCTs we use in the empirical analysis below. Table 3.1 presents mean consumption expenditures (in 2011 PPP terms) in each of those RCTs' control group for food overall, but also for staples, tubers, protein, fruits and vegetables, and other foods. It is noteworthy that in three out of five contexts (i.e., Nicaragua RSP, Philippines PPPP, and Uganda WFP) mean expenditures on staples are larger than mean expenditures on protein, and that the two cases where mean expenditures on protein are larger than mean expenditures on staples are in Mexico. This is consistent with the fact that Mexico is an upper-middle-income country, whereas Nicaragua, the Philippines, and Uganda are all lower-middle-income countries.

3.3. Empirical Framework

The empirical approach we follow in this section is straightforward. We begin by estimating the following equation:

$$\ln y_{1ijk} = \alpha_1 + \beta_1 D_{ik} + \delta_{1k} + \epsilon_{1ijk}, \tag{3.1}$$

where y denotes the expenditures of household i on food category j in the context of RCT $k \in \{1, ..., 5\}$, D is a dummy variable equal for whether the household is in the treatment group (i.e., whether the household has been randomly assigned to receiving a cash transfer), δ is an RCT fixed effect, and ϵ is an error term with mean zero. We apply the inverse hyperbolic sine (or arcsinh) transformation to approximate logarithmic values to estimate effects at the extensive and intensive margin by retaining zero-valued observations. We account for this transformation in elasticity calculations following Bellemare and Wichman (2020).

In this context, β_1 is an intent-to-treat (ITT) estimate capturing the effect of being randomly assigned to the treatment group on expenditures on food category j for the average household in our data. By looking at expenditures on specific food categories, Equation 3.1 allows testing whether those categories of foods are normal goods ($\beta_1 > 0$), inferior goods ($\beta_1 < 0$), or neither ($\beta_1 = 0$). Because the randomization unit across all five RCTs we consider is the village, clustering has to do with design rather than sampling, and so we cluster standard errors at the village level following recent recommendations by Abadie et al. (2022).

We then estimate the following equation:

$$\ln\left(\frac{y_{2ijk}}{y_{2i\ell k}}\right) = \alpha_2 + \beta_2 D_{ik} + \delta_{2k} + \epsilon_{2ij\ell k}, \tag{3.2}$$

where all right-hand side variables are defined as before, but where the dependent variable is now the ratio of expenditures on food categories j and ℓ. By looking at expenditure ratios, Equation 3.2 allows testing whether cash transfers cause expenditures to increase faster ($\beta_2 > 0$), slower ($\beta_2 < 0$), or the same ($\beta_2 = 0$) in food category j as in food category ℓ. Here, too, we cluster standard errors at the village level.

What hypothesis tests are required to test Bennett's Law? Bennett's Law makes two explicit, testable predictions:

1. As the income of poor households increases, they will spend relatively more on fine staples relative to coarse staples, and

2. As the income of those same households increases even further, they will spend relatively more on protein relative to staples.

Implicitly, Bennett's Law also posits that as the income of poor households increases, they will not spend less on fine staples or protein. In other words, Bennett's Law implies that neither fine staples nor protein are inferior goods, although it leaves open the possibility that coarse staples are inferior goods.

3.4. Results

We now turn to our empirical results. Table 3.2 presents estimation results for Equation 3.1 looking respectively at all staples in columns 1 and 2, coarse staples in columns 3 and 4, and fine staples in columns 5 and 6. Odd-numbered columns use the logarithm of expenditures on a given category as their dependent variable, and even-numbered columns use standardized expenditures on a given category as their dependent variable. Panel A of Table 3.2 treats only grains as staples, and Panel B treats both grains and tubers as staples by including them in both the all-staples and coarse staples category.

In all specifications in Table 3.2, the ITT effect of income on food expenditures is positive and statistically significant at conventional levels. In other words, an exogenous

Table 3.2: Results for staples and tubers

	Staples		Coarse staples		Fine staples	
	(1) Log(exp)	(2) Std. exp	(3) Log(exp)	(4) Std. exp	(5) Log(exp)	(6) Std. exp
Panel A: staples						
Treated	0.192***	0.127***	0.108*	0.098***	0.190***	0.136***
	(0.047)	(0.032)	(0.056)	(0.037)	(0.028)	(0.023)
Constant	1.643***	-0.001	0.902***	0.000	1.083***	-0.005
	(0.042)	(0.025)	(0.047)	(0.028)	(0.024)	(0.014)
N	55,744	55,744	48,326	48,326	55,079	55,079
No. clusters	843	843	715	715	715	715
Panel B: staples and tubers						
Treated	0.220***	0.148***	0.183***	0.121***	0.190***	0.136***
	(0.054)	(0.032)	(0.056)	(0.035)	(0.028)	(0.022)
Constant	1.870***	-0.002	1.219***	-0.000	1.083***	-0.005
	(0.037)	(0.024)	(0.043)	(0.027)	(0.024)	(0.014)
N	55,744	55,744	54,983	54,983	55,079	55,079
No. clusters	843	843	715	715	715	715

Note: Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps. Staples and tubers means that expenditure on tubers is added to the expenditure on staples and on coarse staples.

increase in incomes increases the demand for all staples, for coarse staples (whether or not one includes tubers in this category), and for fine staples. When excluding (including) tubers, expenditures on all staples increase by 0.13 (0.15) standard deviation, expenditures on coarse staples increase by 0.10 (0.12) standard deviation, and expenditures on fine staples increase by 0.14 (0.14) deviation. Table C.3 displays the results for only tubers, showing that expenditures increase by 0.15 standard deviation. Staples and tubers are thus a normal good on average across the five contexts we study.

Table 3.3 presents estimation results for Equation 3.1 looking respectively at protein in columns 1 and 2 and fruits and vegetables in columns 3 and 4. Again, odd-numbered columns use the logarithm of expenditures on a given category as their dependent variable, and even-numbered columns use standardized expenditures on a given category as their dependent variable.

In all specifications in Table 3.3, the ITT effect of income on food expenditures is again positive and significant at conventional levels. In other words, an exogenous increase in income increases the demand for both protein as well as fruits and vegetables: expenditures on protein increase by 0.19 standard deviation, and expenditures on fruits and vegetables

Table 3.3: Results for protein and vegetables

	Protein		Vegetables +fruits	
	(1) Log(exp)	(2) Std. exp	(3) Log(exp)	(4) Std. exp
Treated	0.282***	0.187***	0.199***	0.160***
	(0.036)	(0.030)	(0.034)	(0.029)
Constant	1.874***	-0.002	1.452***	-0.002
	(0.033)	(0.023)	(0.027)	(0.022)
N	55,739	55,739	55,744	55,081
No. clusters	843	843	843	715

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps.

increase by 0.16 standard deviation. Like staples, protein as well as fruits and vegetables are a normal good on average across the five contexts we study.

Table 3.4 presents estimation results for Equation 3.2 looking respectively at the fine-to-coarse-staples expenditures ratio in column 1, the protein-to-staples expenditures ratio excluding tubers from staples in column 2, the protein-to-coarse staples expenditures ratio in column 3, the protein-to-fine-staples expenditures ratio in column 4, and the protein-to-fruits-and-vegetables expenditures ratio in column 5.

Table 3.4: Results for expenditure ratios

	Log ratios of expenditures				
	(1) Fine/ Coarse	(2) Protein/ Staples	(3) Protein/ Coarse	(4) Protein/ Fine	(5) Protein/ Veg+fruits
Treated	0.089*	0.009	0.124**	0.002	0.000
	(0.053)	(0.038)	(0.056)	(0.028)	(0.024)
Constant	-1.111***	0.406***	-0.259***	0.985***	0.737***
	(0.047)	(0.033)	(0.045)	(0.022)	(0.020)
N	12,766	38,344	14,143	34,735	42,144
No. clusters	650	839	694	677	831

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps.

Here, the ITT effect of income on expenditures ratios is only significant for the fine-to-coarse-staples expenditures ratio in column 1 and for the protein-to-coarse-staples expenditures ratio in column 3. These results indicate that in response to an exogenous increase in income, expenditures on fine staples increase faster than expenditures on coarse staples, and that expenditures on protein increase faster than expenditures on coarse staples. Strikingly, the protein-to-fine-staples expenditures ratio in column 4 and the protein-to-fruits-and-vegetables expenditures ratios in column 5 both look like true zeros. These results indicate that in response to an exogenous increase in income, expenditures on protein and on fine staples and expenditures on protein as well as fruits and vegetables respond identically.

Tables 3.5 and 3.6 show estimated elasticities computed in two ways. In Table 3.5, elasticities are computed taking into account the size of the transfer received by each household—a number that is positive for treated household, and equal to zero for control households. These elasticities are thus income elasticities of the demand for each food category, or the ITT effect on food expenditures (measured in percentage points) of a one-percent increase in income. In Table 3.6, elasticities are computed with respect to the dummy variable for whether a household is treated. These elasticities thus represent the percentage change in income due to being randomized into the treatment group.

Table 3.5: Results for elasticities using transfer size

	(1) Staples	(2) Coarse staples	(3) Fine staples	(4) Protein	(5) Vegetables +fruits
Transfer size	0.081***	0.049**	0.080***	0.119***	0.085***
	(0.016)	(0.022)	(0.011)	(0.018)	(0.014)
Constant	1.637***	0.894***	1.076***	1.865***	1.444***
	(0.036)	(0.050)	(0.026)	(0.034)	(0.029)
N	55,744	48,326	55,079	55,739	55,744
No. clusters	843	715	715	843	843

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps. Coefficient of transfer size (in arcsinh) can be interpreted as elasticity.

The results in Table 3.5 indicate that a one-percent exogenous increase in income is associated with a 0.08 percent increase in expenditures on food staples, a 0.08 percent increase in expenditures on fine staples, a 0.12 percent increase in expenditures on protein, and a 0.09 percent increase in expenditures on fruits and vegetables.[16]

While the elasticities in Table 3.5 may appear modest at first sight, the elasticities in Table 3.6, for their part, indicate that being randomized into the treatment group is associated with a 21-percent increase in expenditures on staples, a 11-percent increase in expenditures on coarse staples, a 21-percent increase in expenditures on fine staples, a

[16] It is worth remembering that our estimates are ITT effects, and so the elasticities presented here are "ITT elasticities", or elasticities that result from being randomized into the treatment group. Given that, we talk of associations rather than direct causal relationships.

33-percent increase in expenditures on protein, and a 22-percent increase in expenditures on fruits and vegetables.

Taken together, the findings in Tables 3.2 to 3.6 show that, on average across the five contexts we study, food is a normal good across all categories. Moreover, these findings show that food is a necessity in that while food expenditures increase in response to exogenous increases in income, they increase at a rate that is less than that at which income increases. These findings support Bennett's Law in that they show that expenditures on fine staples rise faster than expenditures on coarse staples and that expenditures on protein rise faster than expenditures on coarse staples in response to an exogenous increase in income. Finally, we find that protein is the food category whose expenditures increase the most in response to the treatment, whether one considers effects in monetary terms or in terms of elasticities.

Table 3.6: Results for elasticities using treatment dummy

	Staples	Coarse staples	Fine staples	Protein	Vegetables +fruits
Treated	0.192***	0.108*	0.190***	0.282***	0.199***
	(0.047)	(0.057)	(0.030)	(0.045)	(0.040)
Constant	1.643***	0.902***	1.083***	1.874***	1.452***
	(0.042)	(0.048)	(0.024)	(0.033)	(0.031)
Calculated elasticity using different formulas:					
$\exp(\hat{\beta}) - 1$	0.212***	0.114*	0.209***	0.326***	0.221***
	(0.058)	(0.064)	(0.033)	(0.056)	(0.044)
$\exp(\hat{\beta} - 0.5\hat{Var}(\hat{\beta})) - 1$	0.211***	0.113**	0.208***	0.325***	0.220***
	(0.051)	(0.057)	(0.036)	(0.053)	(0.048)
N	55,744	48,326	55,079	55,739	55,744
No. clusters	843	715	715	843	843

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps. Elasticities are calculated using the formulas indicated in the table, with displaying $\frac{P}{100} = formula$.

3.5. Discussion

Aggregating data from five cash-transfer RCTs across four countries, we have looked at the effect of income on food demand (as proxied by food expenditures). Our results show that food is a normal good and a necessity across all categories, viz. staples both coarse (with and without tubers) and fine, protein, as well as fruits and vegetables. Moreover, we have found support for Bennett's Law in that expenditures on fine staples rise faster than expenditures on coarse staples and expenditures on protein rise faster than expenditures on coarse staples in response to an exogenous increase in income. Finally, we have found that, of all food categories, protein responds most to changes in income. In contrast to the previously estimated income elasticities reported in the nutrition literature, these estimates are coming from data from different RCTs across three continents allowing for conclusions with external validity. An additional advantage is that they are causal because they leverage randomized treatment assignment.

While we have harmonized the five datasets for our analysis, important differences may persist across contexts. In particular, there may be important quality differences that are not accounted for in the data. For instance, households may have different tastes for the different grades of rice, and that these grades may have significant price differences, and a positive income shock may cause a household to consume a higher grade of rice. We generally do not observe such granularity in the data, and assume that all rice is one grade, but of course, households could be spending more on a higher quality version of a coarse staple in addition to the observed changes in allocation across food groups. Such quality upgrading is consistent with Bennett's Law and would result in our underestimating the impacts of the income shock. Similarly, the transfers may enable otherwise cash-constrained households to purchase food items in bulk, potentially leading to a lower total expenditure on staples than if they were only able to purchase smaller quantities. This in turn may free up more income for proteins or finer grains, etc., further increasing demand for such categories. Such compensatory behavior by households is part of the estimated income effect underlying Bennett's Law.

These findings have important consequences for development policy. First off, if a policy maker's goal is to improve nutrition, our results show that cash transfers can help. This is especially so if the goal is to either increase the number of calories consumed or increase the consumption of protein. Second, given that the land use requirement and carbon footprint of animal-sourced protein protein are the higher than for other food categories (Nijdam, Rood and Westhoek, 2012), these findings suggest that as households in low- and middle-income country get wealthier, increasing amounts of land are likely to be dedicated to protein, and carbon emissions are likely to rise sharply, giving rise to a number of problems. This means that, without other solutions or adjustments, consumers in high-income countries would have to sharply reduce their consumption of animal-sourced protein in order to offset the effects of increased animal-sourced protein consumption in low- and middle-income countries.

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A. APPENDIX TO CHAPTER 1

A.1. Data

Food prices and nutrition investments

To capture nutritional diversity, nutrition investments are proxied by the number of food groups. Food groups in the consumption data are carbohydrates, protein, dairy, vegetables, and fruits. If the household expenditure on one food group is more than 5% of the total expenditure, it is counted as an investment in this food group. Due to data constraints, I cannot identify if household consumption aligns with the child's nutrition. However, I assume that it is a good enough proxy for nutritional diversity since it is unlikely that children receive entirely different food than the one bought by the household. Nutrition diversity is expressed by a measure between 1 and 5, with $n_t = 5$ meaning that a child consumes all five food groups and $n_t = 1$ that it consumes only one food group.

For food prices, I rely on the community surveys in the IFLS, which surveys food prices in the community markets and shops. I construct unit prices of protein, carbohydrates, and vegetables, which are the most prominent consumption expenditure groups and have the most reliable price data (in terms of units).

Then I build the food price by weighting prices by the median consumption fraction for households in the sample consuming all three groups. This leads to a weight of 0.43 for carbs, 0.14 for vegetables, and 0.43 for meat. These prices are then scaled by the average kilograms consumed by households using equivalence scales for Indonesia estimated by Olken (2006) for different ages and household compositions. These are close to the modified OECD scale. I use these equivalence scales and median prices to find the median amount of kg consumed by a household. This amount I then multiply by the factor an additional child of the corresponding age from the household equivalence scale and the median regional food price mentioned above.

Schooling prices and investments

For each household, I have detailed information on what they spend on schooling, e.g., the school fees and books, uniforms, and transport. As investments, I define all registration costs, exam costs, and fees, which the household pays for the child's education. I add the investments into books. I restrain from adding food, uniforms, and transport costs, since I do not assume them to measure the school's quality and influence skill formation. However, this neglects potential budget constraints for these items. The schooling price is assumed to be equal to 1.

Household income and assets

I sum all income reported for the household. This includes business and farm business income, as well as all other income received by any of the household members. Further, this entails non-labor income, the number of transfers, retirement payments, and scholarships received. I adjust household income by the household size for the calibration. For that, I use Olken (2005) equivalence scales derived for Indonesia. As these are derived from aid allocated by the Raskin rice program to different family structures, I assume they will mimic the family's income and how it translates into consumption. Deaton and Zaidi (2002) and Batana, Bussolo and Cockburn (2013) state that the wildly used modified OECD scale or square root scales suit high-income countries. Using the scale for low-income countries might overestimate the degree of the economics of scale, as durables are easier to share than food, a significant fraction of the expenditure in low-income countries. Further, they tend to overestimate the cost of children. Hence, I use Olken's estimated scale, which is higher. Thus the economics of scale are lower. Most scales are convertible in the following:

$$N^{eq} = (n_a + \alpha n_c)^{\theta} \tag{A.1}$$

where n_a is the number of adults in the household, and n_c is the number of children. α is the cost of children, and θ expresses the economies of scale. In the scare root scale, $\alpha = 1$ and $\theta = 0.5$. In contrast Olken estimates $\alpha = 0.93$ and $\theta = 0.85$, which confirms Deaton and Zaidi (2002)'s claim that the economies of scale are lower, thus θ higher in low-income countries. This also goes with Santaeulàlia-Llopis and Zheng (2017), who estimate scale parameters in Malawi to be higher than the OECD ones.

For assets, I sum all assets reported in the data, which are expressed in monetary value. This entails real estate owned, land, livestock, machinery, household appliances, savings, jewellery and furniture. I substract from assets the reported amount of dept of the households. Then I adjust the left-over assets with the household equivalence scale.

Skill measures

For health skills, the following measures are used: height and weight. With the help of the WHO Child Growth Standards and WHO Reference 2007 composite data files as the reference data, I build z-scores for children under 20 years old (Vidmar, Cole and Pan, 2013). Hereby the height-for-age, weight-for-age, BMI-for-age and weight-for-height z-scores are computed. BMI is taken as an indicator for older individuals, thus the parents and adults. In period 1, early childhood, the measures used are height-for-age and weight-for-age since no cognitive measures are available.

For cognitive skills outcomes, cognitive tests conducted by the survey team are available, which I standardize by age. The IFLS has several test score metrics available: In 1997, a math test with 40 questions was conducted for the following age groups: 7-9, 10-12, and

13-24, and the same was done for a language evaluation. For younger ages, no test scores are available. Therefore, in the early childhood period, only health outcomes can serve as a measure of skills. For 2000, 2007, and 2014 a raven test was conducted with 12 questions, followed by a math test of 5. These were designed in 2 versions, one for age group 7 to 14, the other 15 to 24. In both cases, the number of correct answers is standardized by age and year. Adult respondents answered a cognitive test in 2007 and 2014. The tests ask them to remember ten words for a short period, and a second round asks how many they remember after some minutes. In 2014 additionally, a simple subtraction exercise was asked. Adult test scores are standardized by year to avoid some candidates being counted double. As cognitive measures during childhood, raven or language and math scores are taken, while for adults, an average for word- and math tests is taken.

