Essays on Inequality in Human Capital Development

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Declaration of own work

I declare that this thesis was written by myself and is the result of my own work. Where work has been carried out with others, or where information is derived from other sources, I confirm that this is clearly indicated within the thesis. All parts of this thesis are original and have not been submitted for any other degree or professional qualifications.

Mark Mitchell
Tuesday 8th June, 2021

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Thesis Abstract

This thesis is comprised of three self-contained essays, each of which attempts to understand the early origins of inequality in “human capital”. Motivated by the unequal rise in rates of childhood obesity over the past four decades, the first focusses on the relationship between socioeconomic status and the incidence of overweight and obesity across childhood in a cohort of children born in the UK between 2000 and 2002. It analyses the relationship between conditions as early as 9 months of age and the likelihood a child is overweight or obese at age 14, and then documents how the contemporaneous relationship between parental income and weight and children’s weight changes over time.

The second chapter then focusses on health more generally among the same cohort, and estimates the developmental path of health over childhood. It also asks how health affects the accumulation of cognitive and socio-emotional skills over the same period. Given evidence of the link between health and socioeconomic status, doing so adds to the evidence on the early origins of disparities in health and how they affect - or are affected by - skills. Because characteristics like health and cognitive and socio-emotional skill cannot be measured perfectly, this chapter uses recent methodological advances for estimating non-linear dynamic factor models to estimate a model of child development that accounts for mismeasurement of children’s human capital and the early environment.

Lastly, the third essay analyses the development of socio-emotional skills in cohort of Peruvian children born in 1994. It also analyses how socio-emotional skills develop alongside cognition and, in early adulthood at age 22, how they affect the likelihood of engagement in risky behaviours. Over the past two decades, socio-emotional skills have been established as important determinants of social and economic outcomes. This chapter uses the same methodology as in Chapter 2 to understand their development, how they are affected by early circumstances and whether they influence young adults’ behaviour.

Lay summary

The focus of this thesis is on broadening the understanding of how and when inequalities emerge in individual characteristics that are important determinants of social and economic outcomes. It is therefore primarily concerned with the question of equality of opportunity, and the role played by early life circumstances in forming aspects of "human capital" in young adults. It is this human capital that determines their decisions about education and work, and that will, in large, determine their social and economic trajectories across their adult lives.

The first chapter focusses on the relationship between socioeconomic status and childhood obesity. Children who are obese are more likely to be obese in adulthood, by which time obesity has acute social, physical and mental health consequences. Obesity is linked to lower earnings and an increased likelihood of developing a wide range on non-communicable diseases. As a consequence, individuals who are obese live shorter and less affluent lives on average than those who are not. Using the Millennium Cohort Study my co-authors and I model the probability children become overweight or obese at the ages of 3, 5, 7, 11 and 14 years of age and quantify the relationship between parental weight and income and unhealthy bodyweight. We find that children in the poorest 20% of families or with an overweight or obese parent are considerably more likely to be overweight or obese themselves at all ages. These relationships in fact strengthen over time, and by age 14 children who have an obese parent are over four times as likely to be obese than their counterparts. Children in the bottom 20% of the income distribution are also more than twice as likely to be obese than those in the top 20% by age 14 irrespective of their parents' weight. Given relatively poorer parents are more likely to be, or become, obese across their children's early lives, this results in much higher rates of obesity in the bottom of the income distribution.

In the next chapter, I study the development of health more generally among the same cohort, and how it interacts with cognitive and socio-emotional skills across childhood. Poor health and its relationship with social and economic outcomes has its antecedents in childhood. Poor health is also associated with having lower levels of skills and education. There is no single definition of health, however, nor are there perfect measures of cognitive and socio-emotional skills. I use recent methodological advances for estimating non-linear dynamic factor models to estimate flexible "production functions" of health, cognition and socio-emotional skill across five stages of childhood. These functions capture the complex nature of development while allowing for multiple measures of health and skills and a latent factor structure. I find that health is highly persistent, but that cognitive and socio-emotional skills begin to influence its development in late childhood. These two skills are affected by family resources, meaning by age 14 a small socioeconomic gradient in health arises. I also find that health is important for developing cognitive skills in early and late childhood, and that excluding it from my analysis leads to over-stating the role of cognition in skill development. Finally, to explore whether it is possible for policy to reduce inequality in human capital, I simulate the effect of several interventions on human capital at the end of childhood. These simulations show that income transfers have little effect on the development of health or skills, but that interventions aimed at improving the health of children or their parents have a long-term impact.

Finally, the third chapter of this thesis is concerned with the development of socio-emotional skills in a cohort of Peruvian children born in 1994. Over the past two decades a substantial body of evidence has gathered as to the importance of socio-emotional skills in the labour market. Recent research into the structural development of these skills has sought to understand how they are affected by the early environment, and how they accumulate alongside cognition over childhood. Much of this work is focussed on developing countries, however there is no reason to believe - and evidence does not suggest - that these skills are any less important in low and middle-income countries. My co-authors and I use the same methodology as in Chapter 2 of this thesis to estimate flexible production functions of socio-emotional and cognitive skill between the ages of 8-12, 12-15, 15-19, and 19-22. Importantly, between the ages of 19-22 we show that socio-emotional skills can, and should, be disaggregated into sub-domains in order to fully understand how skills develop over the period. We find that cognition drives socio-emotional skill development between 8 and 22, and that cognition itself is increasingly self-productive and strongly influenced by family investments. As a result, a socioeconomic gradient emerges in socio-emotional skills between the ages of 8-12 that persists until age 19. Between 19-22, we show that two disaggregated components of socio-emotional skill - that we label *task effectiveness* and *social skills* - develop differently, particularly with respect to time-use and cognition accumulated by the end of adolescence (age 19). We then provide some evidence that task effectiveness is associated with a lower likelihood of engaging in risky behaviour, particularly smoking, using drugs and engaging with gangs.

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Chapter 1

Quantifying Socioeconomic Inequality in Childhood Obesity

Note: *This chapter was co-authored with Justus Laugwitz, a Post-Doctoral Research and Teaching Fellow at the University of Edinburgh (justus.laugwitz@ed.ac.uk), and Patricio Valdivieso Massa, a Research Associate at Heriot-Watt University (p.valdivieso_massa@hw.ac.uk). Both have agreed that this research represents in the majority my work, and that it can appear in this thesis.*

1.1 Introduction

The prevalence of childhood obesity around the world has risen dramatically over the past three decades. The World Health Organization (WHO) estimates that the proportion of children and adolescents who are overweight or obese around the world has increased from 4% to 24% since 1975.[1] In 2016, it is estimated that roughly 18% of school age children in the USA were obese, whilst in England one fifth of children are obese upon beginning secondary school (Hales et al., 2017; NHS Digital, 2019). In both countries, being from a disadvantaged area or having an overweight parent is highly correlated with childhood obesity (Ogden et al., 2018; NHS Digital, 2019). The consequences of obesity are acute. Childhood obesity is associated with reduced physical health and mental health, reduced skill accumulation and academic performance, and a lower quality of life (Cawley and Spiess, 2008; Sahoo et al., 2015). Obese children are significantly more likely to be overweight or obese in adulthood, and by adulthood, obesity is linked to reduced productivity, including lower wages, and poorer physical and mental health.[2] Overweight and obese adults also live shorter lives (Peeters et al., 2003), a fact recently brought into focus by the high rate of serious illness and mortality among those classified as obese during

[1] https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

[2] Childhood and Adulthood obesity: Ebbeling et al. (2002); Reilly et al. (2003); wages: Cawley (2004); Baum and Ford (2004); Han et al. (2009); physical and mental health: Mokdad et al. (2003); McElroy et al. (2004); Scott et al. (2008); Dixon (2010);

the Covid-19 pandemic (Public Health England, 2020; Lighter et al., 2020). Obesity has therefore become an important channel through which disadvantage is transmitted across generations.

There is much still to be understood about the economic factors that have given rise to inequality in obesity. This is in spite of the emergence over the past two decades of a wide literature on the childhood origins of inequalities in important components of human capital, including health (Currie and Almond, 2011; Heckman and Kautz, 2012; Almond et al., 2018). Obesity is a distinct adverse health problem, and one whose "development" is almost surely linked to social and economic circumstances in a similar manner as other broad aspects of human capital (e.g. Cunha and Heckman (2007, 2008); Cunha et al. (2010)). Our main aim in this study is to establish empirical facts about intergenerational and income gradients in overweight and obesity. We use the Millennium Cohort Study (MCS) - a cohort of roughly 11,000 children born in the UK between 2000-2002 - to model the probability a child is overweight or obese at the ages of 3, 5, 7, 11, and 14 based on both their contemporaneous socioeconomic conditions and those when they were 9 months old. By doing so, we quantify the strength of the relationship between early conditions and the likelihood children become overweight or obese, and how it evolves over childhood.

We establish three salient features of the relationship between early conditions and childhood overweight and obesity. First, we find that parental income and weight at birth largely predict whether or not a child is overweight or obese at age 14: children who had an obese parent at 9 months of age in both the richest and poorest 20% of families are more than four times as likely to be obese at 14 as those with the same income who did not. Further, we find that irrespective of their parents' weight, children in families in the bottom 20% of the income distribution when they are 9 months old are two times as likely to be obese at 14 than those in families in the top 20%. Second, the relationships between family income, parental weight, and the likelihood a child is overweight or obese holds up at every age for which we have data. Moreover, these relationships strengthen over time, to the extent that the gap in the rate of overweight and obesity between children in the bottom 20% and top 20% of the income distribution triples between the age of 3 and 14. This age gap is even more pronounced between those with an obese and normal weight main parent, where the difference in the probability of obesity quadruples between the age of 3 and 14 (18 % - 27% and 13% - 37%). Third, we show healthy behaviour - measured by reported dietary and exercise habits - also differs across income levels and parents' weight at each of these ages, and that some healthy behaviour is associated with a decreased likelihood of overweight and obesity in later childhood, between 11-14 years old. However, observed differences in healthy behaviour between income groups do not explain the observed obesity gap between them.

Our results add to a body of work from epidemiology and the social sciences that has established correlations between socioeconomic status, parents' weight and children's weight across various stages of childhood.[3] We build on this work in two ways. First, our analysis quantifies socioeconomic and intergenerational gradients explicitly in the onset of overweight and obesity across five different ages, whereas other similar studies have focused on relationships at one or two points in time. This allows us to analyse how they change over the whole of childhood. Second, we examine how circumstances at 9 months of age predict obesity at age 14. Many studies concerned with these relationships concentrate on correlations at one or two points in time, meaning they are unable to observe how and when they emerge or the extent of their persistence.[4] We also show that differences in the diet and exercise related home environment exist across childhood, adding to the growing evidence as to the disparities in aspects of children's home-lives that lead to the emergence of socioeconomic gradients in human capital (e.g. Carneiro et al. (2013), Cunha et al. (2013), Attanasio et al. (2019)). Again, our results extend findings from similar studies in epidemiology that have shown evidence of the relationship between socioeconomic status and healthy behaviour at various points in the early years (e.g. Reilly et al. (2005), Goisis et al. (2016)) by considering the healthy environment across multiple stages of childhood.

Importantly, the relationships we document suggest that the recent rise in childhood obesity is largely an economic problem. Parental income and weight do not *cause* children to become overweight or obese (over and above any genetic component of body composition), but the fact that we observe such strong correlations shows the extent to which they are associated with unobserved behavioural and environmental factors that do. It is likely common knowledge that a healthy diet and regular physical activity are required to maintain a healthy bodyweight, and it is unlikely that two parents from opposite ends of the income or weight distribution would not be aware of this. However, our results show that these parents do not appear to follow these principles to the same extent, suggesting that there are different shared circumstances across either distribution which underpin the relationship between income and weight - circumstances that could encompass a wide range of cognitive, psychological and financial "constraints". For example, Cawley (2010, 2011) discuss the role of economic mechanisms, suggesting that - among other factors - cheaper food, increases in maternal employment and time-saving technology have played a part in the rise of childhood obesity. From a policy perspective, Downs et al. (2009) and Loewenstein et al. (2012) have discussed the psychological causes of the rise in unhealthy dietary choices - for example, present bias. Similarly, a review of the evidence on psychosocial stressors in the household by Gundersen et al. (2011) shows that there is evidence that measures of family closeness, financial stress and maternal physical and mental health are all correlated with the likelihood a child is overweight or obese. To understand how they have contributed

[3]For example, birthweight (Currie and Hyson, 1999; Currie, 2009); early weight gain Griffiths et al. (2010); and Body Mass Index (BMI) at different stages of childhood (Crossman et al., 2006; Ludwig et al., 2013; Costa-Font and Gil, 2013; Goisis et al., 2016; Biroli et al., 2020).

[4]For example, Goisis et al. (2016) use the MCS to analyse the relationship between socioeconomic status and children's weight, but only using data from two rounds, ages 5 and 11. Nader et al. (2006) evaluate the persistence of overweight/obesity over time in a cohort of US children born in 1991, but they do not focus on socioeconomic disparities.

to the socioeconomic inequality that we show exists in childhood obesity, however, a greater understanding of how these factors affect families differently is required.

The economics literature has seen significant progress toward building an understanding of how many social and economic factors act to shape parents' investments in their children's development, and how differences in investments lead to the emergence of early inequality in skills (e.g. Cunha et al. (2010)). Many of the concepts in this literature straightforwardly extend and are well-suited to conceptualise many aspects of the relationship between family background, the home environment and children's weight. For example, recent research has focused on beliefs about the returns to "investments" in child development (Cunha et al., 2013; Attanasio et al., 2019). In fact, in a UK sample (Biroli et al., 2020) elicit that parents with lower levels of education systematically underestimate the importance of healthy habits for their children, and these beliefs are predictive of investment behaviour. They also show a strong correlation parental and children's weight, however their analysis covers one point in time - age 14, at the end of the period we analyse in this study. Our focus is on describing the evolution socioeconomic gradients in overweight and obesity across childhood, from age 3 up until age 14. This branch of literature has also analysed the effect of parents' human capital, networks and neighbourhoods, economic and financial constraints and government social security policy on early inequalities in development.[5] All of these factors are likely to affect the emergence of gradients in overweight and obesity to some extent. Understanding how and to what extent they do can broaden understanding of the interaction between the environment and weight across childhood, and help inform policy targeting inequality in obesity.

The results of this paper are descriptive. We do not focus on causal relationships, or the inevitably complex dynamics of the emergence of overweight and obesity that result in the emergence of inequality. Instead, we seek to lay out some facts about socioeconomic inequality in childhood obesity, to highlight the strength of the relationship between family circumstances and a key component of health. While we do not identify the causes of childhood obesity, the results show that there are many open questions for future research. For policy, the magnitude, persistence and strengthening of the relationship we find between socioeconomic background and children's weight suggests two things. First, that the eventual emergence of inequality in childhood overweight and obesity could perhaps be curtailed through interventions targeted before age 3, but that policy interventions would have to consider conditions across all ages. Second, they suggest that such interventions would benefit from being designed to understand and improve the social and economic conditions faced by disadvantaged families.

The remainder of this paper is structured as follows. Section 1.2 introduces the data and presents evidence on the effect of early conditions on overweight and obesity at age 14; Section 1.3 then estimates how income and parental weight affect the likelihood a child is overweight or obese over different stages of childhood; Section 1.4 examines the relationships between family

[5] Currie and Almond (2011) and Almond et al. (2018) provide two comprehensive reviews of the literature on childhood circumstances and socioeconomic outcomes in later life.

background, healthy behaviour and overweight and obesity in children; and Section 1.5 concludes with a discussion of the results.

1.2 The Effect of Conditions at Birth on Overweight at Fourteen

1.2.1 Defining Overweight and Obesity Across Childhood

Whether or not an individual is overweight or obese is defined by placing their BMI - the ratio of their weight to height squared - relative to a threshold. For adults, a BMI of between 25 and 29.9 is considered to indicate being overweight, and between 30 and 39.9 to indicate obesity. Severe, or *morbid*, obesity is consistent with a BMI of above 40. These thresholds apply at all ages after 18.[6] For children, thresholds are not fixed given that they experience large growth through childhood and adolescence. This means that the distribution of both height and weight changes dramatically over these periods, as do the appropriate thresholds for defining overweight and obesity. At each age in our analysis, we define overweight and obesity according to the International Obesity Task Force (IOTF) thresholds (Cole et al., 2000), shown in Table 1.1. These thresholds differ for boys and girls and are defined for children above the age of 2 by estimating growth curves consistent with a BMI of 25 and 30 at age 18 respectively. There are alternative BMI thresholds derived by Cole et al. (1995), however these define overweight and obesity relative to estimates of the distribution of BMI among UK children in 1990. We favour using the IOTF thresholds to those of Cole et al. (1995) because the bulk of our analysis is interested in the relationship between the weight of children and their parents - overweight/obesity for the latter is defined according to having a BMI above 25/30. The IOTF definitions are also stricter that those of Cole et al. (1995) in that they result in lower rates of overweight and obesity in children.[7]

Using these age-specific definitions of obesity circumvents many of the issues that arise when comparing raw measures of weight over time at young ages, however two common criticisms of obesity measures as defined by BMI persist. Firstly, BMI does not consider body *types*. As a result, two individuals could be classed as overweight or obese although having very different body compositions - a BMI in the overweight range gives no indication as to whether the reason for being overweight is excess adipose or muscle tissue. While this shortcoming must be considered with the BMI of parents, we consider it less likely to cause differences in children given there are far fewer external factors and lifestyle choices affecting their body composition (i.e. exercise habits, hobbies etc.). Secondly, when defining obesity by a cutoff, we are not creating a variable that perfectly indicates healthy weight and unhealthy weight. It is not necessarily the case that

[6] See the WHO definitions: https://www.who.int/topics/obesity/en/ and https://www.worldobesity.org/about/about-obesity/obesity-classification.

[7] 7% vs 20% for obesity at age 11 based on data from children in all state maintained schools (NHS Digital, 2019). Similar national figures for other nations of the UK are not available.

Table 1.1: Thresholds for overweight and obesity in children in the MCS, by age and gender

	Boys		Girls	
	Overweight	*Obese*	*Overweight*	*Obese*
3 years	17.89	19.57	17.56	19.36
5 years	17.42	19.30	17.14	19.17
7 years	17.92	20.63	17.75	20.51
11 years	20.55	25.10	20.74	25.42
14 years	23.29	28.30	23.94	29.11

Source: International Obesity Task Force (IOTF) Body Mass Index (BMI) cutoffs for overweight and obesity, Cole et al. (2000).

being below the threshold indicates a better outcome for a child. For example, a child might be severely underweight and classified as a zero in the binary definition of obesity.

Much of our analysis focuses on determining the relationship between household and parental characteristics and overweight and obesity among children. Given overweight and obesity are defined relative to BMI thresholds, this analysis focuses on ages at which measures of both height and weight are available; in our data this is from age 3 onwards. The data on birth weight and weight at 9 months of age are only used as explanatory variables for children's weight when appropriate. It is also not common to describe toddlers under 2 years old as "obese", but rather as under or overweight relative to their peers. Consequently, Cole et al. (2000) only provide obesity and overweight thresholds for ages 2-18 and we do not use the birth and 9 month data to define obesity.[8]

1.2.2 Data and Sample

We use detailed longitudinal data on roughly 11,000 UK born children who took part in the Millennium Cohort Study (MCS). At the time of writing, the MCS survey has 6 waves, the first of which was conducted between June 2001 and January 2003 when the children were aged 9 months, with five follow-ups at ages 3, 5, 7, 11 and 14.[9] The survey contains information on the children's family background, home environment and health at each age. It also collects detailed information on the weight and height of parents in all but its last round. Given that our interest is the relationship between parents' and children's weight across the entire period of the study, we

[8]In the few cases where we define relative weight and 9 months or birth, we instead use definitions of under- and/or over-weight. We consider a weight of less than 2,500 grams at birth as to indicate low birth weight, and a weight of 2 standard deviations below/above the mean weight in the sample as indicating under/overweight at 9 months - both of which are internationally recognised thresholds that are widely used in both epidemiological and economic studies of weight. See (WHO, 2018) for the definitions of underweight at these early ages.

[9]MCS sampling was carried out so as to sample children of the same age at interview. There are some exceptions to this. The age of cohort members at wave 1 ranges from 6-12 months, however the average age is 9.2 months with a standard deviation of only 0.5 months - 16,500 out of 18,552 (excluding twins and triplets) cohort members are aged 9 or 10 months.

would like to extend our analysis to this round. We therefore use either parents' weight from the second to last round (age 11) or as predicted based on their weight in all previous rounds. Although neither will perfectly capture parents' weight at age 14, it does allow this extension and for us to compare results under two assumptions. Appendix A.1.4 describes how parents' weight was predicted.

The MCS is administered to a "main parent" as opposed to being explicitly aimed at the children's mothers. As a result, in theory, the survey can be completed by either the mother or the father of a child at each age. In practice, however, the main parent is almost exclusively the mother: 99.85% and 94% of main respondents were the mothers at ages 9 months and 14 years respectively. The MCS over-sampled children from disadvantaged backgrounds, and so is not nationally representative by design.[10] There is also considerable attrition in the study - there are almost 8,000 less respondents at age 14 than at 9 months.

An important feature of this attrition is that families from disadvantaged economic backgrounds drop out of the study disproportionately more than those from wealthier backgrounds. Table 1.2 provides a statistical summary of the sample at each age. Columns (5) and (6) are identical except for the measures of parents' overweight and obesity; column (5) uses parents' weight from the previous (age 11) round, and column (6) their predicted weight. A higher share of parents and children become overweight or obese over time, indicating that body composition changes for both over the period of the study. The sample also gets richer on average, with the income distribution at 9 months becoming skewed towards the higher income quintiles by age 14. This is in spite of it initially being skewed in the opposite direction. The ethnic composition of the sample remains relatively similar across rounds, and by age 14 there are less parents with no qualifications than in the initial wave.

The change in composition of the sample is due to both lower-income families dropping out, and movements along the distribution of those who remain in the sample: families from the lowest quintile drop out of the sample with a 50% probability by wave 6, compared to 29% for the highest quintile. Furthermore, the remaining families from all quintiles are much more likely to move up the income distribution than down (Table A1). In Table 1.2 we can see that the lowest income quintile makes up only 16% of the sample by wave 6, whereas the highest income quintile makes up 24%. Looking at column (1) of the same table, the MCS sampled 25% from the lowest quintile and only 16% from the highest quintile, meaning this is a substantial change in the sample composition. Furthermore, overweight and obese parents were also more likely to drop out of the MCS sample by the final wave than normal weight parents: roughly 54% of obese or morbidly obese parents dropped out of the study between rounds 1 and 5. This is compared to slightly less than a 50% of parents whose weight was in the overweight range, and 47% of those whose weight was normal in the first round (Table A2).

[10]"Importantly, certain sub-groups of the population were intentionally over-sampled, namely children living in disadvantaged areas, children of ethnic minority backgrounds and children growing up in the smaller nations of the UK." https://cls.ucl.ac.uk/cls-studies/millennium-cohort-study/

Table 1.2: Characteristics of the full MCS sample across waves

	(1) 9 months	(2) Age 3	(3) Age 5	(4) Age 7	(5) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Weight							
Overweight	0.02	0.19	0.17	0.15	0.23	0.18	0.18
	[360]	[2,398]	[2,266]	[1,788]	[2,633]	[1,797]	[1,797]
Obese	.	0.06	0.06	0.07	0.07	0.06	0.06
	.	[765]	[863]	[881]	[879]	[669]	[669]
Main parent overweight	0.30	0.31	0.32	0.34	0.37	0.37	0.53
	[4,085]	[3,353]	[3,305]	[3,183]	[2,778]	[2,778]	[3,766]
Main parent obese	0.12	0.13	0.14	0.15	0.18	0.18	0.22
	[1,913]	[1,691]	[1,752]	[1,704]	[1,678]	[1,678]	[1,997]
Main parent morbidly obese	0.01	0.01	0.01	0.02	0.02	0.02	0.02
	[142]	[149]	[157]	[171]	[199]	[199]	[211]
Equivalised UK household income quintile							
Lowest quintile	0.25	0.22	0.22	0.21	0.21	0.17	0.17
	[4,580]	[3,307]	[3,346]	[2,820]	[2,752]	[1,934]	[1,934]
Second quintile	0.23	0.22	0.21	0.21	0.21	0.17	0.17
	[4,103]	[3,335]	[3,209]	[2,830]	[2,698]	[1,933]	[1,933]
Third quintile	0.19	0.20	0.19	0.20	0.21	0.20	0.20
	[3,450]	[2,992]	[2,908]	[2,768]	[2,723]	[2,333]	[2,333]
Fourth quintile	0.17	0.19	0.19	0.19	0.20	0.23	0.23
	[3,172]	[2,863]	[2,855]	[2,653]	[2,573]	[2,633]	[2,633]
Highest quintile	0.16	0.18	0.18	0.19	0.18	0.23	0.23
	[2,909]	[2,699]	[2,614]	[2,590]	[2,366]	[2,609]	[2,609]
Parents' education							
None	0.17	0.15	0.15	0.14	0.14	0.14	0.14
NVQ level 1	0.09	0.08	0.08	0.08	0.08	0.08	0.08
NVQ level 2	0.30	0.30	0.30	0.30	0.29	0.29	0.29
NVQ level 3	0.15	0.15	0.15	0.15	0.15	0.15	0.15
NVQ level 4	0.26	0.29	0.28	0.29	0.29	0.30	0.30
NVQ level 5	0.03	0.04	0.04	0.04	0.04	0.04	0.04
Ethnicity							
White	0.84	0.85	0.85	0.85	0.83	0.84	0.84
Mixed	0.01	0.01	0.01	0.01	0.03	0.01	0.01
Indian	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Pakistani and Bangladeshi	0.07	0.06	0.06	0.06	0.07	0.07	0.07
Black or Black British	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Other Ethnic group (inc. Chinese, Other)	0.02	0.02	0.02	0.02	0.01	0.02	0.02
N	18,276	14,647	15,018	13,677	13,109	12,768	12,768

Note: For all variables except income numbers are proportions. Numbers in square brackets are counts. Household income is equivalised using the OECD equivalisation scales, and is in 2010 prices. Exchange rates were retrieved from https://www.bankofengland.co.uk/monetary-policy/inflation/inflation-calculator. The scales adjust income for family size and composition relative to the income of a couple with no children. Hansen et al. (2014) provide detail on the OECD equivalisation used in the MCS, and how it compares to other commonly used scales.

It is possible that this attrition is based solely on the observables the MCS measures. However, in light of the substantial movement up the income distribution we observe for the remaining sample, this seems implausible. Partially that is expected as the working members of the families gain an additional 14 years of experience. However, this is unlikely to be the only explanation in light of the UK's low income mobility, particularly for low-earners or those from disadvantaged areas - two sub-populations over-represented in the initial the MCS.[11] More plausibly, there is likely a correlation between those unobserved heterogeneities that influence workplace productivity and those that impact how likely you are to attrite from the sample. This is particularly worrisome as workplace productivity is a known correlate to obesity and overweight, which in turn is positively correlated with children's weight, and suggests that the final sample consists of overachievers. With this observation in mind we conclude that the MCS sample likely suffers from self-selection bias in our primary variables of interest - obesity and income. The nature of the suspected bias would imply that any raw results we obtain understates the relationship between income and overweight/obesity and might be better interpreted as conservative estimates of true relationships between income or parents' weight and overweight and obesity in children. To account for the MCS sampling design and the likelihood of attrition, we use sampling weights that adjust for both in our analysis. The weights are the inverse of the predicted conditional probability each child is sampled from the UK population in the initial wave and then remains in the sample.[12] At its root, this adjustment for attrition relies on the assumption that selection into the sample can be predicted based on observable characteristics. If there are unobservable differences between those who do and do not remain in the sample like those we discuss above, however, this method will not fully correct our estimates to be representative. We bear this in mind throughout and in some cases compare our main estimates with unweighted results to assess the potential impact of attrition.

1.2.3 Early Conditions and Overweight

We begin with the observation that circumstances very early in children's lives strongly predict whether or not they will be obese or overweight in adolescence.

$$Pr[W_{i,14} = 1 \mid \mathbf{\Omega}] = F\big(\delta_{14} + \boldsymbol{\gamma}_{14}\mathbf{Y}_{i,9m} + \boldsymbol{\rho}_1 4\mathbf{MPW}_{i,9m} + \mathbf{x_{i,9m}}'\boldsymbol{\beta}_{i,14} + \varepsilon_{i,14}\big) \quad \text{for } W_{i,14} \in \{OW, OB\} \tag{1.1}$$

In 1.1, $\mathbf{\Omega} = (\mathbf{Y}_{i,9m}, \mathbf{MPW}_{i,9m}, \mathbf{x}_{i,9m})$ contains all information on the right-hand-side of the equation; $F()$ is the logistic cumulative density function; $\boldsymbol{Y}_{i,9m}$ is a vector of dummies indicating whether or not equivalised household income[13] at 9 months of age is in one of five quintiles;

[11] See for example a recent report by Carniero et al. (2020) for the UK's Social Mobility Commission.

[12] Hansen et al. (2014) provides detail on how non-response weights are calculated.

[13] In the MCS, household income is equivalised using the OECD equivalisation scales, which adjust family income for family size and composition. Hansen et al. (2014) provide detail on the OECD equivalisation used in the MCS, and how it compares to other commonly used scales.

$\mathbf{MPW}_{i,9m}$ is a vector of dummies indicating whether the main parents' weight was in the normal, overweight or obese or morbidly obese (hereafter, obese for brevity) range when the child was 9 months old; $\mathbf{x_{i,9m}}$ is a vector of control variables; and the outcomes $OW_{i,14}$ and $OB_{i,14}$ are whether a child is overweight or obese at 14 respectively. In $\mathbf{x_{i,9m}}$, we include controls for gender, birth weight, weight gain between birth and 9 months, ethnicity, the number of siblings in the household and the parent's age at birth, level of education, and whether or not they have a long-term illness.

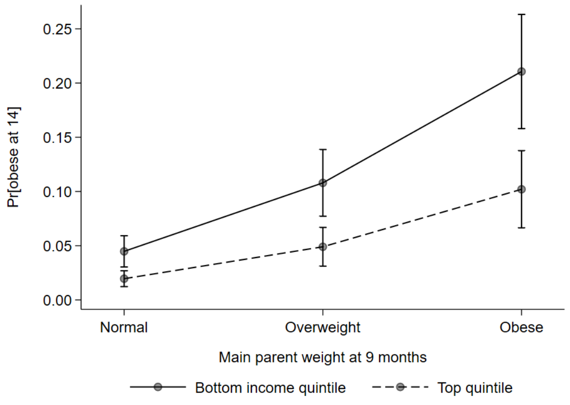
For this portion of our analysis, fixing income and parental weight at their values when children are aged 9 months - in equation 1.1 or in any analysis that follows - we hope to measure *initial* and opposed to *long-run* conditions. As we discussed in the previous section and in describing the MCS sample, there is significant variation in parental income and weight across childhood. It is also well established that pregnancy and the associated weight gain can affect the trajectory of mothers' weight long after birth, particularly for those who experience excess weight gain (Ohlin and Rössner, 1990; Mannan et al., 2013). There is evidence from studies evaluating postpartum weight retention that, on average, mothers' return close to their preconception weight between 6 and 18 months after giving birth (Gunderson and Abrams, 1999; Mannan et al., 2013). We therefore treat BMI at 9 months as a proxy of these initial conditions, which is inclusive of any effect of pregnancy.

Appendix Table A3 shows the predicted marginal effect of family income and whether or not the main parent is overweight or obese on the probability of children being obese (column (1)) or overweight (column (2)) at age 14, holding all other control variables fixed at their sample means. Being in the lowest as opposed to the highest quintile of the income distribution at 9 months is associated with a 4.4 and 7.6 percentage point increase in the likelihood of being obese or overweight, respectively. Similarly, having a main parent who is obese at the same age is associated with respective increases of 11.7 and 18.6 percentage points. These effects are large relative to the probability of each outcome: the bottom of Table A3 shows that the expected conditional probability of being obese or overweight is 0.043 and 0.169 respectively. Columns (3) and (4) of Table A3 also show analogous results, but unweighted for attrition or the MCS sampling strategy. They are in line with our intuition in the previous section as to the effect sample design and attrition might have on results - the effects of income quintiles in columns (3) and (4) are less pronounced.[14]

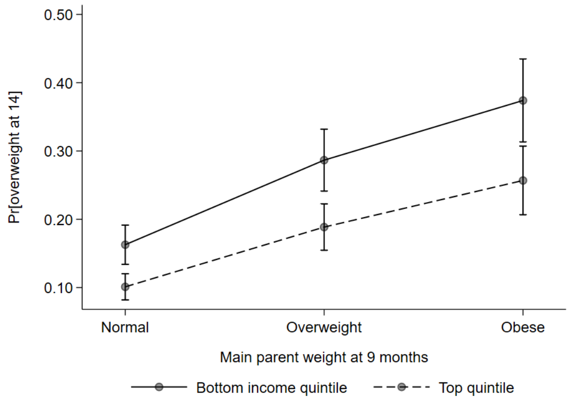
As might be expected, the likelihood of a child in the bottom of the income distribution being overweight or obese is relatively high. Calculated from the same regressions used to obtain the marginal effects in Table A3, Figure 1.1 shows the difference in the conditional probability of children being obese (panel (a)) or overweight (panel (b)) across the lowest and highest income quintiles conditional on having a parent whose weight is in the normal, overweight or obese

[14]Note here that although when weighting we use all available observations, there are fewer observations in the weighted regressions in Table A3. This is because the balanced (i.e. to those available in the initial and last waves) and unrestricted samples are identical, and a missing value for the weighting variable.

Figure 1.1: Predicted conditional probabilities of being obese and overweight at 14



(a) Obese at age 14



(b) Overweight at 14

Note: Each panel shows the predicted conditional probability of being overweight or obese at 14 under the values of either income or weight of the parent indicated on the x axis. All other variables are fixed at their mean. Dots represent estimated conditional probabilities and vertical lines their 95% confidence interval. The regressions from which they were calculated controlled for children's gender, birth weight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). Appendix Table A3 shows the full results.

range. Figure 1.1(a) shows two contrasts. Firstly, children at both ends of the income distribution who have an obese parent are over *four times* more likely to be obese than those whose parents' weight are in the normal range. Those with an overweight parent are almost three times as likely to be obese relative to the same group. Second, irrespective of their parent's weight those in the bottom 20% of the income distribution are consistently twice as likely to be obese at 14 than those in the top 20%. Although the slopes in Figure 1.1(a) are slightly different across income quintiles, the difference is not statistically significant. We also estimate versions of 1.1 that include interactions of income and parental obesity, however these interaction effects were not statistically significantly different from zero. Together, these results do not provide any evidence that the likelihood a child will be obese given their parent is obese differs significantly between those in the top and bottom of the income distribution. Rather, they suggest that it is differences in income, and the wider environment it captures, that result in higher rates of obesity among the relatively poor children.