A.2. Stylized facts and descriptives

Table A.1: Sample characteristics by period

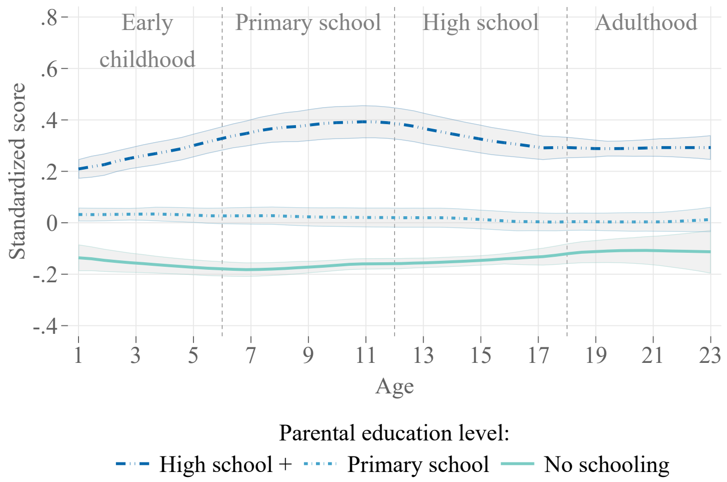
	Early childhood	Primary school	High school
Food groups	3.67	3.61	3.58
Schooling spending	0.24	2.61	6.00
Age	3.02	8.84	15.34
In school	0.06	0.93	0.73
Observations	4,563	6,329	8,451

Note: Monetary values are deflated and reported in 100,000 Rupees.

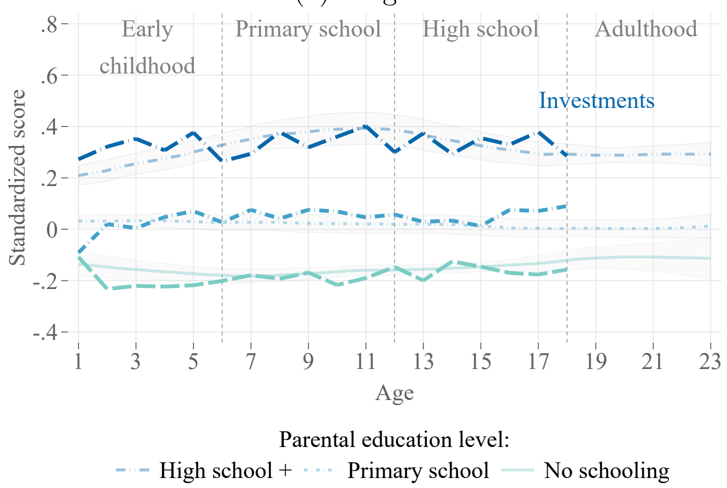
Table A.2: Sample characteristics

	Mean	SD	Min	Max
Female	0.50	0.50	0	1
Rural	0.54	0.50	0	1
Islam	0.88	0.33	0	1
Mother's years of education	5.50	4.12	0	18
Father's years of education	6.58	4.38	0	18.5
Birth year	1990.88	6.53	1979	2007
Household income	270.65	331.2	0	3982.9
Weight-by-age	-1.16	1.44	-4.99	4.92
Height-by-age	-1.49	1.27	-4.98	4.97
Stunting	0.34	0.47	0	1
Wasting	0.09	0.28	0	1
Mother's age	41.30	9.15	17	78
Father's age	46.84	10.5	20	96
Adult household members	3.93	1.82	0	8
Household members <18	1.86	1.36	0	5
Observations	19,343			

Note: Monetary values are deflated and reported in 100,000 Rupees.



(a) Height



(b) Height and investments

Figure A.1: Children skills and investments over age by parental education

Note: Skills are fitted with local mean smoothing by age and parental education groups. Parental education groups correspond to the average education of both parents. Confidence intervals displayed are at 95% level. Investments plotted are standardized nutrition investments. Scores of skills and investments are standardized by age to have a mean of 0 and SD of 1.

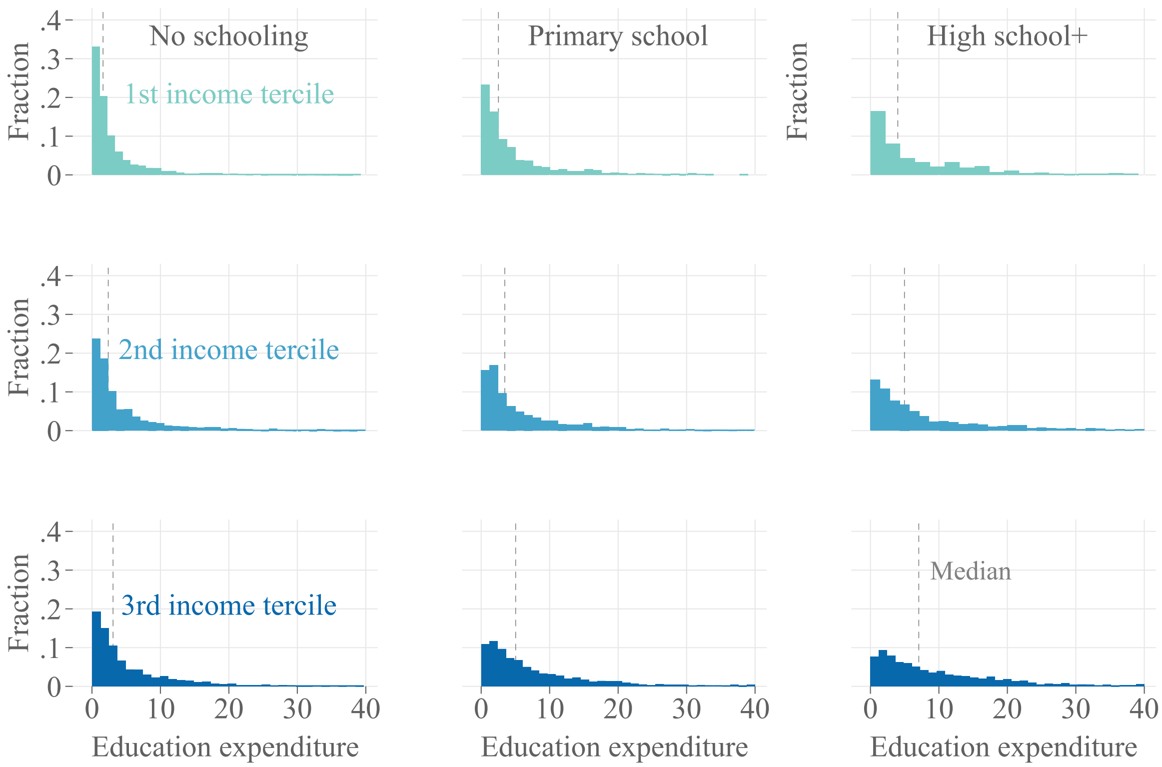


Figure A.2: Heterogeneity in education spending by parental background

Note: Education spending histograms by parental education level and household income (in terciles). Parental education groups correspond to the average education of both parents. Expenditures are expressed in 100,000 rupees. The grey-dashed line indicates the median value for that category.

A.3. Estimation and calibration details

K-means algorithm

I follow Bonhomme, Lamadon and Manresa (2022) to estimate the unobserved types of parenting skills outside of the model. To do so, I build means over the life-cycle of schooling, nutrition investments, and household income for each parent couple. I then standardize these and run the k-means clustering procedure, which will allocate each household to the cluster whose moments have the least distance to the cluster mean.

To estimate heterogeneity groups using the k-means clustering algorithm, I need to choose the number of clustering groups K. As this is a data-driven approach, they are not known before but data can be used to determine them. To do so, I use the commonly used Elbow statistic. For a given number of clusters K, the algorithm minimizes the total within-cluster variance:

$$\min_{k\in\{1,..,K\}^N} \sum_{t=1}^{N}\sum_{c=1}^{C} ||\boldsymbol{m_{t,c}} - \boldsymbol{\overline{m}_k}||^2 = SSE_k \tag{A.2}$$

To compare Elbow statistics, the variance SSE_k is calculated for each number of clusters run, $k = 1; ...; K_{max}$. These statistics are then plotted against their corresponding number of clusters, as seen in Figure A.3a. With an increasing number of clusters, the variance decreases as observations within a cluster become more similar. The optimal number of clusters is at the kink in the plot, the point where the decrease in SSE changes the most. Adding more clusters than at this kink would have limited value in explaining the variation in the data. Another commonly used measure is the silhouette criterion in Figure A.3b. The higher the criteria value, the more the two clusters are different from each other. Thus, the borders between them are well defined.

As shown in Figure A.3a, the elbow criteria determines the optimal amount of clusters K to be 4. The silhouette criterion is maximized at two but also high at 4. To check if the number of clusters drives the results, I run the GMM estimation for $K \in \{2, 3, 4, 5\}$ clusters. As one can see the results for $K = 2$ in Table A.10, $K = 3$ in Table A.11, $K = 5$ in Table A.12 are comparable to the main results in Table A.4 with $K = 4$. Coefficients and standard errors only vary marginally. Thus, the amount of clusters does not drive the results and, if anything, adds explanatory power. More clusters seem to explain more unobserved heterogeneity in investments, as schooling productivity varies by type. However, after $K = 4$, the amount of observations decreases by type, as shown in Table A.6. Hence, increasing the computational burden further has little reward. This is confirmed by the fact that these amounts exceed the amount determined to be optimal by the elbow criterion.

Household income

To estimate household income, I regress parental education, number of household members (adults and children), rurality and age of the household head, and parenting skills on household income. Additionally, I include year and province fixed effects. Thus:

$$\ln(y_t) = Z'_{y,t}\gamma_y + \eta'\gamma_\eta + \epsilon_{y,t} \tag{A.3}$$

Here, $Z_{y,t}$ are the named household characteristics that can vary by period. η are the unobserved parenting skills I assume to influence household income, as it is likely that characteristics resulting in productive parents also translate at least partly into higher wages. Results can be found in Table A.3. I use the resulting coefficients to predict future household income for the calibrations and simulations. Further, I assume the income shocks to be i.i.d. normally distributed. Thus $\epsilon \overset{i.i.d}{\sim} N(0, \sigma_y)$.

Transition of other household characteristics

I assume all household characteristics to be stable over time, except the year, age, and age of the household head. As period one observations I use for the calibration start are either in 1997 or 2000 for the transition to the next period, I get either 2000 or 2007 for 1997 or 2007 for 2000 (observed for the first period, as I know next period). Afterward, due to the survey design, all future waves are seven years apart. Thus, I apply that to simulate the year in which the child is observed in the next period. Then I apply this gap to its age and the father's age. Knowing the next year then allows me to allocate the correct food price for the given community in that year to the simulated period. Thus, I assume households do not move. Further, I assume the number of household members and other children in the household to be stable across childhood, the same for the location in a rural or urban area. To relax this assumption could be a potential future extension.

Skill formation estimation

Regarding the GMM estimation, two obstacles driven by data constraints occur. Firstly, only nutrition inputs are available to measure investments in the first period. Thus, there is no stage with relative investment input ratios, which can then be plugged into the human capital parameters. Hence the food groups are directly plugged into this equation. Further, I do not observe cognitive skills in the early childhood. Hence, I use height and weight as a proxy. Therefore, $\delta_{2,1}$, the persistence of skills cannot be directly compared to the parameters in later periods, as it measures the persistence of height and weight on future cognitive skills.

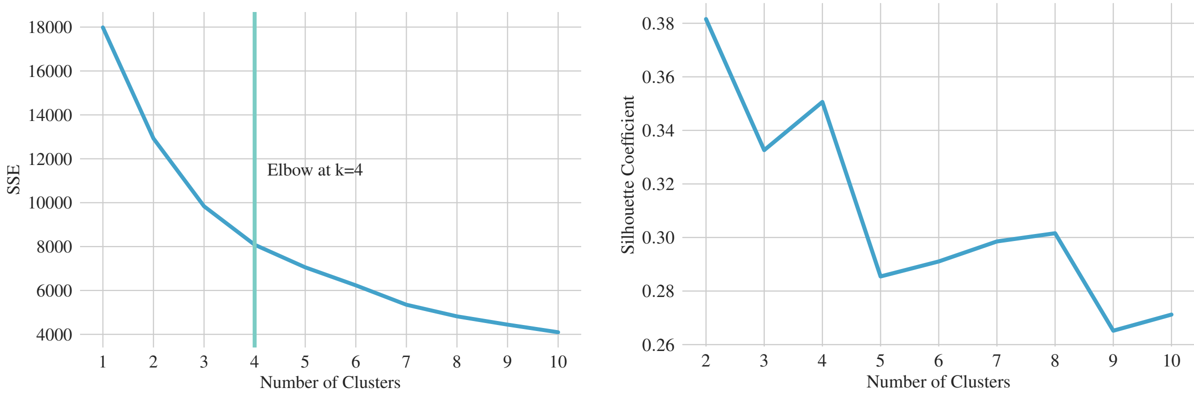
Second, I assume nutrition is unconstrained, however I only observe food groups up to five. Therefore, I conduct robustness checks in case it is constrained to 5. If nutrition is constrained, the optimal demand ratios for the GMM moments hold only if $n_t < 5$ (see

Appendix A.5 for details for $n_t = 5$). In the main specifications, I also include $n_t = 5$, assuming that it does not drive the results. As a robustness check, I dropped them and ran the results without using observations with $n_t = 5$ to estimate the relative demand equations (see Table A.13). The results are relatively similar, which indicates that this subgroup does not drive the general results. If anything, the estimates are less precise, but this could also come from the smaller sample. However, dropping them introduces selection. Thus the results have to be taken with a grain of salt. Future work should exploit how these constraints bias the estimation results. For the calibration, I calibrate the model with and without the constraint without assets and do not see substantial differences. As with assets the constraint induces complex solutions, I then proceed without constraint, assuming that I observe only up to 5 food groups which can translate into 5 or more as investment in reality.

Calibration

To calibrate the model, I use the optimal solution for investments and assets derived in Appendix A.5. I match model and data investment means by parental education and childhood period and assets by childhood period to get γ_e and α_e and ζ. To calibrate the model, I use the data from period one and simulate periods two to four with it, to then compare it to the data I observe in those periods in the survey. For a_{min}, the maximum amount households can borrow, I use the average debt I observe in the data in a given year.

A.4. Estimation results



(a) Elbow criterion (b) Silhouette criterion

Figure A.3: Criterion plots to determine number of clusters for parenting skills

Note: K-means algorithm run for different number of clusters to determine correct number for the following estimation. Plotted are on the right-hand side the within cluster variance, on the left-hand side the Silhouette coefficient by number of clusters used.

Table A.3: Estimation results for household income

	Log(income)	
Father primary education	0.152***	(0.014)
Father high school+	0.422***	(0.016)
Mother primary education	0.112***	(0.014)
Mother high school+	0.294***	(0.017)
Parenting type 1	-0.375***	(0.012)
Parenting type 2	0.671***	(0.028)
Parenting type 3	1.441***	(0.027)
Father age	0.053***	(0.003)
Father age squared	-0.001***	(0.000)
Rural area	-0.348***	(0.012)
Adult household members	0.104***	(0.003)
Non-adult household members	0.016***	(0.004)
Constant	2.733***	(0.079)
Year fixed effects	Yes	
Province fixed effects	Yes	
Observations	36,169	

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.

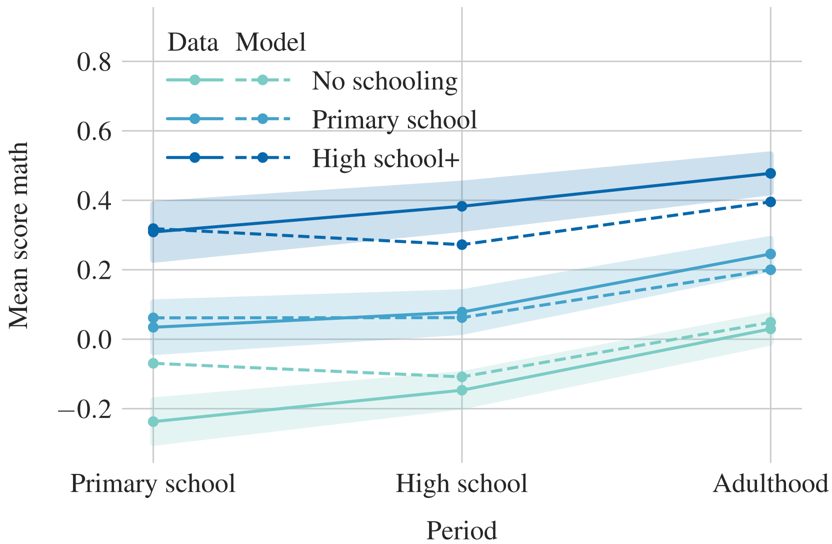


Figure A.4: Model fit for untargeted children's skills by period

Table A.4: Estimation results for skill formation parameters

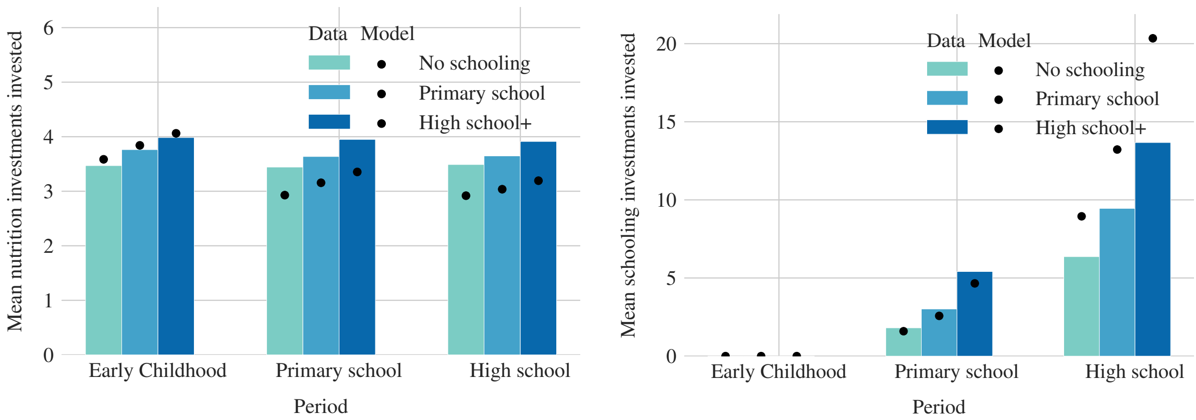
	Early childhood		Primary school		High school	
Investment elasticity:						
Substitution parameter ρ_t			-3.75	(0.86)***	-11.38	(5.11)**
Implied elasticity			0.21		0.08	
Schooling investment productivity $\phi_{s,t}$:						
Constant			-3.68	(0.51)***	-42.17	(16.55)**
Mother primary			1.10	(0.25)***	3.06	(1.32)**
Mother high			1.87	(0.39)***	5.04	(2.15)**
Father primary			0.09	(0.16)	0.63	(0.47)
Father high			-0.08	(0.19)	0.51	(0.50)
Age			-0.05	(0.04)	3.14	(1.30)**
Female			0.05	(0.13)	1.29	(0.61)**
Rural area			-2.64	(0.53)***	-5.19	(2.22)**
No. of siblings			-0.73	(0.14)***	-2.14	(0.88)**
Mother not Islam			0.39	(0.22)*	1.68	(0.85)**
Parenting type 1			-0.24	(0.14)*	0.06	(0.34)
Parenting type 2			4.74	(0.97)***	9.62	(4.10)**
Parenting type 3			1.64	(0.50)***	2.47	(1.29)*
Human capital formation:						
$\delta_{1,t}$ (investment)	0.28	(0.06)***	0.16	(0.05)***	0.18	(0.03)***
$\delta_{2,t}$ (skills)	0.10	(0.02)***	0.19	(0.02)***	0.22	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.73	(0.08)***	-0.02	(0.12)	-0.22	(0.09)**
Mother primary	0.02	(0.04)	0.06	(0.04)	0.05	(0.02)**
Mother high	0.22	(0.03)***	0.25	(0.04)***	0.16	(0.03)***
Father primary	0.02	(0.04)	0.13	(0.04)***	0.03	(0.03)
Father high	0.11	(0.03)***	0.07	(0.04)*	0.11	(0.03)***
Age	0.10	(0.01)***	-0.02	(0.01)**	0.01	(0.01)
Factor loading for skills $\lambda_{ts_2,s}$:						
$\lambda_{t,ts}$	1.00	(0.07)	1.07	(0.01)	1.09	(0.01)
$\lambda_{4,ts}$					1.21	(0.04)
Observations	27,366					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

Table A.5: Model fit - targeted moments

	Model	Data	SD	Difference
No schooling:				
Early childhood	3.60	3.47	0.80	0.16
Primary school	2.90	3.08	0.94	-0.20
High school	2.82	2.78	1.13	0.04
Primary school:				
Early childhood	3.87	3.76	0.83	0.13
Primary school	3.13	3.22	0.99	-0.09
High school	2.94	2.90	1.16	0.04
High school+:				
Early childhood	4.06	3.98	0.80	0.10
Primary school	3.29	3.43	1.08	-0.13
High school	3.08	3.06	1.26	0.01
Assets:				
Early childhood	620.00	763.38	829.21	-0.17
Primary school	818.75	937.98	1045.17	-0.11
High school	1222.53	1128.23	1172.96	0.08

Note: Calibration method used: simulated methods of moments. Differences are expressed in standard deviations. Values are total investments by parental education and childhood period and for assets by period.