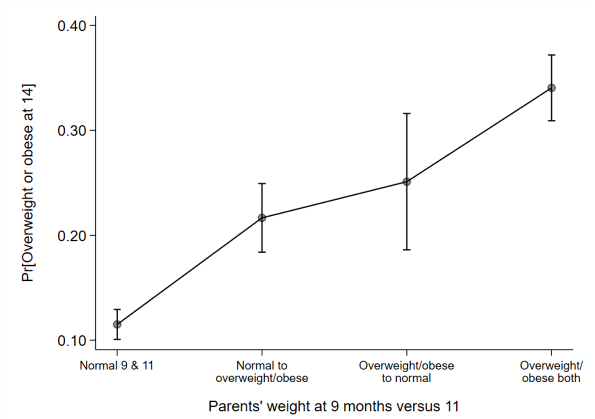
To understand when these gradients emerge over childhood, Figure 1.3 plots the proportion of children in the top and bottom quintile of the income distribution who are overweight (panel (a)) and obese (panel (b)) at each age. It shows that at all ages between 3 and 14 a larger proportion of those in the bottom quintile are classified as either. The difference stays relatively stable between the ages of 3 and 7, but thereafter an increasing number of those in the bottom income quintile are classified as overweight or obese, meaning that by age 14 the difference is stark.

Importantly, and as we noted in the discussion of our sample, parents' income and weight change over time. It is plausible that the strong correlation between the parent's weight at 9 months and the child's weight at 14 years is due to initial conditions linked to the parent's weight. At the same time, their weight, or how it changes at later stages of childhood, influences the child's weight at adolescence. Figure 1.2 shows the predicted conditional probability that a child is overweight or obese at 14 depending on whether the parent changes their weight (panel (a)) or income (panel (b)) category or not. In panel (a), we can observe a significant gradient: those who either were originally obese and were not by 14 or vice versa were significantly more likely to have an overweight/obese child at 14. However, if the parent was obese at both points the probability is significantly larger than if only one condition is present. This evidence points to the importance of both initial conditions as well as conditions later in childhood in determining the likelihood a child becomes overweight or obese. If, for example, only initial conditions mattered then we would not expect children of parents whose weight was normal at 9 months but in the range of overweight or obese at 14 to be significantly more likely to be overweight than those whose weight was normal at both ages. Similarly, if only later conditions mattered we would not expect that switching in the opposite direction would result in a significantly different probability of children being overweight or obese relative to those parents who are in the normal/overweight weight at both ages.

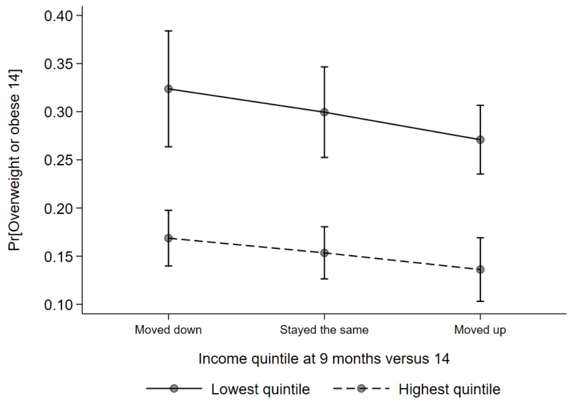
Of course this type of comparison does not necessarily consider the magnitude of changes in BMI that led to switches. For example, an increase in BMI from 20 to 31 is treated that same as an increase in BMI from 29-31 - both result in a change from being in the normal/overweight to the obese range. With this in mind, we found the trend from Figure 1.2 to be robust to excluding those whose BMI only changes marginally: restricting the analysis to only those whose category switched as a result of an increase in BMI of, for example, 5 or greater, the picture is broadly unchanged.

Figure 1.2(b) shows the difference in likelihood a child is overweight or obese conditional on whether or not their family moved up or down the income distribution in the lowest and highest income quintiles. Relative to those who stayed in the same position, the probability a child is overweight or obese is slightly higher among those whose families moved down the distribution, and slightly lower among those who moved up. These differences are not statistically significant, however, meaning we cannot infer a strong correlation between moving quintiles and children being overweight or obese. Two broad messages therefore emerge from Figures 1.2(a) and 1.2(b). Firstly, both initial conditions and those thereafter matter for the likelihood a child is overweight or obese. Secondly, the difference in this likelihood is greater when comparing initial versus later weight than income conditions. Again, it is not that we would like to infer causal effects of changes in weight or income category here, but rather understand how group characteristics are correlated with overweight and obesity in children. This, in turn, allows us to understand what underpins our results in following sections.

Figure 1.2: Predicted conditional probabilities of being overweight or obese and overweight at 14, given changes in parents' weight and income



(a) By changes in parents' weight



(b) By movements across the income distribution

Note: No parents in the sample moved from classified as obese at 9 months to a normal/overweight at 14. Each panel shows the predicted conditional probability of being overweight or obese at 14 under the values of either income or weight of the parent indicated on the x axis. All other variables are fixed at their mean. Dots represent estimated conditional probabilities and vertical lines their 95% confidence interval. The regressions from which they were calculated controlled for children's gender, birth weight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014).

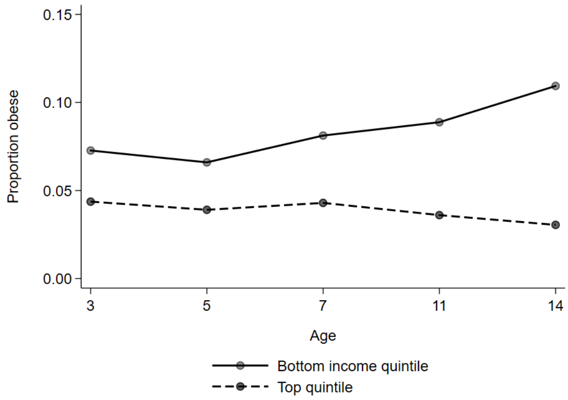
1.2.4 Height, Weight and Circumstances Across Childhood

Given that overweight and obesity are ultimately defined by relative weight and height, Figures 1.3(c) and 1.3(d) also show how these two characteristics evolve in the MCS over time respectively. For comparison over time, the figure plots the average, height (panel (c)) and weight (panel (d)) z-scores at the ages for which we have data. Together the two panels show that the prevalence of overweight and obesity (panels (a) and (b)) at the bottom of the income distribution relative to the top results from two features of the groups. Firstly, children in the bottom quintile are relatively shorter, on average, at every age, and that this gap widens over time. Secondly, although the same group are much lighter very early, by age 3 their weight converges very close to those in the top quintile. After age 7 weights diverge and those at the bottom of the income distribution become relatively heavier, and those at the top relatively lighter.[15]

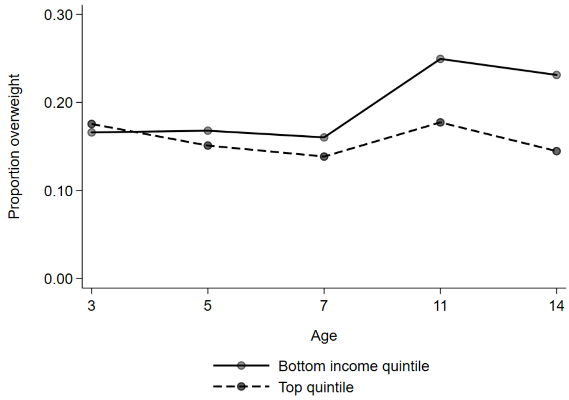
These descriptive trends raise questions about what occurs or changes that leads to the emergence of gaps in obesity across income levels. The age at which these gaps begin to widen,

[15]Figure 1.3 uses income quintiles based on income in each round. The trends are identical, if not even more pronounced, when fixing income at its level at 9 months (Appendix Figure A1)

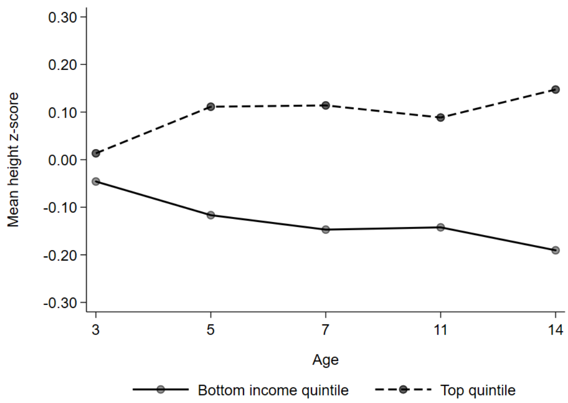
Figure 1.3: Overweight and obesity across childhood in the MCS in the top and bottom income quintiles



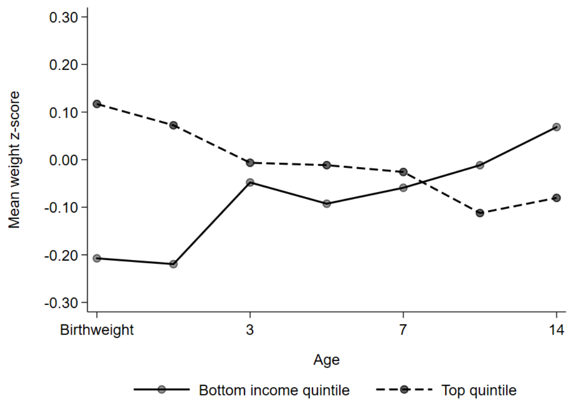
(a) Obesity



(b) Overweight



(c) Height z-score



(d) Weight z-score

Note: Income quintiles are relative to the UK income distribution are defined in sample using households' equivalised income, calculated using the OECD equivalisation scales to adjust for family size and composition. Panel (a) shows the proportion of children at each age that classified as obese and panel (b) the proportion classified overweight. Both definitions are based on the International Obesity Task Force age-specific BMI thresholds (see Table 1.1). Panel (c) shows the average height Z-score of children and panel (d) the average weight Z-score in each of these quintiles at each age. For comparability, the sample includes 11,714 children who remained in the sample across all waves.

between the ages of 7 and 11, undoubtedly coincides with a time of increasing self-determination for children - by age 11 the children in the MCS sample (a UK-based study) are soon to be entering their high school years. It is likely that over the adolescent years, children begin to engage in more obesogenic - obesity causing - behaviours themselves outside their homes (Nelson et al., 2006; Brodersen et al., 2007). It is also possible that parents' behaviour changes at this time, and that as children get older they reduce the enforcement of lifestyle choices. At the same time, it could be the case that at the onset of puberty the accumulation of lifestyle and/or genetic factors begin to take effect as children begin the largest period of growth they will experience outside of gestation.

If lifestyle choices have an intergenerational component, then it is very likely that all three of these factors are intertwined. Although it is not the aim of this paper fully pick them apart, among the sample we do observe that the gap between rates of obesity also widens for *parents* over time. Initial small differences in the proportion of parents considered obese widen such that at children's age 14 parents at the bottom of the income distribution are far more likely to be classified as such (see Appendix Figure A2). This suggests that relatively poor parents are not only more likely to be obese shortly after children are born, but also much more likely to become so at later ages, and that, when considered alongside Figure 1.2(a), the trends in children's weight across childhood are somewhat tied to the unequal changes in parents' weight. We explore the relationship between healthy behaviour and overweight and obesity among children in Section 1.4.

In summary, this section has described the following five stylised facts about gradients in overweight and obesity among children. (i) Low-income children are considerably more likely to be overweight at adolescence than high-income children. (ii) This trend is a consequence of both lower height and higher body weight. (iii) Obese parents are more likely to have children who become overweight by adolescence. (iv) Moreover, low-income obese parents are more likely to have overweight children at adolescence than high-income obese parents. Finally, (v) the above stylised facts are far more pronounced for children who become obese by adolescence than children who become only overweight. The next section quantifies the differences suggested by these trends among the sample, and Section 1.4 explores the role of healthy behaviour as a contributory factor in explaining them.

1.3 Socioeconomic Status and Overweight Across Childhood

So far we have analysed the relationship between initial conditions (at 9 months) and obesity and overweight in children at 14, and descriptively documented how children's weight evolves across categories of parents' weight and income over childhood. We have not, however, considered the wide range of circumstantial factors that might be driving this relationship at each point in time. In this section we quantify the relationship between income, parents' weight and overweight and obesity in children at each age - 3, 5, 7, 11, and 14 - net of a wide range of family and background characteristics. In specifying determinants of the probability of a child being overweight or obese, our primary interest is in the two transmission mechanisms discussed so far: parents' weight and family income. In a similar fashion to Equation 1.1, we assume that whether or not a child is classified as overweight or obese at each age is determined as follows:

$$Pr[W_{it} = 1 \mid \mathbf{\Omega}] = F\big(\delta_t + \boldsymbol{\gamma}_t \mathbf{Y}_{it} + \boldsymbol{\rho}_t \mathbf{MPW}_{it} + \mathbf{x_{it}}' \boldsymbol{\beta}_t + \varepsilon_{it}\big) \quad \text{for } W_{it} \in \{OW, OB, OWOB\}\,, \quad (1.2)$$

where $\mathbf{\Omega} = (\mathbf{Y}_{it}, \mathbf{MPW}_{it}, \mathbf{x}_{it})$ now contains all *contemporaneous* information on the right-hand-side of the equation; $F()$ is the logistic cumulative density function; $\boldsymbol{Y}_{it}$ is a vector of dummies indicating whether or not equivalised household income at age t is in one of five quintiles; $\mathbf{MPw}_{it}$ is a vector of dummies indicating whether the main parents' weight is in the normal, overweight or obese range; $\mathbf{x_{it}}$ is a vector of control variables; and the outcomes OW_{it}, OB_{it} and $OWOB_{it}$ indicate whether a child is overweight, obese or either at age t. We estimate Equation 1.2 separately at each age ($t \in \{3, 5, 7, 11, 14\}$), and interpret $\boldsymbol{\gamma}_t$ and $\boldsymbol{\rho}_t$ - the main parameter vectors of interest - as indicating the strength of the relationship between parental income and obesity and children's probability of overweight/obesity at each point in time.

In estimating Equation 1.2, we are not attempting to estimate the causal relationships between parents' weight and income and children's weight, which would require guaranteeing that both are conditionally uncorrelated with ε_{it}. Overweight/obesity in children is an anthropometric outcome, meaning that ε_{it} is almost surely comprised of both individual heterogeneity that is correlated with these characteristics as well as a purely random component. For our purposes it makes little sense to treat income and parents' weight in a way that represents a search for a causal relationship, given that these two features of the early environment do not necessarily *cause* obesity, but rather are correlated with unobservables that do. This heterogeneity could capture, among others, aspects of health, the family environment, economic constraints, or psychological or cognitive factors which affect both parents' income and weight, and the likelihood a child is overweight or obese.

We do not explicitly model this heterogeneity here, however we do condition on an extensive range of characteristics in order to control for the effects of health and demographics: in our main specifications, $\mathbf{x_{it}}$ contains controls for gender, birth weight, weight gain between birth and 9 months, number of siblings in the household, ethnicity, health conditions and long-term illnesses of the main parent and the child, and the age and education level of the main parent. Doing so captures components of this individual heterogeneity within income and weight groupings with which they are correlated. In estimating $\boldsymbol{\rho}$ we therefore aim to capture the combined behavioural and genetic channel through which parental weight affects the likelihood a child becomes overweight or obese. Our estimates of $\boldsymbol{\gamma}$s should capture only the behavioural channel through which income affects the same outcome. For example, if the marginal effect of being in the bottom as opposed to the top income quintile is positive, we would infer that the associated increase in probability of being overweight or obese is due to a combination of, for example, economic, cognitive or psychological constraints that induce unhealthy behaviour. If the same were true of our estimate of $\boldsymbol{\rho}$, we could infer that it also captures all of these things, as well as any remaining genetic influences. We do not un-pick how any specific factor contributes to these channels or how they change over time but rather focus on the magnitude of these overall correlations:[16] these give an indication of the extent to which differences in these remaining unobservables across groups affect the likelihood children become overweight. However, in the next section we do examine differences in healthy behaviour over childhood and the extent to which they explain any of them.

Lastly, in Section 1.2 we discussed how our sample was likely comprised of over-achievers, and that parents who change weight or income classification over time are likely to differ systematically from those who do not. At the end of this section, we therefore examine how initial conditions (at 9 months) affect the likelihood of overweight and obesity net of the effect of contemporaneous conditions.

1.3.1 Income and Intergenerational Gradients in Overweight from 3 to 14

Table 1.3 reports the marginal effects of **MPW** and ***Y*** on the probability of overweight (panel A), probability of obese (panel B) and the probability of overweight or obese (panel C), using the thresholds presented in Table 1.1. Results with the complete set of covariates are reported are in Appendix Tables A8-A10. Given that we do not have information on parents' BMI at age 14, we report marginal effects at age 14 treating parents' BMI in two ways: in column (5) we assume it is constant between 11 and 14, while in column (6) we use predicted values, the estimation of which is outlined in Appendix A.1.4.[17]

Across all outcomes and all ages there is a large effect of having an obese parent relative to one whose weight is in the normal range. This effect is broadly increasing over time, such that by age 14 having an obese parent increases the probability of a child being overweight or obese themselves by roughly 24 percentage points. Again, this effect is large: it is larger than the estimated conditional probability of being overweight or obese, shown at the bottom of panel C. This appears to be driven by the relationship between parental and child obesity: Panel B shows that across all ages the marginal effect of having an obese parent is greater than the overall estimated conditional probability of being obese, shown at the bottom of the Panel. By age 14, it is *2.5* times as large.

Similarly, the income quintile of a child's family positively affects the probability of being obese or overweight in each period. Panel C of Table 1.3 shows the marginal effect of being in the lowest, second, third, and fourth income quintile as opposed to the highest on overweight or obesity is increasing over time, particularly for those in families in the bottom quintile: between ages 3 and 14, this marginal effect increases by around 12 percentage points. The result is a relative effect of around 17 percentage points on the likelihood of being overweight or obese

[16] In some instances we use the term "correlations" to loosely refer to marginal effects from our logit models. These marginal effects coefficients represent the effect of a change in some explanatory variable on the predicted probability of our binary outcome keeping other covariates fixed, but for the ease of exposition we might at some particular instances refer to these marginal effects coefficients as correlations to accentuate the fact that our estimates do not represent causal effects.

[17] In Table 1.3 all standard errors are calculated using the delta method, including those using predicted parental weight. These are unchanged when using a bootstrap, however.

Table 1.3: The determinants of child overweight and obesity across childhood

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Panel A: Probability of overweight						
Main parent overweight	0.022**	0.061***	0.065***	0.101***	0.105***	0.074***
	(0.010)	(0.010)	(0.010)	(0.012)	(0.014)	(0.012)
Main parent obese/morbidly obese	0.062***	0.126***	0.097***	0.197***	0.170***	0.172***
	(0.014)	(0.014)	(0.013)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.038**	0.025*	0.011	0.030	0.117***	0.122***
	(0.016)	(0.015)	(0.016)	(0.025)	(0.033)	(0.034)
Second quintile	0.035**	0.008	0.018	0.055***	0.055***	0.054***
	(0.015)	(0.014)	(0.015)	(0.021)	(0.021)	(0.021)
Third quintile	0.030**	–0.005	0.013	0.057***	0.041**	0.042***
	(0.013)	(0.012)	(0.013)	(0.018)	(0.016)	(0.016)
Fourth quintile	0.024*	0.023*	0.002	0.019	0.012	0.012
	(0.013)	(0.012)	(0.012)	(0.015)	(0.014)	(0.014)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.133	0.124	0.198	0.155	0.156
N	10.143	10.485	9.405	7.887	6.674	6.674
Panel B: Probability of obesity						
Main parent overweight	0.021***	0.026***	0.035***	0.037***	0.026***	0.025***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Main parent obese/morbidly obese	0.048***	0.065***	0.087***	0.084***	0.104***	0.098***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)	(0.010)
Income quintiles						
Lowest quintile	0.020**	0.018*	0.017*	0.039***	0.081***	0.082***
	(0.009)	(0.009)	(0.010)	(0.014)	(0.020)	(0.020)
Second quintile	0.013	0.012	0.012	0.042***	0.033***	0.034***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)	(0.012)
Third quintile	0.003	0.007	0.007	0.022**	0.019**	0.020**
	(0.007)	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)
Fourth quintile	0.015*	0.007	0.006	0.010	0.011	0.010
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.038	0.039	0.042	0.043	0.039	0.039
N	10.714	11.119	10.186	8.426	7.067	7.067
Panel B: Probability of overweight or obesity						
Main parent overweight	0.036***	0.078***	0.087***	0.122***	0.121***	0.092***
	(0.011)	(0.010)	(0.010)	(0.013)	(0.014)	(0.013)
Main parent obese/morbidly obese	0.091***	0.166***	0.161***	0.246***	0.241***	0.238***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.054***	0.036**	0.026	0.060**	0.166***	0.171***
	(0.017)	(0.016)	(0.017)	(0.026)	(0.032)	(0.032)
Second quintile	0.042***	0.017	0.025	0.081***	0.077***	0.077***
	(0.015)	(0.014)	(0.015)	(0.021)	(0.021)	(0.022)
Third quintile	0.030**	0.000	0.019	0.070***	0.054***	0.056***
	(0.014)	(0.013)	(0.014)	(0.018)	(0.017)	(0.017)
Fourth quintile	0.031**	0.026**	0.007	0.025	0.019	0.019
	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)	(0.014)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.199	0.175	0.165	0.242	0.196	0.197
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is indicated by Panels A-C, and are defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. The omitted income category is the highest quintile. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted income category is the highest quintile. The regressions from which they were calculated controlled for children's gender, birth weight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. Appendix Tables A8-A10 show full results. $\mathbb{E}[Pr(outcome)|\boldsymbol{x}]$ represents the estimated conditional expectation of each outcome. The *main parent* is the mother for 99% of children at 9 months. Ns differ in Panel A because these regressions exclude obese children. Ns differ across columns because of missing data.

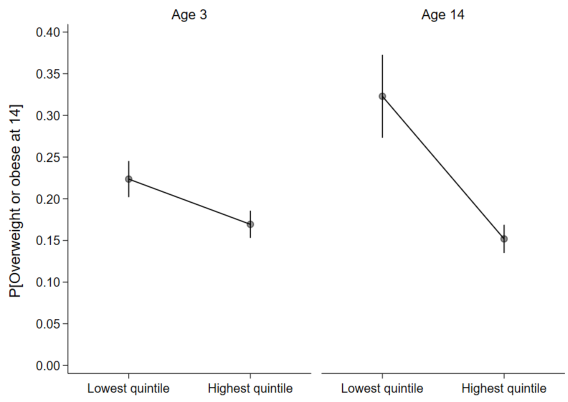
by this age, about 85% of the overall conditional probability. As was the case with parents' weight, although the broad patterns are similar and result in clear differences by age 14, the effect of income varies in magnitude when considering overweight and obesity separately. Again, the marginal effects on the likelihood of being overweight are large, however they are more striking for obesity: by age 14 being in the bottom relative to the top of the income distribution is associated with an increase in probability of being obese of 8 percentage points, over double the size of the conditional probability of being obese. Using the balanced sample and not adjusting for attrition and sampling design, the change in the relationship between parental income and weight and children's weight over time is less pronounced (Appendix Table A6). Again this is in line with our previous intuition that the MCS was comprised of overachievers. Although the estimated marginal effects differ slightly in magnitude across the balanced an unbalanced samples, we do not find evidence that these differences are statistically distinguishable from zero: in Appendix Table A7 we show results from regressions analogous to those in Table 1.3, but including interactions of parental income and weight categories with and indicator of whether a child dropped out at any stage of the survey. There is no consistent statistical difference between the effects for those who remain in the sample across all waves versus those who drop out at some point. Of course, we still cannot rule out that there are unobservables which determine selection into the sample further affecting our estimates.

These results imply two things about the relationship between children's weight and parents' weight and income over childhood. Firstly, over and above a rich set of controls they affect the likelihood that children are overweight or obese at every age we study. Second, the relationship between the three strengthens over time, such that the differences in the prevalence of overweight and obesity across parents' weight and income at the end of childhood are very pronounced. Figures 1.4(a) and Figures 1.4(b) show the predicted probability of being overweight or obese across the top and bottom of the income distribution and whether or not a parent is obese at age 3 and 14. They show the extent to which both gradients increase over time, and the magnitude of the increase. Children in the lowest income quintile are initially about 32% more likely to be overweight or obese than those in the highest quintile, but by age 14 this gap more than triples and they are over 100% more (or twice as) likely to be so. Similarly, children who have an obese parent are about 53% more likely to be overweight or obese themselves at 3 than those who do not, but at 14 this difference increases to over 200%, or more than three times the likelihood. Panel (c) then shows that conditioning on parents' weight being in each of the three categories, children in the lowest income quintile are consistently twice as likely to be overweight or obese by age 14.

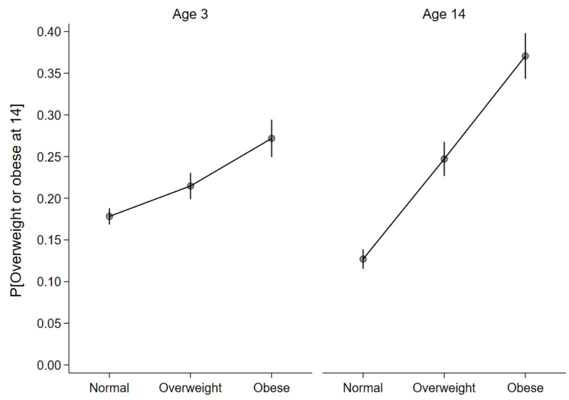
There are also various demographic and circumstantial factors that are correlated with the likelihood children are overweight or obese across ages. For example, we find that females are consistently more likely to be overweight or obese across all of childhood.[18] Parental level of

[18]This could also partly reflect differences in thresholds for overweight/obesity.

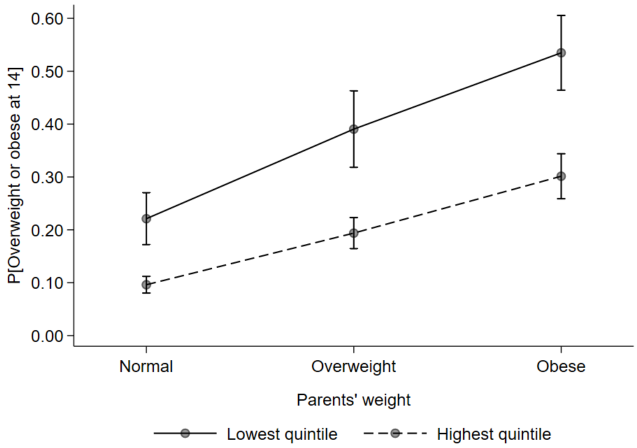
Figure 1.4: Predicted conditional probabilities of being obese and overweight at 3 and 14, by income and parents' weight



(a) In the top and bottom income quintiles



(b) By whether or not the main parent is overweight or obese



(c) Across income quintiles and parents' weight at 14

Note: Each panel shows the predicted conditional probability of the outcome on their y axis under the values of either income or weight of parents indicated on their x axis. Probabilities were calculated after estimating Equation 1.2 at age 3 and 14 for each outcome. Dots represent estimated conditional probabilities and vertical lines their 95% confidence interval. The regressions from which they were calculated controlled for children's gender, birth weight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). Appendix Tables A8-A10 show full results. All other variables were fixed at their mean.

qualifications also appears to be important across various ages. Both birthweight and weight gain between 9 months and 3 years of age also consistently have a positive marginal effect on this outcome, whereas number of siblings consistently has a negative effect. For other factors, such as health conditions of the parent or child, there is no such consistent pattern in their correlation with overweight and/or obesity. The full results are shown in Appendix Tables A8-A10. Importantly, they highlight that the strong correlation of children's weight with parental income and weight exists over and above these factors and that suggests that income groupings - although highly correlated with, for example, educational groupings - better capture group characteristics that explain the likelihood of overweight and obesity.

1.3.2 Initial Versus Contemporaneous Conditions

As we outlined above, the effects in Table 1.3 are estimates of the overall relationship between parental weight and income and children's weight at each point in time. However, we have also discussed how circumstances change over childhood. On average, among those who remain in the sample, more parents/families move up both the income and weight distribution over the study period.[19] Furthermore, as shown in Section 1.2, parents in the bottom quintile of the income distribution are far more likely to become obese or overweight during the sample period than parents in the highest quintile.

We can classify two broad channels through which the correlation between parents' weight and income and children's weight arises: (i) initial conditions (the parent's weight/income at birth/early childhood) and (ii) current conditions (the parent's contemporaneous weight/income if it has changed). Understanding to what extent the child's weight is linked to either of these channels is of crucial importance for the design of effective intervention and policy. However, by using contemporaneous income and weight groupings at every age to obtain the point-in-time relationships in Table 1.3, we mix these two effects. Initial conditions in income and weight are strongly correlated with current conditions. Using only current parental weight and income, we cannot attempt to understand whether the effects capture relationships at the current age or if they are due to "scarring" effects from initial conditions.

We therefore replace contemporaneous income and weight classifications in Equation 1.2 with their counterpart when children were aged 9 months. Doing this does not isolate the "effect" of initial conditions. Instead, it captures how the relative likelihood of overweight/obesity evolves in children based on these conditions. Changes in, for example, the γs we estimate over time will result from both changes in the rates of overweight/obesity in children of parents who were obese at 9 months, *and* the changing role of conditions/unobservables. Using changes in parental weight and income classification we can attempt to separate to some extent the effect of current from initial conditions/unobservables, however.[20] We therefore also include in our new version of Equation 1.2 dummy variables indicating whether, and how, parents' contemporaneous positions in the distribution of income and weight have changed.

Table 1.4 shows the marginal effects of these regression using overweight or obesity as the

[19]Tables A1 and A2 show this in the form of transition matrices for parents' income and weight class. A higher proportion of parents move up from the overweight class than down, and roughly 22% of those who were obese at 9 months were in the overweight weight range at 11. The group of parents in the normal weight range is also much larger than the obese group, and so the overall size of the overweight and obese groups increase (Table 1.2).

[20]This is an imperfect estimate as we are not capturing all weight changes. For example, moving from a BMI of 40 to 31 would be indexed as no change. Using BMI changes rather than change of weight-class however comes with its own set of problems due to the non-linearity of BMI.

outcome.[21] The estimates show that both initial and current parental weight significantly affect the likelihood of being overweight or obese across all ages. Comparing the results with those in panel C of Table 1.3, the estimated marginal effects of having an obese parent at 9 months are greater than the contemporaneous estimates at all ages between 3 and 14. Moreover, the estimated effects are again large in magnitude relative to the conditional probability a child is overweight or obese (shown at the bottom of Table 1.4). The parent changing to a heavier weight classification is associated with a large and significant increase in the likelihood a child is overweight or obese across all estimations. We do not estimate there to be no strong relationship with parents moving to a lighter weight classification at any age, however. This suggests that those who become obese are more likely to have overweight or obese children, but that weight declines in parents are not necessarily associated with differences in children's weight

Given that we know from Section 1.2 that low income parents are far more likely to become overweight or obese across the MCS, it is likely that these increases in weight are concentrated among low-income households. Despite this, the marginal effect of low-income remains large and significant and therefore the effect of low-income is not solely explained by an increased likelihood of children's parents becoming overweight and obese. Overall, these findings predict an even stronger relationship between initial and contemporaneous parental weight and child weight than Table 1.3 suggests.

The picture is less clear with the effect of moving up or down the income distribution. There are small negative (positive) point estimates of the effect of moving up (down) the income distribution at many ages. These findings are in line with intuition but often not statistically different from zero. Overall they suggest that initial conditions in parental income are more important than changes in income in predicting your likelihood of overweight and obesity, perhaps because the constraints parents face when their child is 9 months old are predictive of those they face across the rest of childhood, even if their income increases. The point estimates of the effects of parental income quintiles at 9 months in Tables 1.4 are broadly similar to their analogues in panel C of Table 1.3.

Overall, the patters shown in marginal effect estimates in Table 1.4 relative to their analogues in Table 1.3 is similar when considering overweight and obesity as outcomes separately. These are shown in Appendix Tables A11 and A12 respectively.

Together, these results suggest that conditions at birth are important in determining overweight and obesity in children. Separating the estimates from Table 1.3 into some measure of contemporaneous and initial conditions accentuates the overall effect of parental income and weight on child weight. Although we do not attempt identify why we observe this relationship, the findings again show its magnitude. More so, they suggest that initial conditions in parental income and weight are predictive of the unobservable group characteristics - the many "constraints" we

[21]Appendix Table A13 reports the full results for Table 1.4, and Tables A11 and A12 show analogous results for overweight and obesity respectively.

Table 1.4: The determinants of child overweight and obesity across childhood fixing income and parents' weight at their level when child was 9 months old

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parent's weight constant	Parent's weight predicted
Main parent's weight at 9 months						
Overweight	0.061***	0.089***	0.102***	0.163***	0.141***	0.147***
	(0.012)	(0.011)	(0.012)	(0.015)	(0.016)	(0.016)
Obese	0.112***	0.189***	0.192***	0.321***	0.311***	0.321***
	(0.016)	(0.017)	(0.018)	(0.022)	(0.025)	(0.026)
Current weight						
Became lighter	0.028	−0.010	−0.006	−0.028	−0.027	−0.035
	(0.018)	(0.015)	(0.016)	(0.020)	(0.020)	(0.024)
Became heavier	0.029*	0.066***	0.058***	0.067***	0.094***	0.075***
	(0.016)	(0.014)	(0.013)	(0.014)	(0.017)	(0.014)
Income quintiles at 9 months						
Lowest quintile	0.064***	0.061***	0.066***	0.121***	0.152***	0.155***
	(0.019)	(0.018)	(0.019)	(0.026)	(0.030)	(0.030)
Second quintile	0.046***	0.035**	0.062***	0.095***	0.096***	0.096***
	(0.017)	(0.016)	(0.016)	(0.022)	(0.022)	(0.022)
Third quintile	0.028*	0.026*	0.046***	0.077***	0.078***	0.079***
	(0.015)	(0.014)	(0.015)	(0.019)	(0.019)	(0.019)
Fourth quintile	0.034**	0.035***	0.037***	0.059***	0.045***	0.045***
	(0.014)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
Current income quintile						
Moved down	−0.010	−0.004	0.010	−0.006	0.010	0.012
	(0.012)	(0.011)	(0.012)	(0.016)	(0.018)	(0.018)
Moved up	−0.019	−0.013	0.009	−0.019	−0.041**	−0.041**
	(0.011)	(0.011)	(0.011)	(0.014)	(0.016)	(0.016)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.196	0.172	0.163	0.237	0.193	0.193
N	9.718	10.065	9.271	7.662	6.435	6.435

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data does not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income at 9 months: highest quintile; current income quintile and weight category: stayed the same; parents' education: no qualifications; ethnicity: white. $\mathbb{E}[Pr(overweight \cup obese)|\boldsymbol{x}]$ represents the estimated conditional expectation a child is overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data. Full results are in Appendix Table A13.

have discussed throughout - that will eventually result in children becoming overweight or obese.