(a) Nutrition

(b) Schooling expenditure

Figure A.5: Untargeted moments for investment input choices by period

Note: Investment inputs means plotted by parental education and childhood periods. Black dots are corresponding simulated moments.

A.5. Derivation Formulas

Inter-temporal solution n_t and s_t and relative demands

To derive the relative demands we take first-order conditions for the minimization problem:

$$\begin{aligned} &\min_{n_t, s_t} \quad p_{n,t} n_t + p_{s,t} s_t \\ &\text{s.t. } It = [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}} \end{aligned} \tag{A.4}$$

The Lagrangian looks the following:

$$\mathcal{L} = p_{n,t} n_t + p_{s,t} s_t - \lambda_{1,t}(I_t - [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}}) \tag{A.5}$$

Deriving first order conditions in period 2 and 3:

$$\frac{\partial \mathcal{L}}{\partial s_t} = p_{s,t} - \lambda_{1,t}(a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t - 1} \rho_t) \times [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t} - 1} \frac{1}{\rho_t} = 0 \tag{A.6}$$

$$\frac{\partial \mathcal{L}}{\partial n_t} = p_{n,t} - \lambda_{1,t}(n_t^{\rho_t - 1} \rho_t) \times [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t} - 1} \frac{1}{\rho_t} = 0 \tag{A.7}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{1,t}} = I_t - [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}} = 0 \tag{A.8}$$

Taking ratios $\frac{\frac{\partial \mathcal{L}}{\partial n_t}}{\frac{\partial \mathcal{L}}{\partial s_t}}$ leads:

$$\frac{p_{n,t}}{p_{s,t}} = \frac{n_t^{\rho_t - 1}}{a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t - 1}} \tag{A.9}$$

which allows to get n_t in terms of s_t:

$$n_t = \left(\frac{p_{n,t}}{p_{s,t}} a_{s,t}(Z_{s,t}, \eta) \right)^{\frac{1}{\rho_t - 1}} s_t = \Phi_1 s_t \tag{A.10}$$

and vice versa:

$$s_t = \Phi_1^{-1} n_t \tag{A.11}$$

Price for total investments Λ_t and relative demands I_t and I_{t+1}

The price for total investments I_t is supposed to mimic the cost for one unit of investment, thus:

$$\begin{aligned} E_t &= \Lambda_t I_t \\ \Lambda_t &= \frac{E_t}{I_t} \\ \Lambda_t &= \frac{p_{n,t} n_t + p_{s,t} s_t}{[a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}}} \end{aligned} \tag{A.12}$$

To calculate prices we use A.10 to get expressions for n_t in terms of s_t:

$$n_t = \left(\frac{p_{n,t}}{p_{s,t}} a_{s,t}(Z_{s,t}, \eta)\right)^{\frac{1}{\rho_t - 1}} s_t = \Phi_1 s_t \tag{A.13}$$

Replacing n_t in yields in Equation A.12 with moving s_t out of E_t:

$$\begin{aligned}\Lambda_t &= \frac{s_t(p_{s,t} + p_{n,t}\Phi_1)}{[a_{s,t}(Z_{s,t}, \eta)s_t^{\rho_t} + (\Phi_1 s_t)^{\rho_t}]^{\frac{1}{\rho_t}}} \\ &= \frac{(p_{s,t} + p_{n,t}\Phi_1)}{[a_{s,t}(Z_{s,t}, \eta) + \Phi_1^{\rho_t}]^{\frac{1}{\rho_t}}}\end{aligned} \tag{A.14}$$

Intra-temporal solution for I_t

We can use the total price of investment Equation A.12 for the maximization problem to derive solutions for I_t, c_t and a_{t+1} :

$$\begin{aligned} V_t(Z_t, a_t, y_t, \Pi_t, \Psi_t) = \max_{c_t, I_t, a_{t+1}} & \; u(c_t) + \alpha_e v(\Psi_t) \\ & + \beta_t V_{t+1}(Z_{t+1}, a_{t+1}, y_{t+1}, \Pi_{t+1}, \Psi_{T+1}) \\ \text{s.t.} \quad c_t + \Lambda_t I_t + a_{t+1} &= (1+r)a_t + y_t \\ a_{t+1} &\geq a_{min,t} \\ \text{with} \quad \Psi_{t+1} &= \theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}} \\ V_{T+1}(\Psi_{T+1}) &= \alpha_e \gamma_e \ln(\Psi_{T+1}) + \zeta \ln(a_{T+1}) \\ u(c_t) &= \ln(c_t) \\ v(\Psi_t) &= \ln(\Psi_t) \end{aligned} \tag{A.15}$$

Which gives the Lagrangian:

$$\begin{aligned}\mathcal{L} = u(c_t) &+ \alpha_e v(\Psi_t) + \beta_t V_{t+1}(Z_{t+1}, a_{t+1}, y_{t+1}, \Pi_{t+1}, \Psi_{T+1}) \\ &- \lambda_t(c_t + \Lambda_t I_t + a_{t+1} - (1+r)a_t - y_t) - \xi_t(a_{min,t} - a_{t+1})\end{aligned} \tag{A.16}$$

T=3 here, because the period 3 is the last one, where the household makes decisions. The first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial I_t} = \beta_t \frac{\partial V_{t+1}}{\partial I_t} - \lambda_t \Lambda_t = 0 \tag{A.17}$$

$$\frac{\partial \mathcal{L}}{\partial c_t} = u'(c_t) - \lambda_t = 0 \tag{A.18}$$

$$\frac{\partial \mathcal{L}}{\partial a_{t+1}} = -\lambda_t + \xi_t + \mathbb{1}\{t < T\}(\lambda_{t+1}\beta_{t+1}(1+r)) + \mathbb{1}\{t = T\}\beta_t \frac{\partial V_{T+1}}{\partial a_{T+1}} \tag{A.19}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_t} = c_t + \Lambda_t I_t + a_{t+1} - (1+r)a_t - y_t = 0 \tag{A.20}$$

$$\frac{\partial \mathcal{L}}{\partial \xi_t} = a_{min,t} - a_{t+1} = 0 \tag{A.21}$$

$$\tag{A.22}$$

Following these one can derive a solution for I_t. First one needs to derive after I_t, which will vary by period due to the continuation value. In period 3, the continuation value looks the following:

$$\begin{aligned} \beta_t V_{T+1}(\Psi_{T+1}) =& \beta_t(\alpha_e \gamma_e \ln(\Psi_{T+1}) + \zeta \ln(a_{T+1})) \\ \text{with } \Psi_{t+1} =& \theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}} \end{aligned} \tag{A.23}$$

Plugging it in V_{t+1}:

$$\beta_t V_{t+1}(\Psi_{t+1}) = \beta_t(\alpha_e \gamma_e \ln(\theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}}) + \zeta \ln(a_{T+1})) \tag{A.24}$$

Thus:

$$\beta_t \frac{\partial V_{t+1}}{\partial I_t} = \frac{\beta_t \delta_{1,t} \alpha_e \gamma_e}{I_t} = \frac{K_t}{I_t} \tag{A.25}$$

For period 2:

$$\beta_t V_{t+1}(\Psi_{t+1}) = \beta_t(u(c_{t+1}) + \alpha_e v(\Psi_{t+1})) + \beta_{t+1}\beta_t(\alpha_e \gamma_e \ln(\Psi_{T+1}) + \zeta \ln(a_{T+1})) \tag{A.26}$$

which is:

$$\begin{aligned} \beta_t V_{t+1}(\Psi_{t+1}) =& \beta_t(\ln(c_{t+1}) + \alpha_e \ln(\theta_t(Z_{\theta,t})) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}}) \\ &+ \beta_{t+1}\beta_t(\alpha_e \gamma_e \ln(\theta_{t+1}(Z_{\theta,t+1}) I_{t+1}^{\delta_{1,t+1}} \Psi_{t+1}^{\delta_{2,t+1}}) + \zeta \ln(a_{t+2})) \end{aligned} \tag{A.27}$$

plugging in Ψ_{t+1}:

$$\begin{aligned} \beta_t V_{t+1}(\Psi_{t+1}) =& \beta_t(\ln(c_{t+1}) + \alpha_e \ln(\theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}})) \\ &+ \beta_{t+1}\beta_t(\alpha_e \gamma_e \ln(\theta_{t+1}(Z_{\theta,t+1}) I_{t+1}^{\delta_{1,t+1}} (\theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}})^{\delta_{2,t+1}}) \\ &+ \zeta \ln(a_{t+2})) \end{aligned} \tag{A.28}$$

Thus:

$$\beta_t \frac{\partial V_{t+1}}{\partial I_t} = \frac{\beta_t \delta_{1,t}(\alpha_e + \beta_{t+1}\delta_{2,t+1}\gamma_e \alpha_e)}{I_t} = \frac{K_t}{I_t} \tag{A.29}$$

For period 1:

$$\begin{aligned}\beta V_{t+1}(\Psi_{t+1}) = \beta_t(u(c_{t+1}) + \alpha_e v(\Psi_{t+1})) + \beta_{t+1}\beta_t(u(c_{t+2}) + \alpha_e v(\Psi_{t+2})) \\ + \beta_{t+2}\beta_{t+1}\beta_t(\alpha_e\gamma_e \ln(\Psi_{t+3}) + \zeta \ln(a_{t+3}))\end{aligned} \tag{A.30}$$

Resulting in:

$$\begin{aligned}\beta_t V_{t+1}(\Psi_{t+1}) =& \beta_t(u(c_{t+1}) + \alpha_e \ln(\theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}})) + \beta_{t+1}\beta_t(u(c_{t+2}) \\ &+ \alpha_e \ln(\theta_{t+1}(Z_{\theta,t+1}) I_{t+1}^{\delta_{1,t+1}} (\theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}})^{\delta_{2,t+1}})) \\ &+ \beta_{t+2}\beta_{t+1}\beta_t(\alpha_e\gamma_e \ln(Z_{\theta,t+2}) I_{t+2}^{\delta_{1,t+2}} (\theta_t(Z_{\theta,t+1}) I_{t+1}^{\delta_{1,t+1}} (Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}})^{\delta_{2,t+1}})^{\delta_{2,t+2}}) \\ &+ \zeta \ln(a_{t+3}))\end{aligned} \tag{A.31}$$

Giving:

$$\beta \frac{\partial V_{t+1}}{\partial I_t} = \frac{\beta_t \delta_{1,t}(\alpha_e + \beta_{t+1}\delta_{2,t+1}(\alpha_e + \beta_{t+2}\delta_{2,t+2}\gamma_e \alpha_e))}{I_t} = \frac{K_t}{I_t} \tag{A.32}$$

Using the FOCs for c_t and I_t, and the values above for K_t, results in:

$$\frac{\partial \mathcal{L}}{\partial I_t} = \frac{K_t}{I_t} - u'(c,t)\Lambda_t = 0 \tag{A.33}$$

Now to derive an optimal solution for I_t, I use:

$$c_t = -\Lambda_t I_t - a_{t+1} + (1+r)a_t + y_t \tag{A.34}$$

plugging in:

$$\begin{aligned}\frac{K_t}{I_t} - \frac{\Lambda_t}{-\Lambda_t I_t - a_{t+1} + (1+r)a_t + y_t} &= 0 \\ \frac{\Lambda_t}{-\Lambda_t I_t - a_{t+1} + (1+r)a_t + y_t} &= \frac{K_t}{I_t} \\ (-\Lambda_t I_t - a_{t+1} + (1+r)a_t + y_t)K_t &= \Lambda_t I_t \\ (-a_{t+1} + (1+r)a_t + y_t)K_t &= \Lambda_t I_t + K_t \Lambda_t I_t\end{aligned} \tag{A.35}$$

Thus, the optimal solution for I_t:

$$I_t = \frac{K_t(-a_{t+1} + (1+r)a_t + y_t)}{\Lambda_t(1+K_t)} \tag{A.36}$$

This solution can also be used for period 1, as $I_t = n_t$ and $\Lambda_t = p_{n,t}$. For the borrowing constrained case, $a_{t+1} = a_{min,t}$, for the non-borrowing constrained case, an optimal solution for a_{t+1} is needed, which is derived in Appendix A.5. If $a_t = 0$ and there are no assets, the amount of I_t depends apart from the parameters and related characteristics only on household income y_t.

Optimal solution for s_t and n_t

With I_t one can derive n_t and s_t:

$$I_t = [a_{s,t}(Z_{s,t},\eta)s_t^{\rho_t} + (\Phi_1 s_t)^{\rho_t}]^{\frac{1}{\rho_t}} = [a_{s,t}(Z_{s,t},\eta) + (\Phi_1)^{\rho_t}]^{\frac{1}{\rho_t}} s_t \tag{A.37}$$

using Equation A.36 for I_t:

$$\frac{K_t(-a_{t+1} + (1+r_t)a_t + y_t)}{\Lambda_t(1+K_t)} = [a_{s,t}(Z_{s,t},\eta) + (\Phi_1)^{\rho_t}]^{\frac{1}{\rho_t}} s_t \tag{A.38}$$

$$s_t = \frac{K_t(-a_{t+1} + (1+r_t)a_t + y_t)}{\Lambda_t(1+K_t)[a_{s,t}(Z_{s,t},\eta) + (\Phi_1)^{\rho_t}]^{\frac{1}{\rho_t}}} \tag{A.39}$$

With Equation A.10:

$$n_t = \Phi_1 \frac{K_t(-a_{t+1} + (1+r_t)a_t + y_t)}{\Lambda_t(1+K_t)[a_{s,t}(Z_{s,t},\eta) + (\Phi_1)^{\rho_t}]^{\frac{1}{\rho_t}}} \tag{A.40}$$

Optimal solution for a_{t+1} and n_t

From the FOC of the optimization problem, one can use:

$$\frac{\partial \mathcal{L}}{\partial a_{t+1}} = -\lambda_t + \xi_t + \mathbb{1}\{t<T\}(\lambda_{t+1}\beta_t(1+r_{t+1})) + \mathbb{1}\{t=T\}\beta_t \frac{\partial V_{T+1}}{\partial a_{T+1}} \tag{A.41}$$

If the household is not borrowing constraint: $\xi_t = 0$. For period 3:
Equation A.41 results in:

$$\frac{1}{-\Lambda_t I_t - a_{t+1} + (1+r_t)a_t + y_t} = \beta_t \zeta \frac{1}{a_{t+1}} \tag{A.42}$$

Plugging in the optimal solution for I_t in Equation A.36:

$$\begin{aligned} \beta_t\zeta(-\frac{K_t(-a_{t+1} + (1+r_t)a_t + y_t)}{(1+K_t)} - a_{t+1} + (1+r_t)a_t + y_t)) &= a_{t+1} \\ \frac{\beta_t\zeta}{K_t+1}(-a_{t+1} + (1+r_t)a_t + y_t) &= a_{t+1} \\ a_{t+1} + \frac{\beta_t\zeta}{K_t+1}a_{t+1} &= \frac{\beta\zeta}{K_t+1}((1+r_t)a_t + y_t) \end{aligned}$$

Follows:

$$a_{t+1} = \frac{\beta_t\zeta}{(1+\beta_t\zeta+K_t)}((1+r_t)a_t + y_t) \tag{A.43}$$

And for I_t:

$$I_t = \frac{K_t(-(\frac{\beta_t\zeta}{(1+\beta_t\zeta+K_t)}((1+r_t)a_t+y_t)) + (1+r_t)a_t+y_t)}{\Lambda_t(1+K_t)} \tag{A.44}$$

Which leads to:

$$I_t = \frac{K_t}{\Lambda_t(1+K_t+\zeta\beta_t)}((1+r_t)a_t+y_t) \tag{A.45}$$

For period 2:

$$\lambda_t = \lambda_{t+1}\beta_t(1+r_{t+1})$$
$$-\Lambda_{t+1}I_{t+1} - a_{t+2} + (1+r_{t+1})a_{t+1} + y_{t+1} = \beta_t(1+r_{t+1})(-\Lambda_t I_t - a_{t+1} + (1+r_t)a_t + y_t)$$

$$\begin{aligned}-(\frac{K_{t+1}((1+r_{t+1})a_{t+1}+y_{t+1})}{(1+K_{t+1}+\beta_{t+1}\zeta)}) - a_{t+2} + (1+r_{t+1})a_{t+1} + y_{t+1} =&\\ \beta_t(1+r_{t+1})(-(\frac{K_t(-a_{t+1}+(1+r)a_t+y_t)}{(1+K_t)}) - a_{t+1} + (1+r_t)a_t + y_t)&\end{aligned} \tag{A.46}$$

Plugging in a_{t+2} and $A = (1+\beta_{t+1}\zeta+K_{t+1})$:

$$\begin{aligned}-(\frac{K_{t+1}}{A}((1+r_{t+1})a_{t+1}+y_{t+1}) + \frac{1+K_{t+1}}{A}(1+r_{t+1})a_{t+1}+y_{t+1}) =&\\ \beta_t(1+r_{t+1})\frac{1}{(1+K_t)}(-a_{t+1}+(1+r_t)a_t+y_t)&\end{aligned} \tag{A.47}$$

$$\begin{aligned}\frac{1}{A}((1+r_{t+1})a_{t+1}+y_{t+1}) =&\\ \beta_t(1+r_{t+1})\frac{1}{(1+K_t)}(-a_{t+1}+(1+r_t)a_t+y_t)&\end{aligned} \tag{A.48}$$

$$\frac{1}{A}(a_{t+1} + \frac{y_{t+1}}{(1+r_{t+1})}) = \beta_t\frac{1}{(1+K_t)}(-a_{t+1}+(1+r_t)a_t+y_t)$$
$$\frac{1}{A}(a_{t+1}) + \frac{\beta_t}{1+K_t}a_{t+1} = -\frac{1}{A}\frac{y_{t+1}}{(1+r_{t+1})} + \frac{\beta_t}{1+K_t}((1+r_t)a_t+y_t))$$

Follows:

$$a_{t+1} = \frac{\beta_t A}{1+K_t+\beta_t A}((1+r_t)a_t+y_t) - \frac{1+K_t}{1+K_t+\beta_t A}\frac{y_{t+1}}{(1+r_{t+1})} \tag{A.49}$$

Plugging in optimal solutions leads to:

$$I_t = \frac{K_t}{\Lambda_t(1+K_t+\beta_t A)}((1+r_t)a_t+y_t+\frac{y_{t+1}}{(1+r_{t+1})}) \tag{A.50}$$

For period 1, following a similar strategy as in period 2, this yields, with $B = (1 + K_{t+1} + \beta_{t+1}(1 + \beta_{t+2}\zeta + K_{t+2}))$:

$$a_{t+1} = \frac{\beta_t B}{1 + K_t + \beta_t B}((1 + r_t)a_t + y_t) \\ - \frac{1 + K_t}{1 + K_t + \beta_t B}(\frac{y_{t+1}}{(1 + r_{t+1})} + \frac{y_{t+1}}{(1 + r_{t+1})(1 + r_{t+2})}) \quad \text{(A.51)}$$

$$I_t = \frac{K_t}{\Lambda_t(1 + K_t + \beta_t B)}((1 + r_t)a_t + y_t + \frac{y_{t+1}}{(1 + r_{t+1})} + \frac{y_{t+1}}{(1 + r_{t+1})(1 + r_{t+2})}) \quad \text{(A.52)}$$

Regarding borrowing constraints, individuals can be never constraint, which is the solution above. Otherwise, they can be constrained always or any combination of order of constrained and unconstrained periods. Exemplary, see here the solution for borrowing constraint in period 3 only:
For period 3:

$$a_{t+1} = a_{min} \quad \text{(A.53)}$$

and

$$I_t = \frac{K_t}{\Lambda_t(1 + K_t)}((1 + r_t)a_t + y_t - a_{min}) \quad \text{(A.54)}$$

For period 2, with $C = 1 + Kt + \beta_t(1 + K_{t+1})$:

$$a_{t+1} = \frac{\beta_t(1 + K_{t+1})}{C}((1 + r_t)a_t + y_t) - \frac{1 + K_t}{C}\frac{y_{t+1} - a_{min}}{1 + r_{t+1}} \quad \text{(A.55)}$$

$$I_t = \frac{K_t}{\Lambda_t C}((1 + r_t)a_t + y_t + \frac{y_{t+1} - a_{min}}{1 + r_{t+1}}) \quad \text{(A.56)}$$

For period 1, with $D = 1 + K_t + \beta_t(1 + K_{t+1} + \beta_{t+1}(1 + K_{t+2}))$:

$$a_{t+1} = \frac{\beta_t C}{D}((1 + r_t)a_t + y_t) - \frac{1 + K_t}{D}(\frac{y_{t+1}}{(1 + r_{t+1})} + \frac{y_{t+2} - a_{min}}{(1 + r_{t+1})(1 + r_{t+2})}) \quad \text{(A.57)}$$

$$I_t = \frac{K_t}{\Lambda_t D}((1 + r_t)a_t + y_t + \frac{y_{t+1}}{(1 + r_{t+1})} + \frac{y_{t+2} - a_{min}}{(1 + r_{t+1})(1 + r_{t+2})}) \quad \text{(A.58)}$$

Similar pathways can be constructed for households being borrowing constraint in period 2 and 1.