1.4 Healthy Behaviour, Socioeconomic Status and Overweight

So far we have found that children's weight is strongly correlated with their parents' weight and income across childhood, particularly over the early teenage years. This raises the question of why trajectories appear to diverge at this point in time. One answer might be that children grow a great deal during this period, and as their bodies undergo large changes the cumulative effects of lifestyle choices up until that point take effect. Another might be that it is at these ages that healthy behaviours and lifestyle choices themselves diverge across the income distribution and, as a consequence, so does children's weight. In this section, we examine whether healthy behaviour similarly varies across the distribution of parents' income and weight and, if so, at what time differences emerge.

1.4.1 Healthy behaviour and parental Income and Weight

The MCS asks parents whether their child takes part in a range of healthy behaviour across all of its rounds. For example, it asks whether the child has regular meal times, how often they have fruit and vegetables, play sports or drink sweetened drinks. Unfortunately, however, the questions asked are not consistent over time. Only some appear consistently in multiple rounds, such as how often a child eats fruit and vegetables or plays sport with their parents. As a result, although we can look at the correlations between income and parents' weight and healthy behaviours at each age, it is difficult to make strict comparisons over time about their relative strength. Furthermore, it is important to emphasise that there is a degree of reverse causality between healthy behaviour and weight. We therefore again do not focus on estimating causal relationships between, for example, regular exercise and overweight. Rather, we analyse the extent to which patterns in the relationship between socioeconomic conditions, parental weight, and children's weight can be explained by any observed discrepancies in healthy behaviour across these groups.

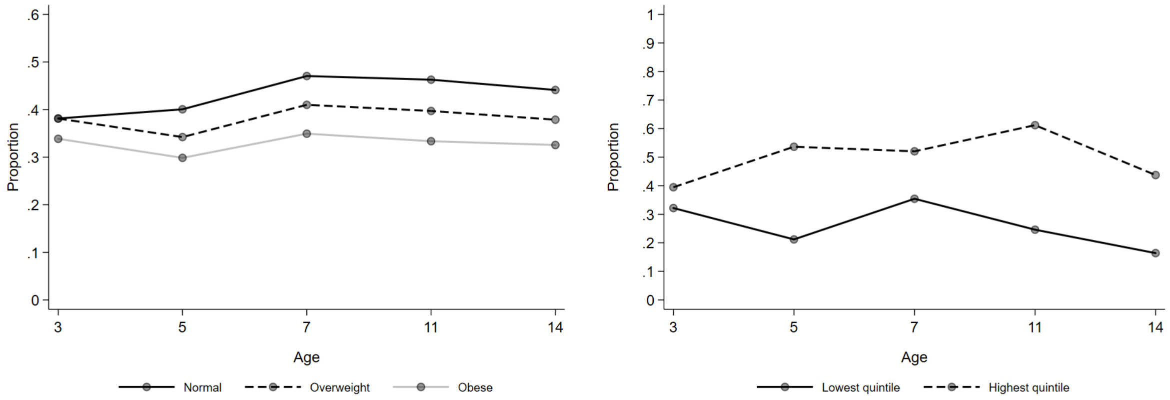
All of the variables we use ask about frequencies with which children/parents engage in healthy behaviours. We transform these to binary variables to indicate presence of a healthy behaviour. In the example of fruit and vegetable consumption, the corresponding MCS question asks "*how many portions of fruit or vegetables does the child have per day*", with answers ranging from "*None*" to "*Three or more*".[22] From this we create an indicator of whether or not the child has fruit or vegetables at least once a day. We then create a composite "index" of healthy behaviour, which indicates whether or not children engage in the majority of the individual healthy behaviours about which parents are asked. For example, at age 3 a child would be assigned a value of 1 if they eat fruit or vegetables once a day, have regular meal times, and play sport at least once a week. This is all three of the measures available at this age, and they cover both diet and exercise. At age 14, a child's lifestyle is marked as healthy if they engage in four of six healthy behaviours. At this age there are no exercise-related measures and so we rely solely on information on diet. With this index we aim to achieve a relatively consistent proportion of children being classified as healthy over time rather than a consistent definition of what is healthy, since the type and number of variables for healthy behaviour in our dataset change over time.[23]

This is not a perfect index of a healthy lifestyle. However, there are several advantages to working with such a composite index. To begin with, a healthy lifestyle is not a unique

[22]This question actually differs slightly across ages. At age 3, it explicitly asks *Does the child have fruit/veg. once a day?*. But at age 14 the question is "*How often [child] eats at least 2 portions of fruit?*" with "*every day*" being a possible response. We define this answer as the measure of this type of health behaviour.

[23]A secondary concern in constructing the index was that the index was healthy relative to the average child in the survey. Although not an explicit target, the index we create classifies between 30%-50% of our sample as healthy across all ages. The qualitative results of this section remain unchanged using various different definitions for the composite measure of healthy behaviour, or the underlying measures from which it is constructed.

Figure 1.5: Proportion of parents reporting diet and exercise related healthy behaviour across waves in the MCS, by parents' weight and income



(a) By whether or not parent is obese **(b)** In the highest and lowest income quintile

Note: The y axis on all panels is the proportion children engaging in one diet based and one exercise based healthy behaviour. Measures of healthy behaviours are described in Table A4a. Panels (a) and (b) chart this outcome by whether or not parents are overweight or obese respectively. Obesity is defined by having a BMI of between 30 and 40, and morbid obesity as a BMI above 40. In panel (b) Income quintiles are relative to the UK income distribution at each age. Income is adjusted for household composition using the OECD equivalisation scales. For comparability, the sample includes parents of children who remained in the sample across all waves.

combination of factors. None of the identified individual behaviour indicators are strictly necessary and the composite can separate individuals by a minimum requirement for a healthy lifestyle. Furthermore, given the measures of healthy behaviour are discrete and highly correlated, the composite index avoids problems of collinearity in our regressions. Finally, our main question of interest in this section is how healthy behaviour varies across parental weight and income groups and how much of the variation in child's weight is explained by behaviour rather than membership of either of these groups. A composite index helps address these questions by attempting to define, albeit imperfectly, the overall environment as either healthy or not, and we will use it jointly with the individual measures available. A full list of the original variables, how we transform them and how they are then used to create our indicator of a healthy lifestyle is in Appendix A.1.2.

Figure 1.5 shows that the healthy behaviour observed in our data - as we measure it with our index - is also strongly connected to the intergenerational and socioeconomic correlates of obesity discussed above. Overweight and obese (panel (a)) parents are less likely to introduce healthy behaviour into their children's lifestyle. Similarly, there is a marked difference in healthy behaviours can be observed across socioeconomic groups. Over 40% of families in the top 20% of the income distribution report healthy behaviour at age 14 and around 60% at age 5 to 11, consistently 20 to 40 percentage points more than in the bottom income quintile for the same ages (panel 1.5(b)).

1.4.2 Healthy Behaviour and Socioeconomic Gradients in Overweight

Parental income and weight are correlated with healthy behaviour across the majority of childhood. To address the question of whether healthy behaviour is associated with lower incidence of overweight and obesity in children, and whether it can explain any of the effect of income and parental weight on children's weight, we return to the specification of Section 1.3, augmenting it with our healthy behaviour index. That is, we augment Equation 1.2 with I_{it} in the following way:

$$Pr[OWOB_{it} = 1 \mid \mathbf{\Omega}] = F\left(\delta_t + \theta_t I_{it} + \boldsymbol{\gamma}_t \mathbf{Y}_{it} + \boldsymbol{\rho}_t \mathbf{MPW}_{it} + \mathbf{x_{it}}'\boldsymbol{\beta}_t + \varepsilon_{it}\right), \tag{1.3}$$

where now $\mathbf{\Omega} = (\mathbf{Y}_{it}, \mathbf{MPW}_{it}, I_{it}, \mathbf{x}_{it})$ but all other variables are as in Equation 1.2. Again, we estimate this equation separately across all ages and assess the extent to which healthy behaviour impacts on overweight and obesity. In Section 1.3 we discussed that we did not seek to account for unobserved behavioural factors that might influence the relationship between parental income and weight and children's weight. Including I_{it} allows us to explicitly capture some of these factors and analyse to what extent these relationships are a result of differences in healthy behaviour. Similarly to Table 1.3, Table 1.5 shows the marginal effects of $\mathbf{MPW}_{it}$ and $\mathbf{Y}_{it}$ on overweight, obesity and either in children across all ages, but with the inclusion of I_{it}.

Healthy behaviour as we measure it in our index only has a statistically significant relationship with children's weight at ages 11 and 14. This effect is present at 11 in both the likelihood a child is overweight (panel A) and obese (panel B) and at 14 only it is only significant for the likelihood a child is either (panel C). This could hint towards the behaviour observed in our dataset only having sizable effects later in childhood. It could also be that the divergence we observe in healthy behaviour across income quintiles in Figure 1.5 plays a role in the widening of rates of overweight and obesity across the income distribution. However, because our index is not entirely consistent over time and because we do not interpret these marginal effects as causal, we can only take this as suggestive evidence. Without a better understanding of both the home environment and the biases present in these regressions, these results are not sufficient evidence to arrive at any strong conclusions.

Comparing the effects of income quintiles and parents' obesity in Table 1.5 with those in 1.3 we can grasp how much of their effect is explained by differences in the healthy behaviour we measure. Focusing on the effect of parental obesity on the likelihood of children's overweight we find that although there is very slight attenuation of the effect, the direction and significance of our estimated effects with and without the inclusion of healthy behaviour are almost identical. The size of the effect is virtually always within one standard deviation of the previous estimates. Finally, the conclusions we draw from comparing Tables 1.3 and 1.5 are the same if, rather than our index of a healthy lifestyle, we use the full set of behaviours used to construct it. For comparison, Appendix Tables A17a-A19b show the marginal effects of $\mathbf{MPW}_{it}$ and $\mathbf{Y}_{it}$ when

Table 1.5: Healthy behaviours and overweight and obesity in children across ages

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 *MPBMI* constant	*MPBMI* predicted
Panel A: Probability of overweight						
Healthy lifestyle	−0.003	0.006	−0.008	−0.028**	−0.018	−0.019
	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)	(0.012)
Main parent overweight	0.022**	0.058***	0.061***	0.099***	0.102***	0.072***
	(0.010)	(0.009)	(0.010)	(0.013)	(0.014)	(0.012)
Main parent obese/morbidly obese	0.061***	0.124***	0.093***	0.197***	0.168***	0.169***
	(0.014)	(0.014)	(0.013)	(0.017)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.037**	0.024*	0.010	0.024	0.112***	0.116***
	(0.016)	(0.014)	(0.015)	(0.025)	(0.033)	(0.033)
Second quintile	0.034**	0.009	0.017	0.049**	0.051***	0.050**
	(0.014)	(0.013)	(0.014)	(0.021)	(0.021)	(0.021)
Third quintile	0.029**	−0.004	0.012	0.053***	0.038**	0.039**
	(0.013)	(0.011)	(0.013)	(0.018)	(0.016)	(0.016)
Fourth quintile	0.023*	0.022*	0.002	0.017	0.011	0.010
	(0.012)	(0.011)	(0.011)	(0.015)	(0.013)	(0.013)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.133	0.124	0.198	0.155	0.156
N	10.143	10.485	9.405	7.887	6.674	6.674
Panel B: Probability of obesity						
Healthy lifestyle	0.009**	−0.001	−0.001	−0.022***	−0.007	−0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
Main parent overweight	0.018***	0.023***	0.031***	0.031***	0.022***	0.021***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Main parent obese/morbidly obese	0.041***	0.057***	0.079***	0.071***	0.092***	0.086***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.011)	(0.010)
Income quintiles						
Lowest quintile	0.017**	0.014*	0.013*	0.026**	0.063***	0.063***
	(0.008)	(0.008)	(0.008)	(0.011)	(0.018)	(0.017)
Second quintile	0.011	0.010	0.010	0.028***	0.024***	0.024***
	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Third quintile	0.003	0.005	0.006	0.015*	0.014**	0.015**
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
Fourth quintile	0.012*	0.005	0.005	0.006	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.038	0.039	0.042	0.042	0.039	0.038
N	10.714	11.119	10.186	8.426	7.067	7.067
Panel B: Probability of overweight or obesity						
Healthy lifestyle	0.005	0.005	−0.009	−0.049***	−0.025*	−0.026*
	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)	(0.013)
Main parent overweight	0.036***	0.077***	0.085***	0.122***	0.119***	0.090***
	(0.011)	(0.010)	(0.010)	(0.013)	(0.014)	(0.013)
Main parent obese/morbidly obese	0.094***	0.169***	0.159***	0.249***	0.241***	0.238***
	(0.015)	(0.015)	(0.014)	(0.017)	(0.018)	(0.018)
Income quintiles						
Lowest quintile	0.054***	0.037**	0.025	0.051**	0.165***	0.169***
	(0.017)	(0.016)	(0.016)	(0.026)	(0.033)	(0.034)
Second quintile	0.042***	0.017	0.023	0.074***	0.073***	0.073***
	(0.015)	(0.014)	(0.015)	(0.022)	(0.022)	(0.022)
Third quintile	0.030**	0.001	0.018	0.066***	0.052***	0.053***
	(0.014)	(0.013)	(0.014)	(0.019)	(0.017)	(0.017)
Fourth quintile	0.031**	0.026**	0.006	0.023	0.018	0.017
	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)	(0.014)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.199	0.175	0.165	0.241	0.196	0.197
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is indicated by Panels A-C, and are defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. The omitted income category is the highest quintile. The regressions from which they were calculated controlled for children's gender, birth weight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. Appendix Tables A8-A10 show the full results. $\mathbb{E}[Pr(outcome)|\boldsymbol{x}]$ represents the estimated conditional expectation of each outcome. The *main parent* is the mother for over 99% of children at 9 months. Ns differ in Panel A because these regressions exclude obese children. Ns differ across columns because of missing data.

doing so.[24]

Looking at the estimates for the impact of being in different income quintiles with and without accounting for the observed behavioural tendencies the conclusions are very similar to the impact of parental weight. Overall, here estimates are again often slightly attenuated when accounting for behaviour, but none of our estimates change significance, or even magnitude by more than one standard deviation. Although we find slightly more attenuation for the estimated effects when accounting for all individual behaviours separately, these conclusions once again are robust to this change.[25]

Overall, although the effects of income and parents' weight are slightly attenuated when healthy behaviours are considered as determinants of overweight and obesity, the difference they make is marginal. This suggests that differences in the healthy behaviours on which we have measures do not explain differences in the likelihood of overweight and obesity in children across the income distribution or whether their parent is obese themselves. Taken together with the fact that, even with our composite index, we observe differences in healthy behaviour over time across groups (Figure 1.5), these results suggest that the variation in healthy behaviour we measure is indicative that there are systematic differences in the wider environment children face across childhood. Measuring these wider differences is key to understanding the mechanisms that give way to the relationship between income and parent's weight we observed in Section 1.3.

1.5 Conclusion

In this paper we studied the evolution of socioeconomic gradients in overweight and obesity amongst a cohort of UK children born at the turn of the millennium. We focus on the extent to which early conditions predict whether children are overweight or obese at 14, and how the relationship between socioeconomic status and children's weight changes between the ages of 3 and 14. We further analyse how accounting for healthy behaviour affects these outcomes and how behaviour is determined by parents' weight and family income.

We find that conditions at 9 months largely predict whether children are overweight or obese at age 14. Children at both the top and bottom of the income distribution are more than *four times* as likely to be obese if they have an obese parent at 9 months of age than if they do not. Moreover, our results show the children from low-income families are also consistently more likely to be obese, whether their parent has normal, overweight or obese BMI: by age 14, children born into the poorest 20% of families as opposed to the richest 20% are *twice* as likely to be obese. After controlling for a rich set of environmental and circumstantial factors, we find that

[24]We note that Tables A17a-A19b show significant positive estimates for the marginal effect of consuming less fast food and sweetened drinks. This shows the effect of reverse causality between weight and dietary behaviour - parents introducing restrictions on their children's diet - and should not be read as evidence that these behaviours reduce the likelihood of obesity.

[25]See Tables A17a-A19b. Again, our qualitative results are robust to various definitions of both the composite index and its underlying measures.

the relationship between children's weight and the income and weight of their parents holds up at all ages for which we have data and in fact strengthens as children age.

In our data, as children age their parents' weight and income changes. We show that both initial and contemporaneous conditions determine weight at any given age. We find that children whose parent's become obese during their childhood have an increased likelihood of becoming overweight or obese themselves, however the effect is smaller than the estimated effect of parental weight at birth. Moreover, movements up or down the income distribution have little effect and it is largely only initial parental income that correlates with children's weight. This suggests that children's socioeconomic background as early as 9 months is predictive of the conditions that result in the onset of overweight or obesity at some point in childhood. Further, despite observing a positive/negative relationship between observed healthy behaviour and parental income/weight, accounting for it in our estimations has very little effect in the sign, significance, and size of the relationships we find between parental income and weight and children's weight.

Our findings highlight the extent to which childhood obesity - and obesity more generally - is an economic problem. Parental income and weight do not cause children to be obese. Obesity is caused by consuming more calories than are burnt for a sustained period of time. This relationship is individually determined in a complex system of social, environmental, biological, economic, psychological, and behavioural factors. Our results show that parental income and weight are strongly correlated to these unobserved factors. Observing the difference in conditions between socioeconomic groups, even without describing exactly what these conditions are, highlights the importance of economic conditions in determining the onset of obesity. It shows that different groups in our society play a separating equilibrium when it comes to healthy behaviour and that this difference is to the detriment of the already disadvantaged. As a result, relatively small differences in children's weight across socioeconomic groups appear as early as age 3, and widen significantly over time to generate inequality in obesity by the teenage years. Both of these facts suggest policies for reducing these inequalities should aim to mitigate the detrimental effects of socioeconomic conditions on the healthy environment early in childhood. Doing so might act to prevent the onset of obesity, and reduce the need for remedial policies in later life.

The economics discipline has made progress toward understanding how inequality in important components of human capital emerge as a result of early social and economic conditions. The same tools that have generated this progress can, and should, be used to shed light on what is driving inequality in obesity and its transmission across generations.

Chapter 2

The Development of Health and Human Capital Accumulation

2.1 Introduction

The longlasting social and economic effects of poor childhood health are now well documented - those who suffer from poor health in childhood on average obtain less education, have lower income, and worse health in adulthood than those who enjoy good health over the same period (Case et al., 2005; Currie, 2009). These disparities are, however, not random: a growing body of evidence suggests strong links between early health and socio-economic status, measured by parental income and education levels (Case et al., 2002; Currie, 2009; Conti et al., 2010). However, relatively little is known about the process through which health is "accumulated" over childhood, or how it interacts with other aspects of the early developmental environment to generate disparities in human capital.

The process of human capital development is also complex. For a child, having good health today does not only increase the likelihood of being in good health tomorrow, but also that they develop important cognitive and socio-emotional skills (Currie, 2009).[1] Similarly, a broad range of cognitive and socio-emotional skills develop in tandem over childhood (Cunha and Heckman, 2008; Cunha et al., 2010), at the same time as households make decisions about the allocation of time and resources both in and outside the household. This creates a rich set of interactions that govern how health - and human capital more generally - is built up over children's early years. Understanding how, when, and to what extent health factors into the human capital development process is crucial in understanding how poor health arises and persists in children. Given that health is positively correlated with various cognitive and socio-emotional skills, it is also essential in order to accurately describe how skills develop and interact with one another over childhood.

[1]Human capital is multidimensional. However, throughout, in line with the literature and in the interest of brevity, I use the term "human capital" to refer to three broad groupings of individual characteristics - "health", "cognitive skills", and "socio-emotional skills" - as these are the focus of this paper.

Using fourteen years of detailed longitudinal data on roughly 11,000 UK-born children, this study makes two contributions to this understanding. Firstly, I estimate flexible health production functions across five stages of childhood between the ages of 9 months and 14 that capture important interactions between health, skills, parents' human capital, and household health investments. Using the detailed nature of the data and recent methodological advances (Agostinelli and Wiswall, 2016a), I estimate these production functions allowing for multiple mismeasured inputs and a latent factor structure. Second, I estimate similar production functions for cognitive and socio-emotional skill, allowing for the impact of health and health investments on their development. I then simulate policy interventions and analyse how income transfers, health improvements, and increases to parents' human capital affect accumulation of health and skills. Together, these exercises build on an important and growing body of work on the early origins of inequality to broaden the understanding of human capital development, and how it is affected by health.

Over the past two decades, the growing economics literature on human capital development has centred mainly on the understanding how cognitive and socio-emotional skills develop and are determined by household behaviour over childhood (e.g. Cunha and Heckman (2008), Cunha et al. (2010), Attanasio et al. (2020b)). The result has been progress towards formalising and quantifying several important aspects of skill accumulation. For example, a central question has been identifying the malleability of skills, when investments in children's development are most productive, and whether their returns are higher in those with low or high levels of skill - what have come to be known as *dynamic complementarities* (Cunha et al., 2010; Agostinelli and Wiswall, 2016a). Three studies to date have analysed the development of health and skills over childhood. By jointly estimating production functions of health and cognition, Attanasio et al. (2017, 2020c) find that health affects early cognitive development, but that there is no impact in the opposite direction. These studies are based on samples of children in developing countries, however, where the health-related environment differs a great deal to that in developed countries.[2] They are also not able to use longitudinal data covering all of childhood or consider health's impact on socio-emotional development (or vice versa). The paper closest to this study is Biroli (2016), which uses another UK based dataset - the Avon Longitudinal Study of Parents and Children (ALSPAC) - to estimate joint production functions of cognitive and socio-emotional skills and health between the ages of 0 and 5. Although this study does have data on general health and behaviour at 16, its focus is on pre-school human capital development rather than across the entirety of childhood.

As a result, there is far less understanding of how, or if, the insights from the literature on skill development extend to health. I find that the development of health - measured for example by long-term illnesses, health conditions, and parents' subjective assessments - is *rigid*. Across all of childhood, health is highly self-productive and unaffected by little other

[2]See for example, Lu et al. (2016) on the prevalence of poor health in low and middle-income countries, and Peters et al. (2008) on access to health care in developing countries.

than parents' health. It is also far less malleable than cognitive or socio-emotional skill, which, although in different settings, is broadly in line with the studies that have estimated the production function of health (Attanasio et al., 2017, 2020c; Biroli, 2016). I do find, however, that cognitive and socio-emotional skills become important determinants of health in the early teenage years. Children's autonomy undoubtedly grows over this period as children increasingly make lifestyle choices of their own, and this suggests children with high levels of skill do so in a manner which positively affects health. In a cross-cohort comparison between the MCS data and a similar, older longitudinal UK survey, Attanasio et al. (2020a) find that socio-emotional skills at age 5 influence BMI and the likelihood a child has tried smoking 14 (16 in the older cohort). The results of this paper add to this evidence, implying that skills have a role to play in health development, and that in early adolescence they begin to affect health more generally.

In estimating the production functions of cognitive and socio-emotional skill, I find that health is an important determinant of cognition in key early and late stages of childhood, between the ages of 9 months and 3, 11 and 14 respectively. This is, in part, similar to the findings of Attanasio et al. (2017, 2020c) and Biroli (2016), who find early health affects cognitive development, but is in contrast to evidence that cognition is primarily self-productive at later stages of childhood (Cunha et al., 2010; Agostinelli and Wiswall, 2016a; Attanasio et al., 2020c). Unfortunately, as is the case in the studies from which this evidence comes, the MCS does not include entirely consistent measures of cognition over time. As a result, the finding of lower self-productivity of cognition in later childhood cannot be interpreted strictly as contradictory evidence. Rather, although it does suggest at least one aspect of cognition is not entirely self-productive, it cannot be ruled out that a portion of the decline in self-productivity is due to differences in the underlying latent concept being measured at this stage.

Further, whilst there is a positive relationship between the two, unlike in Biroli (2016), I do not find strong evidence that health affects socio-emotional skill development in the pre-school years, however. Health investments are also important in developing both cognitive and socio-emotional skills, implying that, although they have no direct effect on health, there are spillovers from investing in health. Various studies have found links between early health or health shocks, parental investment and cognitive skills later in life (e.g. Yi et al. (2015),Bharadwaj et al. (2018)), however I find that health investments have an impact on cognitive - and to a lesser extent socio-emotional - skill development across several different stages of childhood. I also find that excluding aspects of health and the healthy environment from the cognitive production function leads to an overstatement of the self and cross-productivity of skills and the impact of cognitive investments at these key stages. This is in line with similar findings from Biroli (2016), and highlights the importance of allowing for the impact of health in a model of skill development, and implies that studies that have not done so have risked overstating elasticities of skill production (e.g. Cunha et al. (2010), Agostinelli and Wiswall (2016a), Attanasio et al. (2020b)).

To show the implications of these results, I then use estimates of the distribution of children's initial conditions to simulate the developmental path of health and cognitive and socio-emotional skill. These simulations result in only a small income gradient in health at the end of childhood that appears between the age of 7 and 14 - one that is significantly smaller than might be inferred from using only one as opposed to multiple measures of health. There is a similar gap in socio-emotional skill, however inequality across the income distribution is largest for cognition. A central question in the human capital development literature is whether or not disparities in human capital that perpetuate disadvantage can be closed using policy interventions. To shed light on possible answers this question I then simulate counterfactual trajectories of health and skills after altering the inputs of the developmental process.

The results suggest that unconditional income transfers have very little effect on health, but that those aimed at improving children's health directly or the health of their parents could have large effects by the end of childhood. In the simulations, health improvements also lead to modest improvements in cognitive and socio-emotional skills, and have their largest impact in late childhood. This finding contrasts much of the literature which has so far argued that interventions have their highest returns in late childhood (e.g. Cunha et al. (2010), Agostinelli and Wiswall (2016a), Attanasio et al. (2020c)). I estimate that the effects of income or health based interventions fade out as opposed to build over time, however, and that health and skills remain malleable over the early teenage years. This means that improving health late has large effects on health itself as well as cognitive skills, and suggests that there is opportunity for interventions to mediate health and skill gaps in later childhood.

The remainder of this paper has five main components. Section 2.2 first outlines an empirical model of human capital development and household investment, as well as the methodology used to estimate it. Section 2.3 then describes the MCS data in more depth, and details the measures of health, cognition, socio-emotional skill, parental human capital and investment it has available. It also shows descriptive evidence as to health inequalities in the sample. Section 2.4 provides estimates of the parameters of the empirical model, and Section 2.5 presents results from using these to simulate the developmental paths of health and skills with and without policy interventions. Finally, Section 2.6 concludes.

2.2 A Conceptual Framework for Human Capital Development

I follow the conceptual framework of Agostinelli and Wiswall (2016a), but focussing on the evolution of health ($H_{h,t}$) over childhood, from age 9 months to 14 years. I then analyse how health impacts on the development of cognitive ($H_{c,t}$) and socio-emotional skill ($H_{s,t}$) over the same period. While health, cognition, and socio-emotional skill are comprised of complex traits and characteristics, I abstract from analysing the development of specific sub-elements of human capital and focus on these "aggregates".[3]

In this framework, childhood consists of T discrete periods and the accumulation of human capital over these periods is governed by four main features. First, the initial conditions a child faces upon birth. These are comprised of initial stocks of health, cognition and socio-emotional skill - denoted by $H_{h,0}$, $H_{c,0}$, and $H_{s,0}$ - the health, cognitive and socio-emotional skill of their parents - $P_h P_c$, and P_s - and income, Y_0. Second, in each of the T periods there is a function determining how parents' investments in health ($I_{h,t}$) and cognition ($I_{c,t}$) are influenced by children's human capital stocks, endowments, and household income. Thirdly, and again in each of the T periods, there is a function that maps some combination of endowments, children's contemporaneous human capital, and parental investments into human capital in the following period. Lastly, I assume that children's and parents' health and cognitive and socio-emotional skill and investments are unobservable.[4] As such, I specify a measurement system that relates these latent variables with observed measures, denoted by $Z_{\theta,m,t}$ for $\theta_t \in \{H_{h,t}, H_{c,t}, H_{s,t}, P_h, P_c, P_s, I_{c,t}, I_{h,t}\}_{t=0}^{T}$ throughout.

2.2.1 Initial Conditions

The vector of initial conditions in the initial period (t=0) can be written as:

$$\mathbf{\Omega} = (\ln H_{h,0}, \ln H_{c,0}, \ln H_{s,0}, \ln P_h, \ln P_c, \ln P_s, \ln Y_0)\,, \tag{2.1}$$

where $H_{k,0}$ and P_k for $k \in \{h, c, s\}$ represent child and parental stock of human capital component k, and Y_0 is family income. I assume that parents' human capital is time invariant and so captured by their stocks of health, cognition and socio-emotional skill in the initial period. In this sense, they can be thought of as capturing wider circumstantial "endowments" that don't vary across childhood.

Further, I assume that

$$\mathbf{\Omega} \sim N(\boldsymbol{\mu}_\Omega, \mathbf{\Sigma}_\Omega)\,,$$

where $\boldsymbol{\mu}_\Omega$ and $\mathbf{\Sigma}_\Omega$ are the mean vector and covariance matrix of the initial conditions respectively. Importantly, this assumption relates to the joint distribution of the latent variables in the initial period only and not over time. Doing so would mean ex-ante restricting the parameters - such as the elasticity of substitution - of the human capital production functions (Cunha et al., 2010). I discuss this in more detail when describing these functions in Section 2.2.3.

[3] This assumption is commonplace in the economics literature on human capital development. For example, Cunha and Heckman (2007, 2008); Cunha et al. (2010), Attanasio et al. (2017, 2020b,c), Agostinelli and Wiswall (2016a) all make similar assumptions, treating components of human capital aggregates or composites of the many underlying dimensions.

[4] Due to data limitations, in the empirical application of this model I do not assume parents' cognition is unobservable. I maintain this assumption here for ease.

2.2.2 Investment

I do not embed the production functions in a structural model of household choice (as in e.g. Del Boca et al. (2013)), but rather specify a reduced form approximation of a household investment policy function. In each of the T periods of childhood, I assume parents make two distinct types of investment in health and cognitive skill, and that their decisions to invest are determined by contemporaneous stocks of child health, cognitive and socio-emotional skill, their own human capital and household income (Y_t).[5] Investment in $j \in \{h, c\}$ can then be written as:

$$\begin{aligned} \ln I_{j,t} = \beta^j_{1,t} \ln H_{h,t} + \beta^j_{2,t} \ln H_{c,t} + \beta^j_{3,t} \ln H_{s,t} + \beta^j_{4,t} \ln P_h \\ + \beta^j_{5,t} \ln P_c + \beta^j_{6,t} \ln P_s + \beta^j_7 \ln Y_t + \pi_{j,t} , \end{aligned} \tag{2.2}$$

where $\pi_{j,t}$ is a mean zero shock to investment with variance $\sigma^2_{\pi_{j,t}}$. Equation 2.2 can be thought of as an approximation to a wide variety of investment functions that might be derived from models of household choice and child development, and have become widely used in similar studies.[6] The flexibility in these functions comes with a cost, as it abstracts from both parental preferences and beliefs about the production technology and the return to their investments (e.g. Cunha et al. (2013), Biroli et al. (2020)), as well as from labour supply decisions (Del Boca et al., 2013). This lack of structure means the parameters of Equation 2.2 have no strict, theoretical interpretation.

Here, however, and as in the literature more generally, I interpret $\beta^j_{i,t} > 0$ for $i = 1, 2, 3$ to broadly indicate reinforcement of skills by parents, and $\beta^j_{i,t} < 0$ for $i = 1, 2, 3$ to indicate compensation. In the former case parents would invest more in their child upon realising they have high stocks of human capital, and in the latter they would invest more upon realising the reverse. The parameters $\beta^j_{i,t}$ for $i = 4, 5, 6$, simply capture how parents' investment decisions are influenced by their own stocks of human capital. In the estimation of this empirical model I consider mainly *time* investments. For example, a health investment may be how often a parent plays active games outdoors with their child or how often they ensure the child has regular meals. In this case, $\beta^h_{4,t} > 0$ would mean healthier parents invest more time in their child's health by these means.

[5] It is difficult to define investments made specifically in socio-emotional skill, so I define investment types in this way and assume they have spillover effects of socio-emotional development. Cunha et al. (2010), Attanasio et al. (2020c), and Agostinelli and Wiswall (2016a) include one investment type in their estimations. Attanasio et al. (2020b) allows for material and non-material investments in their evaluation of the impact of a Randomized Control Trial (RCT) on the production of cognitive and socio-emotional skill. The production function of health over childhood has also been less widely studied than that of cognitive and socio-emotional skill.

[6] For example, Cunha et al. (2010), Attanasio et al. (2017, 2020b,c), and Agostinelli and Wiswall (2016a) all specify similar relationships between investments, child human capital, endowments, and household characteristics.

2.2.3 Health Production Functions

I assume that in each of the T periods of childhood, a child's future health is a function of their current health, and cognitive and socio-emotional skill, their parent's human capital, and health investments made by their parents ($I_{h,t}$). To allow for flexibility in the relationship between inputs, I specify the following translog health production function:

$$\ln H_{h,t+1} = \ln A_t + \rho^h_{h,t} \ln H_{h,t} + \rho^h_{c,t} \ln H_{c,t} + \rho^h_{s,t} \ln H_{s,t} + \alpha^h_{h,t} \ln P_h + \alpha^h_{c,t} \ln P_c + \alpha^h_{s,t} \ln P_s + \gamma^h_{h,t} \ln I_{h,t} + \kappa^h_{hh,t}(\ln I_{h,t} \times \ln H_{h,t}) + \eta_{h,t}\,, \tag{2.3}$$

where $\eta_{h,t}$ is a shock to health production assumed to be independent of all the inputs and distributed normally with zero mean and variance $\sigma^2_{\eta_h,t}$. The parameter $\rho^h_{h,t}$ indicates the level of *self-productivity* (or *persistence*) of health over time, whereas $\rho^h_{c,t}$ and $\rho^h_{s,t}$ represent the *cross-productivity* of cognitive and socio-emotional skill in health accumulation respectively. The function in Equation 2.3 can also be expanded to include interactions between any two inputs. Here, I focus on the interaction between health and health investments so admit only the interaction between the two. The elasticity of health production with respect to health investment, $\ln I_{h,t}$, is then given by:

$$\frac{\partial \ln H_{h,t+1}}{\partial \ln I_{h,t}} = \gamma^h_{h,t} + \kappa^h_{hh,t} \ln H_{h,t}$$

When the coefficient on the interaction term is constrained to equal 0, i.e. $\kappa^h_{hh,t} = 0$, then the elasticity is simply given by $\gamma^j_{k,t}$, and the production function is Cobb-Douglas. An important feature of the technology in Equation 2.3 is that it allows these coefficients to be different from 0, and the elasticity of substitution between investments and other inputs to vary across the distribution of skill. More generally, it does not impose that the elasticity of substitution be constant without further restrictions on the parameters of the production function. For example, it allows the degree of substitutability between health and investments ($H_{h,t}$ and $I_{h,t}$), and health endowments and investment (P_h and $I_{h,t}$) to differ in the production of health ($\ln H_{h,t+1}$). Assuming a constant elasticity of substitution (CES) function, would mean imposing that, for example, these two elasticities were equal (e.g. Cunha et al. (2010) and Attanasio et al. (2017, 2020b,c)).