Optimal solution for c_t

If values for I_t, by that s_t and n_t, and a_{t+1} are determined, the optimal c_t simply is:

$$c_t = (1 + r)a_t + y_t - p_{n,t}n_t - p_{s,t}s_t - a_{t+1} \quad \text{(A.59)}$$

Optimal solution if n_t is constrained

To derive the relative demands we take first-order conditions for the minimization problem:

$$\begin{aligned}
&\min_{n_t, s_t} \quad p_{n,t} n_t + p_{s,t} s_t \\
&\text{s.t. } n_t \leq 5 \\
&\qquad It = [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}}
\end{aligned} \tag{A.60}$$

The Lagrangian looks the following:

$$\mathcal{L} = p_{n,t} n_t + p_{s,t} s_t - \lambda_{1,t}(I_t - [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}}) - \lambda_{2,t}(n_t - 5) \tag{A.61}$$

Deriving first order conditions in period 2 and 3:

$$\frac{\partial \mathcal{L}}{\partial s_t} = p_{s,t} - \lambda_{1,t}(a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t - 1} \rho_t) \times [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t} - 1} \frac{1}{\rho_t} = 0 \tag{A.62}$$

$$\frac{\partial \mathcal{L}}{\partial n_t} = p_{n,t} - \lambda_{1,t}(n_t^{\rho_t - 1} \rho_t) \times [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t} - 1} \frac{1}{\rho_t} - \lambda_{2,t} = 0 \tag{A.63}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{1,t}} = I_t - [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + n_t^{\rho_t}]^{\frac{1}{\rho_t}} = 0 \tag{A.64}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{2,t}} = n_t - 5 = 0 \tag{A.65}$$

If constraints are not binding, $\lambda_{2,t} = 0$, since $n_t < 5$. Then see solution above. If they are binding, this means $n_t = 5$ and $I_t = [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]^{\frac{1}{\rho_t}}$. If I_t is given, it follows:

$$s_t = \left(\frac{(I_t^{\rho_t} - 5^{\rho_t})}{a_{s,t}(Z_{s,t}, \eta)} \right)^{\frac{1}{\rho_t}} \tag{A.66}$$

In case the household is constrained ($n_t = 5$), this price does not apply, as it uses the fact that, s_t can be expressed as a share of n_t given the level of investments. In the case that $n_t = 5$, therefore, the household maximizes differently (see next section). In period 1 $\Lambda_t = p_{n,t}$ as investment input decisions only take place for nutrition. This means $n_t = 5$ and $I_t = [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5]^{\frac{1}{\rho_t}}$

$$
\begin{aligned}
V_t(Z_t, a_t, y_t, \Pi_t, \Psi_t) = \max_{c_t, s_t, a_{t+1}} & \; u(c_t) + \alpha_e v(\Psi_t) \\
& + \beta V_{t+1}(Z_{t+1}, a_{t+1}, y_{t+1}, \Pi_{t+1}, \Psi_{T+1}) \\
\text{s.t.} \quad c_t + 5p_{n,t} + p_{s,t}s_t + a_{t+1} &= (1+r)a_t + y_t \\
a_{t+1} &\geq a_{min,t} \\
\text{with} \quad \Psi_{t+1} &= \theta_t(Z_{\theta,t}) I_t^{\delta_{1,t}} \Psi_t^{\delta_{2,t}} \\
V_{T+1}(\Psi_{T+1}) &= \alpha_e \gamma_e \ln(\Psi_{T+1}) + \zeta \ln(a_{T+1}) \\
u(c_t) &= \ln(c_t) \\
v(\Psi_t) &= \ln(\Psi_t) \\
I_t &= [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]^{\frac{1}{\rho_t}}
\end{aligned}
\tag{A.67}
$$

Then:

$$
\frac{\partial \mathcal{L}}{\partial s_t} = \beta \frac{\partial V_{t+1}}{\partial I_t} \frac{\partial I_t}{\partial s_t} - \lambda_t(p_{s,t}) = 0 \tag{A.68}
$$

Drawing from the non-binding case, therefore:

$$
\beta \frac{\partial V_{T+1}}{\partial I_t} = \frac{K_t}{I_t} = \frac{K_t}{[a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]^{\frac{1}{\rho_t}}} \tag{A.69}
$$

which results in:

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial s_t} = \frac{K_t}{[a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]^{\frac{1}{\rho_t}}} & (a_{s,t}(Z_{s,t}, \eta) s_t^{(\rho_t - 1)} [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]^{\frac{1}{\rho_t} - 1}) \\
& - u'(c,t) p_{s_t} = 0
\end{aligned}
\tag{A.70}
$$

which yields:

$$
u'(c,t) p_{s_t} = \frac{K_t}{[a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]} a_{s,t}(Z_{s,t}, \eta) s_t^{(\rho_t - 1)} \tag{A.71}
$$

Plugging in the budget constraint:

$$
\begin{aligned}
& \frac{p_{s_t}}{-5p_{n_t} - p_{s_t}s_t - a_{t+1} + (1+r)a_t + y_t} = \\
& \qquad \frac{K_t}{[a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}]} a_{s,t}(Z_{s,t}, \eta) s_t^{(\rho_t - 1)}
\end{aligned}
\tag{A.72}
$$

yields:

$$
\begin{aligned}
0 = {} & p_{s_t} [a_{s,t}(Z_{s,t}, \eta) s_t^{\rho_t} + 5^{\rho_t}] \\
& - K_t a_{s,t}(Z_{s,t}, \eta) s_t^{(\rho_t - 1)} (-5p_{n_t} - p_{s_t}s_t - a_{t+1} + (1+r)a_t + y_t)
\end{aligned}
\tag{A.73}
$$

which can only be solved numerically.

GMM equations for investment parameters

To derive the relative demand ratios, one goes back to Equation A.9 and takes logs to get linear equations, using that $a_{s,t}(Z_{s,t},\eta) = exp(\phi_{s,t}Z_{s,t} + \eta)$:

$$\ln(\frac{p_{n,t}}{p_{s,t}}) = -\phi_{s,t}Z_{s,t} + (\rho_t - 1)\ln(\frac{n_t}{s_t}) - \eta$$
$$\ln(\frac{n_t}{s_t}) = \frac{1}{\rho_t - 1}Z'_{s,t}\phi_{s,t} - \frac{1}{1-\rho_t}\ln(\frac{p_{n,t}}{p_{s,t}}) - \frac{1}{1-\rho_t}\eta$$

Adding $\ln(\frac{p_{n,t}}{p_{s,t}})$ to both sides yields:

$$\ln(\frac{p_{n,t}n_t}{p_{s,t}s_t}) = \frac{1}{\rho_t - 1}Z'_{s,t}\phi_{s,t} + \frac{\rho_t}{\rho_t - 1}\ln(\frac{p_{n,t}}{p_{s,t}}) - \frac{1}{1-\rho_t}\eta$$

GMM equations for human capital parameters

$$\Psi_{t+1} = \theta_t(Z_{\theta,t})I_t^{\delta_{1,t}}\Psi_t^{\delta_{2,t}} \tag{A.74}$$

Using the human capital formation with $\theta_t(Z_{\theta,t}) = \exp(\phi_{\theta,t}Z_{\theta,t})$, taking logs:

$$\ln(\Psi_{t+1}) = \phi_{\theta,t}Z_{\theta,t} + \delta_{1,t}\ln(I_t) + \delta_{2,t}\ln(\Psi_t) \tag{A.75}$$

Since Ψ_t are latent skills, I assume the underlying measurement system with $S_{hs,t}$ and $S_{ts,t}$, which are observed height and test scores:

$$S_{ts_1,t} = \lambda_{ts_1,t}\ln(\Psi_t) + \epsilon_{ts_1,t} \tag{A.76}$$

and:

$$S_{ts_2,t} = \lambda_{ts_2,t}\ln(\Psi_t) + \epsilon_{ts_2,t} \tag{A.77}$$

Since height is observed in all periods, I can normalize $\lambda_{ts_1} = 1$ to allow for comparability of measures (see Cunha, Heckman and Schennach (2010)).

Replacing the latent skills with the measurements leads too:

$$S_{ts_1,t+1} = \phi_{\theta,t}Z_t + \delta_{1,t}\ln(I_t) + \delta_{2,t}S_{ts_1} \tag{A.78}$$

and:

$$\frac{1}{\lambda_{ts_2,t+1}}S_{ts_2,t+1} = \phi_{\theta,t}Z_t + \delta_{1,t}\ln(I_t) + \delta_{2,t}\frac{1}{\lambda_{ts_2,t}}S_{ts_2} \tag{A.79}$$

To identify $\lambda_{ts_2,t}$ further equations are needed. To get these I exploit the covariance structure, similar to (Cunha, Heckman and Schennach, 2010). One can replace Ψ_t in Equation A.76 with using Equation A.76:

$$\frac{Cov(S_{ts_1,t}, S_{ts_1,t+1})}{Cov(S_{ts_2,t}, S_{ts_1,t+1})} = \lambda_{ts_2,t} \tag{A.80}$$

and:

$$\frac{Cov(S_{ts_1,t}, S_{ts_1,t+1})}{Cov(S_{ts_1,t}, S_{ts_2,t+1})} = \lambda_{ts_2,t+1} \tag{A.81}$$

Using that these measures have mean 0, the covariance can be rearranged to:

$$0 = \text{E}[(S_{ts_1,t+1} - \lambda_{ts_2,t+1} S_{ts_2,t+1}) S_{ts_1,t}] \tag{A.82}$$

and:

$$0 = \text{E}[(S_{ts_1,t} S - \lambda_{ts_2,t} S_{ts_2,t}) S_{ts_1,t+1}] \tag{A.83}$$

A.6. Additional tables

Table A.6: Distribution of parenting skill types η by total amount of types

	Observations for type:				
Amount of types	Type 0	Type 1	Type 2	Type 3	Type 4
K=2	4,417	2,020			
K=3	2,990	2,833	614		
K=4	2,956	2,813	391	277	
K=5	2,664	547	2,863	9	354

Note: This table summarizes the amount of observation for each set of types, for different total amount of types secified.

Table A.7: Investment gap decomposition by childhood period

	Investment gap (%):		
	Early childhood	Primary school	High school
Baseline gap	12.08	11.95	7.36
Closing the gap by:			
Preferences	86.46	91.83	89.64
+ Investment productivities	86.46	105.50	131.42
+ Skill productivities	86.46	105.50	131.42
+ Income	16.37	14.81	16.09
+ Assets	1.30	-1.20	-1.31

Note: Gap indicated are between high school parents and parents with no schooling. Rest of the gap derives from differences in initial skills and prices and survey year.

Table A.8: Policy counterfactuals - investment change

	Cash transfer	Nutrition subsidy	Schooling subsidy	Cash+ nutrition	Cash+ schooling	Nutrition+ schooling
Change in mean investments (%):						
Primary school	1.52	16.57	4.49	17.77	5.34	20.35
High school	1.77	16.02	13.04	17.34	15.42	32.31

Note: Policies are designed to have the same costs (in 100,000 rupees ∼ $7), resulting in a 3% cash transfer, 20% nutrition subsidy and 99% schooling subsidy.

Table A.9: Policy counterfactuals by income decile

Income decile:	1	2	3	4	5	6	7	8	9	10
Change in mean skills (SD):										
Cash	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nutrition	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Schooling	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02
Change in mean investements (%):										
Cash	1.97	1.40	0.69	0.62	0.75	0.44	0.46	0.30	0.24	0.03
Nutrition	17.65	15.23	13.47	13.58	11.84	10.68	10.52	8.59	8.94	5.40
Schooling	8.02	9.54	7.66	8.73	8.39	8.79	9.13	8.96	9.25	6.77
Cost by 0.01 SD increase per child:										
Cash	1.42	2.04	2.47	3.15	2.81	5.54	5.91	5.84	14.21	61.71
Nutrition	0.18	0.24	0.30	0.33	0.45	0.37	0.51	0.64	0.71	1.29
Schooling	0.24	0.33	0.45	0.55	0.60	0.67	0.90	1.02	1.40	3.94

Note: Costs are expressed in 100,000,000 rupees (∼ $0,007), simulated are a 3% cash transfer, 20% nutrition subsidy and 99% schooling subsidy.

Table A.10: Estimation results for skill formation parameters for 2 types

	Early childhood		Primary school		High school	
Investment elasticity:						
Substitution parameter ρ_t			-3.10	(0.65)***	-10.12	(4.16)**
Implied elasticity			0.24		0.09	
Schooling investment productivity $\phi_{s,t}$:						
Constant			-2.24	(0.39)***	-35.08	(12.33)***
Mother primary			0.88	(0.19)***	2.58	(1.02)**
Mother high			1.51	(0.30)***	4.14	(1.62)**
Father primary			0.01	(0.14)	0.38	(0.38)
Father high			-0.18	(0.17)	0.20	(0.41)
Age			-0.04	(0.04)	2.80	(1.05)***
Female			0.06	(0.11)	1.21	(0.52)**
Rural area			-2.27	(0.41)***	-4.47	(1.74)**
No. of siblings			-0.61	(0.11)***	-1.90	(0.71)***
Mother not Islam			0.32	(0.19)*	1.35	(0.67)**
Parenting type 1			-1.53	(0.29)***	-3.13	(1.23)**
Human capital formation:						
$\delta_{1,t}$ (investment)	0.28	(0.07)***	0.14	(0.06)**	0.23	(0.03)***
$\delta_{2,t}$ (skills)	0.08	(0.03)**	0.18	(0.02)***	0.20	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.75	(0.10)***	-0.06	(0.13)	-0.26	(0.10)***
Mother primary	0.06	(0.04)	0.08	(0.04)*	0.05	(0.03)**
Mother high	0.24	(0.04)***	0.26	(0.05)***	0.14	(0.03)***
Father primary	-0.01	(0.05)	0.13	(0.04)***	0.04	(0.03)
Father high	0.08	(0.04)**	0.08	(0.04)*	0.10	(0.03)***
Age	0.10	(0.01)***	-0.02	(0.01)	0.01	(0.01)
Factor loading for skills $\lambda_{ts_2,s}$:						
$\lambda_{t,ts}$	0.97	(0.11)	1.06	(0.01)	1.12	(0.01)
$\lambda_{4,ts}$					1.26	(0.04)
Observations	27,257					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

Table A.11: Estimation results for skill formation parameters for 3 types

	Early childhood		Primary school		High school	
Investment elasticity:						
Substitution parameter ρ_t			-3.37	(0.74)***	-10.37	(4.36)**
Implied elasticity			0.23		0.09	
Schooling investment productivity $\phi_{s,t}$:						
Constant			-3.68	(0.47)***	-38.98	(14.12)***
Mother primary			1.01	(0.22)***	2.84	(1.14)**
Mother high			1.71	(0.34)***	4.54	(1.81)**
Father primary			0.05	(0.15)	0.51	(0.41)
Father high			-0.12	(0.17)	0.37	(0.44)
Age			-0.05	(0.04)	2.89	(1.11)***
Female			0.03	(0.12)	1.19	(0.53)**
Rural area			-2.44	(0.46)***	-4.75	(1.89)**
No. of siblings			-0.67	(0.12)***	-1.98	(0.76)***
Mother not Islam			0.33	(0.20)	1.43	(0.71)**
Parenting type 1			0.14	(0.13)	0.03	(0.31)
Parenting type 2			3.49	(0.68)***	6.45	(2.55)**
Human capital formation:						
$\delta_{1,t}$ (investment)	0.28	(0.07)***	0.14	(0.06)**	0.22	(0.03)***
$\delta_{2,t}$ (skills)	0.08	(0.03)**	0.18	(0.02)***	0.20	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.75	(0.10)***	-0.06	(0.13)	-0.25	(0.09)***
Mother primary	0.06	(0.04)	0.08	(0.04)*	0.05	(0.03)**
Mother high	0.24	(0.04)***	0.26	(0.05)***	0.14	(0.03)***
Father primary	-0.01	(0.05)	0.13	(0.04)***	0.04	(0.03)
Father high	0.08	(0.04)**	0.08	(0.04)*	0.10	(0.03)***
Age	0.10	(0.01)***	-0.02	(0.01)*	0.01	(0.01)
Factor loading for skills $\lambda_{ts_2,s}$:						
$\lambda_{t,ts}$	0.97	(0.11)	1.06	(0.01)	1.13	(0.01)
$\lambda_{4,ts}$					1.26	(0.04)
Observations	27,257					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

Table A.12: Estimation results for skill formation parameters for 5 types

	Early childhood		Primary school		High school	
Investment elasticity:						
Substitution parameter ρ_t			-3.19	(0.68)***	-9.81	(3.92)**
Implied elasticity			0.24		0.09	
Schooling investment productivity $\phi_{s,t}$:						
Constant			-3.61	(0.44)***	-37.26	(12.76)***
Mother primary			0.98	(0.21)***	2.71	(1.04)***
Mother high			1.61	(0.31)***	4.39	(1.66)***
Father primary			0.06	(0.14)	0.54	(0.40)
Father high			-0.12	(0.17)	0.39	(0.42)
Age			-0.04	(0.04)	2.75	(1.00)***
Female			0.04	(0.11)	1.10	(0.48)**
Rural area			-2.37	(0.43)***	-4.63	(1.74)***
No. of siblings			-0.64	(0.11)***	-1.89	(0.69)***
Mother not Islam			0.36	(0.19)*	1.41	(0.67)**
Parenting type 1			1.52	(0.35)***	2.32	(1.01)**
Parenting type 2			-0.04	(0.12)	0.36	(0.33)
Parenting type 3			-0.04	(2.44)	16.02	(7.23)**
Parenting type 4			4.25	(0.82)***	8.36	(3.17)***
Human capital formation:						
$\delta_{1,t}$ (investment)	0.28	(0.07)***	0.14	(0.06)**	0.23	(0.03)***
$\delta_{2,t}$ (skills)	0.07	(0.03)**	0.18	(0.02)***	0.20	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.75	(0.10)***	-0.06	(0.13)	-0.27	(0.09)***
Mother primary	0.06	(0.04)	0.07	(0.04)*	0.06	(0.03)**
Mother high	0.24	(0.04)***	0.26	(0.05)***	0.13	(0.03)***
Father primary	-0.01	(0.05)	0.13	(0.04)***	0.04	(0.03)
Father high	0.08	(0.04)**	0.08	(0.04)*	0.10	(0.03)***
Age	0.10	(0.01)***	-0.02	(0.01)*	0.01	(0.01)
Factor loading for skills $\lambda_{ts_2,s}$:						
$\lambda_{t,ts}$	0.98	(0.11)	1.07	(0.01)	1.13	(0.01)
$\lambda_{4,ts}$					1.27	(0.04)
Observations	27,257					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