The interpretation of the elasticity above depends on the sign of each $\kappa^h_{hh,t}$. If, for example, $\kappa^h_{hh,t} > 0$ then health investments are more productive in children who are already in good health. Conversely, if $\kappa^h_{hh,t} < 0$ the opposite is true: investments in health are more efficient when made in children with relatively poorer health. In the former case, these *dynamic complementarities* can contribute to the widening of human capital gaps across childhood (Cunha et al., 2010). In the latter case ($\kappa^h_{hh,t} < 0$), however, it is possible that investments are a channel through which human capital disparities can be reduced. How this elasticity evolves over time also determines the efficacy of investments, and when interventions might have their largest impact. If $\kappa^h_{hh,t} = 0$ then these dynamic relationships do not exist. Similarly, how $\rho^h_{h,t}$ evolves across periods determines the extent to which improvements in health will persist. In combination, it is these features of the developmental process that determine whether the effects of increases in investments or health improvements build over time or fade.

2.2.4 Health and Skill Development

I again specify a flexible translog technology for the production functions of cognitive and socio-emotional skill, and assume t+1 skills are a function of the same three types of input: lagged human capital, parents' human capital and investments. For skills I include both cognitive ($I_{c,t}$) *and* health investments ($I_{h,t}$) to allow for spillovers from the latter to skill production. The production function of $H_{j,t+1}$ for $j \in \{c, s\}$ can be written as:

$$\begin{aligned} \ln H_{j,t+1} =& \ln A_t + \rho^j_{h,t} \ln H_{h,t} + \rho^j_{c,t} \ln H_{c,t} + \rho^j_{s,t} \ln H_{s,t} + \alpha^j_{h,t} \ln P_h + \alpha^j_{c,t} \ln P_c + \alpha^j_{s,t} \ln P_s \\ &+ \gamma^j_{h,t} \ln I_{h,t} + \gamma^j_{c,t} \ln I_{c,t} + \kappa^j_{jh,t}(\ln I_{h,t} \times \ln H_{j,t}) + \kappa^j_{jc,t}(\ln I_{c,t} \times \ln H_{j,t}) + \eta_{j,t} \,, \end{aligned} \tag{2.4}$$

where, again, $\eta_{j,t}$ is a shock to production assumed to be fully independent of all inputs and distributed normally with zero mean and variance $\sigma^2_{\eta_j,t}$. All of the parameters of Equation 2.4 have identical interpretations to their analogues in Equation 2.3. For example, $\rho^j_{j,t}$ represents self-productivity, $\rho^j_{k,t}$ for $k \neq j$ cross-productivity, and $\kappa^j_{jk,t}$ for $k \in \{h, c\}$ dynamic complementarity between skill j and investment k. Given the focus of this study is health, of particular interest here is $\rho^j_{h,t}$ - the cross-productivity of health in skill production. The elasticity of $\ln H_{j,t+1}$ with respect to, for example, health investment is given by:

$$\frac{\partial \ln H_{j,t+1}}{\partial \ln I_{h,t}} = \gamma^j_{h,t} + \kappa^j_{jh,t} \ln H_{j,t} \tag{2.5}$$

These give us an indication of the role of the healthy environment in the development of both cognitive and socio-emotional skills. The same interpretation of the elasticities of skills with respect to investments and their self-productivities applies here - together their evolution over time determines how and when skill gaps emerge, as well as how they might be reduced.

2.2.5 A Measurement System for Unobservables

Given that there are no perfect measures of the inputs into the investment and human capital production functions, they cannot be straightforwardly estimated from data. The data I use to estimate the model contains various imperfect measures, each of which proxies, for example, latent health or household investment with some error. As such, I further assume a relationship between observed variables and unobservable inputs into the human capital production and investment functions. For observable measure $Z_{\theta,m,t}$ and corresponding unobservable variable $\theta_t \in \{H_{c,t}, H_{s,t}, H_{h,t}, P_s, P_h, I_{c,t}, I_{h,t}\}_{t=0}^{T}$ I assume that

$$Z_{\theta,m,t} = \mu_{\theta,m,t} + \lambda_{\theta,m,t} \ln \theta_t + \varepsilon_{\theta,m,t} \qquad m = 1, ..., M_{\theta_t} \, , \tag{2.6}$$

where $\mu_{\theta,m,t}$ is an intercept, $\lambda_{\theta,m,t}$ a factor loading, and $\varepsilon_{\theta,m,t}$ an idiosyncratic measurement error assumed to be mean zero.[7] The factor loading $\lambda_{\theta,m,t}$ indicates how movements in θ_t are observed in $Z_{\theta,m,t}$. The set of measures of each latent variable, M_{θ_t}, can vary across time. This means the latent variables can be expressed as a function of error-contaminated measures in a standard errors-in-variables fashion. From 2.6 I can define:

$$\ln \theta_t \equiv \frac{Z_{\theta,m,t} - \mu_{\theta,m,t}}{\lambda_{\theta,m,t}} - \frac{\varepsilon_{\theta,m,t}}{\lambda_{\theta,m,t}} = \tilde{Z}_{\theta,m,t} - \tilde{\varepsilon}_{\theta,m,t} \tag{2.7}$$

Given that these latent variables have no inherent origin or scale, normalizations must be imposed on the parameters of Equation 2.6 to identify their marginal distributions. They are also required in order to identify and interpret the parameters of the human capital production and investment functions. A standard approach is to fix the location and scale of each latent variable in each period by imposing $\lambda_{\theta,m,t} = 1$ and $\mathbb{E}(\ln \theta_t) = 0$ for all t for some arbitrary measure. Agostinelli and Wiswall (2016b) show that these restrictions are unnecessary to separately identify the measurement system and the technologies in Equations 2.2 and 2.3 after the initial period, and that they in fact bias estimates of their parameters. These re-normalizations can be avoided and a range of flexible production functions identified, through two broad classes of restrictions: those on the relationship between measurement parameters over time, or those one the parameters of production technology directly (Agostinelli and Wiswall, 2016a).

To capture as much flexibility in their functional form as possible, it is desirable to only restrict the measurement system in the initial period and let the parameters of the production and investment functions be freely estimated. Which set of assumptions can or cannot be imposed partly depends on the properties of the observable measures of their outputs, however. Specifically, in order to avoid renormalisation and imposing restrictions on the structural production and investment parameters, it must be that for one measure $\mu_{H_h,m,t} = \mu_{H_h,m,t'}$ and $\lambda_{H_h,m,t} = \lambda_{H_h,m,t'}$ for all $t' \neq t$. This means assuming that, for example, a child who is equally healthy at two points in time be expected to have the same observable value of $Z_{H_h,m,t}$ and $Z_{H_h,m,t'}$ respectively, a property of a measure Agostinelli and Wiswall (2016a) define as *age invariance*. If this condition is met, it is possible to normalise onto this measure in the initial period, and then freely estimate the parameters of the health production functions in all periods. I create one measure

[7] I have omitted the t subscript from θ when indexing the measures and their parameters to save on notation. I have also omitted parental cognitive skill here (P_c) since it is treated as observable in estimating the model due to limitations in the data.

of health that meets this criteria across all periods, and after the initial period there is at least one for socio-emotional skill. For health, I therefore impose the initial period normalisations, $\lambda_{H_h,1,0} = 1$ and $\mathbb{E}(\ln H_{h,0}) = 0$, on this age-invariant measure. For socio-emotional skill I impose normalisations in both the initial and first period i.e. $\lambda_{H_s,1,t} = 1$ and $\mathbb{E}(\ln H_{s,t}) = 0$ for $t = 0, 1$. Although re-normalising onto the age-invariant measure might restrict the technology in this period, it allows me to estimate flexible production functions of socio-emotional skill and health at all ages.

For cognition, there are no age-invariant measures available. In fact, whereas the set of measures of health and socio-emotional skill are consistent over time, those of cognitive skill differ substantially across periods. In this case, re-normalisation is even less desirable as it would limit comparisons of parameter estimates over time. In order to avoid this, I restrict the parameters of the cognitive skill production functions directly. I discuss these restrictions in the following subsection. Parental stocks of human capital are assumed to be time-invariant so I fix their location and scale to one arbitrary initial measure[8], and I re-normalise investments in every period.

[8]Again, in the application of this model to data I do not treat parental cognition as unobservable due to data limitations. I maintain the assumption when outlining the model for completeness.

With regards to the measurement errors (($\varepsilon_{\theta,m,t}$)), I assume they are fully independent:

1. across alternative measures at a point in time, $Cov(\varepsilon_{\theta,m,t}, \varepsilon_{\theta,m',t}) = 0 \,\forall\, m' \neq m$;
2. across all measures at all other points in time, $Cov(\varepsilon_{\theta,m,t}, \varepsilon_{\theta,m',t'}) = 0 \,\forall\, m'$ and $t' \neq t$; and
3. across all latent skills at every point in time, $Cov(\varepsilon_{\theta,m,t}, \theta'_{t'}) = 0 \,\forall\, \theta'$ and t'.

These assumptions are stricter than what is required to identify the distribution of the latent variables in the initial period, however they are exhaustive of the assumptions required to obtain consistent estimates of the investment and production functions using the methodology I employ. I discuss this in more detail in the next sub-section.

An auxiliary feature of Equation 2.6 is that it assumes any variation in $Z_{\theta,m,t}$ can be straightforwardly decomposed into contributions from either the latent variable -the *signal* - or measurement error - the *noise*. That is, it implies

$$V(Z_{\theta,m,t}) = \lambda^2_{\theta,m,t} V(\ln\theta_t) + V(\varepsilon_{\theta,m,t})$$

As a result, signal ($s_{\theta,m,t}$) in each measure, can be given by ratio:

$$s_{\theta,m,t} = \frac{\lambda^2_{\theta,m,t} V(\ln\theta_t)}{\lambda^2_{\theta,m,t} V(\ln\theta_t) + V(\varepsilon_{\theta,m,t})},$$

with the noise being calculated as $(1 - s_{\theta,m,t})$. This allows for a simple analysis of how well the observable measures capture variation in the underlying latent variables they proxy.

2.2.6 Specification and Estimation

I estimate Equations 2.2, 2.3 and 2.4 across five periods covering the ages of 9 months-3 years (period 1), and 3-5 (2), 5-7 (3), 7-11 (4), and 11-14 (5). Below, I outline the restrictions I impose on these equations given the assumptions about the measurement parameters outlined above.

Structural parameter restrictions

For the health production functions, given the initial normalisation and the assumption of age-invariant measurement parameters for one measure - i.e. $\mu_{H_h,m,t} = \mu_{H_h,m,t'}$ and $\lambda_{H_h,m,t} = \lambda_{H_h,m,t'}$ for all t' - it is possible to estimate Equation 2.3 with no restrictions in any period. They therefore include a TFP term (A_t) and their Returns to Scale (RTS) is freely estimated. This is also the case for the socio-emotional skill production function, although the first period re-normalisation onto the age-invariant measure means the production function in this initial period might be ex-ante restricted. Re-normalising investments in every period also means it is possible to estimate these functions with no restrictions despite the absence of an age-invariant measure. When considering cognitive production, however, age-invariance cannot be assumed between for any measure or period. This is because of both inconsistencies in the measures of cognition across time and the construction of the measures themselves. I therefore assume the cognitive production functions have Constant Returns to Scale (CRS) and omit TFP, which implies the following restriction on its parameters:

$$\sum_{k\in\{h,c,s\}} \rho^c_{k,t} + \sum_{k\in\{h,c,s\}} \alpha^c_{k,t} + \gamma^c_{h,t} + \gamma^c_{c,t} + \kappa^c_{ch,t} + \kappa^c_{cc,t} = 1$$

$$\ln A_t = 0$$

In the following subsection I provide an example of the algorithm used to estimate the production functions to make clear the relationship between the measurement and production function parameter restrictions. As a baseline, I estimate all of the production technologies as Cobb-Douglas, which requires restricting $\kappa^j_{jh,t} = \kappa^j_{jc,t} = 0$ for $j \in \{h, c, s\}$. Including interactions between investments and skills terms then allows me to test this restriction.

Since the scale of the latent variables depends on the initial period normalisations, so does the interpretation of the parameters of the investment and production. As a result, there is no clear way to interpret their meaning if the normalizing measure is not cardinal, given that any order preserving transformation of a measure could be consistent with a given stock of human capital. Cunha et al. (2010) “anchor” their test results in adult outcomes - such as years of education or earnings - to give the parameters a cardinal interpretation. The data used in this paper began with children born in the year 2000 and, as a result, do not yet contain information on adult or even intermediate outcomes. For health the normalizing measure is of the number of illnesses a child has, and so can plausibly be seen as cardinal. It is slightly less clear that observable cognitive and socio-emotional measures capture “how much” skill children have, however, partly because it is difficult to measure skills cardinally at such a young age. For cognition, the normalising measure is of the number of developmental milestones reached, and for socio-emotional skills of the number of symptoms children display that indicate certain traits indicative of mood regularity or conduct problems, and I also take these as cardinal. The next section describes the measures in detail.

Estimating the Model

As an example of my application of the estimation algorithm of Agostinelli and Wiswall (2016a), consider a simple model of the joint evolution or health and cognition with one household investment. With three measures of health and cognitive skill in the initial period, the measurement parameters can be recovered by the ratio of their covariances:

$$\lambda_{\theta,m,0} = \frac{\text{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,m',0})} = \frac{\lambda_{\theta,m,0}\lambda_{\theta,m',0}Var(\theta)}{\lambda_{\theta,m',0}Var(\theta)} \qquad \text{for } \theta \in \{H_{h,0}, H_{c,0}\}$$

The measurement means are simply estimated by the unconditional mean of the measures under the normalisation $\mathbb{E}(\theta) = 0$. Latent health and cognition can then be defined as in Equation 2.7:

$$\ln \theta_0 \equiv \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} - \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} \qquad \text{for } \theta \in \{H_{h,0}, H_{c,0}\}$$

Substituting an investment function into one investment measurement equation, using the definition of θ_0 above, and rearranging gives the following reduced form investment equation:

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_1 \ln H_{h,0} + \beta_2 \ln H_{c,0} + \beta_3 Y_0 + \pi_0\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_1(\tilde{Z}_{H_h,m,0} - \tilde{\varepsilon}_{H_h,m,0}) + (\beta_2 \tilde{Z}_{H_c,m,0} - \tilde{\varepsilon}_{H_c,m,0}) + \beta_3 Y_0 + \pi_0\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \delta_{0,0} + \delta_{1,0}\tilde{Z}_{H_h,m,0} + \delta_{2,t}\tilde{Z}_{H_c,m,0} + \nu_0$$

where:

$$\delta_{0,0} = \mu_{I,m,0}$$

$$\delta_{i,0} = \lambda_{I,m,0}\beta_{i,0} \quad \text{for} \quad i = 1, 2$$

$$\nu_0 = \varepsilon_{I,m,0} + \lambda_{I,m,0}\big(\pi_0 - \beta_1 \tilde{\varepsilon}_{H_h,m,0} - \beta_2 \tilde{\varepsilon}_{H_c,m,0}\big)$$

Estimating the above reduced form equation by ordinary least squares will result in inconsistent estimates of the δ_is since:

$$\mathbb{E}(\tilde{Z}_{\theta,m,0}\nu_0) = \mathbb{E}\Big(\big(\ln\theta + \tilde{\varepsilon}_{H_\theta,m,0}\big)\big(\varepsilon_{I,m,0} + \lambda_{I,m,0}\big(\pi_0 - \beta_1\tilde{\varepsilon}_{H_h,m,0} - \beta_2\tilde{\varepsilon}_{H_c,m,0}\big)\big)\Big)$$
$$= \mathbb{E}(\tilde{\varepsilon}_{\theta,m,0}\beta_i\tilde{\varepsilon}_{\theta,m,0}) = \beta_i\sigma^2_{\varepsilon_{\theta,m,0}} \quad \text{for} \quad \theta \in \{H_{h,0}, H_{c,0}\},$$

where all other expected cross-products are zero based on the assumptions that latent measurement errors and production shocks are fully independent. This former assumption also means that the remaining measures of latent inputs are valid instruments, and they can be used to consistently estimate the reduced form investment parameters. With the normalisation that $\lambda_{I,m,0} = 1$, the reduced form and structural parameters become equivalent, i.e. $\beta_{i,0} = \delta_{i,0}$, and the scale of latent investment is defined by the scale of the observable measure $Z_{I,m,0}$. A residual investment measure can be constructed by simply de-meaning this observable measure. An identical process can then be followed to estimate the parameters of the production functions.

Substituting a simplified, Cobb-Douglas health and cognitive production functions into one $t+1$ health and cognition measurement equation and further using the fact that $\ln I_0 = \tilde{Z}_{I,m,0} - \tilde{\varepsilon}_{I,m,0}$, the following reduced form health and cognitive skill production function equations can be expressed:

$$Z_{H_j,m,1} = \tau^j_{0,0} + \tau^j_{1,0}\tilde{Z}_{H_h,m,0} + \tau^j_{2,0}\tilde{Z}_{H_c,m,0} + \tau^j_{3,t}\tilde{Z}_{I,m,0} + \upsilon_{j,1} \quad \text{for } j \in \{h,c\}$$

Where now:

$$\begin{aligned}
\tau^j_{i,0} &= \lambda_{H_j,m,1}\rho^j_{i,0} \quad \text{for} \quad i = 1,2 \\
\tau^j_{3,0} &= \lambda_{H_j,m,1}\gamma^j_0 \\
\upsilon_{j,1} &= \varepsilon_{H_j,1} + \lambda_{H_j,m,1}\left(\eta_{j,0} - \rho^j_{1,0}\tilde{\varepsilon}_{H_h,m,0} - \rho^j_{2,0}\tilde{\varepsilon}_{H_c,m,0} - \gamma^j_0\tilde{\varepsilon}_{I,m,0}\right) \\
\tau^j_{0,0} &= \mu_{h_j,m,1} + \ln A_0
\end{aligned}$$

Again, the assumption of independent measurement errors mean alternative measures of the inputs can be used as instruments to obtain consistent estimates of the reduced form production parameters. To recover the structural health production parameters, the restrictions on the measurement parameters can be exploited. Since the assumption that $Z_{H_h,m,1}$ is age-invariant implies that $\lambda_{H_h,m,0} = \lambda_{H_h,m,1}$ and $\mu_{H_h,m,0} = \mu_{H_h,m,1}$, the structural parameters of the health production function can be calculated as:

$$\begin{aligned}
\rho^h_{i,0} &= \frac{\tau^h_{i,0}}{\lambda_{H_h,m,0}} = \frac{\lambda_{H_h,m,1}\rho^h_{i,0}}{\lambda_{H_h,m,0}} \quad \text{for} \quad i = 1,2 \\
\gamma^h_0 &= \frac{\tau^h_{3,0}}{\lambda_{H_h,m,0}} = \frac{\lambda_{H_h,m,1}\gamma^h_0}{\lambda_{H_h,m,0}} \\
\ln A_0 &= \tau^h_{0,0} - \mu_{H_h,m,0} \\
\text{RTS} &= \sum_i \frac{\tau^h_{i,0}}{\lambda_{H_h,m,0}}
\end{aligned}$$

For cognitive skill production, without the assumption of age-invariance I restrict the structural cognitive production to have CRS and no TFP. The structural parameters can then be separately identify from the measurement parameters as:

$$\lambda_{H_h,m,1} = \sum_i \tau^c_{i,0} = \sum_i \lambda_{H_c,m,1}\rho^c_{i,0} + \lambda_{H_c,m,1}\gamma^c_0 \quad \text{since RTS} = \rho^c_{1,0} + \rho^c_{2,0} + \gamma^c_0 \equiv 1$$

$$\rho^c_{i,0} = \frac{\tau^c_{i,0}}{\sum_i \tau^c_{i,0}} = \frac{\lambda_{H_c,m,1}\rho^c_{i,0}}{\lambda_{H_c,m,1}} \quad \text{for} \quad i = 1, 2$$

$$\gamma^c_0 = \frac{\tau^c_{3,0}}{\sum_i \tau^c_{i,0}} = \frac{\lambda_{H_c,m,1}\gamma^c_0}{\lambda_{H_c,m,1}}$$

$$\tau^c_{0,0} = \mu_{H_c,m,1} \quad \text{since } \ln A_t = 0$$

The estimation procedure requires that a "lead" measure be used as the outputs/inputs of the investment and production functions, leaving the remaining measures to be used as instruments. I use the age-invariant measures of health and socio-emotional skill as the lead measures. For cognition, where this is not an option, I use the measure which ex-ante appears to be most highly correlated with its latent cognitive skill as the lead measure. For investment, which I re-normalise every period, I use the same approach.

This simplified example also highlights how omitting health from an analysis of skill development might lead to over or under-estimating their production parameters. If, for example, having good health leads to higher levels of cognition, then $\rho^c_{c,0}$ above will be biased upwards to they extent that $H_{c,0}$ is correlated with $H_{h,0}$. The same will be true in all periods in which health is not considered. Given that the magnitude of $\rho^c_{c,t}$ shows how malleable cognition is at any point, this upward bias might incorrectly lead to the conclusion that cognitive skill is highly self-productive when in fact it can be increased through health improvements or health investments. I return to this point when discussing the results in Section 2.4.

2.3 Data and Measures

I use data from the first six waves - covering the ages of 9 months, 3, 5, 7, 11 and 14 - of the Millennium Cohort Study (MCS), a longitudinal survey tracking the physical, socio-emotional and circumstantial development of a sample of children born in the United Kingdom between 2000 and 2002. Its first wave took place between June 2001 and January 2003 when the children were aged 9 months, and oversampled children from disadvantaged backgrounds.[9] As a result, the baseline MCS sample is not nationally representative by design. The study includes a wide variety of information on the mental and physical health of the cohort members as well as detailed information regarding their family circumstances. The MCS does not explicitly survey the mother

[9]MCS sampling was carried out so as to sample children of the same age at interview. There are some exceptions to this. The age of cohort members at wave 1 ranges from 6-12 months, however the average age is 9.2 months with a standard deviation of only 0.5 months - 16,500 out of 18,552 cohort members are aged 9 or 10 months. For simplicity in all that follows I will refer to the waves by the corresponding target age at which they were carried out.

as the main respondent to the survey, meaning the parental interview can be completed by either the mother or the father of a child at each wave. In practice, mothers almost exclusively answered the surveys as the main respondent - 99.85% and 94% of main respondents were the mothers at ages 9 months and 14 years respectively.

Table 2.1: Household characteristics in the MCS baseline survey and follow-ups

	(1) *Age 9 months*	(2) *Age 3*	(3) *Age 5*	(4) *Age 7*	(5) *Age 11*	(6) *Age 14*
Median equivalised household income	288.58	328.12	345.19	381.50	520.91	409.95
Mean	238.43	283.94	298.33	333.70	503.21	394.70
s.d.	(196.38)	(218.64)	(217.07)	(227.47)	(219.00)	(178.10)
Equivalised household income quintiles						
Lower quintile	0.25	0.22	0.22	0.21	0.21	0.17
Second quintile	0.23	0.22	0.21	0.21	0.21	0.17
Third quintile	0.19	0.20	0.19	0.20	0.21	0.20
Fourth quintile	0.17	0.19	0.19	0.19	0.20	0.23
Highest quintile	0.16	0.18	0.18	0.19	0.18	0.23
Parent's age at birth						
12-19	0.06	0.05	0.05	0.05	0.05	0.04
20-29	0.44	0.42	0.43	0.42	0.43	0.42
30-39	0.46	0.49	0.48	0.49	0.49	0.50
40 +	0.03	0.04	0.04	0.04	0.04	0.04
UK country						
England	0.62	0.65	0.64	0.64	0.65	0.66
Wales	0.15	0.14	0.14	0.14	0.14	0.14
Scotland	0.13	0.12	0.12	0.12	0.11	0.11
Northern Ireland	0.10	0.09	0.10	0.10	0.10	0.09
Ethnicity						
White	0.84	0.85	0.85	0.85	0.83	0.84
Mixed	0.01	0.01	0.01	0.01	0.03	0.01
Indian	0.03	0.03	0.03	0.03	0.03	0.03
Pakistani and Bangladeshi	0.07	0.06	0.06	0.06	0.07	0.07
Black or Black British	0.04	0.03	0.03	0.03	0.03	0.03
Other Ethnic group (inc. Chinese, Other)	0.02	0.02	0.02	0.02	0.01	0.02
Household Language						
English only	0.85	0.84	0.85	0.86	0.87	0.87
Mostly English	0.11	0.12	0.05	0.05	0.06	0.05
Half English, half other	0.04	0.03	0.05	0.04	0.04	0.04
Mostly other	0.00	0.00	0.04	0.03	0.03	0.04
Other only	0.00	0.00	0.01	0.01	0.01	0.00
N	18,296	15,381	15,042	13,681	13,112	11,558

Note: The table provides a statistical summary of the entire sample in each round of the MCS. Income is in 2010 prices. Conversion rates were accessed here: https://www.bankofengland.co.uk/monetary-policy/inflation/inflation-calculator. All numbers are proportions except for median, mean and the standard deviation (s.d.) of income. Income quintiles are relative to the UK income distribution, not the sample distribution.

Table 2.1 provides a statistical description of the MCS households at baseline and each follow-up round. An important feature of the MCS is the large rate of attrition: there are roughly 8,000 fewer individuals present in the sample at age 14 than there are at age 3. This attrition is also not random, and is concentrated among low-income households. In Table 2.1, average income of the sample increases across rounds, and the spread of the sample across income quintiles changes as a result. This is, in part, a result of increases in parents' income as they gain 14 years of experience in the labour market, however it is also a result of higher attrition among low-income families. Appendix Table B7 shows the proportion of families in each income quintile when children are aged 14 based on their income quintile at age 9 months. In the last column it shows that those in the bottom of the income distribution were far more likely to drop out of the sample by age 14. It also suggests that those who remained in the sample were more likely to move up the income distribution than down. This suggests that not only is the attrition non-random, but that those who have taken part in all six rounds of the survey are also relatively high-achieving families. In my analysis, to allow for comparability of results over time I restrict the sample used to estimate the model to children present in all five rounds of the survey, leaving a maximum of 11,714 observations in each of the five rounds. A central interest in this study is whether or not there is inequalities in health across the income distribution. In light of the features of the restricted sample discussed above, it is possible that any results will understate the relationship between health, or human capital more generally, and income.

2.3.1 Measurements

The MCS contains many potential measures on each of the unobservable inputs/outputs of investment and production. However, the measurement system outlined in Section 2.2.5 posits that each measures is *dedicated* to only one unobservable. Prior to "assigning" measures to unobservables, I used an Exploratory Factor Analysis (EFA) to verify the two assumptions underpinning this system: that observable measures contain rich enough variation to capture unobservables; and that each observable measures only one unobservable. With regards to the latter, measures that were estimated to be highly correlated with more than one unobservable were discarded, as were those that shared little variation with their corresponding latent variable. This is in line with the approach in Attanasio et al. (2020b), in which the authors also have a variety of measures available with which to measure their latent inputs - skills and investments - but no prior knowledge that they capture only one. Not doing so would result in, for example, overestimating the cross-productivities of cognitive and socio emotional skills if the measures used for each correlate with one another - in this scenario, estimates of the parameters of the investment and production functions would capture both the effect of their respective latent variable, and the misspecification of the measurement system. Having a dedicated measurement system and well-defined groupings of measures also helps interpret and understand estimates of the model parameters. Understanding exactly which observable measures are being used to capture the inputs provide context for the results that would be lost if all measures were allowed freely allowed to load on all latent variables. This would provide no idea of what, for example, "health" represents. Appendix B.3 describes the two components of this EFA in detail, and below I describe the measures retained to be used in estimations.

Child Health: The detailed nature of the MCS allows measures of children's physical health to be constructed consistently across ages. Across all ages, parents are asked whether their child has experience a variety of health conditions and/or illnesses. From these individual questions, I create indicators of whether or not a child has each of the conditions mentioned by at least one parent. I then categorise the conditions into two categories: long-term illnesses and transitory health conditions. Within each of these two categories and at each age I then sum the total number of positive responses to create variables representing the number of health conditions and long-term illnesses from which a child suffers. My definition of long term illnesses is in line with the World Health Organization's (WHO) International Classification of Diseases (ICD), and health conditions fall into the category of symptoms a child has displayed that are not necessarily chronic or indicative of a long-standing illness (WHO, 2018). For example, a health condition might be the flu, diarrhoea, viruses or transitory ear nose and throat infections. On the other hand, examples of long-term illnesses are eczema, recurring infections, persistent allergies, gastrointestinal problems, or congenital diseases. I use the number of health conditions at 9 months as the normalising measure for child health. At the same age I also make use of information on the length of a child's gestation period and, in a similar manner as with the measures of health conditions and long-term illnesses, I construct a measure of the number of complications the mother experienced during pregnancy. These "complications" include bleeding or a threatened miscarriage, high blood pressure, urinary tract infections and anaemia. [10] At ages 3, 5, 7, 11 and 14 I also use a count of the number of times cohort members have had to visit the hospital for treatment over and above regular check-ups. At ages 7, 11, and 14, I also use parent's subjective evaluation of the child's health on a scale of 1 (poor) to 5 (excellent). Appendix Table B10 provides a statistical summary of the health measures at each age. Many of the measures described in the table have an entirely negative range and, subsequently, a mean below zero. If left positive, these measures would represent *poorer* health. For example, a relatively higher value for the variable recording the number of health conditions a child had would indicate they are less healthy. In order that the measures used represent *positive* measures of health, I have reversed their scales to be negative. This is also true for some measures of cognitive and socio-emotional skill, discussed below.

Child Cognitive Skill: Because it covers ages of 9 months to 14 years, the MCS has not administered a consistent set of cognitive assessments. At 9 months old, cognitive skill

[10]There is a large literature, reviewed by Almond and Currie (2011), on the "fetal origins" hypothesis and the implications of in-utero conditions for health at birth and lifetime outcomes. Gluckman et al. (2008) reviews the extensive epidemiological literature on in-utero conditions, and aspects of mothers' health such as disease that affect fetal development and subsequently both early and later life health.

is measured by parental questionnaire. At this age, I use parental responses to a subset of questions from the Denver Developmental Screening Test (DDST) and the MacArthur-Bates Communicative Development Inventory (CDI), alongside a measure of the number of concerns the respondent has about their child's cognitive development. I interpret the normalising measure, the DDST, as cardinal as it measures how many developmental milestones a child has reached and measures fine and gross motor-skill development (Frankenburg and Dodds, 1967).[11] From age 3 onward I use children's scores on assessments of recognition/understanding of colours, letters, numbers and patterns, as well as assessments of their language, mathematics and working memory skills. At age 3, the assessment instruments are questions from the Bracken School Readiness (BSR) and British Ability Scales (BAS) tests. BAS tests are administered again at ages 5, 7, 11, alongside A National Foundation for Education Research (NFER) numerical skills test (age 7), Cambridge Neurophysical Test Automated Battery (CANTAB) gambling and spatial working memory tasks (age 11 and 14), and a word recognition assessment (age 14). Appendix B.2.1 provides detail on the cognitive assessments used from the MCS survey across ages and Appendix Table B11 summarises them statistically. Again, there are measures at age 7 whose scale has been reversed in order to represent positive measures of cognition.

Child socio-emotional Skill: Socio-emotional assessments are administered more consistently across the MCS rounds. At 9 months I use responses to questions from the Carey Infant Temperament Scale mood, regularity, and adaptability and withdrawal assessments. The normalising measure here is a child's score on the "mood" scale which indicates the degree of positivity towards interactions such as feeding, being changed, and arriving in new environments. At age 3, I then use sub-scales from a Strengths and Difficulties Questionnaire (SDQ) indicating how many symptoms of conduct problems, hyperactivity, emotional instability, peer problems and pro-sociality children display. I re-normalise onto the conduct problems sub-scale which measures the extent to which a child displays behaviours such as stealing, lying, fighting, disobeying and having tantrums. I also use sub-scales from the Child Social and Behavioural Questionnaire (CSBQ) which are aimed at measuring the degree of emotional (in)stability children display. The SDQ is administered to parents again at ages 5, 7, 11 and 14, and the CSBQ questions at ages 5 and 7. Appendix B.2.2 provides detail on the socio-emotional measures used from the MCS data and Appendix Table B12 summarises them statistically. As with the measures of health in Table B10, in their raw form many of the measures of socio-emotional skill are negative. As such, the scale of the majority of measures in Table B12 has been reversed so a higher value represents a higher level of skill.

Investments: To measure investments, I exploit questions from the MCS regarding how

[11]For example, it assesses how often the child performs actions which indicate the development of either fine or gross motor skills such as smiling, clapping their hands, holding small objects, or passing toys when asked to. It is difficult to measure cognitive development at 9 months of age, however there is evidence that these skills are strongly linked to future cognitive development - Diamond (2000) discusses in detail the evidence on the interrelation between cognitive development and early motor skills. Johnson et al. (2015) describes in detail the sub-set of questions the MCS uses from both the DDST and MacArthur-Bates CDI.

frequently parents take part in certain activities with their children, or encourage them to do so. Such measures capture how much *time*, as opposed to *resources*, parents invest in their children. Whilst these two forms of investment are distinct, they are jointly determined alongside parental labour supply in models of household choice and child development - a result of the intrinsic relationship between time, labour supply and income (Bernal, 2008; Del Boca et al., 2013, 2016; Aizer and Cunha, 2012). Here, however, I focus on time investments as there is no information on material investments in the MCS. There is growing evidence that time spent on child care is an important determinant of their human capital development (Cunha et al., 2010; Boneva and Rauh, 2016; Attanasio et al., 2020b), and that large portions of the impact of early interventions based on cash transfers on this process come through mothers' substitution of their time from work to childcare (Del Boca et al., 2013, 2016; Agostinelli and Sorrenti, 2018).

I assume the activities about which parents of the MCS subjects are asked belong to two distinct categories - those aimed at fostering cognitive skills, and those that are intended to improve health or promote a healthy lifestyle. This structure was confirmed as part of the preliminary EFA, outlined in Appendix B.1, and I define these categories as cognitive and health investments respectively. For cognitive investments, at ages 3, 5, and 7 I use the parents' responses to questions regarding how often they read, write, sing/play music and practice maths with the child in a week. At ages 11 and 14, I use their responses when asked how often they help the child with homework, how often they check the child's homework, the number of hours per week a child spends studying and how often they talk to the child about important subjects. As measures of health investments, I make use of a range of questions the parents are asked about their child's lifestyle. Across all ages I use some combination of measures of how frequently the child has regular meals and regular bed times, how often they take part in a sport or the parents plays sports/active games with them, the portions of fruit they eat in day, and the number of days a week they have breakfast. Appendix Tables B13 and B14 provide a statistical summary of the health and cognitive investment measures used across ages.

Parental human capital: Given the assumption that parents' human capital is time-invariant and a proxy for wider environmental endowments, I measure their cognitive and socio-emotional skill and health based on information from the main respondent when children are aged 9 months.[12] There are not explicit measures of parents' cognition at 9 months, so I use the parents' highest level of qualification as a proxy and do not treat cognition as unobservable.[13] The

[12]Many of the MCS questions are also administered to the secondary parent, however the survey does not require partners to be present, meaning response rates to these questions are low. Requiring a combination of both parents' skills as a proxy for endowments would require a large non-random reduction in the sample. At 9 months 99.9% of main partner interviews were achieved in full or partial in person. This contrasts to only 71.3% of partner interviews being achieved at least in partial in person - a difference of 5,307 observations. The approach of using only one parent's, typically the mother's, skills at the earliest survey is common in the human capital development literature (e.g. Cunha et al. (2010), Agostinelli and Wiswall (2016a), and Boneva and Rauh (2016))

[13]There are several questions on whether or not parents have difficulty reading and writing when children are 9 months, however they vary very little across parents. There is also a word score test given to parents when children are aged 14, however this was very highly correlated with socio-emotional measures. Although they are assumed time-invariant, sing measures from 9 months maintains consistency.

implications of this assumption for interpreting its associated elasticity is discussed in the next section. For socio-emotional skill I make use of four measures - the Rosenberg self-esteem scale, the Rutter Malaise psychological distress scale and a measure of the respondent's locus of control. To measure health, I use the main respondent's subjective health, a variable indicating whether or not they have and long-standing illnesses, and a measure of the number of health conditions from which they suffer. Again, Appendix Table B15 gives a statistical summary of these measures.

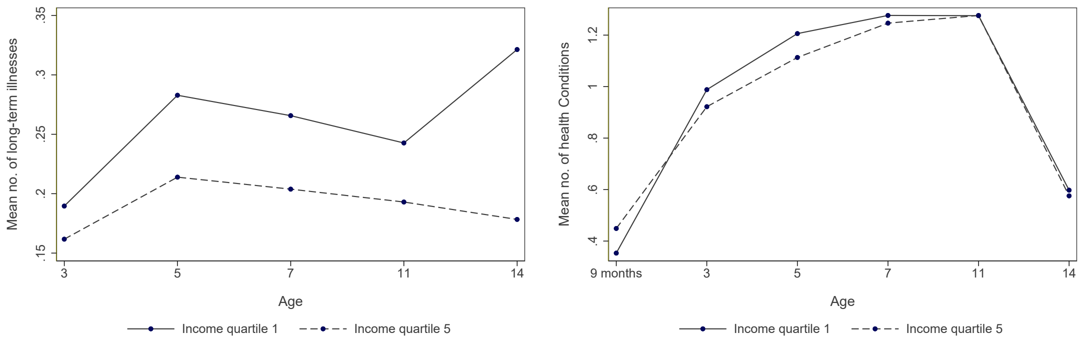
Income: For income, I use data on total net household income that is standardised to account for family size. In the MCS, this equivalisation of household income is applied using the OECD equivalisation scales, which adjust family size and composition by transforming income of each family to be relative to that of a couple with no children. For example, a couple with one child aged under 14 would have an equivalisation scale of 1.2. If their income was nominally identical to the couple with no children, its equivalised value would be roughly 17% lower. This equivalised income therefore represents a more accurate representation of family resources. The income data on which this equivalisation is carried out are estimated from a range of questions to parents on sources of income, including earnings from work and state benefits. Hansen et al. (2014) provide detail on the income data collected and OECD equivalisation used in the MCS, and how it compares to other commonly used scales.

2.3.2 Observable Health and Investment Gradients

As an initial look at potential socioeconomic gradients in the observable health measures defined above, Figure 2.1 plots how the mean number of long-term illnesses (panel (a)) and mean number of health conditions (panels (b)) changed over time in the bottom and top quartiles of the MCS sample income distribution. Whilst the number of health conditions at each end of the income distribution track each other closely over time, there are differences in the development of health in terms of long-term illnesses. Figure 2.1(a) shows that, on average, children in the lowest quartile of the income distribution suffer from more long term illnesses than those in the top quartile at all ages. By age 3, this gap begins to widen and, although it narrows slightly between ages 5 and 7, this difference becomes stark at age 14. This large decrease in health among the poorest 25% of the sample does not appear to be a feature of the data, or any external events that might explain such a divergence; for example, medical screening that would disproportionately affect the answers of parents in the lower end of the income distribution. The survey also asks parents about the same health conditions at every wave. Similarly there is no clear explanation as to why in 2.1(a) there is a sharp *increase* in health in this last period among those in both the top and bottom quartiles of the income distribution. These changes in observable health measures between the ages of 11 and 14 could indicate an important period in the early teenage years during which children experience changes in their health

Appendix Tables B8 and B9 provide summaries of the health and cognitive investment measures used in period 1 - between the ages of 9 months and 3 years - respectively, by quartile

Figure 2.1: Observable health measures over time for those in the top and bottom income quartiles in the MCS



(a) **(b)**

Note: Panel (a) shows the mean number of long-term illnesses and Panel (b) the mean number of health conditions among children in the top (dashed line) and bottom (solid line) income quartiles of the MCS sample family income distribution at each age. Family income is equivalised to adjust for household composition using the OECD equivalisation scales (Hansen et al., 2014). Quartiles are calculated based on family income at each age. Section 2.3 describes the variables in each panel.

of the income distribution. In both tables there are small gradients investments. For example, Table B8 shows that the proportion of parents who say their child has fruit or vegetables once a day, or who report to play sport with their child increases across income quartiles. Similarly, those in the top quartile of the income distribution are more likely to report their child having regular meals and bed times *usually* or *always* than those in the bottom. The gradients in Table B9 are generally less pronounced, however there are still large differences in the proportion of parents who report reading to their child every day across the income distribution.

2.4 Results

2.4.1 Measurement System

Appendix tables B16-B21 report estimates of the measurement system, which show the informational content of measures across unobservables and ages. Table B16 suggests that health is measured relatively well by the observable data, other than in the first and last periods. For example, at 9 months the signal in measures ranges from 3% to 6%, whereas at age 5 they range from 30% to 56%. There is similar pattern across measures of cognition (Table B17) socio-emotional skill (Table B18), with first and last period measures being, on average, the noisiest. This highlights the importance of counting for measurement error in estimating the process of human capital development. If the raw measures were used as proxies of the inputs of the investment and production functions, the corresponding parameters would be biased downwards in proportion to the signal/noise ratios. It also shows that it is perhaps more difficult to measure human capital at the "extreme" ends of childhood.

Table B19 shows that the signal in health investment measures also varies both across and within periods. At age 7, the measures are particularly noisy, with the largest signal being roughly 13%, however in all other periods at least one measure has over one-quarter of its variation shared with latent health investment. The measures of cognitive investment are generally less noisy than those of health investment. At three ages (5, 11, and 14) one measure of cognitive investment has a signal of less than 10%, however the signal in the other measures in these periods are relatively large. Table B21 shows that observable measures of the parent's human capital appear to measure health and socio-emotional skill well - across the two, the smallest signal is 23%. I note here again that I use only parents' education as a proxy for cognitive skill, this means that estimates of its corresponding elasticity in the investment and production functions that follow may in fact be downward biased.

2.4.2 The Determinants of Household Investment

Whilst it is not possible to know the underlying mechanism that maps parental characteristics into investment, the parameters of the investment functions provide insight as to the investment behaviours of parents.

Health Investment

Table 2.2 shows the estimates of the parameters of the health investment functions. Family income, is positively associated with health investment in all period. The relative strength of this relationship is in fact increasing with children's age, implying that family income becomes increasingly important in determining health investments over time. Similar empirical studies of human capital development have found family income and/or resources to be an important determinant of educational and recreational investment in a variety of contexts.[14] However, that a similar gradient exists in the health investments of families highlights a further aspect of the early environment affected by income.

Similarly, the results in Table 2.2 also indicate a positive gradient in health investments across parents' education and socio-emotional skill in three of the five periods. The former influence investment decisions early and late (9 months-5, and 11-15), whereas the latter do so through the middle of childhood (3-11). These effects come over and above the influence of family income, suggesting it is not only finances that constrain parental investments but also information, education and perhaps understanding of child development process.

[14] Attanasio et al. (2020c,b, 2017)and Agostinelli and Wiswall (2016a) all find that investments are strongly responsive to either family income or wealth relative to their estimates of the investment function parameters. These studies predominantly measure investments with the reported educational and recreational inputs of families. Attanasio et al. (2017) do include two health investments in their aggregate, however they do not separately include health investment in their empirical model. It should also be noted that Attanasio et al. (2020c,b, 2017) are all studies of human capital development in developing countries, and so the results may not be directly applicable to those from a model using UK data.

Table 2.2: Estimates of health investment function parameters

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.021	0.005	0.022	-0.024	-0.453***
	(0.234)	(0.105)	(0.067)	(0.059)	(0.116)
	[-0.364,0.406]	[-0.167,0.177]	[-0.088,0.132]	[-0.121,0.073]	[-0.644,-0.263]
$\ln H_{c,t-1}$	-1.192***	0.136***	-0.014	-0.081**	0.057***
	(0.243)	(0.048)	(0.049)	(0.032)	(0.021)
	[-1.592,-0.792]	[0.057,0.215]	[-0.094,0.066]	[-0.133,-0.029]	[0.023,0.092]
$\ln H_{s,t-1}$	0.855***	0.013	0.014	0.041**	0.183***
	(0.128)	(0.013)	(0.019)	(0.018)	(0.032)
	[0.644,1.067]	[-0.008,0.033]	[-0.017,0.046]	[0.011,0.070]	[0.131,0.236]
Parental human capital (fixed over time)					
$\ln P_h$	0.064	0.014	0.014	0.007	0.097*
	(0.039)	(0.033)	(0.039)	(0.039)	(0.058)
	[-0.001,0.128]	[-0.041,0.068]	[-0.050,0.079]	[-0.058,0.072]	[0.001,0.192]
$\ln P_c$	0.295***	0.079***	0.054	0.020	0.277***
	(0.041)	(0.030)	(0.040)	(0.043)	(0.051)
	[0.228,0.362]	[0.030,0.129]	[-0.012,0.120]	[-0.051,0.090]	[0.193,0.361]
$\ln P_s$	0.004	0.086***	0.138***	0.097***	0.000
	(0.022)	(0.022)	(0.022)	(0.019)	(0.029)
	[-0.031,0.040]	[0.049,0.122]	[0.102,0.175]	[0.065,0.128]	[-0.047,0.048]
Income					
$\ln Y_t$	0.070***	0.088***	0.043	0.216***	0.525***
	(0.022)	(0.025)	(0.029)	(0.048)	(0.058)
	[0.035,0.105]	[0.047,0.130]	[-0.006,0.091]	[0.136,0.295]	[0.429,0.621]
$\sigma^2_{\pi_h}$	0.222***	0.050***	0.657***	0.203***	1.289***
	(0.010)	(0.011)	(0.021)	(0.019)	(0.052)
	[0.205,0.239]	[0.032,0.069]	[0.622,0.692]	[0.172,0.234]	[1.204,1.375]
N	8,237	6,976	7,824	7,729	7875

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each column is health investment measured by the observables in Appendix Table B19. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left-most are lagged child health, cognitive skill and socio-emotional skill; parental health cognitive skill and socio-emotional skill; and family income, respectively. All with the exception of parental cognitive skill and family income are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and estimates of their measurement parameters are shown in Tables B16-B21.

Parental responses to children's revealed human capital in Table 2.2 differ substantially across periods. There are responses to cognitive skill that are statistically different from zero in all but one period. By far the largest of these is a compensatory effect in the earliest period, between 9 months and 3 years of age. In this period, a 1% increase in cognition is associated with a 1.2% decrease in health investment. In the same period, the opposite is true for socio-emotional skill, with their being a large reinforcing response. Parents' responses to socio-emotional skills remain reinforcing, albeit to a much smaller extent, throughout childhood. Conversely, cognition affects health investments alternating directions across periods, suggesting how parents make health investments based on their children's human capital differs across stages of childhood. Children's health only influences health investments in the last period, covering the early teenage years, when there is a large compensatory effect with respect to health. Table 2.2 suggests that, overall, parental health investment decisions are influenced most by children's human capital at the earliest and latest stages of childhood; a finding that is perhaps unsurprising given they cover key developmental phases, when children are in their pre-school years or in the early stages of high school.

Cognitive Investment

Estimates of the cognitive investment functions are provided in Table 2.3. They show a less pronounced income effect than was estimated for health investment, suggesting that income plays a relatively smaller role in determining cognitive investments. Parents' education is not estimated to be a strong determinant of cognitive investment at any age, however socio-emotional endowments are in periods 2 (3-5), 4 (7-11) and 5 (11-14), albeit to a small extent.

Children's health significantly affects cognitive investments between the ages of 9 months and 5. In the first period, there is a strong compensatory effect with a 1% reduction in health estimated to increase investment by around 1.47%. Although also compensatory, the response in the following period is about one-eighth of the magnitude, and its effect fades thereafter. This is slightly different to recent evidence from Nicoletti and Tonei (2020), who find that parental investments are compensatory with respect to health up until age 9. Cognitive skill affects cognitive investment behaviours in every period, again to different extents and in different directions. In the first period, there is a large reinforcement effect. This is in the same period in which there is a large compensatory effect of cognition on *health* investment, meaning parents in the sample invest more resources into their child's cognitive development upon realising they have high levels of cognition, but try to make up for deficits they observe by making healthy lifestyle choices. The response to cognition remains reinforcing in the next period, but switches to being compensatory from period 3 onward when children enter primary school. Socio-emotional skills have a positive effect on cognitive investments in all but one period, between the ages of 5 and 7. In general, this period stands out from the rest in that the only statistically significant determinant of investment is cognition. The estimated variance of shocks is also very large in this period, suggesting that there are substantially more external factors influencing cognitive investment behaviours during it than across all others that covering school years.

2.4.3 Health Production Functions

The production function estimates lend themselves to a more structural interpretation than those of the investment equations. Each elasticity illustrates the malleability of health - and later cognitive and socio-emotional skill - with respect to its corresponding input. These measures capture not only the long-term health accumulated over childhood, but also some aspects of transitory health experienced over the period in question.

Table 2.3: Estimates of cognitive investment function parameters

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	-1.467***	-0.181	-0.052	0.011	0.024
	(0.391)	(0.111)	(0.080)	(0.049)	(0.064)
	[-2.110,-0.825]	[-0.364,0.001]	[-0.183,0.080]	[-0.070,0.092]	[-0.082,0.130]
$\ln H_{c,t-1}$	2.188***	0.117**	-0.416***	-0.094***	-0.055***
	(0.519)	(0.050)	(0.064)	(0.021)	(0.014)
	[1.334,3.041]	[0.035,0.199]	[-0.521,-0.311]	[-0.129,-0.059]	[-0.078,-0.033]
$\ln H_{s,t-1}$	0.794***	0.040***	0.053	0.061***	0.051***
	(0.201)	(0.010)	(0.033)	(0.011)	(0.016)
	[0.464,1.125]	[0.023,0.057]	[-0.001,0.107]	[0.043,0.078]	[0.024,0.078]
Parental human capital (fixed over time)					
$\ln P_h$	-0.021	-0.003	-0.080	-0.014	-0.010
	(0.070)	(0.030)	(0.055)	(0.026)	(0.025)
	[-0.137,0.094]	[-0.053,0.047]	[-0.171,0.010]	[-0.056,0.028]	[-0.052,0.031]
$\ln P_c$	0.046	0.049*	0.050	0.007	-0.014
	(0.083)	(0.030)	(0.052)	(0.026)	(0.028)
	[-0.090,0.183]	[0.000,0.097]	[-0.036,0.137]	[-0.036,0.049]	[-0.060,0.031]
$\ln P_s$	-0.004	0.067***	-0.029	0.050***	0.034**
	(0.037)	(0.017)	(0.033)	(0.015)	(0.015)
	[-0.066,0.057]	[0.040,0.095]	[-0.083,0.025]	[0.025,0.075]	[0.010,0.059]
Income					
$\ln Y_t$	0.111**	0.045*	0.014	0.067**	0.043
	(0.045)	(0.024)	(0.038)	(0.028)	(0.032)
	[0.038,0.185]	[0.006,0.084]	[-0.048,0.076]	[0.020,0.113]	[-0.010,0.095]
$\sigma^2_{\pi_c}$	3.293***	0.044***	1.958***	0.411***	0.066***
	(0.096)	(0.005)	(0.037)	(0.023)	(0.011)
	[3.136,3.451]	[0.036,0.052]	[1.897,2.018]	[0.373,0.449]	[0.048,0.083]
N	8,236	6,901	7,817	7,707	8079

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each column is cognitive investment measured by the observables in Appendix Table B20. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left-most are lagged child health, cognitive skill and socio-emotional skill; parental health cognitive skill and socio-emotional skill; and family income, respectively. All with the exception of parental cognitive skill and family income are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

To compare the contribution of each of the inputs of health production, I first show estimates of a baseline Cobb-Douglas production function. Table 2.4 highlights the persistence of health across childhood: in all stages health is highly self-productive and there is very little evidence it is affected by investments. The elasticity of health with respect to lagged stocks of itself is never estimated to lower than 0.45, and is as high as 1.2 between the ages of 3 and 5.

Perhaps intuitively, there is no evidence of cross-productivities between skills and health in early childhood. Biroli (2016) did find some evidence that socio-emotional skills are related to health development in the very early years between the ages of 0 and 5, but that this relationship

Table 2.4: Estimates of Cobb-Douglas health production function

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.466^{***}	1.221^{***}	0.810^{***}	0.539^{***}	0.819^{***}
	(0.137)	(0.080)	(0.035)	(0.042)	(0.056)
	[0.241,0.691]	[1.089,1.354]	[0.752,0.868]	[0.470,0.608]	[0.726,0.912]
$\ln H_{c,t-1}$	0.091	0.036	0.003	0.089^{***}	0.005
	(0.113)	(0.025)	(0.015)	(0.015)	(0.007)
	[-0.095,0.277]	[-0.005,0.077]	[-0.022,0.028]	[0.065,0.113]	[-0.007,0.016]
$\ln H_{s,t-1}$	0.030	-0.002	0.002	0.063^{***}	0.061^{***}
	(0.056)	(0.008)	(0.008)	(0.011)	(0.015)
	[-0.062,0.123]	[-0.014,0.011]	[-0.011,0.015]	[0.045,0.081]	[0.036,0.086]
Parental human capital (fixed over time)					
$\ln P_h$	0.034^{*}	0.060^{***}	0.023	0.066^{***}	0.034
	(0.018)	(0.021)	(0.016)	(0.020)	(0.022)
	[0.005,0.064]	[0.026,0.094]	[-0.003,0.049]	[0.033,0.098]	[-0.002,0.070]
$\ln P_c$	0.026	-0.005	-0.008	-0.049^{***}	-0.011
	(0.019)	(0.021)	(0.013)	(0.018)	(0.018)
	[-0.005,0.057]	[-0.039,0.030]	[-0.031,0.014]	[-0.079,-0.019]	[-0.040,0.019]
$\ln P_s$	0.014	-0.005	0.000	-0.018^{*}	0.007
	(0.009)	(0.011)	(0.008)	(0.011)	(0.012)
	[-0.001,0.029]	[-0.023,0.013]	[-0.014,0.014]	[-0.037,-0.000]	[-0.013,0.026]
Investments					
$\ln I_{h,t-1}$	0.014	0.005	-0.013	-0.038	-0.010
	(0.020)	(0.046)	(0.012)	(0.035)	(0.013)
	[-0.019,0.047]	[-0.071,0.081]	[-0.034,0.007]	[-0.095,0.020]	[-0.031,0.011]
$\ln A_t$	0.227^{***}	0.160^{***}	0.181^{***}	0.212^{***}	0.166^{***}
	(0.020)	(0.023)	(0.016)	(0.018)	(0.019)
	[0.194,0.260]	[0.123,0.198]	[0.155,0.207]	[0.182,0.243]	[0.135,0.198]
RTS	0.676^{***}	1.311^{***}	0.817^{***}	0.652^{***}	0.905^{***}
	(0.121)	(0.081)	(0.035)	(0.049)	(0.048)
	[0.477,0.875]	[1.179,1.444]	[0.758,0.875]	[0.571,0.733]	[0.825,0.984]
$\sigma^2_{\eta_h}$	0.025^{***}	0.056^{***}	0.031^{***}	0.037^{***}	0.027^{***}
	(0.006)	(0.005)	(0.004)	(0.006)	(0.010)
	[0.015,0.035]	[0.048,0.064]	[0.024,0.038]	[0.026,0.047]	[0.011,0.043]
N	8,300	7,012	7,947	7,716	7,823

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each column is children's health measured by the observables in Appendix Table B16. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left-most are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; and health investment, respectively. All with the exception of parental education are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B19-B18.

was explained by dietary behaviours being highly correlated with socio-emotional skills.[15] There is evidence that both cognitive and socio-emotional skills affect health at later stages, however. Socio-emotional skills are estimated to positively influence the production of health in between the ages of 7-11 and 11-14, as are cognitive skills between 7 and 11. At these later ages, it is plausible that cognitive and socio-emotional skills enable children to make health-conscious decisions or self-invest in their health. This is in line with recent evidence that socio-emotional skills are important in determining health and health behaviour among children in both the MCS and an older UK cohort born in 1970 (Attanasio et al., 2020a). If it is the case that cognitive and socio-emotional skills promote good health as early as adolescence, one way in which to reduce health inequality is through ensuring children are equipped with the necessary skills to understand the health implications of their behaviour and/or lifestyle choices.

Moving to the role of parental human capital, parents' health is estimated to positively affect health to much the same, relatively small, extent in all periods. Between the ages of 9 months-3, 3-5 and 7-11 these elasticities are statistically different from zero, with a 1% increase in log health endowment being associated with a 0.034%, .06% and 0.066% increase in health respectively. There is not any consistent pattern in the role of parents' education or socio-emotional skill in the production of health. Both only enter significantly into the health production function between the ages of 7 and 11, when their elasticities are small and negative. It appears then that the most important parental characteristic in health development across childhood is the past health of children themselves and parents' health. Table 2.4 also shows that health investments do not influence health development in any period.[16] This lack of an investment effect speaks to the high level of self-productivity in health across all ages, suggesting investments of the type measured here - for example, having regular meals, healthy diet and exercising frequently - do not have an impact on overall health as it is measured by illnesses and health conditions. This leaves open the possibility that there are other types of health investment these measures do not capture that might in fact be associated with better health. For example, the measures used are of healthy behaviours and time spent in healthy activities, but do not capture many aspects of the home environment and parental choice such as cleanliness, handling of sickness/illness, vaccinations or nutrition. The self-productivity of health production is further highlighted by the relatively small TFP estimates, and the fact the RTS are estimated to be small or close to constant in all but one period - a period, between the ages of 3 and 5, in which health development is driven entirely by health itself. The estimated variance of shocks is also small across all periods, but statistically different from zero and larger than the impact of, for example, health endowments. This suggests that there are factors other than those captured by the inputs of the health production function

[15] Biroli (2016) does not explicitly estimate investment equations, but rather introduces investments into their production technologies to assess their impact on the production parameters. An initially high level of cross-productivity of socio-emotional skill in the production of health is explained by the introduction of preventive investments - for example dietary habits - however.

[16] Although they are statistically not different from zero, the point estimates are negative. It is again worthwhile bearing in mind that some of the measures of health investments used measure children's engagement in sports, and relationships like this might pick up any accidents, injuries, or hospital visits that were experienced as a result.

that consistently influence the development of health.

Given that there might be higher returns to investment in children with poorer health, it could be that the investment elasticities shown in Table 2.4 are close to zero as they represent a simple average across the sample distribution of health. To test this, Appendix Table B24 shows estimates of the health production function with interacted health investment and child health at each age. It is not possible to reject that that these interaction effects are equal to zero in any period, however, suggesting that no such complementarity exists. This further confirms the results of Table 2.4 that investments have no strong effect on health accumulation, even when it is allowed to vary across the distribution of health.

2.4.4 Health and Skill Accumulation

Cognitive Skill Production Functions

Table 2.5 shows estimates of the baseline Cobb-Douglas cognitive skill production function, with its RTS constrained to equal one. Cognitive skill is estimated to be self-productive to varying extents across childhood. Over the first 4 periods, between the ages of 9 months and 11, cognition becomes increasingly persistent, with its self-productivity being close to one by age 11. In the last period however, between 11 and 14, this reduces to around one-sixth of its size in the previous period. This is in contrast to much of the literature on skill development, in which evidence has consistently found that cognition is increasingly or highly self-productive across all of the ages covered in this study (e.g. Cunha et al. (2010), Agostinelli and Wiswall (2016a), Attanasio et al. (2020c)). Given the measurements of cognition differ across ages, however, this decline in self-productivity between 11 and 14 cannot be viewed as entirely resulting from changes in the parameters of the production function. Both the methodology I use to estimate the production functions and the EFA described at the beginning of the previous section aimed to reduce the effect this might have on the comparability of parameter estimates. However, it might be the case that the latent concept of cognition being measured in this stage differs slightly to those measured in previous periods.

In the first period, when the self-productivity of cognition is at its lowest, health is estimated as an important determinant of cognitive development, with an elasticity of roughly 0.26 - substantially higher than that found by Biroli (2016). Although the effect of health on cognitive development fades over the next 3 periods, it becomes important to its development again in the final period, between 11 and 14, when cognitive self-productivity drops from its peak at age 11. This suggests that during these ages, good health is important in developing cognitive skill and that the impact of health of cognitive development is felt both early and late in childhood - again, important phases in skill accumulation. There is also evidence of cross productivities between socio-emotional skill and cognition in the first two periods, between 9 months and 5.

Health investments are estimated to factor significantly in the production of cognitive skill

Table 2.5: Estimates of Cobb-Douglas cognitive skill production function

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.258***	0.150	-0.047	-0.043	0.240**
	(0.098)	(0.106)	(0.063)	(0.094)	(0.120)
	[0.096,0.419]	[-0.023,0.324]	[-0.151,0.057]	[-0.198,0.112]	[0.042,0.438]
$\ln H_{c,t-1}$	0.138	0.643***	0.884***	0.931***	0.154***
	(0.141)	(0.104)	(0.053)	(0.124)	(0.028)
	[-0.094,0.370]	[0.472,0.815]	[0.797,0.971]	[0.727,1.136]	[0.108,0.200]
$\ln H_{s,t-1}$	0.173**	0.044***	0.028	0.012	-0.045
	(0.068)	(0.017)	(0.018)	(0.028)	(0.034)
	[0.061,0.285]	[0.017,0.072]	[-0.002,0.058]	[-0.035,0.059]	[-0.102,0.012]
Parental human capital (fixed over time)					
$\ln P_h$	-0.015	0.027	-0.004	-0.059	-0.035
	(0.025)	(0.034)	(0.030)	(0.053)	(0.051)
	[-0.056,0.025]	[-0.029,0.083]	[-0.053,0.046]	[-0.147,0.029]	[-0.120,0.049]
$\ln P_c$	0.284***	0.066*	0.142***	0.103**	0.310***
	(0.036)	(0.037)	(0.029)	(0.046)	(0.060)
	[0.226,0.342]	[0.005,0.127]	[0.094,0.190]	[0.027,0.180]	[0.211,0.409]
$\ln P_s$	0.012	-0.033	0.013	0.035	0.029
	(0.011)	(0.021)	(0.018)	(0.034)	(0.023)
	[-0.007,0.031]	[-0.067,0.001]	[-0.017,0.042]	[-0.020,0.090]	[-0.009,0.066]
Investments					
$\ln I_{h,t-1}$	0.082***	0.203*	0.015	0.286**	0.176***
	(0.024)	(0.106)	(0.025)	(0.118)	(0.038)
	[0.044,0.121]	[0.029,0.377]	[-0.026,0.056]	[0.093,0.480]	[0.113,0.239]
$\ln I_{c,t-1}$	0.068***	-0.101	-0.032***	-0.266**	0.172*
	(0.012)	(0.107)	(0.011)	(0.110)	(0.096)
	[0.049,0.087]	[-0.277,0.075]	[-0.050,-0.013]	[-0.448,-0.084]	[0.013,0.331]
$\sigma^2_{\eta_c}$	0.451	0.103***	0.082***	2.062***	0.120***
	(1.155)	(0.024)	(0.022)	(0.776)	(0.032)
	[-1.449,2.352]	[0.065,0.142]	[0.045,0.118]	[0.785,3.339]	[0.067,0.172]
N	7,998	6,898	7,853	7,373	7,404

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each column is children's cognitive skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left-most are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; and health and cognitive investment, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

in four of the five periods, albeit marginally in one (between 3 and 5). Cognitive investments affect cognitive development positively in between 9 months-3 and 11-14, but negatively in periods covering 3-11. This negative effect is driven by parents' strong, compensatory response to cognition when making cognitive investments across these periods not being matched by increases in cognitive skill (Table 2.3).[17] To examine whether the impact of investment might vary across the distribution of skill, Tables B25 and B26 show estimates of the cognitive production function with interactions of cognitive skill with health and cognitive investments respectively. In neither is there any strong evidence that the efficacy of investments in producing cognition depends on contemporaneous levels of skill. The only interaction effect that is statistically different from zero is between health investments and cognition in the final period (Table B25). In this period, the interaction effect is positive, suggesting that health investments are more productive in producing cognition when made in children with already high levels of skill. This is points to the importance of the health-related environment in this period in determining the divergence of cognitive skill.

Socio-emotional Skill Production Functions

Table 2.6 shows estimates of the baseline Cobb-Douglas socio-emotional production parameters. Like health and cognition, socio-emotional skill is self-productive across childhood. In the last period, and similar to cognition, its self-productivity is low in comparison to the preceding periods, however. Health enters positively into the socio-emotional production function in all periods, however its 90% confidence interval only does not contain zero marginally in one, between and 7. This contrasts slightly with Biroli (2016) who find stronger evidence of the positive effect of health on socio-emotional development between 0 and 5.

Parental education and socio-emotional skill have a similar impact in the production of socio-emotional skill across all of childhood. Both have a positive effects on its development, particularly in the earliest periods, between 9 months and 5. Parents' health on the other hand has little effect in any period. Health investments positively affect socio-emotional development in all periods, and their elasticity is large and statistically different from zero in first and fourth periods. In the first period, when children are aged between 9 months and 3 years old, health investments are in fact the strongest determinant of next period skill behind socio-emotional skill itself. The same is true for cognitive investments in the following period, meaning that early socio-emotional skill appears to be particularly influenced by household investment behaviours. Appendix Tables B27 and B28 also show estimates of the socio-emotional production function with interactions of socio-emotional skill with health and cognitive investments respectively. In neither table is there evidence of dynamic complementarities between skills and investments.

[17] It is not possible to rule out that this is not partly a result of the methodology used. Despite minimising the extent to which measures capture variation in more than one latent variable, using many instruments for many endogenous regressors means counterintuitive results like this might be driven by correlations across measures of different unobservables. I discuss this in more detail at the end of this section.

Table 2.6: Estimates of Cobb-Douglas socio-emotional skill production function

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.233	0.117	0.125*	0.022	0.109
	(0.289)	(0.144)	(0.070)	(0.075)	(0.077)
	[-0.243,0.709]	[-0.121,0.354]	[0.009,0.240]	[-0.102,0.145]	[-0.019,0.236]
$\ln H_{c,t-1}$	0.295	0.033	0.006	0.071**	0.017
	(0.412)	(0.054)	(0.037)	(0.032)	(0.011)
	[-0.383,0.972]	[-0.056,0.122]	[-0.054,0.067]	[0.019,0.123]	[-0.001,0.035]
$\ln H_{s,t-1}$	0.438**	0.409***	0.788***	0.678***	0.313***
	(0.204)	(0.015)	(0.022)	(0.022)	(0.023)
	[0.102,0.774]	[0.385,0.434]	[0.753,0.824]	[0.642,0.715]	[0.276,0.350]
Parental human capital (fixed over time)					
$\ln P_h$	0.006	-0.015	-0.009	0.049	0.047
	(0.059)	(0.045)	(0.035)	(0.040)	(0.033)
	[-0.091,0.103]	[-0.090,0.060]	[-0.067,0.048]	[-0.017,0.114]	[-0.006,0.101]
$\ln P_c$	0.524***	0.044	0.139***	0.076*	0.084***
	(0.070)	(0.048)	(0.035)	(0.040)	(0.029)
	[0.408,0.640]	[-0.036,0.123]	[0.082,0.197]	[0.010,0.142]	[0.036,0.132]
$\ln P_s$	0.396***	0.097***	0.058**	0.044	0.035*
	(0.037)	(0.025)	(0.023)	(0.027)	(0.020)
	[0.335,0.457]	[0.056,0.138]	[0.020,0.096]	[-0.000,0.088]	[0.002,0.069]
Investments					
$\ln I_{h,t-1}$	0.714***	0.137	0.048	0.325***	0.026
	(0.083)	(0.122)	(0.029)	(0.088)	(0.017)
	[0.577,0.850]	[-0.064,0.339]	[-0.000,0.097]	[0.181,0.469]	[-0.001,0.054]
$\ln I_{c,t-1}$	0.061***	0.469***	-0.011	0.021	0.074
	(0.018)	(0.102)	(0.012)	(0.069)	(0.080)
	[0.031,0.092]	[0.301,0.637]	[-0.030,0.009]	[-0.091,0.134]	[-0.058,0.206]
$\ln A_t$	-0.471***	1.089***	1.127***	1.138***	0.156***
	(0.065)	(0.055)	(0.049)	(0.046)	(0.037)
	[-0.577,-0.364]	[0.999,1.178]	[1.047,1.208]	[1.063,1.214]	[0.096,0.217]
RTS	2.667***	1.291***	1.146***	1.286***	0.705***
	(0.338)	(0.156)	(0.072)	(0.107)	(0.098)
	[2.111,3.223]	[1.034,1.548]	[1.027,1.265]	[1.110,1.462]	[0.544,0.866]
$\sigma^2_{\eta_n}$	0.919***	0.349***	0.384***	0.384***	0.152***
	(0.085)	(0.032)	(0.033)	(0.029)	(0.011)
	[0.780,1.059]	[0.297,0.401]	[0.329,0.439]	[0.337,0.432]	[0.134,0.171]
N	8,195	6,908	7,892	7,578	7,619

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each column is children's socio-emotional skill measured by the observables in Appendix Table B18. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left-most are lagged child health, cognitive skill and socio-emotional skill; parents' health, cognitive skill and socio-emotional skill; and health and cognitive investment, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

Socio-emotional skill is considerably more malleable than health. The estimates of its RTS are far larger than that of health in each period. Its RTS are actually estimated to be statistically greater than one across the first four periods, and in the first period they are estimated to be greater than 2 - a 1% increase in each of its inputs are associated with a 2.7% increase in socio-emotional skill at age 3. The estimates of TFP are also substantially higher across all but the last period.