Table A.13: Robustness check: GMM without constrained individuals

	Early childhood		Primary school		High school	
Investment elasticity:						
Substitution parameter ρ_t			-3.33	(0.76)***	-14.60	(8.71)*
Implied elasticity			0.23		0.06	
Schooling investment productivity $\phi_{s,t}$:						
Constant			-3.42	(0.48)***	-53.02	(28.45)*
Mother primary			1.10	(0.24)***	4.10	(2.34)*
Mother high			1.78	(0.37)***	7.24	(4.12)*
Father primary			0.23	(0.16)	0.79	(0.69)
Father high			0.05	(0.19)	0.25	(0.62)
Age			-0.04	(0.04)	4.05	(2.26)*
Female			0.02	(0.13)	1.53	(0.94)
Rural area			-2.36	(0.46)***	-6.64	(3.80)*
No. of siblings			-0.68	(0.13)***	-2.71	(1.51)*
Mother not Islam			0.21	(0.21)	2.06	(1.34)
Parenting type 1			-0.37	(0.15)**	-0.68	(0.56)
Parenting type 2			4.26	(0.90)***	12.26	(6.99)*
Parenting type 3			1.62	(0.52)***	2.93	(1.99)
Human capital formation:						
$\delta_{1,t}$ (investment)	0.28	(0.06)***	0.16	(0.05)***	0.17	(0.03)***
$\delta_{2,t}$ (skills)	0.10	(0.02)***	0.19	(0.02)***	0.22	(0.01)***
Total factor productivity $\phi_{\theta,t}$:						
Constant	-0.73	(0.08)***	-0.02	(0.12)	-0.21	(0.09)**
Mother primary	0.02	(0.04)	0.06	(0.04)	0.05	(0.02)**
Mother high	0.22	(0.03)***	0.25	(0.04)***	0.16	(0.03)***
Father primary	0.02	(0.04)	0.13	(0.04)***	0.03	(0.03)
Father high	0.11	(0.03)***	0.07	(0.04)*	0.10	(0.03)***
Age	0.10	(0.01)***	-0.02	(0.01)**	0.01	(0.01)
Factor loading for skills $\lambda_{ts_2,s}$:						
$\lambda_{t,ts}$	1.00	(0.07)	1.07	(0.01)	1.09	(0.01)
$\lambda_{4,ts}$					1.21	(0.04)
Observations	27,366					

Note: Standard errors in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. All coefficients are from a single GMM estimation.

B. APPENDIX TO CHAPTER 2

Data and descriptives

Table B.1: Description of parenting dimensions in the LSAC

Dimension	Description
Parental warmth	Parent shows affection with hugs, kisses and holds the child often, hugs the child without a reason, expresses happiness about child, has warm and close times with the child, enjoys listening to child and doing things with them, parent feels close to child when it is happy or upset
Parental hostility	Frequency with which parents react to child's behaviour with praise or disapproval, parents react with anger when punishing child, feel to have problems managing child
Parental consistency	Frequency of making sure child completes requests, punishment if child does not complete requests, how often child gets away with things which parents feel they should be punished for, child gets out of punishment or ignores it
Parental reasoning	Frequency with which parent explains why child gets corrected, reasons about misbehaviour and why rules should be obeyed, explains consequences of behaviour, emphasizes reasons for rules

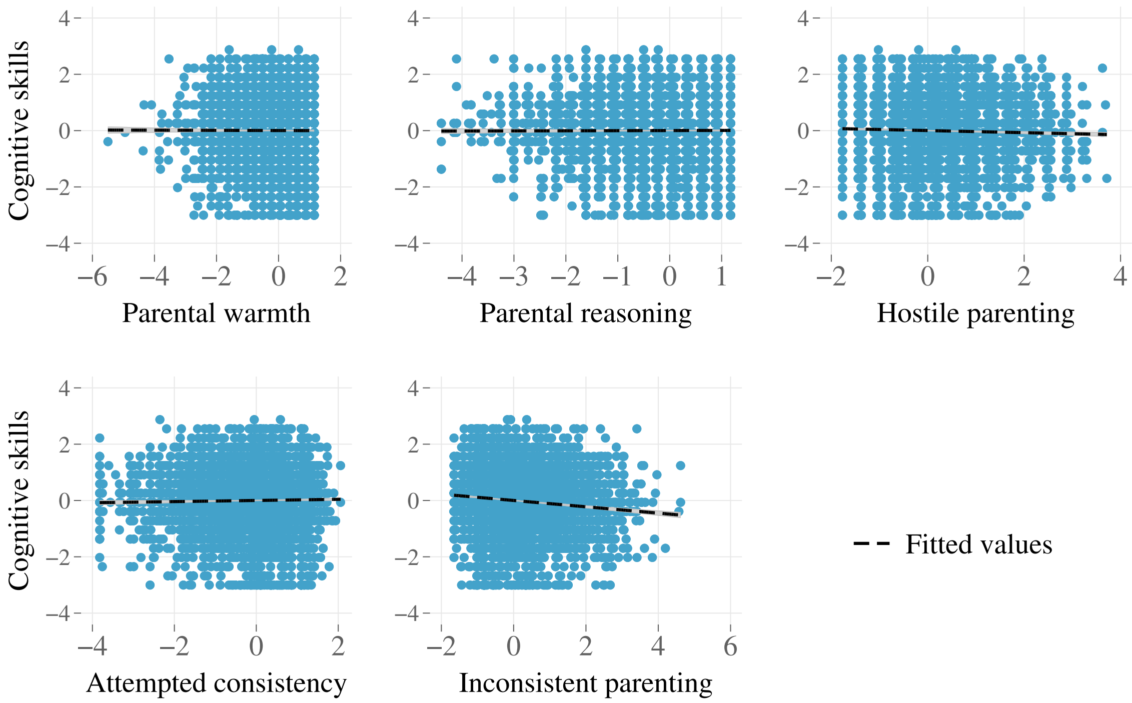


Figure B.1: Correlation of parenting dimensions with cognitive skills

Note: The figure displays the relationship between cognitive skills (measured by the MRT) and different parenting styles. Each data point represents a child from the 8-9 age group. In addition to the data points, a line is plotted on the graph, which represents the fitted values based on a linear regression analysis. The line slope is estimated using population weights.

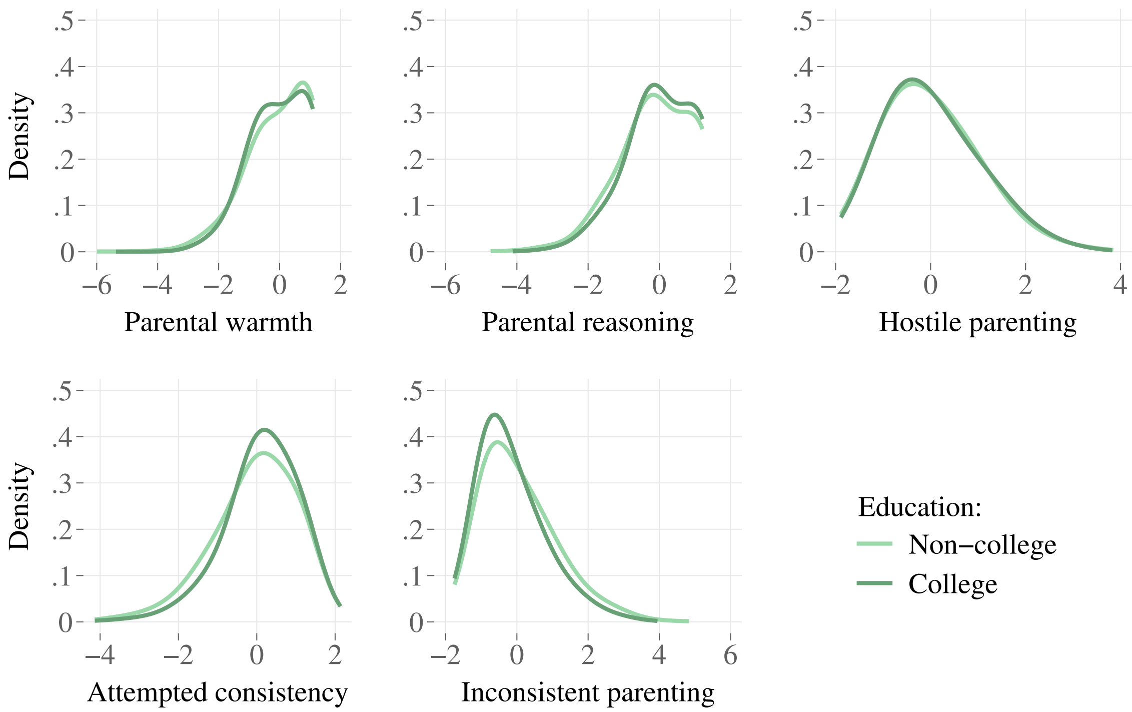


Figure B.2: Distribution of parenting dimensions by primary care giver's education

Note: The figure displays the empirical distribution (smoothed using the kernel function approach with population weights) of different parenting styles by primary care giver education for children aged 8-9.

Table B.2: Rotated factor loadings for single factors

	Age:					
	4-5	6-7	8-9	10-11	12-13	14-15
Parental warmth:						
Expresses affection	**0.739**	**0.817**	**0.829**	**0.835**	**0.850**	**0.848**
Hugs child	**0.741**	**0.775**	**0.776**	**0.792**	**0.805**	**0.795**
Expresses happiness	**0.757**	**0.771**	**0.796**	**0.796**	**0.790**	**0.794**
Warm/close times together	**0.797**	**0.829**	**0.850**	**0.850**	**0.847**	**0.843**
Enjoy time together	**0.747**	**0.786**	**0.812**	**0.795**	**0.792**	**0.801**
Feels close to child	**0.753**	**0.796**	**0.796**	**0.803**	**0.800**	**0.793**
Parental hostility:						
Praise child	**-0.550**	**-0.555**	**-0.641**	**-0.649**	**-0.688**	**-0.711**
Disapproval	**0.731**	**0.754**	**0.763**	**0.780**	**0.805**	**0.804**
Angry when punishing	**0.673**	**0.678**	**0.659**	**0.692**	**0.676**	**0.682**
Having problems managing	**0.743**	**0.744**	**0.733**	**0.752**	**0.760**	**0.756**
Parental consistency: Factor 1						
Ensures requests complete	-0.053	-0.055	-0.035	-0.043	-0.031	-0.050
Punishes child	-0.245	-0.223	**-0.279**	**-0.263**	-0.232	-0.188
Child gets away	**0.779**	**0.771**	**0.774**	**0.802**	**0.805**	**0.828**
Child gets out of punishment	**0.804**	**0.800**	**0.815**	**0.809**	**0.816**	**0.824**
Child ignores punishment	**0.793**	**0.812**	**0.800**	**0.808**	**0.818**	**0.842**
Parental consistency: Factor 2						
Ensures requests complete		**0.847**	**0.860**	**0.864**	**0.853**	**0.838**
Punishes child		**0.779**	**0.750**	**0.771**	**0.778**	**0.787**
Child gets away		**-0.259**	**-0.259**	-0.204	-0.202	-0.166
Child gets out of punishment		-0.147	-0.124	-0.144	-0.123	-0.131
Child ignores punishment		-0.021	-0.038	-0.060	-0.035	-0.039
Parental inductive reasoning:						
Explains corrections	**0.870**	**0.887**	**0.881**	**0.887**	**0.897**	**0.904**
Reasons when misbehaves	**0.870**	**0.819**	**0.751**	**0.738**	**0.756**	**0.746**
Reasons for rules		**0.882**	**0.867**	**0.864**	**0.882**	**0.887**
Explains consequences			**0.892**	**0.896**	**0.913**	**0.906**
Emphasizes reasons			**0.888**	**0.894**	**0.905**	**0.907**

Note: Factor loadings larger than 0.25 in absolute value printed in bold. To summarize the variation of all measures, one factor was sufficient expect for parental consistency from wave 4 onward. Eigenvalues of bigger than 1 indicated which factors to include in the analysis.

Table B.3: Rotated factor loadings for joint analysis

	Age:					
	4-5	6-7	8-9	10-11	12-13	14-15
Factor 1:						
Parental warmth	**0.849**	**0.730**	**0.693**	**-0.544**	**-0.645**	**-0.668**
Hostile parenting	**-0.260**	-0.152	-0.103	**0.876**	**0.883**	**0.886**
Attempted consistency	0.055	**0.637**	**0.637**	0.193	0.108	0.075
Parental inconsistency		0.030	0.037	**0.766**	**0.767**	**0.787**
Parental reasoning	**0.856**	**0.848**	**0.856**	-0.041	0.011	0.053
Factor 2:						
Parental warmth		**-0.352**	**-0.433**	**0.612**	**0.513**	**0.480**
Hostile parenting		**0.851**	**0.859**	-0.049	0.073	0.116
Attempted consistency		0.201	0.213	**0.664**	**0.703**	**0.697**
Parental inconsistency		**0.808**	**0.778**	0.059	0.084	0.094
Parental reasonig		-0.039	-0.017	**0.854**	**0.859**	**0.860**

Note: Factor loadings larger than 0.25 in absolute value printed in bold. To summarize the variation of all measures, two factors were sufficient to summarize the data expect for wave 3. Eigenvalues of bigger than 1 indicated which factors to include in the analysis. From wave 6 factor 1 is factor 2 and wise versa which is why we swap them in the data to get consistent measures across waves.

Table B.4: Rotated factor loadings at age 4-5 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.808**	-0.070	0.024	0.014
Hugs child	**0.812**	-0.061	0.016	0.024
Expresses happiness	**0.660**	0.001	-0.157	**0.335**
Warm/close times together	**0.742**	0.012	-0.118	0.238
Enjoy time together	**0.609**	0.001	-0.225	**0.357**
Feels close to child	**0.649**	-0.003	-0.217	**0.277**
Parental hostility:				
Praise child	**0.276**	0.076	**-0.468**	**0.319**
Disapproval	-0.143	0.122	**0.686**	0.038
Angry when punishing	-0.020	0.077	**0.684**	-0.050
Having problems managing	-0.113	**0.289**	**0.674**	-0.034
Parental consistency:				
Ensures requests complete	0.053	**-0.424**	0.062	**0.479**
Punishes child	0.023	**-0.668**	**0.286**	**0.257**
Child gets away	-0.018	**0.747**	0.212	-0.021
Child gets out of punishment	-0.020	**0.763**	0.176	0.037
Child ignores punishment	-0.077	**0.621**	**0.437**	0.019
Parental inductive reasoning:				
Explains corrections	0.212	-0.072	-0.011	**0.761**
Reasons when misbehaves	**0.256**	-0.016	-0.033	**0.741**

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency. As in wave 3 factor 2 describes inconsistency, when assign it to the variable consistency, but we reverse values of factor 2 before assignment to ensure comparability across waves. Instead we assign factor 4 as reasoning.

B.1. Estimation tables

B.1.1. Non-cognitive skills

Table B.5: Rotated factor loadings at age 6-7 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.837**	0.104	0.002	-0.057
Hugs child	**0.799**	0.121	0.021	-0.057
Expresses happiness	**0.677**	**0.336**	-0.188	0.011
Warm/close times together	**0.787**	0.234	-0.119	-0.014
Enjoy time together	**0.701**	**0.268**	-0.172	-0.031
Feels close to child	**0.736**	0.213	-0.170	-0.036
Parental hostility:				
Praise child	**0.400**	0.162	**-0.449**	0.110
Disapproval	-0.197	0.038	**0.699**	0.065
Angry when punishing	-0.039	-0.083	**0.687**	0.011
Having problems managing	-0.150	0.021	**0.686**	**0.272**
Parental consistency:				
Ensures requests complete	0.151	**0.254**	0.105	**-0.537**
Punishes child	0.037	0.198	0.218	**-0.722**
Child gets away	-0.024	-0.044	**0.330**	**0.715**
Child gets out of punishment	0.003	0.003	**0.298**	**0.691**
Child ignores punishment	-0.059	0.012	**0.534**	**0.543**
Parental inductive reasoning:				
Explains corrections	0.196	**0.866**	-0.023	-0.077
Reasons when misbehaves	**0.285**	**0.736**	0.007	-0.067
Reasons for rules	0.212	**0.855**	-0.003	-0.068

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency. As in wave 4 factor 4 describes inconsistency, when creating the variable consistency, we reverse values of factor 4 before assignment to ensure comparability across waves.

Table B.6: Rotated factor loadings at age 8-9 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.833**	0.155	0.001	-0.053
Hugs child	**0.794**	0.144	0.009	-0.055
Expresses happiness	**0.705**	**0.319**	-0.179	0.034
Warm/close times together	**0.787**	**0.269**	-0.114	-0.014
Enjoy time together	**0.729**	**0.256**	-0.179	-0.048
Feels close to child	**0.736**	0.212	-0.191	-0.043
Parental hostility:				
Praise child	**0.437**	0.121	**-0.479**	0.067
Disapproval	**-0.268**	0.088	**0.680**	0.020
Angry when punishing	-0.047	-0.025	**0.690**	0.008
Having problems managing	-0.163	0.059	**0.688**	**0.254**
Parental consistency:				
Ensures requests complete	0.139	0.219	0.132	**-0.549**
Punishes child	0.020	0.181	0.203	**-0.747**
Child gets away	-0.027	-0.050	**0.355**	**0.698**
Child gets out of punishment	-0.000	-0.028	**0.339**	**0.672**
Child ignores punishment	-0.072	0.012	**0.536**	**0.538**
Parental inductive reasoning:				
Explains corrections	0.170	**0.864**	-0.017	-0.073
Reasons when misbehaves	**0.271**	**0.687**	0.033	-0.107
Reasons for rules	0.180	**0.852**	0.002	-0.047
Explains consequences	0.202	**0.864**	0.037	-0.061
Emphasizes reasons	0.171	**0.874**	0.003	-0.035

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency. As in wave 5 factor 4 describes inconsistency, when creating the variable consistency, we reverse values of factor 4 before assignment to ensure comparability across waves.

Table B.7: Rotated factor loadings at age 10-11 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.840**	0.156	-0.009	-0.066
Hugs child	**0.817**	0.121	0.002	-0.076
Expresses happiness	**0.724**	**0.277**	-0.185	0.021
Warm/close times together	**0.792**	0.245	-0.147	-0.019
Enjoy time together	**0.697**	**0.261**	-0.237	-0.022
Feels close to child	**0.724**	0.196	-0.235	-0.005
Parental hostility:				
Praise child	**0.454**	0.085	**-0.474**	0.051
Disapproval	**-0.291**	0.117	**0.690**	-0.041
Angry when punishing	-0.103	0.002	**0.689**	-0.005
Having problems managing	-0.191	0.046	**0.716**	0.167
Parental consistency:				
Ensures requests complete	0.114	0.208	0.109	**-0.598**
Punishes child	0.031	0.187	0.124	**-0.772**
Child gets away	-0.024	-0.015	**0.445**	**0.653**
Child gets out of punishment	-0.000	-0.018	**0.415**	**0.630**
Child ignores punishment	-0.082	-0.012	**0.581**	**0.488**
Parental inductive reasoning:				
Explains corrections	0.151	**0.876**	-0.007	-0.076
Reasons when misbehaves	**0.258**	**0.693**	0.013	-0.088
Reasons for rules	0.149	**0.861**	-0.016	-0.026
Explains consequences	0.185	**0.873**	0.057	-0.079
Emphasizes reasons	0.161	**0.883**	0.020	-0.050

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency. As in wave 6 factor 4 describes inconsistency, when creating the variable consistency, we reverse values of factor 4 before assignment to ensure comparability across waves.