How Does Excluding Health Affect Estimates of Skill Production Functions?

To show the importance of considering health in an analysis of skill development, I also estimate the investment and productions functions excluding heath. Table 2.7 shows results from this exercise for the parameters of the cognitive production functions. I focus on these results here since health was estimated to have the strongest effect on cognitive as opposed to socio-emotional development. Whilst the qualitative results remain unchanged, excluding children's and parents' health and health investments from the skill production functions results in several significant changes to parameter estimates. In Table 2.7, the elasticity of cognition with respect to socio-emotional skill in the first period almost doubles, and in the second period its self-productivity increases by one-third. Omitting health investments also increases the estimated effect of cognitive investments in the first and last periods, when they were estimated to positively affect cognitive development.

This also highlights a result of the previous section as it relates to health investments - cognitive investments affect cognitive development negatively in periods 2, 3 and 4 as compensatory investments are not met with increases in cognition. When excluding health investments, the magnitude of these negative effects increase in absolute terms due to the negative correlation between investments - likely a product of parents trading off investments for one another.

For socio-emotional skill, Appendix Table B30 shows that excluding health also results in its self-productivity more than doubling in the first period and the effect of cognition reversing direction to be *negative*. Taken at face-value, this would suggest babies with high level of cognition at 9 months have lower stocks of socio-emotional skill at age 3. However, this relationship arises due to the exclusion of health *investments* from the socio-emotional skill production function, as opposed to *health* itself. Returning to the results presented in Table 2.2, there is a very large compensatory investment response to cognition in the first period, and in Table 2.6 these investments have a large positive effect on socio-emotional skill production in the same period. As a result, excluding health investments results in the appearance of a negative relationship between cognitive and socio-emotional skills in this period. The conclusions about the process of socio-emotional development are broadly unchanged thereafter, again suggesting that cognitive development is tied more to health.

Table 2.7: Estimates of Cobb-Douglas cognitive skill production function, excluding health

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{c,t-1}$	0.180	0.962***	0.749***	0.993***	0.123***
	(0.132)	(0.185)	(0.045)	(0.145)	(0.019)
	[-0.037,0.396]	[0.658,1.267]	[0.675,0.823]	[0.754,1.231]	[0.092,0.154]
$\ln H_{s,t-1}$	0.312***	0.097***	0.043	0.029	0.013
	(0.090)	(0.035)	(0.027)	(0.043)	(0.036)
	[0.164,0.460]	[0.039,0.155]	[-0.001,0.087]	[-0.042,0.100]	[-0.046,0.073]
Parental human capital (fixed over time)					
$\ln P_c$	0.397***	0.168**	0.236***	0.239***	0.472***
	(0.065)	(0.073)	(0.045)	(0.074)	(0.080)
	[0.291,0.503]	[0.048,0.288]	[0.161,0.310]	[0.117,0.360]	[0.340,0.604]
$\ln P_s$	0.023	-0.004	0.019	0.081*	0.033
	(0.016)	(0.037)	(0.025)	(0.045)	(0.028)
	[-0.003,0.048]	[-0.065,0.057]	[-0.023,0.061]	[0.006,0.156]	[-0.013,0.079]
Investments					
$\ln I_{c,t-1}$	0.089***	-0.223	-0.047**	-0.341*	0.359***
	(0.018)	(0.246)	(0.019)	(0.178)	(0.105)
	[0.060,0.118]	[-0.627,0.182]	[-0.078,-0.017]	[-0.633,-0.049]	[0.186,0.531]
$\sigma^2_{\eta_c}$	1.226	0.284***	0.218***	5.415**	0.173***
	(43.914)	(0.064)	(0.067)	(2.491)	(0.041)
	[-71.006,73.458]	[0.178,0.390]	[0.107,0.328]	[1.317,9.512]	[0.106,0.240]
N	8002	6906	7866	7390	7468

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's cognitive skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child cognitive and socio-emotional skill; parental cognitive and socio-emotional skill; and cognitive investment, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

2.5 Simulating Counterfactual Development Paths

In this section I explore the implications of the estimated model for health and skill development. I then simulate how health and skills evolve when three inputs into the developmental process are altered across different stages of childhood:

1. family income;
2. children's health; and
3. the early environment through parental health and education.

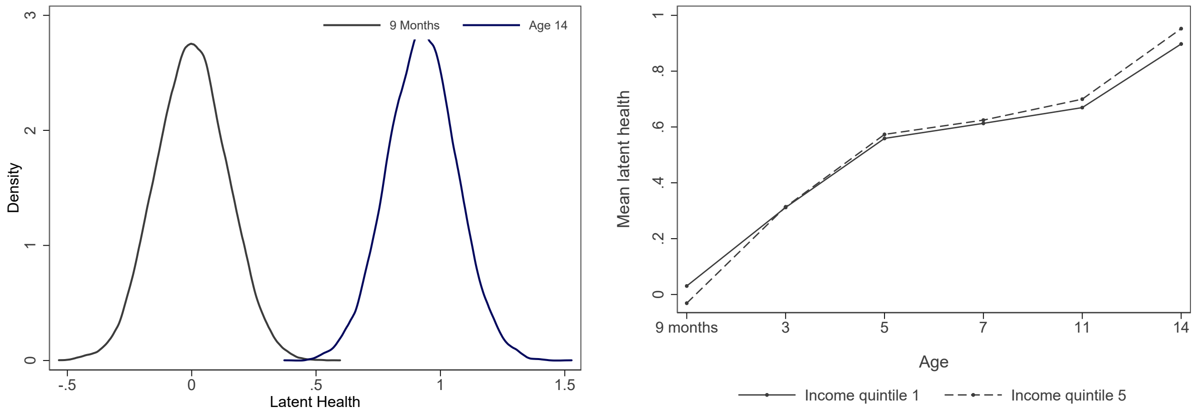
In all three scenarios, I examine how such changes might directly and indirectly affect the development of health and socio-emotional and cognitive skills. To do so, I draw a sample of 10,000 observations from the estimated joint distribution of initial conditions - shown in Appendix Tables B22 and B23 - and simulate the developmental paths of health and skills with and without these "interventions" using estimates of the production and investment functions from section 2.4.

2.5.1 The Estimated Developmental Path of Health and Skills

Figure 2.2 shows this estimated development path of health in the absence of any change to inputs from two perspectives. Firstly, Panel (a) shows its simulated distribution at 9 months and age 14 - the initial and end period of the model. As might be expected given its estimated persistence, the distribution of latent health stays similar over time. This also makes clear that I have modelled health as a stock of human capital that builds across childhood, a conceptual approach that differs from the view of health production of, for example, Grossman (1972) in which health is viewed a stock that depreciates over time, and "improves" only through investments. This approach is focussed on human capital in adulthood, however, and is less suitable here given that the phase of life being studied is one in which children grow and develop into young adults.

Figure 2.2(b) then plots the mean level of log latent health at the top and bottom of the simulated income distribution over time. This shows that children's health is not dissimilar across the income distribution over much of childhood, but by age 14 there is a small income inequality in health that is equal to roughly one-half of a standard deviation of its distribution. This implies that although health is persistent over time, small differences across the income distribution emerge mainly in the latter stages of childhood. Bearing in mind the results of the previous section, it is likely that this is driven by disparities in cognitive and socio-emotional skills. Comparing the gradient here with that in the observables measures in Figure 2.1 also highlights the importance of using multiple measures to back out latent health - using either of the two panels of the figure to draw conclusions about health might lead to the under or overstating the extent of the relationship between health and income.

Figure 2.2: The estimated path of health capital over time



(a) **(b)**

Note: Panel (a) the simulated distribution of health at 9 months and age 14, and panel (b) shows the simulated evolution of mean latent health in the top and bottom quintiles of the income distribution. Both were estimated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions.

Appendix Figure B5 provides analogous plots for cognitive and socio-emotional skills. It shows that health and health inequalities evolve differently to those in skills. The distribution of socio-emotional skill becomes narrower over time, and early inequalities across the income distribution reduce in later childhood. The resulting income gradient is similar than that of health.[18] On the other hand, the distribution of cognition flattens over time, and there is a much larger difference in the average level of cognitive skill at the top and bottom of the income distribution.

2.5.2 Short and Long-Term Effects of Altering Inputs of the Developmental Process

Before presenting the estimated developmental path after altering inputs, it is first useful to consider their potential short (i.e. immediate effect in t) and long-term effects (i.e. at the end of childhood) in terms of the parameters of the production and investment functions. Here I outline these effects using the example of income transfer, however the intuition can then be applied to all interventions considered.

The effects of income transfers will initially come through the effects of changes in investment. Any increases in human capital induced by these changes will then be propagated through childhood. Formally, given endowments, child human capital and income, the immediate, marginal impact of a one-time change to income in any of the t periods on next period's $(t + 1)$

[18] The decline in socio-emotional skill in the last period is driven by the very low RTS and TFP estimates between 11 and 14.

health can be expressed as:[19]

$$\Delta^{Y}_{h,t+1}(\mathbf{\Omega}_t) = \frac{\partial \ln H_{h,t+1}}{\partial Y_t} = \frac{\partial \ln H_{h,t}}{\partial \ln I_{h,t}} \frac{\partial \ln I_{h,t}}{\partial Y_t},$$

where $\mathbf{\Omega}_t = \{H_{h,t}, H_{c,t}, H_{s,t}, P_h, P_c, P_s, Y_t\}$ is the vector of state variables which are observed at the beginning of the period. In the baseline, Cobb-Douglas form of the health production function this marginal effect is equivalent to:

$$\Delta^{Y}_{h,t+1}(\mathbf{\Omega}_t) = \frac{\partial \ln H_{h,t}}{\partial Y_t} = \gamma^{h}_{h,t} \times \frac{\beta^{h}_{7,t}}{Y_t} \tag{2.8}$$

Given that this effect can vary with household income, it is possible to analyse how the impact of transfers would differ depending on family resources.[20] The results in Section 2.4 showed that investment did not enter significantly (statistically or economically) into the health production function, however. As a result, these short-term effects will be (or be very close to) zero. Cognitive and socio-emotional skills can impact health development, meaning it is possible that income transfers have an impact on health in the long-run. Too see how, the impact of changes to income on health at the end of childhood can be written as a function of all short term impacts up until that point:

$$\begin{aligned}\Delta^{Y}_{h,L}(\mathbf{\Omega}_t) = {} & \underbrace{\Delta^{Y}_{h,L-1}(\mathbf{\Omega}_t) \times \left(\frac{\partial \ln H_{h,L}}{\partial \ln H_{h,t+L-1}} + \frac{\partial \ln H_{h,L}}{\partial \ln I_{h,L-1}} \frac{\partial \ln I_{h,L-1}}{\partial \ln H_{h,L-1}} \right)}_{\text{effect of the change in \textit{lagged} health induced by income change}} \\ & \underbrace{+ \sum_{j \in \{c,s\}} \Delta^{Y}_{j,L-1}(\mathbf{\Omega}_t) \times \left(\frac{\partial \ln H_{h,L}}{\partial \ln H_{j,L-1}} + \frac{\partial \ln H_{h,L}}{\partial \ln I_{h,L-1}} \frac{\partial \ln I_{h,L-1}}{\partial \ln H_{j,L-1}} + \frac{\partial \ln H_{h,L}}{\partial \ln I_{c,L-1}} \frac{\partial \ln I_{c,L-1}}{\partial \ln H_{j,L-1}} \right)}_{\text{effect of the change in \textit{lagged} cognitive and socio-emotional skill induced by income change}},\end{aligned} \tag{2.9}$$

where $t + L = t + (T - t)$; the end of childhood.[21] Above, implicit in $\Delta_{k,t+\tau-1}$ for $k \in \{h, c, s\}$ is the full history of marginal effects on skill accumulation up until that point. For example, if childhood had only 3 periods (i.e. $L = 3$), the long-term impact of increasing income in period 1 on health is given by:

[19] This presentation of the marginal effects of an income transfer follows from Agostinelli and Wiswall (2016a)

[20] If an interaction of health with health investment was included in the production function, the short-term effect would also capture dynamic complementarities through an additional term: $\kappa^{h}_{hh,t} \times \frac{\beta^{h}_{7,t}}{Y_t} \times H_{h,t}$. Given the results provided no evidence of these relationships, I exclude them here.

[21] Note here that the cognitive and socio-emotional skill cross-productivity components of Equation 2.9, have an additional term as both are affected by health *and* cognitive investments

$$
\begin{aligned}
\Delta^{Y}_{h,3}(\mathbf{\Omega}_1) = & \left[\gamma^{h}_{h,t} \times \frac{\beta^{h}_{7,t}}{Y_1}\right] \times \left(\rho^{h}_{h,2} + \gamma^{h}_{h,2}\beta^{h}_{1,2}\right) \\
& + \left[\left(\gamma^{c}_{h,t} \times \frac{\beta^{h}_{7,t}}{Y_1}\right) + \left(\gamma^{c}_{c,t} \times \frac{\beta^{c}_{7,t}}{Y_1}\right)\right] \times \left(\rho^{h}_{c,2} + \gamma^{h}_{h,2}\beta^{h}_{2,2} + \gamma^{h}_{c,2}\beta^{c}_{2,2}\right) \\
& + \left[\left(\gamma^{s}_{h,t} \times \frac{\beta^{h}_{7,t}}{Y_1}\right) + \left(\gamma^{s}_{c,t} \times \frac{\beta^{c}_{7,t}}{Y_1}\right)\right] \times \left(\rho^{h}_{s,2} + \gamma^{h}_{h,2}\beta^{h}_{3,2} + \gamma^{h}_{c,2}\beta^{c}_{3,2}\right)
\end{aligned} \tag{2.10}
$$

The change in income initially has an impact on health through increased investments. Increased income in period 1 then has two effects at the end of childhood. Firstly, there is a direct effect on the accumulation of health, realised through self-productivity ($\rho^{h}_{h,2}$) and any investment response ($\gamma^{h}_{h,2}\beta^{h}_{1,2}$). Secondly, there is an indirect impact that comes through the cross productivity of cognitive and socio-emotional skill in the development of health ($\rho^{h}_{c,2}, \rho^{h}_{s,2}$), as well as any investment response in period 2 to changes in their stocks ($(\gamma^{h}_{h,2}\beta^{h}_{2,2} + \gamma^{h}_{c,2}\beta^{c}_{2,2})$). The short and long-term effects on cognitive and socio-emotional skill can be expressed in an identical manner.

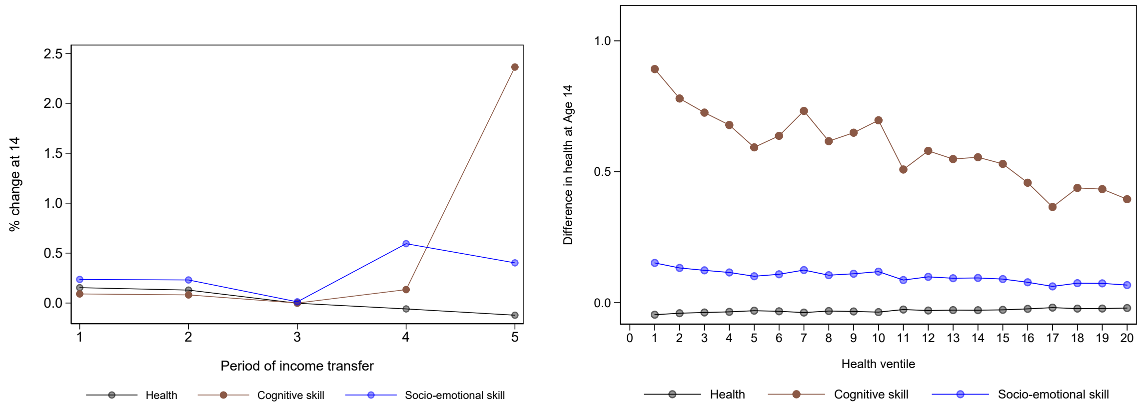
2.5.3 The Impact of Increasing Family Income Across Childhood

To understand the potential effects of increasing family income on child health and skills, I simulate the impact of a one-time £5,000 increase to family income - equivalent to around one-third of median equivalised annual income in sample - to all children in the sample in each period. I assume that all of the income is spent in the period in which it is given. Generally, the income transfers have the largest long-term impact on cognitive and socio-emotional skill when given late (7-11; 11-14), and have no effect on health when given in any period (see Appendix Figure B6(a) and Table Appendix Table B31).[22] There is also little evidence that the effects of these transfer differs across the distribution of income or health (Figure B6). This is because the marginal effect of investments can vary across the income distribution.

It is also possible to estimate the potential effects of increasing income only for those in the poorest families. Given that changes in children's human capital after of un-conditional transfers were constant across the income and health distribution (Figure B6), the effects of these targeted increases to income will be no different in magnitude to those that result from a transfer to the whole sample. Figure 2.3(a) confirms this. However, a concern of targeted transfers such as this is whether or not they can reduce inequalities. Figure 2.3(b) shows the overall change in the composition of skills among *all* children in ventiles of the health distribution at 14 given a

[22]For health, the short-term effects in Figure B6(a) are negative in all but the first period because investments were estimated to have a small, statistically insignificant negative elasticity in health production. All estimated parameters are used to forward simulate the model regardless of their statistical significance.

Figure 2.3: The long-term human capital impacts of a £5,000 increase in income across childhood for these in the bottom quartile of the income distribution



(a) Long-term effects on recipients by round of increase to income

(b) Overall change in average human capital among health ventiles given a targeted increase to income at age 11

Note: Panel (a) shows the % increase in health and cognitive and socio-emotional skill at 14 given an increase in income of £5,000 to those in the bottom 25% of the income distribution at the age shown on the x-axis. Panel (b) shows the % increase in each component of human capital at 14 among all children in each health ventile given an increase in income at age 11 to those in the bottom 25% of the income distribution. The effects were calculate by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without directed changes to income in each period. It is assumed that the income is spent fully in the period of increase.

an increase in income for only the 25% poorest children at age 11 (again the period when their effect is largest). It shows that this targeted increase in income affects the composition of skills most at the lower end of the health distribution: because poorer children have lower health on average by age 11, these transfers have the largest effect on average cognitive and, to a lesser extent, socio-emotional skill among those in the bottom of the health distribution. Still, however, the estimated model suggests there would be no effect on health. Appendix Table B32 shows both the short and long-term effect of these targeted increase to family income on the children who benefited by the period in which they were given.

The estimated model suggests that the impact of income changes on cognitive and socio-emotional skill are small due for two reasons. Firstly, the effect of income on investments was often relatively small, meaning increases in income are not necessarily translated into large increases in investment. This is perhaps intuitive given the measures used are of *time* as opposed to *material* investments. Second, long-term effects are driven by self-productivities, and there are no dynamic complementarities present between skills and investments. The result is that any small short-term impacts fade over time.

There is a large body of evidence on the importance of the timing of increases in parental income on skill development itself, as well as on the eventual link between socioeconomic outcomes of children and their parents' income. For example, Attanasio et al. (2020c) also simulate income transfers and find that they have a larger impact when given before 5 for cognition and between 5 and 8 for health. They find that their measures of investments do impact health production, however. That I find changes to income later in childhood impact skills to a greater extent than those early is in contrast to Agostinelli and Wiswall (2016a), who find that income transfers have their largest effect on when given as early as age 5. This is driven by the fact they estimate cognition to have high returns to scale in early childhood, and its technology to displays dynamic complementarities between cognition and investments. Whilst they provide contrary evidence, the results of the simulations here alongside those of Agostinelli and Wiswall (2016a) and Attanasio et al. (2020c) are somewhat in line results in Carneiro et al. (2021) which suggest increases in income are, conditional on permanent income, more productive in promoting improved socioeconomic outcomes in adulthood when experienced in early and late - as opposed to middle - childhood. Carneiro et al. (2021) do suggest that given the complementarity between skills and investments across periods, however, children who experience a balanced income profile across these stages of childhood have improved outcomes in adulthood relative to those whose income is primarily concentrated in either.

Overall, beyond the timing of income, the simulations here can perhaps be interpreted as evidence that it is difficult to impact health, or cognitive and socio-emotional development simply using one-off, unconditional income transfers. This echoes the findings of similar studies that have sought to estimate the impact of income transfers on child development or adult outcomes as they act through increased levels of household investment (Del Boca et al., 2013, 2016).

2.5.4 The Impact of Health Improvements Across Childhood

Altering the early environment by simulating "health improvements" somewhat abstract relative to increasing income. Policies aimed at doing so would not be straightforward to design. *How* they were conducted would also require a clear definition of the aspects of health they sought to improve. As discussed in Section 2.3, I measure health by long-term illnesses and short-term health conditions. A health-improving intervention in this context would therefore require reductions in both of these things, perhaps through home-visitation or additional health care for children in the poorest health. Such supplemental health care programmes have been implemented in England and Germany, and there is evidence they have improved children's health both directly and indirectly.[23]

The short-term impact of health improvements differ from those of an increase in income due to their direct effect in health (and skill) production in the period of the improvement. This immediate increase in health then gives rise to a long-term change in an identical manner as

[23]Cattan et al. (2019) outline and analyse the effects of England's "Sure Start" policy, and Sandner et al. (2018) do the same for Germany's "Pro Kind" intervention.

shown in Equation 2.9.[24] Appendix Figure B7(a) shows the simulated long-term (age 14) changes in health and skills arising as a result a one standard deviation health improvement by the period in which it occurs. Again, these improvements are estimated to affect human capital the most when made in the final period, between the ages of 11 and 14. For example, a one standard deviation increase in health at age 11 is associated with an increase in health at 14 by 10%, and an increase in cognitive and socio-emotional skills of 2% and 1.2% respectively. As in the case of increasing income, the relatively large effects of this late health improvements are a consequence of short-term effects fading out. Appendix Table B33 shows the simulated short and long-term changes in health and skills.[25]

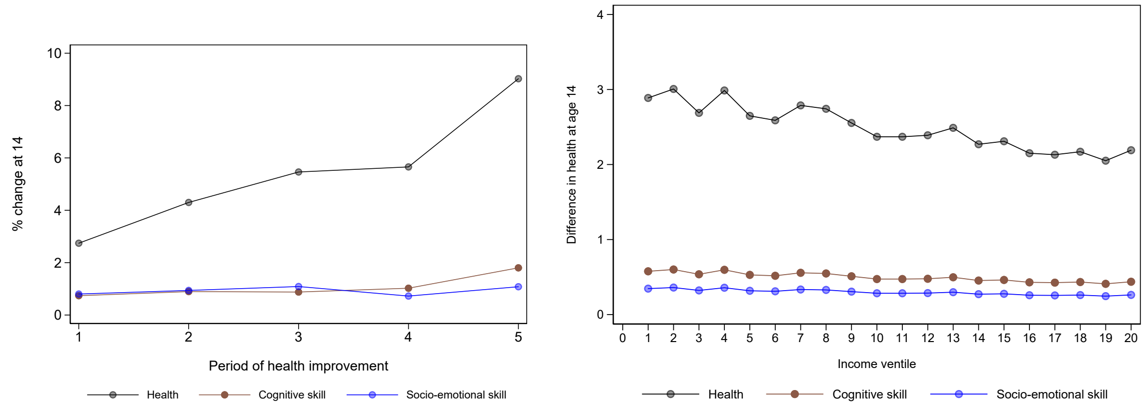
Improving health at age 11 increases cognition at 14 because it is estimated to be an important determinant in cognitive production in late childhood. Similarly, although it did not enter significantly into the socio-emotional skill production function, the two are still highly correlated. Not considering health in the analysis of policy interventions therefore bypasses an important channel through which skills can be affected in late childhood. Appendix Figures B7(b) and B7(c) show that the changes in health and skills arising after a health improvement in the final period are constant across the income and health distributions. The results of this simulation differ slightly from those in Attanasio et al. (2020c). Although in a different setting, they estimate that health improvements have their largest long-term effect on cognition at 12 when they are received between 5 and 8. This is because they find health does not affect cognition in the latter period of their model, between 8 and 12. As I find here, however, they find that health improvements have their largest effect on health itself when given in this last period, due to its high self-productivity.

Again, it is possible to evaluate the potential effects of directing these improvements to children who are in the poorest health, and whether they affect inequalities. Once more, given the effects of health improvements are homogeneous across income and health levels, the impact of these improvements will be the same as when given to the whole sample. This is shown in Figure 2.4(a). Figure 2.4(b) shows, however, that improving health for the unhealthiest 25% of children in the sample at age 11 (when the effects of improvements are largest) changes the composition of health at 14 in the lower end of the income distribution to a larger extent. This also true for the skill composition, however the magnitude of these changes is estimated to be much smaller. Again, this is because low-income children are more likely to have poor health and less skill at age 11. Appendix Table B34 shows estimates of the short and long-term effects of these directed health improvements.

[24]Formally, conditional on $\mathbf{\Omega}_t$, the short-term effect is: $\frac{\partial \ln H_{h,t+1}}{\partial \ln H_t} = \frac{\partial \ln H_{h,t+1}}{\partial \ln H_{h,t}} + \frac{\partial \ln H_{h,t+1}}{\partial \ln I_{h,t}} \frac{\partial \ln I_{h,t}}{\partial \ln H_{h,t}}$. This differs to the short-term effect of an income transfer by the first term.

[25]Some of the short-term the effects of a health improvement on cognition are negative - i.e. in periods 3 and 4 (5-7; 7-11) - because there is a negative, statistically insignificant effect of health on cognition in these periods. Again, all estimated parameters are used to forward simulate the model regardless of their statistical significance.

Figure 2.4: The long-term human capital impacts of a one standard deviation improvement in health across childhood for those in the bottom quartile of the health distribution



(a) Long-term effects on those whose health improved by round of improvement

(b) Overall change in average human capital among income ventiles given a health improvement at age 11

Note: Panel (a) shows the % increase in health and cognitive and socio-emotional skill at 14 given one standard deviation improvement in health for those in the bottom 25% of the health distribution at the age shown on the x-axis. Panel (b) shows the % increase in each component of human capital at 14 among all children in each income ventile given a health improvement at age 11 to those in the bottom 25% of the health distribution. The effects were calculate by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without directed improvements in health in each period.

2.5.5 The Impact of Increases in Parental Health and Education

Finally, I simulate the developmental path of health and skills given increases to two components of parental human capital: a one standard deviation improvement to their health, and in increase in educational attainment. The increase in education is equivalent to moving parents up one level in the UK's National Vocational Qualification (NVQ) scale. For example, if a parent obtained failing grades in lower high school exams (ages 14-16), the intervention would increase their attainment to having passed these exams. Similarly, if they had obtained an undergraduate degree, they would be up-skilled to master's level attainment.[26] Improvements to parents' health might come through the home-visitation style programmes discussed when outlining the effects of improvements to children's health. These increases to parental human capital influence short-term development through their effect on both investments and the production process. As I have assumed they are time-invariant, the initial increases in parental human capital affect development through the same channels in all subsequent periods.

Table 2.8 shows the changes in children's health and skills at each age when these increases are

[26]There are 8 NVQ levels in total. See https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels for a full list of NVQ qualification levels in England, Wales and Northern Ireland. Sottish qualifications are converted by the MCS to their NVQ equivalents.

Table 2.8: The impacts on human capital of increases in parents' human capital across childhood

Period	**Health**		**Cognition**		**Socio-emo.**	
	Parents' edu.	*Health endow.*	*Parents' edu.*	*Health endow.*	*Parents' edu.*	*Health endow.*
Age 3	0.2554	2.1751	2.6119	-0.6960	6.1862	3.1119
	(0.1125)	(0.0000)	(1.1507)	(0.0000)	(2.7254)	(0.0000)
Age 5	0.3619	6.3300	2.6635	1.9098	3.5417	0.4409
	(0.1594)	(0.0000)	(1.1734)	(0.0000)	(1.5603)	(0.0000)
Age 7	0.2316	6.5451	3.6449	1.3896	4.0489	0.6960
	(0.1020)	(0.0000)	(1.6058)	(0.0000)	(1.7838)	(0.0000)
Age 11	0.2913	7.7631	4.3185	-2.3240	3.6722	3.7797
	(0.1283)	(0.0000)	(1.9026)	(0.0000)	(1.6178)	(0.0000)
Age 14	0.3605	8.6578	3.6877	-0.3516	2.0300	4.9764
	(0.1588)	(0.0000)	(1.6246)	(0.0000)	(0.8944)	(0.0000)
N	10,000	10,000	10,000	10,000	10,000	10,000

Note: Each cell shows $100 * E[\ln H_{j,t}^{H_h} - \ln H_{j,t}]$, the average change in human capital component j - indicated by the master column - given an increase in the component of parents' human capital indicated by each sub-column at 9 months of age. Parents' health is increased by one standard deviation and their education increased by one National Vocation Qualification level. For example, if a parent reports to have obtained lower higher school level qualifications, their education will be increased to having obtained upper high school qualifications. The differences are calculated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions, with and without the increases to parents' human capital at 9 months. Standard errors of the difference are in parentheses.

realised at 9 months. Each major-column represents the relevant component of children's human capital and each sub-column the component of parental human capital increased. The simulations suggest that increasing parents' education has the largest impact on cognitive and socio-emotional development, and little effect on health. By age 14, cognition and socio-emotional skill are estimated to be 3.7% and 2% higher than in the absence of the increase to parents' education, whereas health is only 0.36% higher. Similarly, improving parental health has the largest effect on children's health - at 8.7%, the simulated impact on health by 14 is in fact almost as large as when improving children's health itself at age 11 (Table B31). This effect builds over time from an initial change in health at age 3 of only 2.2%. Socio-emotional skill at 14 also increases as a result of improving parents' health, and is just under 5% higher than in the absence of the improvement. There is little effect on cognition.[27]

Appendix Figure B8 shows that the long-term changes in health and skills of increases in parents' education are larger for children in the lower end of the income and health distributions (panels (a) and (b)), but that the effects of improvements to parents health are constant (panels

[27]There is a small negative effect at 14 due to the small, statistically insignificant negative elasticity on parents' health in the production of cognition. See Table 2.5.

(c) and (d)). This is because parents are estimated to make investments independently of their health, but not their education. As a result, in the simulations increases in their attainment impact development through two channels, whereas those to health do so only through one. Second, the marginal effect of investments can vary across the income distribution (Equation 2.8), and investments impact cognitive but not health production.

Turning again to directed interventions, Figure the change in the composition of health and skills at 14 is more pronounced among those in lower end of the income distribution when parental health is only improved for the unhealthiest 25% of children. Similarly targeting health of parents in the *poorest* 25% of families results in the largest changes in health and skill composition among the unhealthiest children (Figure B9). Again, this is an artefact of the negative relationship between skills, health and parents' health at age 11.

Overall, the parameter estimates and simulations of this section suggest that increasing income directly is perhaps the least effective channel through which long-run health improvements can be targeted. Second, they suggest that, perhaps unsurprisingly, improvements to children's health across all stages of childhood could lead to sustained improvements in health by age 14, and that targeting them at either the poorest of unhealthiest children might reduce socioeconomic health inequalities. These simulated health improvements also lead to modest increases in skills at age 14. Lastly, they provide evidence that improving early conditions by increasing parental education and health can have similar effects on long-term health of children as improving the health of children themselves.

2.6 Conclusion

This study analysed health development between the ages of 9 months and 14, and how it affects the accumulation of two important components of human capital; cognitive and socio-emotional skills. Using detailed longitudinal data on a large sample of children born at the turn of the millennium in the UK, I have estimated investment and human capital production functions across childhood, correcting for mismeasurement of health, skills and household investments.

The results highlight several important features of health development and its role in skill accumulation. First, I find that health is highly persistent and mainly affected by past and parental health, but that in later childhood, cognitive and socio-emotional skills begin to influence its development. Cognitive and socio-emotional skills are affected by investments at various stages of childhood, and so there is a small socio-economic gradient in health by age 14. Second, I found that health affects the accumulation of cognitive skills early and late in childhood, crucial periods of development before school entry and during early high-school years. Further, my the results show that excluding health from human capital production functions results in overstating the self and cross productivities of skills in the developmental process.

Gaining a broader perspective of child development is essential to understanding if and how early disparities in human capital emerge. A growing policy concern in many high-income countries is equality of opportunity, and understanding the extent to which children's future economic opportunities are predetermined by early circumstances. I therefore simulate the impact of altering several inputs of the child development process across different stages of childhood to analyse how they might affect health and skills at 14.

In these simulations, improving parents' health had a large and persistent effect on child health at the end of childhood, and increasing their education resulted in small gains. Simulated increased to family income had almost no impact on health development, and very little effect on cognitive and socio-emotional skill. The effects of improvements to children's health are more sizable on all three components of human capital, and were largest when given in late childhood. This is in contrast to results in the literature so far which have found dynamic complementarities between skills and investments, high-persistence of human capital in late-childhood or increasing returns to scale in skill production mean interventions have their highest returns when made early. I find no evidence of dynamic complementarities in the production of any component of human capital and that health and skills are malleable between 11 and 14. As a result, early interventions are note estimated to build over time. In all simulations, targeting them towards the unhealthiest/poorest children results in larger changes to the health and skill composition among children in the lower end of the income/health distribution. This perhaps suggests that policies aimed at reducing socioeconomic disparities in human capital can be effective when targeted to early adolescence and provides evidence supporting the design of policy that considers all stages of development.