Table B.8: Rotated factor loadings at age 12-13 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.849**	0.140	-0.021	0.086
Hugs child	**0.820**	0.113	-0.002	0.106
Expresses happiness	**0.715**	**0.260**	-0.203	-0.084
Warm/close times together	**0.794**	0.210	-0.148	0.013
Enjoy time together	**0.715**	0.192	-0.232	0.024
Feels close to child	**0.728**	0.163	**-0.258**	0.007
Parental hostility:				
Praise child	**0.482**	0.037	**-0.467**	-0.154
Disapproval	**-0.311**	0.166	**0.661**	0.159
Angry when punishing	-0.099	0.034	**0.684**	0.156
Having problems managing	-0.236	0.113	**0.716**	-0.073
Parental consistency:				
Ensures requests complete	0.108	0.249	0.030	**0.595**
Punishes child	0.026	0.196	0.004	**0.766**
Child gets away	-0.091	0.009	**0.584**	**-0.531**
Child gets out of punishment	0.005	0.002	**0.549**	**-0.531**
Child ignores punishment	-0.130	0.042	**0.675**	**-0.368**
Parental inductive reasoning:				
Explains corrections	0.121	**0.889**	0.012	0.070
Reasons when misbehaves	0.240	**0.707**	0.021	0.076
Reasons for rules	0.129	**0.877**	0.034	0.017
Explains consequences	0.154	**0.890**	0.065	0.092
Emphasizes reasons	0.126	**0.898**	0.047	0.048

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency.

Table B.9: Rotated factor loadings at age 14-15 - joint estimation

	Factor 1	Factor 2	Factor 3	Factor 4
Parental warmth:				
Expresses affection	**0.854**	0.105	-0.023	0.110
Hugs child	**0.818**	0.083	-0.009	0.121
Expresses happiness	**0.745**	0.235	-0.153	-0.074
Warm/close times together	**0.792**	0.193	-0.155	-0.032
Enjoy time together	**0.721**	0.180	-0.222	-0.039
Feels close to child	**0.725**	0.152	-0.246	-0.067
Parental hostility:				
Praise child	**0.522**	-0.006	**-0.407**	-0.201
Disapproval	**-0.347**	0.226	**0.568**	**0.294**
Angry when punishing	-0.121	0.083	**0.600**	**0.322**
Having problems managing	-0.239	0.121	**0.718**	0.097
Parental consistency:				
Ensures requests complete	0.082	0.223	-0.134	**0.640**
Punishes child	0.011	0.206	-0.197	**0.736**
Child gets away	-0.094	0.037	**0.744**	**-0.292**
Child gets out of punishment	-0.042	0.020	**0.706**	**-0.313**
Child ignores punishment	-0.148	0.052	**0.771**	-0.166
Parental inductive reasoning:				
Explains corrections	0.100	**0.904**	0.022	0.055
Reasons when misbehaves	0.230	**0.713**	0.052	0.122
Reasons for rules	0.102	**0.890**	0.033	0.021
Explains consequences	0.138	**0.889**	0.072	0.091
Emphasizes reasons	0.101	**0.899**	0.066	0.076

Note: Factor loadings larger than 0.25 in absolute value printed in bold. Factors can be assigned the following across waves: factor 1: parental warmth, factor 2: reasoning, factor 3: hostile and inconsistent parenting, factor 4: consistency.

Table B.10: Estimated parameters of production function for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.050***	0.011	0.036***	0.032**	0.037	0.038
	(0.015)	(0.012)	(0.013)	(0.013)	(0.030)	(0.025)
Parental reasoning	-0.084***	-0.026***	-0.033***	-0.035***	-0.059***	-0.043**
	(0.012)	(0.009)	(0.010)	(0.010)	(0.023)	(0.018)
Hostile parenting	-0.382***	-0.177***	-0.170***	-0.161***	-0.303***	-0.213***
	(0.014)	(0.012)	(0.013)	(0.013)	(0.028)	(0.023)
Inconsistent parenting	-0.145***	-0.068***	-0.053***	-0.077***	-0.129***	-0.110***
	(0.014)	(0.011)	(0.013)	(0.013)	(0.029)	(0.022)
Attempted consistency	0.015	-0.002	0.006	0.006	-0.010	-0.009
	(0.011)	(0.009)	(0.010)	(0.010)	(0.021)	(0.017)
Educational time parents	-0.001	-0.002	-0.000	-0.001	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Educational time others	-0.001	-0.000	-0.003	0.003	0.015*	0.011
	(0.005)	(0.004)	(0.005)	(0.004)	(0.009)	(0.007)
Care time parents	-0.002	-0.001	-0.000	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.007***	0.004**	0.001	0.002	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Lagged test outcome		0.634***		0.253***		0.646***
		(0.013)		(0.019)		(0.021)
Observations	7,299	6,703	6,599	6,463	2,267	2,264
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.11: Estimated parameters of production function for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.052***	0.028**	0.028**	0.044***	0.077**	0.064**
	(0.016)	(0.012)	(0.012)	(0.013)	(0.032)	(0.025)
Parental reasoning	-0.082***	-0.035***	-0.030***	-0.026***	-0.052**	-0.025
	(0.012)	(0.009)	(0.009)	(0.010)	(0.024)	(0.018)
Hostile parenting	-0.386***	-0.184***	-0.178***	-0.180***	-0.316***	-0.267***
	(0.017)	(0.013)	(0.013)	(0.014)	(0.030)	(0.026)
Inconsistent parenting	-0.121***	-0.053***	-0.065***	-0.059***	-0.055*	-0.054**
	(0.016)	(0.012)	(0.012)	(0.012)	(0.031)	(0.024)
Attempted consistency	0.025*	0.009	0.002	0.005	0.008	0.010
	(0.013)	(0.009)	(0.010)	(0.010)	(0.021)	(0.017)
Educational time parents	-0.004*	-0.000	0.000	0.001	-0.008*	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Educational time others	-0.006	-0.003	-0.004	-0.005	-0.012	-0.011
	(0.005)	(0.004)	(0.004)	(0.004)	(0.012)	(0.009)
Care time parents	0.001	0.000	0.001	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.000	-0.001	0.001	0.000	0.003	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Lagged test outcome		0.658***		0.253***		0.651***
		(0.013)		(0.019)		(0.022)
Observations	6,544	6,346	6,599	6,463	2,067	2,066
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.12: Estimated parameters of production function for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.054***	0.019	0.032**	0.036**	-0.020	0.002
	(0.017)	(0.013)	(0.014)	(0.014)	(0.039)	(0.028)
Parental reasoning	-0.086***	-0.037***	-0.040***	-0.033***	-0.041*	-0.044**
	(0.013)	(0.010)	(0.011)	(0.011)	(0.024)	(0.019)
Hostile parenting	-0.363***	-0.179***	-0.167***	-0.158***	-0.253***	-0.216***
	(0.019)	(0.015)	(0.016)	(0.015)	(0.036)	(0.028)
Inconsistent parenting	-0.157***	-0.085***	-0.103***	-0.080***	-0.175***	-0.135***
	(0.018)	(0.014)	(0.015)	(0.015)	(0.038)	(0.031)
Attempted consistency	0.024*	0.004	0.025**	0.016	0.017	-0.005
	(0.013)	(0.011)	(0.011)	(0.011)	(0.024)	(0.020)
Educational time parents	0.001	0.002	0.002	0.002	0.005*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Educational time others	0.002	0.000	-0.002	-0.002	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Care time parents	-0.001	-0.001	-0.001	-0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Lagged test outcome		0.635***		0.253***		0.653***
		(0.014)		(0.019)		(0.023)
Observations	5,726	5,531	6,599	6,463	1,753	1,753
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.13: Estimated parameters of production function without parenting style for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.004	0.002	0.000	0.003	0.003	0.004
	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
Educational time others	0.000	0.007	-0.013	-0.002	0.008	-0.000
	(0.016)	(0.014)	(0.011)	(0.012)	(0.016)	(0.012)
Care time parents	-0.003	-0.001	-0.001	-0.001	-0.003	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Care time others	0.003	-0.002	0.000	-0.002	0.003	-0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)
Lagged test outcome		0.717^{***}		0.202^{***}		0.712^{***}
		(0.018)		(0.019)		(0.017)
Observations	2,876	2,759	6,605	6,508	2,606	2,570
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.14: Estimated parameters of production function without parenting style for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.000	-0.001	0.000	-0.000	-0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.007)	(0.003)
Educational time others	-0.003	-0.001	-0.004	0.002	0.014	0.008
	(0.006)	(0.004)	(0.005)	(0.005)	(0.012)	(0.008)
Care time parents	-0.001	-0.000	-0.001	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.005^{**}	0.003^{*}	-0.000	0.001	-0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Lagged test outcome		0.731^{***}		0.202^{***}		0.735^{***}
		(0.012)		(0.019)		(0.018)
Observations	7,328	6,728	6,605	6,508	2,454	2,441
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.15: Estimated parameters of production function without parenting style for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.001	0.002	0.001	0.001	0.001	0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Educational time others	0.001	0.001	0.001	-0.002	-0.020	-0.007
	(0.007)	(0.004)	(0.005)	(0.004)	(0.018)	(0.013)
Care time parents	0.003**	0.001	0.000	-0.000	0.004*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.002	-0.000	0.001	0.001	0.006**	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Lagged test outcome		0.762***		0.202***		0.740***
		(0.012)		(0.019)		(0.021)
Observations	6,574	6,371	6,605	6,508	2,237	2,233
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.16: Estimated parameters of production function without parenting style for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.002	0.002	0.001	0.003	0.007*	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Educational time others	0.003	0.000	-0.002	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Care time parents	0.002	0.000	-0.000	-0.000	0.004**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	-0.002	-0.002	-0.001	-0.001	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Lagged test outcome		0.748***		0.202***		0.731***
		(0.014)		(0.019)		(0.022)
Observations	5,765	5,564	6,605	6,508	1,905	1,897
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.17: Estimated parameters of production function with aggregated parenting dimensions for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Emphatic style	0.011	-0.014	0.021	0.004	0.010	0.019
	(0.020)	(0.014)	(0.016)	(0.013)	(0.022)	(0.016)
Harsh style	-0.450***	-0.195***	-0.205***	-0.138***	-0.363***	-0.231***
	(0.019)	(0.016)	(0.018)	(0.015)	(0.024)	(0.019)
Educational time parents	-0.001	0.000	0.001	0.004	-0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Educational time others	0.005	-0.001	-0.013	-0.012	0.009	-0.001
	(0.014)	(0.012)	(0.010)	(0.010)	(0.015)	(0.012)
Care time parents	-0.003	-0.001	-0.001	-0.000	-0.002	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.005	-0.001	0.000	-0.003	0.004	-0.001
	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)
Lagged test outcome		0.645***		0.252***		0.640***
		(0.020)		(0.019)		(0.020)
Observations	2,780	2,667	6,599	6,463	2,419	2,417
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: We define emphatic parenting style as one that is high on warmth, reasoning, and attempted consistency, while harsh parenting is defined as one that is high on hostility and inconsistency. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.18: Estimated parameters of production function with aggregated parenting dimensions for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Emphatic style	-0.020*	-0.012	0.006	-0.001	-0.026	-0.013
	(0.011)	(0.009)	(0.011)	(0.010)	(0.022)	(0.019)
Harsh style	-0.467***	-0.209***	-0.202***	-0.211***	-0.376***	-0.281***
	(0.013)	(0.011)	(0.013)	(0.013)	(0.029)	(0.026)
Educational time parents	-0.002	-0.002	-0.000	-0.000	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Educational time others	-0.000	0.000	-0.003	0.002	0.013	0.010
	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)	(0.007)
Care time parents	-0.002	-0.001	-0.000	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.007***	0.004**	0.001	0.002	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Lagged test outcome		0.646***		0.252***		0.652***
		(0.013)		(0.019)		(0.021)
Observations	7,299	6,703	6,599	6,463	2,267	2,264
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: We define emphatic parenting style as one that is high on warmth, reasoning, and attempted consistency, while harsh parenting is defined as one that is high on hostility and inconsistency. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.19: Estimated parameters of production function with aggregated parenting dimensions for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Emphatic style	-0.065***	-0.027***	-0.024**	-0.009	-0.032	-0.006
	(0.013)	(0.009)	(0.010)	(0.009)	(0.023)	(0.018)
Harsh style	-0.465***	-0.217***	-0.220***	-0.228***	-0.372***	-0.315***
	(0.014)	(0.011)	(0.012)	(0.013)	(0.030)	(0.027)
Educational time parents	-0.003	0.000	0.000	0.001	-0.008*	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Educational time others	-0.008	-0.004	-0.004	-0.005	-0.010	-0.010
	(0.005)	(0.004)	(0.004)	(0.004)	(0.011)	(0.008)
Care time parents	0.001	0.000	0.000	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.000	-0.001	0.001	0.000	0.004	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Lagged test outcome		0.669***		0.252***		0.662***
		(0.013)		(0.019)		(0.022)
Observations	6,544	6,346	6,599	6,463	2,067	2,066
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: We define emphatic parenting style as one that is high on warmth, reasoning, and attempted consistency, while harsh parenting is defined as one that is high on hostility and inconsistency. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.20: Estimated parameters of production function with aggregated parenting dimensions for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Emphatic style	-0.088***	-0.048***	-0.026**	-0.018*	-0.075***	-0.068***
	(0.013)	(0.010)	(0.011)	(0.011)	(0.025)	(0.020)
Harsh style	-0.485***	-0.238***	-0.243***	-0.220***	-0.372***	-0.309***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.039)	(0.031)
Educational time parents	0.002	0.002	0.002	0.002	0.005*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Educational time others	0.002	0.000	-0.002	-0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Care time parents	-0.001	-0.001	-0.001	-0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Lagged test outcome		0.644***		0.252***		0.655***
		(0.014)		(0.019)		(0.023)
Observations	5,726	5,531	6,599	6,463	1,753	1,753
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: We define emphatic parenting style as one that is high on warmth, reasoning, and attempted consistency, while harsh parenting is defined as one that is high on hostility and inconsistency. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.21: Estimated parameters of production function with interaction between parenting styles and time investments for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	-0.007	-0.004	0.001	0.005	-0.002	0.001
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
parents x high emphatic style	0.012	0.006	0.000	-0.002	0.005	0.003
	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
parents x high harsh style	0.005	0.005	-0.000	-0.000	0.001	0.001
	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
others	0.018	-0.017	-0.003	0.001	0.026	0.004
	(0.036)	(0.032)	(0.028)	(0.030)	(0.040)	(0.030)
others x high emphatic style	-0.011	0.009	-0.018	-0.017	-0.011	-0.014
	(0.036)	(0.031)	(0.027)	(0.029)	(0.040)	(0.029)
others x high harsh style	-0.002	0.021	0.008	-0.002	-0.013	0.004
	(0.033)	(0.030)	(0.027)	(0.026)	(0.039)	(0.027)
Care time:						
parents	0.000	0.003	0.001	-0.000	-0.002	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
parents x high emphatic style	0.002	-0.002	-0.003	-0.001	0.004	0.000
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
parents x high harsh style	-0.008**	-0.005*	-0.002	-0.000	-0.004	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
others	0.013	0.001	0.003	0.001	0.023*	0.007
	(0.012)	(0.007)	(0.007)	(0.006)	(0.012)	(0.007)
others x high emphatic style	-0.027	-0.010	-0.003	-0.001	-0.036	-0.013
	(0.022)	(0.011)	(0.009)	(0.008)	(0.023)	(0.010)
others x high harsh style	0.000	0.001	-0.004	-0.005	-0.008	-0.004
	(0.016)	(0.008)	(0.008)	(0.007)	(0.015)	(0.008)
Observations	2,780	2,667	6,599	6,463	2,419	2,417
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.22: Estimated parameters of production function with interaction between parenting styles and time investments for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	-0.001	-0.000	-0.002	0.001	0.012	0.006
	(0.004)	(0.003)	(0.004)	(0.003)	(0.011)	(0.006)
parents x high emphatic style	-0.005	-0.003	0.001	-0.003	-0.019	-0.006
	(0.006)	(0.004)	(0.004)	(0.004)	(0.013)	(0.006)
parents x high harsh style	0.006	0.001	0.003	0.001	-0.010	-0.005
	(0.006)	(0.004)	(0.004)	(0.004)	(0.013)	(0.006)
others	0.002	-0.002	-0.008	-0.001	-0.035*	-0.030**
	(0.006)	(0.004)	(0.009)	(0.009)	(0.020)	(0.013)
others x high emphatic style	-0.001	0.001	0.009	0.005	0.061***	0.050***
	(0.011)	(0.008)	(0.011)	(0.010)	(0.016)	(0.012)
others x high harsh style	-0.004	0.004	0.001	0.003	0.030	0.023*
	(0.010)	(0.007)	(0.009)	(0.010)	(0.018)	(0.012)
Care time:						
parents	0.000	0.001	-0.002	-0.001	0.003	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
parents x high emphatic style	-0.002	-0.000	0.002	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
parents x high harsh style	-0.002	-0.002	0.001	-0.001	-0.005	-0.005*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
others	0.002	0.000	-0.002	-0.001	-0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.004)
others x high emphatic style	0.003	-0.001	0.003	-0.000	-0.007	-0.006
	(0.004)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
others x high harsh style	0.006	0.007**	0.001	0.005	0.002	0.006
	(0.004)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
Observations	7,299	6,703	6,599	6,463	2,267	2,264
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.23: Estimated parameters of production function with interaction between parenting styles and time investments for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	0.003	0.006**	0.002	0.002	0.005	0.005
	(0.004)	(0.003)	(0.002)	(0.002)	(0.006)	(0.005)
parents x high emphatic style	-0.005	-0.006*	-0.004	-0.004	-0.001	-0.003
	(0.005)	(0.003)	(0.004)	(0.003)	(0.009)	(0.007)
parents x high harsh style	-0.005	-0.004	0.003	0.004	-0.026***	-0.006
	(0.005)	(0.004)	(0.004)	(0.003)	(0.009)	(0.007)
others	0.001	0.005	-0.002	-0.000	0.031	0.039***
	(0.010)	(0.007)	(0.006)	(0.006)	(0.020)	(0.011)
others x high emphatic style	-0.002	-0.007	0.003	-0.005	-0.076**	-0.067**
	(0.012)	(0.008)	(0.009)	(0.008)	(0.039)	(0.028)
others x high harsh style	-0.011	-0.011	-0.005	0.000	-0.054**	-0.053***
	(0.014)	(0.011)	(0.009)	(0.009)	(0.026)	(0.016)
Care time:						
parents	0.001	0.002	0.001	-0.000	-0.002	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
parents x high emphatic style	0.001	-0.001	-0.001	0.000	0.004	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
parents x high harsh style	0.001	-0.001	0.000	-0.000	0.004	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
others	-0.000	-0.002	0.001	-0.001	0.008**	0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
others x high emphatic style	0.006	0.004	0.001	0.004	-0.001	0.005
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
others x high harsh style	-0.002	0.000	0.000	0.000	-0.007	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Observations	6,544	6,346	6,599	6,463	2,067	2,066
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.24: Estimated parameters of production function with interaction between parenting styles and time investments for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	0.006**	0.004*	0.004*	0.003	-0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
parents x high emphatic style	-0.003	-0.002	-0.004	-0.001	0.014**	0.006
	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)
parents x high harsh style	-0.004	-0.002	0.001	0.000	0.002	-0.003
	(0.005)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
others	0.005*	0.004*	0.003	0.004	0.001	0.007
	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
others x high emphatic style	-0.008*	-0.007**	-0.007*	-0.007**	-0.005	-0.011*
	(0.004)	(0.003)	(0.004)	(0.003)	(0.007)	(0.006)
others x high harsh style	0.001	-0.002	-0.003	-0.005	0.005	-0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
Care time:						
parents	0.001	0.000	-0.001	0.001	-0.003	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
parents x high emphatic style	-0.001	-0.001	-0.001	-0.000	0.006	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
parents x high harsh style	0.000	-0.000	0.002	-0.002	0.006	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
others	-0.006	-0.005*	-0.001	-0.007**	0.004	-0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
others x high emphatic style	-0.000	0.003	-0.000	0.008**	-0.002	0.006
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)
others x high harsh style	0.011**	0.004	0.001	0.003	-0.004	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)
Observations	5,726	5,531	6,599	6,463	1,753	1,753
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.25: Estimated parameters of production function with non-linear parenting styles for non-cognitive skills at age 8-9

	Quartile		
	2nd	3rd	4th
Parental warmth	0.068*	0.014	0.012
	(0.035)	(0.034)	(0.043)
Parental reasoning	-0.040	-0.004	-0.040
	(0.034)	(0.034)	(0.044)
Hostile parenting	-0.097***	-0.121***	-0.268***
	(0.033)	(0.032)	(0.041)
Inconsistent parenting	-0.029	-0.021	-0.083**
	(0.034)	(0.034)	(0.039)
Attempted consistency	-0.032	-0.036	-0.060
	(0.036)	(0.036)	(0.037)
Observations		6,463	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

Table B.26: Estimated parameters of production function with non-linear parenting styles for non-cognitive skills at age 10-11

	Quartile		
	2nd	3rd	4th
Parental warmth	0.013	0.028	0.043
	(0.027)	(0.026)	(0.030)
Parental reasoning	-0.021	-0.069***	-0.067**
	(0.024)	(0.026)	(0.030)
Hostile parenting	-0.114***	-0.164***	-0.330***
	(0.025)	(0.024)	(0.031)
Inconsistent parenting	-0.049*	-0.119***	-0.167***
	(0.026)	(0.026)	(0.028)
Attempted consistency	-0.034	0.020	-0.026
	(0.026)	(0.027)	(0.028)
Observations		6,463	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

Table B.27: Estimated parameters of production function with non-linear parenting styles for non-cognitive skills at age 12-13

	Quartile		
	2nd	3rd	4th
Parental warmth	0.085***	0.094***	0.123***
	(0.025)	(0.028)	(0.031)
Parental reasoning	-0.055**	-0.078***	-0.073***
	(0.027)	(0.022)	(0.027)
Hostile parenting	-0.035	-0.171***	-0.337***
	(0.022)	(0.025)	(0.032)
Inconsistent parenting	-0.054**	-0.066***	-0.151***
	(0.024)	(0.024)	(0.028)
Attempted consistency	0.025	0.003	0.007
	(0.024)	(0.024)	(0.026)
Observations		6,463	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

Table B.28: Estimated parameters of production function with non-linear parenting styles, lagged for non-cognitive skills at age 14-15

	Quartile		
	2nd	3rd	4th
Parental warmth	0.026	0.018	0.103***
	(0.031)	(0.031)	(0.036)
Parental reasoning	-0.047*	-0.087**	-0.097***
	(0.026)	(0.034)	(0.032)
Hostile parenting	-0.056**	-0.114***	-0.321***
	(0.027)	(0.029)	(0.036)
Inconsistent parenting	0.023	-0.024	-0.160***
	(0.029)	(0.029)	(0.034)
Attempted consistency	-0.012	0.059**	0.030
	(0.029)	(0.030)	(0.031)
Observations		6,463	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

B.1.2. Cognitive skills

Table B.29: Estimated parameters of production function for cognitive skills (MRT) at age 10-11

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.025	-0.010	-0.024	-0.018	-0.014	-0.007
	(0.017)	(0.014)	(0.022)	(0.031)	(0.036)	(0.029)
Parental reasoning	0.000	0.005	-0.006	-0.019	-0.046*	-0.033
	(0.015)	(0.013)	(0.021)	(0.028)	(0.028)	(0.025)
Hostile parenting	0.001	0.009	0.012	0.010	0.010	0.011
	(0.016)	(0.014)	(0.022)	(0.030)	(0.031)	(0.026)
Inconsistent parenting	-0.082***	-0.052***	-0.029	0.003	-0.053	-0.036
	(0.016)	(0.013)	(0.020)	(0.030)	(0.032)	(0.026)
Attempted consistency	0.017	0.006	0.012	-0.001	0.025	0.025
	(0.014)	(0.012)	(0.020)	(0.026)	(0.027)	(0.023)
Educational time parents	-0.001	-0.002	-0.002	0.002	0.001	0.002
	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)	(0.004)
Educational time others	0.003	0.002	-0.009	-0.001	0.005	-0.001
	(0.005)	(0.004)	(0.008)	(0.012)	(0.008)	(0.005)
Care time parents	0.001	0.001	0.004**	0.003	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.005**	0.005***	0.007**	0.003	0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Lagged test outcome		0.496***		0.179***		0.464***
		(0.012)		(0.039)		(0.019)
Observations	7,266	7,055	7,428	2,504	2,262	2,256
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.30: Estimated parameters of production function without parenting style for cognitive skills (MRT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.015***	0.007*	-0.001	0.002	0.015***	0.006
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)
Educational time others	0.024	0.019	0.015	0.013	0.005	0.003
	(0.017)	(0.016)	(0.015)	(0.016)	(0.017)	(0.015)
Care time parents	-0.000	0.000	0.002	0.003	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.004	0.003	0.002	0.008	0.010	0.006
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Lagged test outcome		0.461***		0.183***		0.461***
		(0.019)		(0.039)		(0.020)
Observations	2,862	2,794	7,497	2,617	2,594	2,587
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.31: Estimated parameters of production function without parenting style for cognitive skills (MRT) at age 10-11

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.001	-0.001	-0.002	0.002	0.001	0.002
	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Educational time others	0.003	0.002	-0.007	0.001	0.009	0.003
	(0.005)	(0.004)	(0.009)	(0.012)	(0.008)	(0.007)
Care time parents	0.000	0.000	0.004^{**}	0.004^{*}	0.000	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.004^{**}	0.004^{**}	0.007^{**}	0.004	0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Lagged test outcome		0.502^{***}		0.183^{***}		0.458^{***}
		(0.012)		(0.039)		(0.019)
Observations	7,349	7,129	7,497	2,617	2,454	2,446
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.32: Estimated parameters of production function without parenting style for cognitive skills (PPVT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time parents	0.018***	0.010***	0.002	-0.004	0.018***	0.010***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Educational time others	0.010	-0.001	-0.017	-0.000	0.003	-0.007
	(0.015)	(0.015)	(0.023)	(0.024)	(0.016)	(0.016)
Care time parents	0.002	0.000	-0.001	-0.003	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	-0.005	-0.005	-0.006	-0.002	0.000	-0.003
	(0.005)	(0.005)	(0.009)	(0.010)	(0.006)	(0.006)
Lagged test outcome		0.499***		0.122***		0.499***
		(0.019)		(0.040)		(0.020)
Observations	2,864	2,732	3,501	2,329	2,596	2,530
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Peabody Picture Vocabulary Test (PPVT) outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.33: Estimated parameters of production function with interaction between parenting styles and time investments for cognitive skills (MRT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	0.010	0.005	0.001	0.007	0.007	0.003
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
parents x high emphatic style	0.000	-0.005	-0.006	-0.003	0.012	0.004
	(0.009)	(0.008)	(0.007)	(0.008)	(0.010)	(0.008)
parents x high harsh style	0.009	0.008	0.003	-0.005	0.007	0.006
	(0.009)	(0.007)	(0.007)	(0.008)	(0.010)	(0.008)
others	0.030	0.021	-0.013	-0.033	0.055	0.043
	(0.038)	(0.036)	(0.037)	(0.039)	(0.039)	(0.033)
others x high emphatic style	0.004	0.008	0.050	0.052	-0.027	-0.014
	(0.040)	(0.039)	(0.038)	(0.039)	(0.040)	(0.036)
others x high harsh style	-0.021	-0.020	-0.012	-0.001	-0.078**	-0.068**
	(0.032)	(0.032)	(0.035)	(0.035)	(0.031)	(0.027)
Care time:						
parents	-0.003	-0.002	-0.001	0.004	-0.005	-0.004
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
parents x high emphatic style	0.003	0.004	0.006	0.006	0.007	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
parents x high harsh style	0.002	0.000	-0.001	-0.006	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
others	0.013	0.011	0.004	0.008	0.017	0.011
	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.012)
others x high emphatic style	-0.006	-0.007	-0.017	0.000	-0.001	-0.011
	(0.016)	(0.016)	(0.016)	(0.015)	(0.018)	(0.016)
others x high harsh style	-0.009	-0.007	0.008	0.008	0.002	0.003
	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)
Observations	2,753	2,690	7,428	2,504	2,399	2,392
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.34: Estimated parameters of production function with interaction between parenting styles and time investments for cognitive skills (MRT) at age 10-11

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	0.005	0.004	-0.002	0.001	0.015	0.011
	(0.005)	(0.004)	(0.007)	(0.009)	(0.010)	(0.008)
parents x high emphatic style	-0.009*	-0.005	0.004	0.004	-0.009	-0.004
	(0.006)	(0.005)	(0.007)	(0.009)	(0.010)	(0.008)
parents x high harsh style	-0.003	-0.006	-0.005	-0.005	-0.016*	-0.012
	(0.006)	(0.005)	(0.007)	(0.009)	(0.009)	(0.007)
others	-0.004	-0.005	-0.021	-0.017	0.001	-0.012
	(0.007)	(0.005)	(0.021)	(0.027)	(0.017)	(0.013)
others x high emphatic style	-0.007	0.001	0.017	0.010	-0.011	0.001
	(0.009)	(0.007)	(0.019)	(0.025)	(0.017)	(0.013)
others x high harsh style	0.018**	0.013*	0.007	0.020	0.012	0.014
	(0.009)	(0.007)	(0.019)	(0.024)	(0.016)	(0.013)
Care time:						
parents	-0.001	-0.001	0.007**	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
parents x high emphatic style	0.003	0.002	-0.003	0.002	-0.001	-0.000
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
parents x high harsh style	0.000	0.001	-0.004	-0.003	-0.004	-0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
others	0.004	0.004	0.006	0.004	-0.004	-0.001
	(0.004)	(0.003)	(0.006)	(0.007)	(0.006)	(0.006)
others x high emphatic style	0.001	-0.000	-0.002	0.003	0.008	0.006
	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.006)
others x high harsh style	0.001	0.002	0.004	-0.005	0.006	0.003
	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.006)
Observations	7,266	7,055	7,428	2,504	2,262	2,256
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.35: Estimated parameters of production function with interaction between parenting styles and time investments for cognitive skills (PPVT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Educational time:						
parents	0.017**	0.008	0.002	-0.003	0.018**	0.008
	(0.007)	(0.006)	(0.008)	(0.009)	(0.007)	(0.007)
parents x high emphatic style	-0.005	-0.001	0.002	-0.004	-0.004	0.000
	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)	(0.008)
parents x high harsh style	0.004	0.005	-0.002	0.001	0.002	0.001
	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)	(0.007)
others	0.003	-0.032	-0.073*	-0.084*	0.008	-0.031
	(0.034)	(0.029)	(0.041)	(0.043)	(0.038)	(0.029)
others x high emphatic style	0.026	0.072**	0.130***	0.150***	0.014	0.067**
	(0.032)	(0.029)	(0.042)	(0.045)	(0.036)	(0.028)
others x high harsh style	-0.009	-0.024	-0.046	-0.054	-0.033	-0.044
	(0.031)	(0.028)	(0.038)	(0.042)	(0.035)	(0.028)
Care time:						
parents	0.003	0.001	-0.001	-0.002	-0.001	-0.001
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
parents x high emphatic style	0.000	-0.001	-0.002	-0.002	0.002	-0.000
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
parents x high harsh style	-0.002	-0.001	0.001	0.001	-0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
others	-0.005	-0.011	-0.016	-0.012	-0.001	-0.009
	(0.011)	(0.008)	(0.010)	(0.011)	(0.013)	(0.009)
others x high emphatic style	0.010	0.003	-0.012	-0.017	0.018	0.005
	(0.012)	(0.011)	(0.015)	(0.017)	(0.013)	(0.012)
others x high harsh style	0.002	0.015	0.031**	0.039**	0.009	0.022**
	(0.012)	(0.011)	(0.015)	(0.018)	(0.014)	(0.011)
Observations	2,755	2,633	3,437	2,156	2,401	2,343
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Emphatic parenting style is defined as high on warmth, reasoning, and attempted consistency. Harsh parenting is defined as high on hostility and inconsistency. In the estimation, we use dummies for high emphatic style and high harsh style if the corresponding parenting style is above median in the age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.36: Estimated parameters of production function with non-linear parenting styles for cognitive skills (MRT) at age 8-9

	Quartile		
	2nd	3rd	4th
Parental warmth	-0.066	-0.014	-0.109
	(0.057)	(0.064)	(0.079)
Parental reasoning	-0.058	0.011	0.038
	(0.057)	(0.062)	(0.076)
Hostile parenting	0.157**	0.093	-0.008
	(0.063)	(0.061)	(0.072)
Inconsistent parenting	-0.085	-0.007	-0.050
	(0.062)	(0.061)	(0.069)
Attempted consistency	-0.040	0.004	-0.039
	(0.060)	(0.059)	(0.067)
Observations		2,504	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

Table B.37: Estimated parameters of production function with non-linear parenting styles for cognitive skills (MRT) at age 10-11

	Quartile		
	2nd	3rd	4th
Parental warmth	-0.142**	-0.051	-0.114
	(0.063)	(0.062)	(0.075)
Parental reasoning	0.006	-0.054	0.041
	(0.059)	(0.065)	(0.075)
Hostile parenting	0.126**	0.040	0.018
	(0.063)	(0.059)	(0.072)
Inconsistent parenting	-0.139**	-0.123**	-0.057
	(0.065)	(0.063)	(0.067)
Attempted consistency	0.046	0.122**	-0.021
	(0.062)	(0.062)	(0.068)
Observations		2,504	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

Table B.38: Estimated parameters of production function with non-linear parenting styles for cognitive skills (MRT) at age 8-9

	Quartile		
	2nd	3rd	4th
Parental warmth	0.041	-0.025	-0.087
	(0.059)	(0.060)	(0.076)
Parental reasoning	0.055	-0.016	0.071
	(0.059)	(0.061)	(0.077)
Hostile parenting	-0.096	0.004	-0.091
	(0.062)	(0.061)	(0.067)
Inconsistent parenting	-0.102	0.005	0.051
	(0.064)	(0.060)	(0.064)
Attempted consistency	0.008	-0.036	0.005
	(0.062)	(0.063)	(0.064)
Observations		2,156	

Note: We use dummy variables to indicate whether a child belongs to the 2nd, 3rd, or 4th quartile of parenting dimensions distributions (with the 1st quartile as the baseline category). Each specification includes the child's fixed effect, the lagged value of non-cognitive skills, time investments such as educational time with parents, educational time with other adults, care time with parents, and care time with other adults, as well as control variables such as the age of the primary caregiver, the number of siblings, the logarithm of family income, and dummy variables for the primary caregiver's college education, the presence of both biological parents at home, the gender of the study child, the study child's cohort, and the day of data collection.

B.2. Robustness checks

B.2.1. Non-cognitive skills

Table B.39: Estimated parameters of production function with jointly estimated parenting dimensions for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Warm style	0.153***	0.061***	0.085***	0.042***	0.128***	0.093***
	(0.018)	(0.013)	(0.017)	(0.013)	(0.022)	(0.018)
Reasoning style	-0.145***	-0.050***	-0.048***	-0.036**	-0.098***	-0.060***
	(0.019)	(0.015)	(0.016)	(0.015)	(0.024)	(0.019)
Hostile/inconstistent style	-0.413***	-0.192***	-0.194***	-0.135***	-0.339***	-0.221***
	(0.019)	(0.015)	(0.015)	(0.014)	(0.022)	(0.018)
Consistent style	0.072***	0.044***	0.019	0.015	0.052***	0.025*
	(0.016)	(0.012)	(0.012)	(0.012)	(0.018)	(0.014)
Educational time parents	-0.003	-0.000	0.001	0.003	-0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Educational time others	0.005	-0.000	-0.013	-0.012	0.009	0.000
	(0.015)	(0.012)	(0.010)	(0.010)	(0.015)	(0.012)
Care time parents	-0.002	-0.001	-0.001	-0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.004	-0.001	0.000	-0.003	0.004	-0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)
Lagged test outcome		0.633***		0.253***		0.631***
		(0.020)		(0.019)		(0.020)
Observations	2,780	2,667	6,599	6,463	2,419	2,417
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.40: Estimated parameters of production function with jointly estimated parenting dimensions for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Warm style	0.162***	0.067***	0.082***	0.075***	0.123***	0.099***
	(0.012)	(0.009)	(0.011)	(0.011)	(0.025)	(0.021)
Reasoning style	-0.109***	-0.048***	-0.045***	-0.061***	-0.073***	-0.064***
	(0.011)	(0.009)	(0.010)	(0.010)	(0.024)	(0.019)
Hostile/inconstistent style	-0.433***	-0.201***	-0.189***	-0.194***	-0.361***	-0.266***
	(0.011)	(0.010)	(0.012)	(0.012)	(0.025)	(0.022)
Consistent style	0.082***	0.032***	0.029***	0.033***	0.066***	0.047***
	(0.010)	(0.008)	(0.009)	(0.009)	(0.020)	(0.016)
Educational time parents	-0.001	-0.002	-0.000	-0.001	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Educational time others	-0.001	-0.000	-0.003	0.003	0.014*	0.011
	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)	(0.007)
Care time parents	-0.002	-0.001	-0.000	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.007***	0.004**	0.001	0.002	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Lagged test outcome		0.632***		0.253***		0.641***
		(0.013)		(0.019)		(0.021)
Observations	7,299	6,703	6,599	6,463	2,267	2,264
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.41: Estimated parameters of production function with jointly estimated parenting dimensions for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Warm style	0.188***	0.093***	0.087***	0.102***	0.186***	0.159***
	(0.013)	(0.009)	(0.011)	(0.011)	(0.027)	(0.022)
Reasoning style	-0.113***	-0.050***	-0.047***	-0.037***	-0.077***	-0.046***
	(0.011)	(0.008)	(0.008)	(0.008)	(0.021)	(0.016)
Hostile/inconstistent style	-0.424***	-0.200***	-0.207***	-0.208***	-0.317***	-0.273***
	(0.013)	(0.011)	(0.011)	(0.012)	(0.028)	(0.025)
Consistent style	0.041***	0.018**	0.020**	0.022**	0.016	0.018
	(0.013)	(0.009)	(0.010)	(0.010)	(0.025)	(0.019)
Educational time parents	-0.004*	-0.000	0.000	0.001	-0.008*	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Educational time others	-0.007	-0.004	-0.004	-0.005	-0.011	-0.010
	(0.005)	(0.004)	(0.004)	(0.004)	(0.011)	(0.009)
Care time parents	0.001	0.000	0.000	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.000	-0.001	0.001	0.000	0.004	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Lagged test outcome		0.658***		0.253***		0.653***
		(0.013)		(0.019)		(0.023)
Observations	6,544	6,346	6,599	6,463	2,067	2,066
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.42: Estimated parameters of production function with jointly estimated parenting dimensions for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Warm style	0.197***	0.091***	0.095***	0.092***	0.096***	0.088***
	(0.014)	(0.010)	(0.012)	(0.012)	(0.034)	(0.025)
Reasoning style	-0.136***	-0.066***	-0.059***	-0.050***	-0.092***	-0.087***
	(0.011)	(0.009)	(0.010)	(0.010)	(0.021)	(0.018)
Hostile/inconstistent style	-0.434***	-0.220***	-0.233***	-0.207***	-0.349***	-0.293***
	(0.015)	(0.012)	(0.013)	(0.013)	(0.035)	(0.028)
Consistent style	-0.052***	-0.028***	-0.006	-0.011	-0.023	-0.038*
	(0.013)	(0.010)	(0.011)	(0.011)	(0.026)	(0.021)
Educational time parents	0.001	0.002	0.002	0.002	0.005*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Educational time others	0.002	0.000	-0.002	-0.002	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Care time parents	-0.001	-0.001	-0.001	-0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	-0.001	-0.001	-0.001	-0.001	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Lagged test outcome		0.635***		0.253***		0.651***
		(0.014)		(0.019)		(0.023)
Observations	5,726	5,531	6,599	6,463	1,753	1,753
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.43: Estimated parameters of production function with extended set of controls for non-cognitive skills at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.065***	0.021	0.049**	0.010	0.048*	0.041**
	(0.022)	(0.017)	(0.020)	(0.017)	(0.027)	(0.020)
Parental reasoning	-0.087***	-0.044***	-0.025*	-0.012	-0.055**	-0.031*
	(0.019)	(0.015)	(0.015)	(0.015)	(0.022)	(0.016)
Hostile parenting	-0.363***	-0.171***	-0.161***	-0.117***	-0.301***	-0.195***
	(0.023)	(0.018)	(0.016)	(0.017)	(0.027)	(0.020)
Inconsistent parenting	-0.147***	-0.059***	-0.062***	-0.045**	-0.101***	-0.070***
	(0.023)	(0.018)	(0.018)	(0.018)	(0.028)	(0.021)
Attempted consistency	0.004	-0.010	-0.016	-0.010	-0.011	-0.007
	(0.018)	(0.015)	(0.015)	(0.014)	(0.021)	(0.016)
Educational time parents	-0.002	-0.000	0.001	0.004	-0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Educational time others	0.010	0.004	-0.012	-0.012	0.016	0.005
	(0.015)	(0.012)	(0.010)	(0.010)	(0.015)	(0.012)
Care time parents	-0.002	-0.000	-0.001	-0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.000	-0.004	-0.000	-0.003	0.000	-0.004
	(0.008)	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)
Lagged test outcome		0.636***		0.254***		0.632***
		(0.020)		(0.019)		(0.020)
Observations	2,735	2,626	6,599	6,462	2,384	2,382
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