Chapter 3

Human Capital Development: New Evidence on the Production of Socio-emotional Skills

Note: *This chapter was co-authored with Marta Favara, Deputy Director of Young Lives at Work and Senior Research Officer of Young Lives at the University of Oxford (marta.favara@qeh.ox.ac.uk); Catherine Porter, a Senior Lecturer at Lancaster University (catherine.porter@lancaster.ac.uk); and Alan Sanchez, a Senior Researcher at the Grupo de Análisis para el Desarrollo (GRADE) in Peru (asanchez@grade.org.pe). All have agreed that it represents in the majority my work, and that it can be included in this thesis. My co-authors received funding for this research from the ESRC-GCRF Grant ES/S004564/1, "Inequality of Opportunity in Peru"*

3.1 Introduction

Understanding how inequalities in skills emerge through childhood into adulthood is one of the most important questions for policy in both developed and developing countries. Inequalities appear very early in life and may perpetuate intergenerational differences in income. Economic research has established that skills which influence earnings are multidimensional in nature and documented the importance of socio-emotional skills[1] in determining life outcomes such as career, income, marriage and health, beyond the effect of cognitive skills (Heckman and Rubinstein, 2001; Chiteji, 2010; Almlund et al., 2011; Heckman and Kautz, 2012). Econometric research shows multidimensional skills development can (and should) be modelled taking into account its dynamic nature, using a latent variable approach to account for imperfect measurement

[1]We use the term socio-emotional skills in this paper, though non-cognitive is also in common usage in the economics literature. They have variously been referred to as soft, social, psychosocial or personality skills in the economics literature to date, as well as personality traits, social-emotional competencies. We discuss the composition of the measures we use in detail in section 3.3.

(Heckman, 2006, 2007; Cunha and Heckman, 2007; Cunha et al., 2010). This has generated important insights into skill formation, including the existence of critical periods for skills development, the role of parental investments, and the potential "cross-productivity", between cognitive and socio-emotional skills (Heckman et al., 2006). Most of the evidence on the formation of socio-emotional skills comes from research on developed countries, arguably due to data availability. However understanding these processes and how skills themselves determine social and economic outcomes is equally, or perhaps even more important for developing countries (Roy et al., 2018).

This paper makes three contributions to the literature on skill formation: first, we estimate flexible socio-emotional skill production functions throughout childhood into early adulthood in a developing country that capture key aspects of the skill development process (e.g. Cunha et al. (2010), Attanasio et al. (2017, 2020b,c), Agostinelli and Wiswall (2016a)). Using data from the Young Lives (YL) study and exploiting recent methodological results for estimating dynamic factor models (Agostinelli and Wiswall, 2016a), we consider how socio-emotional skills and cognition develop as a function of parental background and measures of household investment between the age of 8, 12, 15, 19 and 22 years. Second, we exploit the careful design of our dataset in its most recent round (age 22) to disaggregate socio-emotional skill formation during early adulthood into two latent skills which are important for future labour market outcomes; (1) 'social skills' - skills which enable individuals to work with others; and (2) 'task effectiveness'- skills incorporating aspects of conscientiousness, self-efficacy and persistence (or grit). Finally, and given that earnings are not fully informative as many in the sample have not yet completed their education, we consider the effect of socio-emotional skills on risky behaviours at 22.

Peru is a middle-income country with persistent levels of inequality according to World Bank estimates (monetary poverty: 20.2% in 2019; Gini coefficient: 0.44 in 2016). The literature on human capital production, particularly in developed countries, has expanded a great deal over the past two decades; Del Boca et al. (2013) and Almond et al. (2018) review much of the evidence. Within this literature, socio-emotional skills have been shown to play a key role in the developmental process and later life social and economic outcomes. Heckman et al. (2013) document that the influential Perry pre-school program improved later life outcomes mainly through its lasting effect on socio-emotional skills, and Cunha et al. (2010) find that whilst 16% of the variation in educational attainment among a sample of adults in the US is explained by adolescent cognition, 12% is due to adolescent socio-emotional traits (see also Duckworth et al. (2007); Almlund et al. (2011)). Analysing how socio-emotional skills are shaped by early circumstances in a country such as Peru is therefore important for understanding how the inequality it has is generated and persists, as well as how and when it can perhaps be reduced - there is a small body evidence on the effectiveness of interventions aimed at improving socio-emotional skills in low- and middle-income countries from small-scale experiments on older girls or young women (Krishnan and Krutikova, 2013; Ashraf et al., 2020; Edmonds et al., 2020). Alan and Ertac (2018) and Alan et al. (2019) have also showed the effectiveness of a larger elementary school-based intervention on the socio-emotional skills of patience and grit (persistence) respectively in Turkey, though for younger children, around the age of ten.

We find that cognitive skills are the most important input of skill development across all stages between the ages of 8 and 19: cognition is not only highly, and increasingly, self-productive over childhood, it is also the driver of socio-emotional skill accumulation. At the same time, we find that socio-emotional skills do not affect cognitive development at any stage. Our results also suggest that socio-emotional skill is positively affected by investments, particularly between the ages of 8 and 12, and that, their returns differ significantly across the distribution of child skills - investments are most productive for children with low levels of cognitive skill. Similarly, cognitive development is affected by investments at all ages. As a result, a socioeconomic gradient in socio-emotional skill emerges between the ages of 8 and 12 and widens over adolescence.

Only three papers to our knowledge estimate the production function for both cognitive *and* socio-emotional skills in a developing country context, however all cover only the period during very early childhood.[2] Notably, two studies (Helmers and Patnam (2011) and Sánchez (2017)) also utilise data from the Young Lives study, which is one of the few available in developing countries that includes detailed longitudinal information on children and families through childhood. We build on this work by providing new evidence on the production of socio-emotional skills going beyond the period of very early childhood that has been studied previously. Using a cohort study in China, Glewwe et al. (2017) do provide reduced-form evidence that a range of socio-emotional skills at age 9-12 are predictive of school to work transitions at age 17-21 after controlling for cognitive skills. Our work builds on this by formalising the process of socio-emotional skill accumulation, and investigating how its dynamic nature gives way to such relationships.

Modelling socio-emotional skill as an aggregate "bundle" as we do between the ages of 8-19 has become commonplace in the economics literature on human capital development, primarily due to limitations in the type of data (that we also face) required to estimate dynamic models of skill accumulation. Paired with recent developments in flexible econometric methods that take account of imperfectly observed skills, this literature has progressed almost independently of the discussion on the definition of socio-emotional skills. Lundberg (2017) notes "a lack of consensus about what non-cognitive (socio-emotional) skills are, and the absence of a consistent set of metrics that can be applied across studies" (p220). In Heckman et al. (2006)'s seminal paper establishing that a low-dimensional vector of latent skills was predictive of life outcomes, just two measures of socio-emotional skills were used: *Locus of Control* and *Self-Esteem*. Whilst this work has spawned a literature that tends to invoke a single factor approach to socio-emotional/non-cognitive skills, the authors note "Since there are many aspects of non-cognitive skills – self-control, time preference, sociability, and so forth – it is less likely that one trait

[2]Attanasio et al. (2020b) investigate socio-emotional skill development in Colombia aged up to four years; Helmers and Patnam (2011) estimate the technology of cognitive and socio-emotional skill formation in India from ages 8 to 12; and Sánchez (2017) provides estimates for a similar model in Peru, but only from ages 1 to 8. There are a handful of studies which estimate human capital production functions in developing countries (e.g. Attanasio et al. (2017, 2020c), Keane et al. (2018)), and these focus mainly on cognitive skills and health.

captures all aspects of these behaviors" (p420).

In its latest round, at age 22, the YL survey was carefully designed to expand its assessment of socio-emotional skills. We make use of the detailed nature of the data at this age to disaggregate socio-emotional skills into distinct domains. From an exploratory factor analysis, we find that a range of measures of socio-emotional skills vary along two distinct dimensions that we label *social skills* and *task effectiveness*. The latent trait we call social skills is correlated with measures of young adults' ability to work in teams, form relationships with their peers and take on leadership roles. Task-effectiveness is measured by indexes of agency: aspects of the ability to act independently and make one's own life choices (Emirbayer and Mische, 1998); self-efficacy: belief in one's own ability to execute tasks that lead to the accomplishment of goals (Bandura, 2010); grit: a measure of perseverance and passion for long-term goals (Duckworth and Quinn, 2009); and conscientiousness, the "tendency to be organized, responsible, and hardworking" (VandenBos, 2007). Social skills, task effectiveness or the indices that we find to measure them have been linked to a range of social and economic outcomes. For example, Duckworth et al. (2007), Duckworth and Quinn (2009) and recently Alan et al. (2019) have shown grit to be associated with attainment and employment outcomes; Borghans et al. (2008) have shown the predictive power of conscientiousness for outcomes like years of education and job performance; and Heckman et al. (2013) showed how the Perry Pre-School programme, which targeted social skills such as working with others and resolving conflict, affected long-term social and economic outcomes of the participants.

We find that the bundles social skills and task effectiveness develop differently over early adulthood (ages 19-22). Aggregate socio-emotional accumulated by the end of adolescence (age 19) strongly, positively affects both social skills and task effectiveness at 22, however cognitive skill enters *negatively* into a production function of the latter, suggesting a substitution effect - those with lower cognitive skills may improve their social skills to compensate. In a similar fashion to Keane et al. (2018), we also examine how early interaction with the labour market or higher education might impact on the formation of socio-emotional skills over the same period by including time use - time spent in paid and unpaid work, care, leisure, and time studying - as a factor affecting their TFP. As with cognition, we find that time use impacts the two domains differently: time spent studying is associated with higher levels of task-effectiveness but hours spent in home production, work or caring for family members has the opposite effect, whereas none have any effect on social skills. By then examining the relationship between skills and risky behaviour, we provide evidence that having higher levels of task effectiveness is associated with a reduced probability of having smoked, taken drugs or engaged in gang activity by age 22. This is in spite of the small sample size and data intensive methods we use to estimate these relationships.

Together, our results suggest that early inequalities in cognitive skills and family background drive the emergence and widening of inequalities in socio-emotional skills, which are in turn important in determining behaviours predictive of future social and economic outcomes. They add to a growing body of evidence on the importance of early conditions in determining the development of human capital, and show that the impact of the family environment goes beyond its effect on cognition to influence young adults' social skills and sense of ability to control their life circumstances.

The remainder of this paper is structured as follows: Section 3.2 outlines our empirical model of human capital development; Section 3.3 describes the data we use to estimate this model and presents some descriptive evidence as to income gradients of cognitive and socio-emotional skills; Section 3.4 discusses the estimates of the model of human capital development between the ages of 8 and 19; Section 3.5 presents evidence on how socio-emotional skills accumulated over early adulthood and impact risky behaviour ate age 22; and Section 3.6 concludes with a discussion of our results.

3.2 An Empirical Model of Skill Development

Our model of skills development follows Agostinelli and Wiswall (2016a). We assume that socio-emotional (s) skill is 'produced' over T discrete periods, where T marks the end of childhood and adolescence. Whilst socio-emotional skills are broad and complex, we focus on the evolution of a one-dimensional *aggregate* across the early periods, a simplification that is now the norm in the literature on human capital development (discussed above), and is relaxed in our final period. At the beginning of the period, $t = 0$, the set of initial conditions are a child's human capital, human capital of their parents, and the resources of their family. In subsequent periods $t = 1, .., T$, we assume that the developmental process has two main features: a function governing the development of human capital and another determining how families make investments. The latter of these determines how present (t) human capital of children and parents and family resources determines household investment behaviour, and the former how future ($t + 1$) human capital is determined by the same inputs (except resources) and investments. We assume an identical process for cognitive (c) skill development over the same period. In our data, initial conditions ($t = 0$) are observed at age 8, and the end of childhood and adolescence ($t = T$) at age 19.

In order to capture potential malleability in skills over early adulthood, we then extend this framework by assuming there is some function mapping skills accumulated by the end of adolescence (T) into socio-emotional skills in early adulthood ($T + 1$). Given the relative breadth of data we have available in early adulthood, we disaggregate socio-emotional skills along two dimensions: social skills and task effectiveness. We do not model the evolution of cognitive skills over this period as the data we use in our empirical application does not measure cognition in early adulthood ($T + 1$). In the data we use to estimate the model, early adulthood ($T + 1$) corresponds to age 22.

Finally, as it is not possible to perfectly measure skills, parental human capital or investments, we follow the literature in assuming a measurement system which specifies a relationship between observable data and the underlying latent variables they measure. Throughout, we denote latent human capital of children and parents by $H_{j,t}$ and P_j for $j \in \{s, c\}$ and investments by I_t. Observable measures are denoted by Z_{θ_t} for $\theta_t \in \{H_{s,t}, H_{c,t}, P_s, P_c, I_t\}_{t=0}^{T+1}$. Specifying a measurement system in this way allows us to "back out" the underlying latent variables to be used as inputs/outputs of the investment and human capital production functions, and has become standard in the literature on human capital development over the past decade (e.g. Cunha and Heckman (2007), Cunha et al. (2010), Attanasio et al. (2017, 2020b,c)). Next we outline in more detail the five main components of our empirical model: the initial conditions; the production function of socio-emotional and cognitive skills and investment functions between $t = 0$ (age 8) and $t = T$ (19); the production function of socio-emotional skill between T and $T + 1$ (22); and the measurement system

3.2.1 Initial Conditions

The vector of initial conditions at t=0 - the beginning of a developmental stage - can be written as

$$\mathbf{\Omega} = (\ln H_{c,0}, \ln H_{s,0}, \ln P_c, \ln P_s, \ln Y_0)\,,$$

where $H_{k,0}$ and P_k for $k \in \{s, c\}$ are child and parental stocks of human capital component k respectively, and Y_0 is family income at $t = 0$. Parents' human capital is assumed to be time invariant and are captured by parental stocks of each component of human capital in the initial period. We assume that these initial conditions are jointly normally distributed:

$$\mathbf{\Omega} \sim N(\boldsymbol{\mu}_\Omega, \mathbf{\Sigma}_\Omega)\,,$$

with $\boldsymbol{\mu}_\Omega$ and $\mathbf{\Sigma}_\Omega$ being the mean vector and covariance matrix of the initial conditions respectively. This assumption of joint normality of the latent variables in the initial period does not restrict their subsequent joint distribution - a restriction Cunha et al. (2010) show would implicitly restrict the functional form of the human capital production function.

3.2.2 Investment

Using a reduced form approximation of a parental investment policy function, we specify investment at time t as

$$\ln I_t = \beta_{1,t} \ln H_{c,t} + \beta_{2,t} \ln H_{s,t} + \beta_{3,t} \ln P_c + \beta_{4,t} \ln P_s + \beta_{5,t} \ln Y_t + \pi_t \quad , \tag{3.1}$$

where Y_t, $H_{k,t}$ and P_k are as in the vector of initial conditions, and π_t is a shock to investment assumed to be mean zero with variance $\sigma^2_{\pi_t}$ but is not necessarily normally distributed. Using this approximation means abstracting from both parents' preferences and beliefs regarding the production technology and the returns to their investments in children. The cost of this flexibility is that the parameters of this investment function do not have a strict theoretical interpretation.

Considering this, the parental behaviour consistent with values of the parameters in Equation 3.1 is ambiguous. However, we interpret $\beta_{i,t} > 0$ for $i = 1, 2$ to indicate reinforcement of skills by parents, and $\beta_{i,t} < 0$ for $i = 1, 2$ to indicate skill compensation. Reinforcement is consistent with parents investing more in their child upon realising they have high stocks of human capital, and compensation with parents investing more upon realising the opposite.[3] The parameters $\beta_{i,t}$ for $i = 3, 4$, simply capture how parents' investment decisions are influenced by their own stocks of human capital. If, for example, $\beta_{4,t} < 0$, parents with higher levels of cognitive skill would invest less in their child's development.

We acknowledge that there are a vast range of possible investments that can be made in human capital, and that in the later stages of adolescence children themselves likely begin to play a role in investment decisions. In our estimation of this model, in line with similar studies (Attanasio et al., 2020c, 2017) we use measures of investment between the ages of 8-19 that cover expenditure on school resources, nutrition and time spent studying. Although very different, all of these measures are positively associated with one another. Our focus across these ages is to capture some measure of the overall investment-related environment. We treat time use as part of this aggregate investment over these ages given that Peru is a middle-income country in which many families face a high opportunity cost between sending their child to school, encouraging them to spend time on study or needing them to work. In many respects this is similar to parental time-use investments used for example in Cunha et al. (2010) and Del Boca et al. (2013). When children reach age 19 and enter early adulthood, we exploit the added flexibility afforded to us by the data at this age to broaden time-use to incorporate a range of activities that may act as direct determinants of skill accumulation. We discuss the measures of investment in Section 3.3, and the skill technology we specify between 19 and 22 below.

3.2.3 Socio-emotional Capital Accumulation

In periods $t = 1, ..T$, we assume socio-emotional skill in $t + 1$ to be a function of three types of input: children's stocks of skill, parental human capital and investments. Assuming a flexible trans-log form for the production function and considering one general type of investment, I_t, the production function of socio-emotional skill can be written as:

$$\ln H_{s,t+1} = \rho^s_{1,t} \ln H_{s,t} + \rho^s_{2,t} \ln H_{c,t} + \alpha^s_{1,t} \ln P_s + \alpha^s_{2,t} \ln P_c + \gamma^s_t \ln I_t + \kappa^s_t (\ln H_{j,t} \times \ln I_t) + \eta^s_t \quad , \quad (3.2)$$

where $H_{k,t}$ and P_k are as in Equation 3.1, and I_t and η^s_{t+1} parental investment and production

[3] Again, a consequence of the reduced form nature of the investment function is that we cannot disentangle realisation from expectations - it might be that parents that perceive returns to investments to be higher in fact invest more.

shocks respectively. The production shock is assumed to be mean zero with variance $\sigma^2_{\eta^s_t}$. The interaction term $(\ln H_{j,t} \times \ln I_t)$ for $j \in \{s, c\}$ captures complementarity between present stocks of skill and investment.[4] Assuming, for example, that $\kappa^s_t = 0$, is equivalent to assuming the production function of socio-emotional skills is Cobb-Douglas. If, however, $\kappa^s_t \neq 0$, investments can be more ($\kappa^s_t > 0$) or less ($\kappa^s_t < 0$) productive in children with higher stocks of skill.

This form of the production function captures several key aspects of human capital accumulation. For example, it allows for self- and cross-productivities in skills, represented by $\rho^s_{1,t} > 0$ and $\rho^s_{2,t} > 0$ respectively. In the case of $\kappa^s_t \neq 0$, it also captures any dynamic complementarities between already accumulated human capital and investments - the dynamic relationship between skills and investments that could result in the opening and widening of inequalities in human capital (Cunha et al., 2010). The trans-log production function can be expanded with the inclusion of further interaction terms, meaning it allows the elasticity of substitution to vary across inputs. This would not be possible if a Constant Elasticity of Substitution (CES) function was specified, as has been the case in much of the human capital development literature to date (e.g. Cunha et al. (2010), Attanasio et al. (2017, 2020b,c)). Doing so, however, is equivalent to assuming that all the inputs on the right-hand-side of Equation 3.2 can substitute equally for one another in production of socio-emotional skills. For example, in our application of the model we use (among others) expenditures on books and time spent at school as proxies for household investment. A CES production function would impose that these investments can 'make-up' equally for socio-emotional skill and cognitive deficits in the production of socio-emotional skills.

A key interest in estimating Equation 3.2 is the role of investments. Attanasio et al. (2020c) show by using Young Lives data in India that investments are endogenous in the production of skills, and that this endogeneity leads to *understating* the role of investments in skill production. Using a similar framework, they find a consistent negative relationship between the residual from their investment equation and cognitive development, suggesting that the responses of parents to negative shocks of human capital could be compensatory, and that not accounting for this could lead to lower estimates of the effect of investments on skill development. We do not explicitly account for this endogeneity here, and do not seek to identify the causal effect of investments on health. Rather, we focus on the describing the potential importance of investments in development, as opposed to obtaining specific point estimates of its importance. We also acknowledge that, given the methodology we use to estimate the model, this endogeneity might have implications for consistent estimation of the parameters of the skills production functions. We discuss the methodology and its assumptions in Sections 3.2.6 and 3.2.7, and bear this in mind when interpreting our results that they might represent underestimates of the impact investments might have.

[4] It is possible to include both $(\ln H_{s,t} \times \ln I_t)$ and $(\ln H_{s,t} \times \ln I_t)$ simultaneously. However, in estimating Equation 3.2 we only include one interaction at a time due to the collinearity between the interaction terms.

3.2.4 Socio-emotional Skill and Cognitive Development

To examine how socio-emotional skill affects cognitive development over childhood and adolescence, we specify the same trans-log functional form as in Equation 3.2 for cognitive development:

$$\ln H_{c,t+1} = \rho^c_{1,t} \ln H_{c,t} + \rho^c_{2,t} \ln H_{s,t} + \alpha^c_{1,t} \ln P_c + \alpha^c_{2,t} \ln P_s + \gamma^c_t \ln I_t + \kappa^c_t (\ln H_{j,t} \times \ln I_t) + \eta^c_t \quad (3.3)$$

In the above equation, all parameters have an identical interpretation to their analogues in Equation 3.2 and the production shock is again assumed to be mean zero with variance $\sigma^2_{\eta^c_t}$. Of particular interest is the level of cross-productivity between socio-emotional skill and cognition, indicated by the sign and size of $\rho^c_{2,t}$. A large, positive value for this coefficient would indicate that socio-emotional skills can have a large influence on cognition, whereas if this parameter close to zero then they have no impact on cognitive development. Given the evidence that cognitive skills are positively associated with a wide range of economic outcomes, estimates of these parameters show the extent to which they can be influenced indirectly through boosting children's socio-emotional skill.

3.2.5 Socio-emotional Skill Development in Early Adulthood

We extend our analysis of socio-emotional skill accumulation beyond adolescence and into early adulthood at $(T + 1)$. In our data, this corresponds to age 22. We treat this period differently to those between $t = 0, .., T$ - covering the ages of 8-19 - given the divergence of circumstances once individuals reach the age of 18. We extend the model laid out so far in two ways.

First, we depart from discussing socio-emotional skills in the aggregate and assume they develop along different dimensions. As discussed in the Introduction, the survey we are using has been designed precisely for this purpose. Guided by the literature and the data available, we group socio-emotional skills into two dimensions found to be important in determining a range of social and economic outcomes: social skills, and task effectiveness skills. The only study we know of which has attempted to disaggregate skills into multiple dimensions is Glewwe et al. (2017), which extracts two factors for cognitive skills, and three for socio-emotional skills. The measures used are quite different from ours and include internalising and externalising behaviour, self-esteem, depression and resilience.

The benefit of this breakdown is threefold. It firstly allows us to understand how specific socio-emotional skills which have been shown as important in the labour market are formed over early adulthood. It also allows us to allow for even more flexibility in the production functions we estimate over this period. In addition, although we do not have complete data on labour market outcomes, it also enables us to analyse how these domains are correlated with intermediate outcomes at over the same period.[5] Doing so with an aggregate index of socio-emotional skill would not allow us to evaluate which of its domains matters and for what. We discuss how this disaggregation allows for additional flexibility when outlining the measurement system in the next subsection. The next section discusses in more detail the measures and framework used to arrive at this disaggregation.

Second, parents can no longer be expected to be the sole 'investors' in children, and experiences at this age diverge considerably - some individuals continue living at home and in full time education, others are working full time either in the world of paid work; are working without pay for their own family; have set up business for themselves; or they are at home either unemployed or raising a family. We therefore do not include an explicit investment input in to the production functions, but rather use their added flexibility at this stage to include aspects of home and labour market experience that might affect the productivity of skill development.

Formally, between T (the terminal period of 'childhood') and $T+1$ (a point in time in early adulthood), we assume that social skills and task effectiveness are formed as a function of both cognition and socio-emotional skill accumulated by the end of adolescence and Total Factor Productivity (TFP), denoted $\ln A_t$. That is, for socio-emotional skill $j \in \{s, t\}$, we assume that:

$$\ln H^{j}_{s,T+1} = \ln A_T + \rho^{s,j}_{1,T} \ln H_{s,T} + \rho^{s,j}_{2,T} \ln H_{c,T} + \eta^{s,j}_{T} \tag{3.4}$$

The coefficients of the above equation have an identical interpretation to those in Equation 3.2. The inclusion of the TFP term allows us to capture the productivity of socio-emotional skill accumulation over the period. We define TFP to include:

$$\ln A_T = \ln\left(e^{\alpha_T + \mathbf{x}'_T \boldsymbol{\beta}_\mathbf{T}}\right) = \alpha_T + \mathbf{x}'_T \boldsymbol{\beta}_\mathbf{T}\,, \tag{3.5}$$

where $\mathbf{x}_T$ is a vector of characteristics which affect the productivity of skill development over the period and α_T represents residual productivity - the extent to which skill production is unexplained by the inputs and characteristics in $\mathbf{x}_\mathbf{T}$. As we discussed in outlining the investment equation, we explicitly model time use as a determinant of skill accumulation here, and include the number hours spent studying, doing paid work, caring for household members and engaging in tasks related to home production in $\mathbf{x}_T$. It is difficult to specify investments between these ages as "children" have become young adults, and many have moved out of the family home or are financially independent. Keane et al. (2018) evaluate the impact of similar vector of time-use on cognitive development in Ethiopia, Peru, India and Vietnam, finding that, when they crowd out school or study time, time spent on domestic chores and home production negatively impact on cognition up until the age of 19. Given we are concerned with the evolution of "soft skills" of task-effectiveness and social skills, time-use is arguably even more relevant, as time spent

[5]There are some measures of labour market outcomes at age 22, however many are either still in education or have not spent a meaningful amount of time in the labour market.

working may arguably improve either of these skills.

3.2.6 A Measurement System for Unobservables

The inputs/outputs of the production and investment equations - $H_{k,t}$, P_k, and I_t - are unobservable. Often, and in the data we use in this paper, there are only various imperfect measures available with which to analyse how they combine in the process of human capital development. Parameter estimates using these raw measures in such an analysis will suffer from bias induced by their measurement error, however. To exploit the multiplicity of measures and circumvent the issue of measurement error, we assume that observable variables in the data are a linear combination of measurement parameters, the log of latent variables they aim to measure, and measurement error. This allows us to use covariances between observable measures to estimate the model laid out in this section using only variation in their respective latent variables.

The Measurement System Over Childhood and Adolescence

More precisely, for observable measure $Z_{\theta,m,t}$ and unobservable variable $\theta_t \in \{H_{c,t}, H_{s,t}, P_c, P_s, I_t\}_{t=0}^{T}$ we assume that

$$Z_{\theta,m,t} = \mu_{\theta,m,t} + \lambda_{\theta,m,t} \ln \theta_t + \varepsilon_{\theta,m,t} \qquad m = 1, ..., M_\theta \, , \tag{3.6}$$

where $\mu_{\theta,m,t}$ is an intercept, $\lambda_{\theta,m,t}$ a factor loading, and $\varepsilon_{\theta,m,t}$ a measurement error. The factor loading has a similar interpretation to a regression coefficient in that it indicates how movements in θ_t are observed in $Z_{\theta,m,t}$. Since the latent variables have no location or scale, we impose the normalisations $\lambda_{\theta,1,0} = 1$ and that $E(\ln \theta_0) = 0$ for each $\theta_0 \in \{H_{c,0}, H_{s,0}, P_c, P_s\}$.[6] This anchors its location and scale to that or the normalising measure in that a one unit increase in the latent variable is equivalent to a one unit increase in the normalising measure. Commonly, these restrictions are imposed on the measurement system in each period as oppose to only in the initial period (e.g. Cunha et al. (2010), Attanasio et al. (2017)), however Agostinelli and Wiswall (2016b) show that doing so can ex-ante restrict the flexibility of the production function and bias estimates of its parameters, and so recent studies have moved away from imposing such restrictions (Attanasio et al., 2020b,c).

Only normalising in the initial period also means that multiple measures are not required to identify the measurement parameters in subsequent periods, and that they can be directly estimated as part of the estimation algorithm (which we outline below). In our setting this result is particularly beneficial since we do not have consistent measures across periods. We therefore assume that our aggregate "bundle" of socio-emotional skill grows across periods but that its

[6]For a given observable measure with known measurement mean and factor loading, there are an infinite number of latent distributions - mean and variance - consistent with observing the distribution of the observed measure. Agostinelli and Wiswall (2016a) refer to this as a problem of *location and scale*.

location and scale remains anchored to that of the initial normalising measure.[7] We can then directly estimate the extent to which the measures we have in each period capture this bundle of socio-emotional skills. It does mean, however, that we have to impose restrictions on the production functions in order to identify their parameters in each period. We discuss this in more detail below.

In addition to the normalizations on the initial period measurement system, we also assume full independence of the measurement errors:

(1) across alternative measures at a point in time, $Cov(\varepsilon_{\theta,m,t},\ \varepsilon_{\theta,m',t}) = 0\,\forall\, m' \neq m$;

(2) across all measures at all other points in time, $Cov(\varepsilon_{\theta,m,t},\ \varepsilon_{\theta,m',t'}) = 0\,\forall\, m'$ and $t' \neq t$; and

(3) across all latent skills at every point in time, $Cov(\varepsilon_{\theta,m,t},\ \theta'_{t'}) = 0\,\forall\,\theta'$ and t'.

These assumptions are stronger than those required to identify the joint distribution of initial conditions, but are exhaustive for consistent estimation of the investment and production function parameters using the methodology we employ, which we outline at the end of this section.

The Measurement System in Early Adulthood

At $T+1$ we disaggregate socio-emotional skill into two domains: social skills (s) and task effectiveness (t). We therefore specify a new measurement system for latent stocks of these skills. For each socio-emotional skill $H^j_{s,T+1}$ for $j \in \{s,t\}$, we again assume a linear-log relationship between observable measures and latent skill:

$$Z_{H^j_s,m,T+1} = \mu_{H^j_s,m,T+1} + \lambda_{H^j_s,m,T+1} \ln H^j_{s,T+1} + \varepsilon_{H^j_s,m,t} \qquad m = 1,\ldots,M_{H^j_s} \tag{3.7}$$

To save on notation, we omit the time subscript on stocks of socio-emotional skill j, $H^j_{s,T+1}$ when it is used as a subscript. To identify the measurement parameters of observables and the distributions of latent socio-emotional skills, we impose normalizations on this $T+1$ measurement system identical to those imposed on the measurement system in the initial period. For each $H^j_{s,T+1}$ we centre their distribution around zero and fix one factor loading to be equal to one. That is, for $j \in \{s,t\}$, we impose $E(\ln H^j_{s,T+1}) = 0$ and $\lambda_{H^j_s,1,T+1} = 1$. This again fixes the location and scale of each domain of socio-emotional skill to that of one of its measures. As we are departing from using an aggregate measure of socio-emotional skill as in the T periods of childhood, these restrictions are normalizations as opposed to *re*-normalizations that might bias estimates of the production functions (Agostinelli and Wiswall, 2016b).

[7]We use "anchoring" here in the standard, classical factor analysis sense that normalising ties the location and scale of the latent variable and normalising measure to one another. This is not the same as the practice of anchoring proposed by Cunha et al. (2010), which is intended to link parameter estimates to cardinal, economic outcomes.

Measurement Signal and Noise

The form of the measurement system in Equation 3.6 allows us to straightforwardly decompose the variance of the observable measures in to the portions attributable to the unobservables - the *signal* - and to measurement error - the *noise*. The signal, $s_{\theta,m,t}$, in each latent variable (θ_t) can be written in terms of the components of Equation 3.6 as:

$$s_{\theta,m,t} = \frac{\lambda^2_{\theta,m,t} V(\ln\theta_t)}{\lambda^2_{\theta,m,t} V(\ln\theta_t) + V(\varepsilon_{\theta,m,t})},$$

with the noise given by $(1 - s_{\theta,m,t})$. We can estimate both of these measures directly and evaluate how well the observables measure their latent counterparts.

3.2.7 Empirical Specification and Estimation

Production and Investment Function Restrictions

We estimate Equations 3.1, 3.2, 3.3 and the measurement system across 3 periods of childhood and adolescence. The starting point of the model, $t = 0$, is age 8, and the three period cover the ages of 8-12, 12-15, and 15-19 respectively. In each of these periods, we restrict both the investment and production functions to have constant returns to scale (CRS) which, in Equations 3.1-3.2 respectively, requires:

$$\sum_{i=1}^{5} \beta_{i,t} = 1$$

and

$$\rho^k_{1,t} + \rho^k_{2,t} + \alpha^k_{1,t} + \alpha^k_{2,t} + \kappa^k_t = 1 \quad \text{for} \quad k \in \{s, c\},$$

This restriction is, in part, imposed by the available data. Relaxing the CRS constraint would require that we either impose restrictions on the measurement parameters or re-normalise the latent variables in each period. The data we use do not contain any measures that satisfy the assumption of age-invariance which Agostinelli and Wiswall (2016a) show is sufficient to relax the CRS assumption, however, and re-normalising in every period would mean repeatedly altering the location and scale of the latent variable.[8] Agostinelli and Wiswall (2016b) show that this could unnecessarily restrict the production functions and limit our ability to make comparisons over time: our assumption - as outlined in our description of the measurement system - is that an initial bundle of socio-emotional (and cognitive) skill as measured and normalised in the initial period is propagated through the model, and captured by the measures we subsequently have available.

[8]Formally, Agostinelli and Wiswall (2016a) define a measure as age-invariant between two points in time if, $\mu_{\theta,m,t} = \mu_{\theta,m,t+1}$ and $\lambda_{\theta,m,t} = \lambda_{\theta,m,t+1}$

Agostinelli and Wiswall (2016a) are able to relax the CRS assumption due to the presence of an *age-invariant* measure in their data and find that returns to scale of cognitive production are different from one only between the ages of 5 and 8. Between 8 and 12, however, they are unable to reject that it is constant. Attanasio et al. (2020c) use Young Lives data from India in which they also have available an age invariant measure and do not find any evidence that the production functions of health and cognition are not CRS.[9] If the data we use contained a similar measure of, for example, socio-emotional skill then it would be possible to test whether or not the technology is in fact CRS. Faced with trade-off between imposing re-normalisations on the measurement system or restricting the production functions, and due to our interest in the dynamic relationships between the inputs of the developmental process, we choose the latter.

We then estimate the socio-emotional skill measurement system and Equation 3.4 in period $T+1$, between the ages of 19-22. Here, as a consequence of the normalizations imposed on latent socio-emotional skills, we do not impose the restriction of CRS on the production function and allow its returns to scale to be freely estimated. That is, we only assume:

$$\text{RTS} = \rho^{s,j}_{1,T} + \rho^{s,j}_{2,T} = k > 0 \tag{3.8}$$

Given the normalizations on the measurement system in this period, we are able to estimate this more general function shown in Equation 3.4, which also includes a free TFP term. The next subsection provides a simple example of our estimation algorithm and the restrictions we impose on the production functions and/or measurement system, and Appendix C.1 outlines in detail its full application.