Table B.44: Estimated parameters of production function with extended set of controls for non-cognitive skills at age 10-11

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.049***	0.011	0.037***	0.033**	0.041	0.042*
	(0.015)	(0.012)	(0.013)	(0.013)	(0.031)	(0.025)
Parental reasoning	-0.085***	-0.026***	-0.033***	-0.035***	-0.066***	-0.045**
	(0.012)	(0.009)	(0.010)	(0.010)	(0.023)	(0.018)
Hostile parenting	-0.386***	-0.179***	-0.170***	-0.160***	-0.308***	-0.216***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.028)	(0.023)
Inconsistent parenting	-0.142***	-0.068***	-0.053***	-0.077***	-0.130***	-0.111***
	(0.014)	(0.011)	(0.013)	(0.013)	(0.030)	(0.023)
Attempted consistency	0.017	-0.001	0.006	0.005	-0.009	-0.007
	(0.011)	(0.009)	(0.010)	(0.010)	(0.022)	(0.017)
Educational time parents	-0.000	-0.001	-0.000	-0.001	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Educational time others	-0.000	-0.000	-0.003	0.003	0.013	0.009
	(0.005)	(0.004)	(0.005)	(0.004)	(0.010)	(0.008)
Care time parents	-0.002*	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.006***	0.004**	0.001	0.002	-0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Lagged test outcome		0.632***		0.254***		0.644***
		(0.013)		(0.019)		(0.021)
Observations	7,200	6,616	6,599	6,462	2,229	2,226
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

Table B.45: Estimated parameters of production function with extended set of controls for non-cognitive skills at age 12-13

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.049***	0.025**	0.028**	0.044***	0.077**	0.058**
	(0.017)	(0.012)	(0.012)	(0.013)	(0.032)	(0.026)
Parental reasoning	-0.081***	-0.035***	-0.031***	-0.026***	-0.054**	-0.024
	(0.012)	(0.009)	(0.009)	(0.010)	(0.024)	(0.019)
Hostile parenting	-0.391***	-0.187***	-0.178***	-0.180***	-0.320***	-0.270***
	(0.017)	(0.013)	(0.013)	(0.014)	(0.030)	(0.026)
Inconsistent parenting	-0.115***	-0.052***	-0.065***	-0.059***	-0.049	-0.053**
	(0.017)	(0.012)	(0.013)	(0.012)	(0.031)	(0.024)
Attempted consistency	0.025*	0.011	0.002	0.005	0.005	0.007
	(0.013)	(0.009)	(0.010)	(0.010)	(0.021)	(0.017)
Educational time parents	-0.003	0.000	0.000	0.001	-0.008**	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Educational time others	-0.005	-0.003	-0.004	-0.005	-0.012	-0.013
	(0.005)	(0.004)	(0.004)	(0.004)	(0.012)	(0.009)
Care time parents	0.001	0.001	0.001	-0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	0.000	-0.001	0.001	0.000	0.003	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Lagged test outcome		0.654***		0.254***		0.644***
		(0.013)		(0.019)		(0.022)
Observations	6,476	6,283	6,599	6,462	2,042	2,041
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

Table B.46: Estimated parameters of production function with extended set of controls for non-cognitive skills at age 14-15

	OLS	VA	FE	AB	CU	CV
Parental warmth	0.053***	0.018	0.032**	0.036**	-0.020	0.000
	(0.017)	(0.013)	(0.014)	(0.014)	(0.039)	(0.028)
Parental reasoning	-0.087***	-0.037***	-0.040***	-0.033***	-0.040*	-0.043**
	(0.013)	(0.010)	(0.011)	(0.011)	(0.024)	(0.019)
Hostile parenting	-0.365***	-0.182***	-0.167***	-0.157***	-0.265***	-0.222***
	(0.019)	(0.015)	(0.016)	(0.015)	(0.036)	(0.028)
Inconsistent parenting	-0.151***	-0.085***	-0.103***	-0.080***	-0.168***	-0.139***
	(0.018)	(0.014)	(0.015)	(0.015)	(0.038)	(0.031)
Attempted consistency	0.023*	0.003	0.025**	0.016	0.016	-0.004
	(0.013)	(0.011)	(0.011)	(0.011)	(0.024)	(0.020)
Educational time parents	0.002	0.002	0.002	0.002	0.005*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Educational time others	0.003	0.001	-0.002	-0.002	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Care time parents	-0.000	-0.001	-0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Care time others	-0.001	-0.001	-0.001	-0.001	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Lagged test outcome		0.631***		0.254***		0.644***
		(0.015)		(0.019)		(0.024)
Observations	5,671	5,478	6,599	6,462	1,733	1,733
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

B.2.2. Cognitive skills

Table B.47: Estimated parameters of production function with jointly estimated parenting dimensions for cognitive skills (MRT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Warm style	-0.037*	-0.040**	-0.041**	-0.018	-0.040	-0.049*
	(0.022)	(0.019)	(0.019)	(0.028)	(0.030)	(0.026)
Reasoning style	-0.052**	-0.028	0.001	0.021	-0.011	0.009
	(0.022)	(0.019)	(0.020)	(0.029)	(0.028)	(0.024)
Hostile/inconstistent style	-0.027	-0.016	-0.008	-0.007	-0.010	-0.007
	(0.021)	(0.019)	(0.019)	(0.027)	(0.027)	(0.024)
Consistent style	0.017	0.020	0.024	0.020	0.036	0.040*
	(0.020)	(0.018)	(0.019)	(0.025)	(0.025)	(0.022)
Educational time parents	0.014***	0.006	-0.001	0.003	0.013***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Educational time others	0.017	0.013	0.012	0.007	0.000	0.000
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.015)
Care time parents	-0.000	0.000	0.002	0.003	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.005	0.003	0.002	0.009	0.012*	0.007
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Lagged test outcome		0.456***		0.178***		0.455***
		(0.019)		(0.039)		(0.020)
Observations	2,753	2,690	7,428	2,504	2,399	2,392
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.48: Estimated parameters of production function with jointly estimated parenting dimensions for cognitive skills (MRT) at age 10-11

	OLS	VA	FE	AB	CU	CV
Warm style	-0.018	-0.008	-0.023	-0.021	-0.012	-0.007
	(0.013)	(0.011)	(0.018)	(0.027)	(0.031)	(0.025)
Reasoning style	-0.062***	-0.035***	-0.024	0.008	-0.047*	-0.034
	(0.013)	(0.011)	(0.018)	(0.028)	(0.027)	(0.023)
Hostile/inconstistent style	-0.040***	-0.021*	0.001	0.013	-0.005	0.000
	(0.013)	(0.011)	(0.018)	(0.025)	(0.028)	(0.023)
Consistent style	0.007	-0.001	0.011	0.024	0.048*	0.031
	(0.013)	(0.011)	(0.018)	(0.024)	(0.025)	(0.022)
Educational time parents	-0.001	-0.002	-0.002	0.002	0.001	0.002
	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Educational time others	0.003	0.002	-0.009	-0.001	0.006	-0.001
	(0.005)	(0.004)	(0.008)	(0.012)	(0.008)	(0.005)
Care time parents	0.001	0.001	0.004**	0.003	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.005**	0.005***	0.007**	0.003	0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Lagged test outcome		0.496***		0.178***		0.463***
		(0.012)		(0.039)		(0.019)
Observations	7,266	7,055	7,428	2,504	2,262	2,256
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.49: Estimated parameters of production function with jointly estimated parenting dimensions for cognitive skills (PPVT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Warm style	-0.034*	-0.033**	-0.052***	-0.038*	-0.032	-0.036
	(0.019)	(0.017)	(0.020)	(0.022)	(0.026)	(0.022)
Reasoning style	-0.084***	-0.025	0.014	0.007	-0.040	-0.018
	(0.021)	(0.018)	(0.021)	(0.022)	(0.028)	(0.024)
Hostile/inconstistent style	-0.032*	-0.025	-0.026	-0.015	-0.004	-0.005
	(0.019)	(0.016)	(0.021)	(0.023)	(0.025)	(0.021)
Consistent style	-0.002	0.005	0.025	0.018	0.014	0.030
	(0.019)	(0.017)	(0.021)	(0.022)	(0.023)	(0.020)
Educational time parents	0.016***	0.010***	0.001	-0.004	0.015***	0.008**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Educational time others	0.013	0.001	-0.016	0.002	0.002	-0.008
	(0.015)	(0.015)	(0.025)	(0.025)	(0.016)	(0.016)
Care time parents	0.002	0.000	-0.001	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	-0.001	-0.003	-0.004	0.003	0.006	0.001
	(0.005)	(0.005)	(0.010)	(0.011)	(0.006)	(0.006)
Lagged test outcome		0.494***		0.151***		0.490***
		(0.019)		(0.044)		(0.020)
Observations	2,755	2,633	3,437	2,156	2,401	2,343
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Peabody Picture Vocabulary Test (PPVT) outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of the study child, the study child's cohort, and the day of data collection.

Table B.50: Estimated parameters of production function with extended set of controls for cognitive skills (MRT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.035	-0.028	-0.033	-0.015	-0.030	-0.029
	(0.027)	(0.025)	(0.024)	(0.033)	(0.034)	(0.031)
Parental reasoning	-0.016	-0.015	-0.007	-0.011	-0.027	-0.025
	(0.024)	(0.021)	(0.021)	(0.028)	(0.028)	(0.025)
Hostile parenting	-0.006	0.006	0.013	0.002	-0.005	0.010
	(0.026)	(0.023)	(0.023)	(0.030)	(0.032)	(0.027)
Inconsistent parenting	-0.061**	-0.045**	-0.027	0.002	-0.025	-0.021
	(0.025)	(0.022)	(0.024)	(0.031)	(0.031)	(0.027)
Attempted consistency	0.007	-0.011	-0.032*	-0.029	-0.026	-0.046*
	(0.022)	(0.020)	(0.019)	(0.025)	(0.027)	(0.023)
Educational time parents	0.013***	0.006*	0.000	0.003	0.013***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Educational time others	0.018	0.015	0.013	0.008	0.007	0.005
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.016)
Care time parents	-0.000	0.000	0.002	0.003	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.005	0.002	0.001	0.009	0.012*	0.005
	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)
Lagged test outcome		0.448***		0.180***		0.447***
		(0.019)		(0.039)		(0.021)
Observations	2,709	2,649	7,428	2,503	2,364	2,357
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

Table B.51: Estimated parameters of production function with extended set of controls for cognitive skills (MRT) at age 10-11

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.031*	-0.014	-0.026	-0.019	-0.022	-0.011
	(0.017)	(0.015)	(0.022)	(0.031)	(0.035)	(0.029)
Parental reasoning	0.002	0.008	-0.006	-0.017	-0.039	-0.030
	(0.015)	(0.013)	(0.021)	(0.028)	(0.028)	(0.025)
Hostile parenting	-0.002	0.007	0.010	0.013	0.013	0.015
	(0.017)	(0.014)	(0.022)	(0.030)	(0.030)	(0.026)
Inconsistent parenting	-0.077***	-0.051***	-0.031	0.005	-0.047	-0.036
	(0.016)	(0.013)	(0.020)	(0.030)	(0.032)	(0.027)
Attempted consistency	0.015	0.004	0.013	-0.002	0.020	0.023
	(0.014)	(0.012)	(0.020)	(0.026)	(0.027)	(0.023)
Educational time parents	0.000	-0.001	-0.002	0.001	0.002	0.003
	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)	(0.004)
Educational time others	0.003	0.002	-0.008	0.001	0.006	-0.001
	(0.005)	(0.004)	(0.009)	(0.012)	(0.008)	(0.006)
Care time parents	0.000	0.000	0.004**	0.003	0.000	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.004**	0.005***	0.006**	0.003	0.001	0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Lagged test outcome		0.491***		0.180***		0.456***
		(0.012)		(0.039)		(0.020)
Observations	7,168	6,965	7,428	2,503	2,224	2,218
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Matrix Reasoning Test outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

Table B.52: Estimated parameters of production function with extended set of controls for cognitive skills (PPVT) at age 8-9

	OLS	VA	FE	AB	CU	CV
Parental warmth	-0.049**	-0.045**	-0.069***	-0.055*	-0.041	-0.041
	(0.024)	(0.021)	(0.026)	(0.028)	(0.031)	(0.026)
Parental reasoning	0.016	0.011	-0.002	-0.003	-0.006	-0.019
	(0.023)	(0.020)	(0.025)	(0.026)	(0.028)	(0.023)
Hostile parenting	-0.014	-0.022	-0.041	-0.035	-0.000	-0.011
	(0.023)	(0.021)	(0.025)	(0.027)	(0.028)	(0.025)
Inconsistent parenting	-0.079***	-0.029	0.014	0.020	-0.038	-0.019
	(0.023)	(0.021)	(0.026)	(0.026)	(0.029)	(0.026)
Attempted consistency	0.027	-0.002	-0.011	0.003	0.004	0.002
	(0.020)	(0.018)	(0.021)	(0.023)	(0.024)	(0.021)
Educational time parents	0.015***	0.009**	0.001	-0.003	0.013***	0.007*
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Educational time others	0.014	0.000	-0.015	0.002	0.005	-0.005
	(0.014)	(0.015)	(0.025)	(0.025)	(0.016)	(0.016)
Care time parents	0.002	0.000	-0.001	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Care time others	0.000	-0.002	-0.005	0.003	0.007	0.001
	(0.005)	(0.006)	(0.010)	(0.011)	(0.006)	(0.006)
Lagged test outcome		0.481***		0.150***		0.478***
		(0.019)		(0.043)		(0.021)
Observations	2,711	2,593	3,437	2,156	2,366	2,308
Lagged dependent	NO	YES	NO	YES	NO	YES
Lagged inputs	NO	NO	NO	NO	YES	YES
Fixed effects	NO	NO	YES	YES	NO	NO

Note: Cognitive skills are measured using Peabody Picture Vocabulary Test (PPVT) outcomes standardized by age group. Each specification includes controls as the age of the primary caregiver, the number of siblings, the log of family income, standardized Social-Economic Indexes for Areas, weight at birth and dummies for the college education of the primary caregiver, the presence of both biological parents at home, the gender of the study child, the indigenous status of th study child, the study child's cohort, the day of data collection, urban area, Australian state and early birth.

C. APPENDIX TO CHAPTER 3

Table C.1: Overview of food types surveyed and categorization in food groups by RCT

Stapels (coarse + fine):	
Pal	Corn, Oats + rice, white bread, sweet bread, box bread
Progresa	Corn + rice, white bread, sweet bread, box bread
Nicaragua	Oats, corn, grained corn + rice, bread, sweet bread
Philippines	Cereals (rice, corn, bread, biscuits, flour etc.)
Uganda	Corn, grained corn, sorghum, millet + rice, bread
Tubers:	
Pal	Potato
Progresa	Potato
Nicaragua	Potato, yucca
Philippines	Roots (e.g. potato, cassava, sweet potato)
Uganda	Potato, sweet potato, cassava, dry cassava
Protein:	
Pal	Chicken, beef, pork, sheep, goat, fish, sardines, tuna, eggs, sausages, milk, yogurt, powder milk
Progresa	Chicken, beef, pork, sheep, goat, fish, eggs, milk
Nicaragua	Beef, pork, bones, chicken, fish, shrimps, tuna, sausage, egg, fried fish, milk, powder milk
Philippines	Fish, meat, dairy (e.g fresh chicken, fresh beef, fresh pork, corned beef)
Uganda	Beef, pork, goat, other red meat, blood, white meat, fish, eggs, milk, powder milk
Vegetables and fruits:	
Pal	Tomato, carrot, leaf vegetables, cactus, squash, chayote, guayaba, mandarin, papaya, orange, banana, apple, lemon, watermelon
Progresa	Tomato, carrot, leaf vegetables, cactus, orange, banana, apple, lemon
Nicaragua	Pepper, tomato, salad, cucumber, carrot, banana, avocado, citrus fruits, tropical fruits, other fruit
Philippines	Fruits and vegetable (e.g. fresh hits, leafy vegetables , coconut)
Uganda	Tomato, orange color vegetables, leafy green, other vegetables, banana, avocado, orange fruits, other fruits

Note: For Philippines coarse and fine staples cannot be distinguished and we use this data only for overall staples.

Table C.2: Overview RCT data used

Country	Program	Evaluation years	Households at endline	Transfer type	Transfer consumption ratio
Mexico	Progresa	1998-1999	18,351	CCT	20%
Mexico	Programa de Apoyo Alimentario (PAL)	2003-2005	2,866	UCT	11.5%
Nicaragua	Red de Protección Social (RPS)	2000-2002	1,433	CCT	20%
Philippines	Pantawid Pamilyang Pilipino Program (PPPP)	2009-2011	1,401	CCT	23%
Uganda	WFP	2010-2011	1,777	UCT	13%

Note: Mexico PAL and Uganda WPF included a in-kind arm, but only the cash-transfer arm data is used.

Table C.3: Results for tubers

	Tubers	
	(1) Log(exp)	(2) Std. exp
Treated	0.169***	0.154***
	(0.031)	(0.028)
Constant	0.565***	-0.003
	(0.026)	(0.021)
N	55,219	54,556
No. clusters	843	715

Note: Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Each row corresponds to a separate regression. All specifications include RCT fixed effects. Standard errors are clustered at the village level (randomization unit) and bootstrapped with 100 reps.