Estimating the Model

We estimate the model from 8 until 22 using an algorithm developed by Agostinelli and Wiswall (2016a), which, in our application, has three main steps:

(1) Estimating the initial period measurement parameters, and the joint distribution of the initial conditions by exploiting the normalisations and covariances in observable measures.

(2) Estimating the first period investment measurement and structural parameters using instrumental variables (IV), with measures of the initial conditions acting as instruments for one another.

(3) Estimating the first period skill measurement and structural parameters using IV, with measures of initial conditions (except resources) again acting as instruments for one another, and measurements of investments also used as instruments for one another.

[9]They do find that the returns to scale of the cognitive production function was less than one, but conclude that jointly they cannot reject that the process governing the development of health and cognition has CRS. The Indian YL cohort contains the Peabody Picture Vocabulary Test, which Attanasio et al. (2020c) use as age-invariant - at all ages, whereas the older Peruvian cohort only has this measure at ages 12 an 15.

We then repeat (2) and (3) for periods 2 and 3 using the contemporaneous measure of skills and investments, and use the same IV-based method to estimate the functions describing the development of social skills and task effectiveness between 19 and 22. The methodology therefore relies on the assumption that measurement errors are independent across latent variables and time to recover unbiased estimates of the investment and production parameters. To see how the algorithm works, consider a simplified model with only child and parental stocks of socio-emotional skill, $H_{s,t}$ and P_s respectively. With three measures of each, and the normalisations that $E(\ln H_{s,0}) = 0$, $\lambda_{H_{s,0},1,0} = 1$, and $E(\ln P_s) = 0$, $\lambda_{P_s,1,0} = 1$ the factor loadings can be recovered as:

$$\lambda_{\theta,m,0} = \frac{\text{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,m',0})} = \frac{\lambda_{\theta,m,0}\lambda_{\theta,m',0}Var(\theta)}{\lambda_{\theta,m',0}Var(\theta)} \qquad \text{for } \theta \in \{H_{s,0}, P_s\}$$

With the factor loadings identified and the scale and location of the latent variables fixed, their joint distribution is identified. We then construct the following residual measures:

$$\frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} - \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln \theta_0 \qquad \text{for } \theta \in \{H_{s,0}, P_s\}$$

Substituting the investment function into one investment measurement equation, using the above definition of $\ln \theta_0$, and re-arranging gives a simple reduced form investment equation:

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_{1,0} \ln H_{s,t} + \beta_{2,0} P_s + \pi_0\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_{1,0}(\tilde{Z}_{H_s,m,0} - \tilde{\varepsilon}_{H_s,m,0}) + \beta_{2,0}(\tilde{Z}_{P_s,m,0} - \tilde{\varepsilon}_{P_s,m,0}) + \pi_t\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \delta_{0,0} + \delta_{1,0}\tilde{Z}_{H_s,m,0} + \delta_{2,t}\tilde{Z}_{P_s,m,0} + \delta_{3,t} \ln Y_t + \nu_0 \quad , \tag{3.9}$$

where the coefficients $\delta_{i,0}$, $i = 1, 2, 3$ are a mixture of the structural investment and measurement parameters, and ν_0 a mixture of the measurement errors and investment shocks:

$$\tilde{Z}_{\theta,m,0} = \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} \quad \text{for} \quad \theta \in \{H_{s,0}, P_s\}$$

$$\delta_{0,0} = \mu_{I,m,0}$$

$$\delta_{i,0} = \lambda_{I,m,0}\beta_{i,0} \quad \text{for} \quad i = 1, 2, 3$$

$$\nu_0 = \varepsilon_{I,m,0} + \lambda_{I,m,0}\big(\pi_0 - \beta_{1,0}\tilde{\varepsilon}_{H_s,m,0} - \beta_{2,0}\tilde{\varepsilon}_{P_s,m,0}\big)$$

Given that the residual measures ($\tilde{Z}$s) are not independent of ν_0, we estimate the parameters of Equation 3.9 using the alternative measures of socio emotional skills for children and parents as instruments. Under the assumptions that measurement errors are independent of one another and of latent variables, these are valid instruments. The structural parameters can then be recovered using the CRS restriction:

$$\beta_{i,0} = \frac{\delta_{i,0}}{\sum_i \delta_{i,0}} = \frac{\lambda_{I,m,0}\beta_{i,0}}{\lambda_{I,m,0}}$$

Residual investment measures can then be constructed, and the production function of next periods socio-emotional skill estimated in an identical manner. Using a Cobb-Douglas functional form, its analogous reduced form representation is:

$$Z_{H_s,m,1} = \tau_{0,0} + \tau_{1,0}\tilde{Z}_{H_s,m,0} + \tau_{2,t}\tilde{Z}_{P_s,m,0} + \tau_{3,t}\tilde{Z}_{I,m,0} + \upsilon_0 \quad , \tag{3.10}$$

with

$$\begin{aligned}
\tau_{0,0} &= \mu_{H_s,m,1} \\
\tau_{1,0} &= \lambda_{H_s,m,1}\rho_0^s \\
\tau_{2,0} &= \lambda_{H_s,m,1}\alpha_0^s \\
\tau_{3,0} &= \lambda_{H_s,m,1}\gamma_0^s \\
\upsilon_0 &= \varepsilon_{H_s,m,1} + \lambda_{H_s,m,1}\left(\eta_0^s - \rho_0^s\tilde{\varepsilon}_{H_s,m,0} - \alpha_0^s\tilde{\varepsilon}_{P_s,m,0} - \gamma_0^s\tilde{\varepsilon}_{I,m,0}\right)
\end{aligned}$$

Again, we estimate the reduced form parameters in Equation 3.10 using alternative measures of socio-emotional skill and investment, their validity being based on the assumption that measurement errors are fully independent. The structural parameters can again be backed out by using the assumption of CRS:

$$\begin{aligned}
\rho_0^s &= \frac{\tau_{2,0}}{\sum_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\rho_0^s}{\lambda_{H_1,m,1}} \\
\alpha_0^s &= \frac{\tau_{2,0}}{\sum_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\alpha_0^s}{\lambda_{H_1,m,1}} \\
\gamma_0^s &= \frac{\tau_{3,0}}{\sum_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\gamma_0^s}{\lambda_{H_1,m,1}}
\end{aligned}$$

This gives an intuition as to how imposing CRS - and the methodology more generally - facilitates comparisons over time when measures are not consistent and not age-invariant. Intuitively, the restriction scales each of the reduced form parameters by the factor loading of the left-hand-side measure. It is this re-scaling that "adjusts" the reduced form coefficient to remove the effect of having a different scale than the latent variable (which in this first period is defined by the normalising measures). If, however, we had one measure of socio-emotional skill for which we could assume $\mu_{H_s,m,0} = \mu_{H_s,m,t}$ and $\lambda_{H_s,m,0} = \lambda_{H_s,m,t}$ for all $t > 0$, then we could allow the RTS of the socio-emotional skill production function to be free, recovering its structural parameters as, for example,:

$$\rho_0^s = \frac{\tau_{1,0}}{\lambda_{H_s,m,0}} = \frac{\lambda_{H_1,m,1}\rho_0^s}{\lambda_{H_s,m,0}}$$

This would also allow us to augment the production functions with a TFP term, recovering it as:

$$\ln A_t = \tau_{0,0} - \mu_{H_1,m,0} = (\mu_{H_s,m,1} + \ln A_t) - \mu_{H_1,m,0}$$

In this case, both the nature of the measure and its presence over time would mean this re-scaling does not require direct estimation of the factor loading and measurement mean, and so no restriction must be made on the parameters of the production function.

In estimating the investment and human capital production functions, a choice must be made as to which measures should be used as *lead* measures, i.e. as outputs and inputs, and which should be used as instruments. We choose to use the measure that shares the most variation with the unobserved bundle of skills in each period as a lead measure, and instrument it with others. Appendix C.1 provides a full description of the estimation algorithm, and the next section describes the data and measures we use in more detail.

3.3 Data and Measures

In our estimations we use data from the Young Lives (YL) longitudinal survey in Peru. The survey was first administered in 2002 to two cohorts of children: 2,052 aged 1 (the younger cohort) and 714 aged 8 (the older cohort).[10] Follow-up surveys have been conducted at ages 5, 8, 12, and 15 for the younger cohort, and 12, 15, 19, and 22 for the older cohort. Although the sample is smaller, we use the older cohort due to the fact it covers adolescence and early adulthood and because there are measures of socio-emotional skills available at all ages. To select the children, a multi-stage sampling procedure was used. First, 20 clusters (districts) were selected within the country at random, then, within each cluster, a village/town (or a group of villages/towns) and a group of eligible households within each village/town was chosen at random respectively. The sample is representative of all but those in the top 5% of the income distribution (Escobal

[10]The survey has also been carried out in Ethiopia, India, and Vietnam. As in Peru the younger cohort samples are 2000 in each country, however with 1000 participants the older cohort is slightly larger than in Peru.

and Flores, 2008).[11] The survey provides information on a variety of aspects related to child development, including child and maternal indicators of perceptions, attitudes and aspirations, cognitive test scores, child and maternal anthropometric measures, as well as a wide array of information on child, family and other contextual characteristics. Attrition in the older cohort sample (14.1% over 15 years, equivalent to an annual rate of 0.9%) is relatively low compared to other longitudinal studies in developing countries. There is evidence that the attrition from the YL survey is not random, with those that remain in the sample more likely to be males, from wealthier households and from urban areas. There is very little evidence, however, that this should induce any bias once household characteristics from the first visit are controlled for (Sánchez and Escobal, 2020).

3.3.1 Sample Characteristics

Table 3.1 shows the characteristics of the older Peruvian cohort in the baseline survey and in each sample we use to estimate our model. For example, comparing the age 12 to the age 8 column shows how the estimation sample in our first period differs to the baseline sample. Given the samples in columns (2)-(5) are our *estimation* samples, they exclude children with any missing values for the measures we use in these estimations. As mentioned above, attrition is very low in the YL sample so the vast majority of differences in sample sizes across columns comes from missing answers to questions we use in our analysis. One thing to note in the baseline sample (column (1)) is the large mean and standard deviation of household income. This is due to the presence of one large, outlying value. Given that we use monetary measures as proxies for investments, we exclude this one observation from our main analysis so it does not skew our results. For this reason, columns (2) -(5) of Table 3.1, which contains descriptive statistics on the samples used in our estimations, have significantly lower mean incomes which are much closer to the median. In practice, our results are not change qualitatively by this exclusion.

3.3.2 Specifying the Measurement System for Unobservables

In each of its waves, the Young Lives survey has detailed information on the developmental, economic, and family circumstances of children. An important feature of the measurement system laid out in Section 3.2 is that it is *dedicated* - it assumes that observables measure only one latent variable. Given the multi-dimensional nature of socio-emotional skills, and the different measures of its constituents in the YL data, we first verify this structure by using an Exploratory Factor Analysis and drawing on measures that satisfy the properties of Core Self Evaluation (CSE).

In the case of socio-emotional skill measures, we first excluded those which could be viewed as measuring some dimension of socio-emotional skill, but that relied on the evaluation of

[11] There were around 1,818 districts in Peru in 2002. From them, the wealthiest 5% was excluded using information from the Peru Map of Poverty from year 2000.

Table 3.1: Sample characteristics in the age 8 baseline and estimation samples

	(1) *Age 8*	(2) *Age 12*	(3) *Age 15*	(4) *Age 19*	(5) *Age 22*
Wealth index	0.47	0.52	0.58	0.64	0.67
	(0.23)	(0.22)	(0.18)	(0.16)	(0.14)
Household income (USD)	434	284	344		
s.d	(4,937)	(290)	(507)		
Median	160	220	239		
Female caregiver	0.97	0.98	0.96	.	.
Female cohort member	0.46	0.46	0.47	0.47	0.48
Caregiver's education					
None	0.13	0.12	0.11	.	.
Primary	0.38	0.38	0.37	.	.
Secondary	0.37	0.38	0.38	.	.
Technical/Vocational	0.09	0.09	0.10	.	.
University	0.02	0.03	0.03	.	.
Adult literacy	0.00	0.00	0.01	.	.
Dependent children					
None	0.09	0.12	0.18	0.26	0.30
One	0.32	0.33	0.31	0.35	0.39
Between 2 and 4	0.51	0.50	0.47	0.37	0.30
More than 5	0.08	0.04	0.03	0.02	0.01
Language					
Spanish	0.88	0.90	0.88	0.90	0.90
Quechua	0.10	0.08	0.10	0.09	0.09
Other	0.00	0.00	0.00	0.00	0.00
N	714	606	607	571	550

Notes: All numbers are proportions. The sex, education, and age of the caregiver were not recorded at age 19 or 22, nor was the income of the cohort member's household. *Dependent children* refers to the number of children aged between 0 and 17 years in the household of the cohort member. Standard errors for the mean wealth index and household income are in parentheses. For household income, the median value is also shown below the mean and its standard deviation.

external circumstances or other people as opposed to the children/adolescents themselves. For example, the data contains a measure of trust, however the items of which it comprises ask children about whether or not "*Most people in the community are honest*", or whether they "*believe the government does what is right for people like me*". We then ensured the remaining observables shared enough variation with which to back out the latent variables. Finally, we grouped measures into those of children's human capital, endowments, and investments and excluded those that loaded heavily on more than on factor, or on the "wrong" factor based on our ex-ante belief about the measure. For example, if a socio-emotional measure loaded heavily on latent cognition it was excluded from our analysis. Below we list the measures of socio-emotional skill, cognition, investments, and endowments we use to estimate the model outlined in Section 3.2. Appendix C.2 describes the YL socio-emotional measures in full, and Appendix C.3 shows the results of the EFA and discusses in more detail how we narrowed measures to the subset used in our analysis.

Socio-emotional skills: In the initial period, $t = 0$, we use five measures from the Child Strengths and Difficulties (SDQ) questionnaire on children's conduct, emotional regulation, hyperactivity, relationships with peers and their social skills. The questions that make up the SDQ are administered to the children's caregiver, and are centred on discerning the number of symptoms of, for example, hyperactivity they display. Similar behavioural indices to these have often been used to identify bundles of early socio-emotional skill (e.g. Cunha et al. (2010), Attanasio et al. (2020b)). Thereafter, however, these behavioural indices are not available, and we use some combination of measures of children's agency, pride, self-efficacy and self-esteem. All of these measures are calculated from children's responses to questions regarding their degree of agreement or disagreement to a number of statements using Likert scales. Prior to its administration, these instruments were piloted and, where necessary, adapted to the local context to they were understood by children (Yorke and Ogando, 2018).

Treating socio-emotional skill as an aggregate in periods 1-3, covering the ages of 8-19, is a constraint imposed mainly by the data as opposed to representing an explicit assumption regarding the dimensionality of socio-emotional skills over this period. This is very similar to many papers in the literature. The majority of the socio-emotional assessments in the YL data are not administered in the initial wave of the YL survey, nor are there multiple measures of particular domains until age 22. As a result, we cannot disaggregate socio-emotional skills until the final period of our model at age 22. At this age we use three measures of each of children's social skills, two of which are sub-scales of the ROPELOC self-evaluation (Richards et al., 2002) scale measuring leadership and teamwork, and one from the Marsh Self-Description Questionnaire Yorke and Ogando (2018) assessing relationships with peers. Task effectiveness skills comprise agency, grit, conscientiousness, emotional stability.

Cognitive skills: For cognitive skill in the initial period we use children's score on a series of Ravens progressive matrices alongside measures of the child's general writing and reading level as assessed through various other assessments. In the periods thereafter, we use combinations of scores on maths and language tests administered as part of the YL survey, and the Peabody Picture Vocabulary Test (PPVT) to measure cognitive skill. Appendix C.2 provides detailed information on the cognitive assessments administered as part of the Young Lives survey that we use.

Investments: As measures of latent investment, we use caregivers' responses to a number of questions about the material and time investments made in children's development. We use measures of expenditure on books, uniforms and food per child in the household alongside those of the time children spend in school and studying. In using hours of schooling and study we assume that caregivers have an important role in determining how time is allocated to these activities. Again, Appendix C.2 describes all the measures considered and Appendix C.3 describes how they were reduced to a subset for analysis.

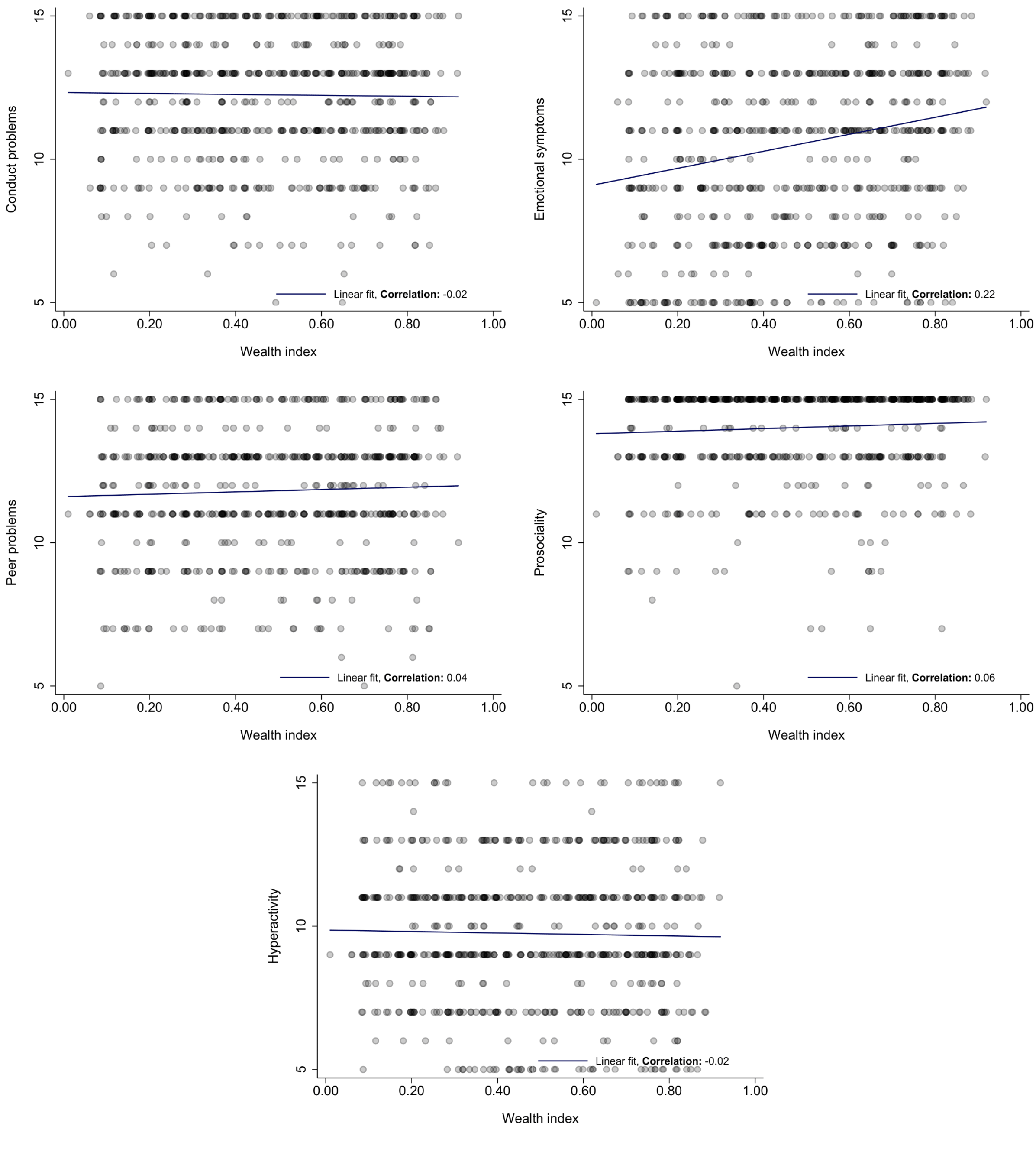
Parental human capital: As measures of cognitive endowments, we use the level of education of the caregiver, an assessment of their ability to understand text written in their native language, and a measure of the degree of difficulty they have reading in general. For socio-emotional skill of the caregiver, we use their responses to questions about their agency, pride and a subjective evaluation of their life circumstances. We use the caregiver as opposed to the mother's and/or father's information for two reasons. Firstly, doing so allows to make use of as much of the sample as possible - for 5% of children their caregiver is not a biological parent. Secondly, measures of socio-emotional skill are available only for the household member recorded as the caregiver, not the parents separately.

Family resources: The YL survey contains household income information for the older Peruvian cohort up until age 15. We use family income as a measure of family resources up until this age. Given there is no information on household income available at age 19, we use the YL wealth index as a measure of family resources at that age. This is a measure of the material resources of the family which ranges from 0 to 1, and is constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. Briones (2017) describes the construction of the YL wealth index in detail.

3.3.3 Observable Skill Gradients

Our main interest is the process of human capital development as it relates to the emergence of skill inequalities and the intergenerational transmission of disadvantage. To first look at this question descriptively, we correlate observable measures of socio-emotional skill with the available measures of the economic wellbeing of the YL children. Figure 3.1 shows the raw correlation between the five available measures of socio-emotional skill at the baseline survey - the SDQ measures of conducts problems, emotional instability, difficulty with peers, prosociality, and hyperactivity - and household wealth. The scale of all of these measures except for prosociality (which is already, in theory, a positive measure) have been reversed to be positive

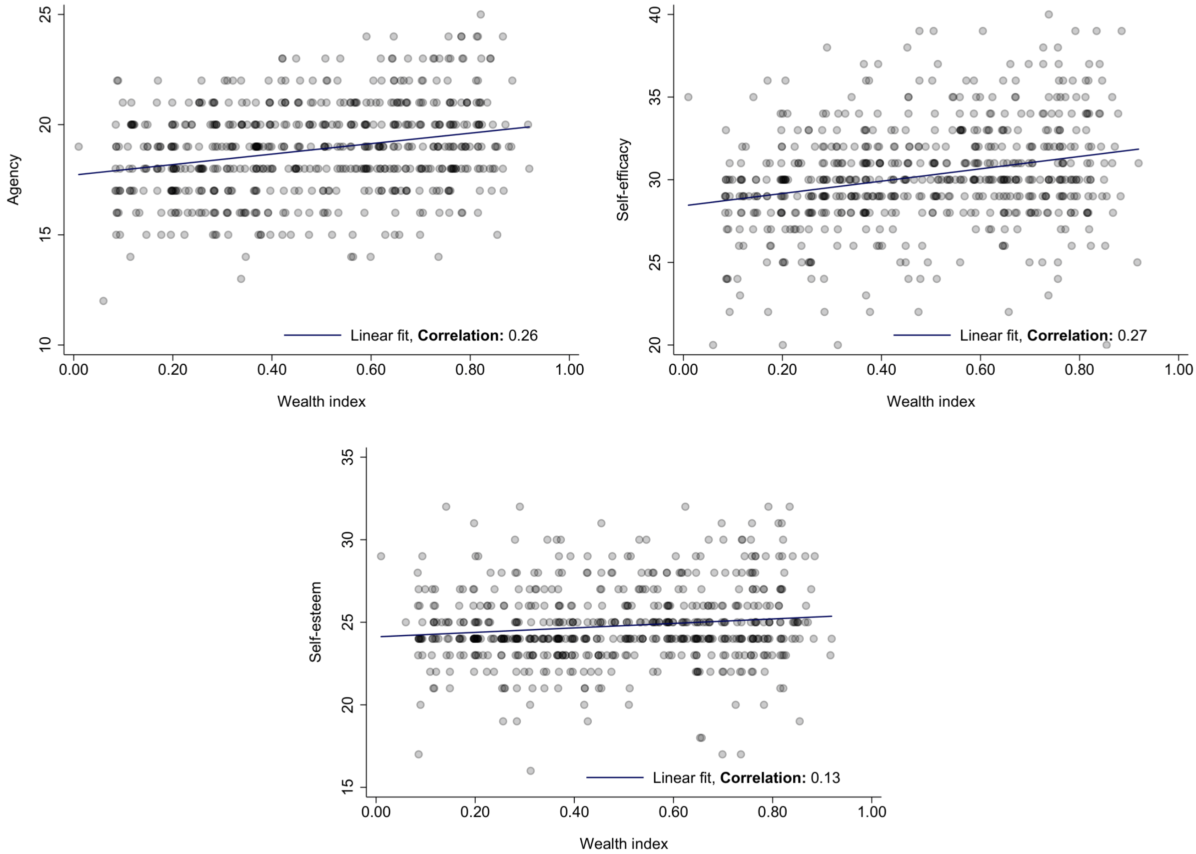
Figure 3.1: Socio-emotional skill measures and household wealth at baseline (Age 8)



Note: The measures used are part of the Strengths and Difficulties Questionnaire, described in Subsection 3.3.2 and Appendix C.2. The scale of all measures except prosociality have been reversed so a higher value indicates more "skill". The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

so a higher value means more "skill". Of the five measures, there only appears to be a somewhat moderate positive relationship between the number of symptoms of emotional instability a child displays and wealth. For the other measures their correlation with wealth is very close to zero. As proxied by these measures then, it appears as though there is only a small gradient in children's socio-emotional skill across the distribution of wealth at age 8.

Figure 3.2: The correlation between socio-emotional skill measures at 19 and initial (age 8) household wealth



Note: The measures of, clockwise from top left, agency, self-efficacy and self-esteem are described in detail in Appendix C.2. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

Figure 3.2 shows analogous plots, correlating the socio-emotional skill measures we use at age 19 - agency, self-efficacy and self-esteem - with wealth at age 8.[12] Across the measures there is evidence of a moderate, positive relationship with family wealth. The measure of self-esteem has the smallest correlation with wealth at 0.13, whereas both agency and self-efficacy have a correlation of around 0.25. The consistent positive correlation across measures suggests that a wealth gradient in socio-emotional skill exists at the end of adolescence. The gradients in

[12]We use wealth at age 8 for comparability and to focus on the correlation between earlier conditions and later skills. Using wealth at age 19 does not in fact alter the results as wealth is persistent across rounds of the YL survey.

measures of socio-emotional skills at age 22 show similar correlations with wealth at age 8 (Appendix Figures C5 and C6). Given that the relationship appears to be stronger than at age 8, this could be seen as descriptive evidence that small gradients apparent in childhood widen over time.

An important issue with drawing this conclusion, however, is that the two sets of measures available at the two ages in Figures 3.1 and 3.2 differ. From a survey design perspective, this is mainly due to the fact it is often deemed unsuitable to assess certain socio-emotional skills in children at particular ages. As a result, the difference in the correlation with wealth might simply reflect the fact the socio-emotional skills measured would correlate differently with wealth, independent of age.

Over and above the problems in comparing mismeasured proxies, this adds another complication in descriptively interpreting how socio-emotional skill develops over time. Here, we interpret the descriptive results at a high-level, and, in estimating the model laid out in Section 3.2, we aim to understand in more detail if and how skill gradients emerge. A key assumption in doing so is that the *group* of measures used at each age loads on the same latent concept of socio-emotional skill. One option to circumvent the problem of inconsistent sets of measures is to focus on the development on one particular type of socio-emotional skill in sub-periods across the span of the data. This would also require a different, data intensive methodology given it would rely on using categorical sub-questions of each measure of socio-emotional skill to explicitly estimate and simulate the joint distribution of skills. This would be similar to the approach in Cunha et al. (2010) and Attanasio et al. (2017, 2020c). However, as the focus of this paper is on socio-emotional skill development across childhood and adolescence, we maintain the assumption that the groups of measures we use capture an aggregate socio-emotional across childhood. We also aim to verify this assumption in our initial EFA - described in the previous subsection - by retaining measures that (a) load on the same latent factor and (b) do not load on latent cognition.

In Appendix Figure C7 we also show that there is a moderate, positive correlation between the baseline measures of cognitive skill and family resources. Children's level of writing and reading as well as their score in the Ravens math test at age 8 all appear to be increasing with the level of household wealth as measured in the YL. Subject to similar caveats, although perhaps to a lesser extent, it also appears that the relationship between the cognitive measures and wealth is stronger than in the case of baseline socio-emotional skill measures.

3.4 Results Over Childhood and Adolescence

3.4.1 Measurement System

Table 3.2 shows the estimated socio-emotional skill measurement parameters and the proportion of variance in each measure attributable to signal and noise. It shows that there is heterogeneity in the extent to which observable measures capture variation in latent aggregate socio-emotional skill, both across and within the four periods. For example, in the initial period, at age 8, a reasonable portion of the variance in all five measures is explained by variation in latent socio-emotional skill: three measures are estimated to have roughly a third of their variance attributable to latent skill, and all more than 10%. In the next period, however, the measure of pride has a signal of 87%, compared with a signal of 1.3% in agency. Both social skills and task effectiveness appear to be well measured by observables in period 4, with no measure sharing less than roughly a fifth of its variance with its respective unobservable. This highlights the importance of using a latent factor structure to estimate the skill production functions: using raw measures as inputs/outputs of the production (and investment) functions would mean estimating their parameters without adjusting for bias induced by measurement error.

Table 3.2: Measurement parameters associated with observable socio-emotional skill

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (age 8) socio-emotional skill				
SDQ conduct problems*	12.263	1.000	0.363	0.637
SDQ emotional symptoms*	10.513	1.326	0.329	0.671
SDQ hyperactivity*	9.752	1.070	0.333	0.667
SDQ peer problems*	11.815	0.788	0.225	0.775
SDQ peer pro-sociality	14.013	0.387	0.105	0.895
Period 1 (age 12)				
Agency	6.991	0.032	0.013	0.987
Pride & self-esteem	11.906	1.244	0.865	0.135
Period 2 (age 15)				
Agency	17.920	0.316	0.212	0.788
Pride & self-esteem	22.112	0.280	0.263	0.737
Period 3 (age 19)				
Agency	18.357	1.160	0.479	0.521
Self-esteem	30.342	1.243	0.193	0.807
Self-efficacy	24.841	0.234	0.042	0.958
Period 4 (age 22) social skills				
Leader	9.586	1.000	0.374	0.626
Peers	9.228	1.340	0.562	0.438
Teamwork	22.921	2.427	0.310	0.690
Period 4 (age 22) task effectiveness				
Agency	16.181	1.000	0.189	0.811
Grit	27.393	2.095	0.640	0.360
Conscientiousness	25.428	1.517	0.292	0.708
Emotional stability	33.064	1.504	0.416	0.584

Note:* indicates negative measures that were reversed so a higher value represented a higher level of skill. The initial and periods 1-4 represent ages 8, 12, 15, 19, and 22 respectively. From left to right the columns represent the observable measure and its estimated mean, factor loading, signal, and noise respectively. All parameters are estimated as outline in Appendix C.1.

Section 3.2 highlighted that the estimation algorithm we use requires selecting "lead" measures of skill to be used as inputs/outputs of the investment and production equations, while others are used as instruments. Although this was partly determined by our EFA of the measures (outlined in Appendix C.3, Table C4) Table 3.2 confirms our selections - in periods 1 and 2 we used pride & self-esteem as lead measures and in period 3 agency. In estimating the investment production functions we exploit only the signal in each observable measure, however there would be efficiency gains if measures consistently shared, for example, two thirds of their variance with latent skill. This has direct implications for the precision of our parameter estimates during periods in which measures are noisy - if observable measures have little shared variation attributable to latent socio-emotional skill, our estimates of the production and investment parameters will imprecise. Given that we use an IV strategy to estimate the production and investment functions, measures having little shared variation - and so being weak instruments - also has implications for consistency. In period 2, for example, the measure of children's agency is used as an instrument, and shares only 1% of its variation with latent skill. In all other periods, the relationship between latent skills and measures appears sufficiently strong.

Table 3.3 shows the measurement parameters and signal/noise proportions associated with measures of cognitive skill, parental human capital and investments. Again, the Table shows the extent to which observable measures share variance with their respective latent variable varies both within and across periods. Measures of cognitive skill - for both the child and caregiver - tend to have relatively large portions of their variance explained by latent cognition. There are larger differences in signal across measures for investments parental socio-emotional skill, however, again highlighting the importance of accounting for measurement error in observable measures.

Table 3.3: Measurement parameters associated with observable cognitive skill, parental human capital and investment

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (age 8) cognitive skill				
Ravens test score	20.822	1.000	0.135	0.865
Writing level	2.418	0.190	0.631	0.369
Reading level	3.582	0.236	0.521	0.479
Period 1 (age 12)				
PPVT score	72.729	9.026	0.583	0.417
Writing level	2.840	0.132	0.251	0.749
Reading level	3.938	0.098	0.167	0.833
Maths test score	5.742	1.062	0.620	0.380
Period 2 (age 15)				
PPVT score	97.137	16.289	0.656	0.344
Cloze language test score	14.749	4.282	0.562	0.438
Maths test score	13.764	4.658	0.490	0.510
Period 3 (age 19)				
Language test score	67.531	15.351	0.751	0.249
Maths test score	59.656	17.959	0.659	0.341
Parental socio-emotional skill				
Agency	12.974	1.000	0.079	0.921
Pride	8.297	1.214	0.375	0.625
Subjective wellbeing	4.848	0.961	0.072	0.928
Parental cognitive skill				
Caregiver's education	7.251	1.000	0.533	0.467
Literacy (first language)	2.502	0.198	0.693	0.307
Understands paper	2.604	0.163	0.571	0.429
Period 1 (age 12) investment				
No. food groups consumed	21.569	2.702	0.433	0.567
School uniform expenditure	62.311	66.103	0.150	0.850
Hours at school	4.741	0.597	0.168	0.832
Hours studying	2.857	0.197	0.032	0.968
Book expenditure	127.540	98.787	0.117	0.883
Period 2 (age 15)				
No. food groups consumed	24.000	3.465	0.332	0.668
School uniform expenditure	186.408	84.414	0.209	0.791
Hours at school	6.514	1.233	0.199	0.801
Hours studying	2.523	0.946	0.278	0.722
Book expenditure	216.107	129.214	0.227	0.773
Period 3 (age 19)				
Hours at school	3.587	1.507	0.323	0.677
Hours studying	1.403	0.754	0.236	0.764
No. food groups consumed	8.496	-0.237	0.015	0.985
Non-food expenditure	616.067	250.154	0.026	0.974
Education expenditure	728.966	615.501	0.239	0.761

Note: Parental human capital is assumed to be time invariant so are measured at only one point in time. From left to right the columns represent the observable measure and its estimated mean, factor loading, signal, and noise respectively. All parameters are estimated as outlined in Appendix C.1. All expenditure variables are per dependent child in the household.

3.4.2 The Determinants of Investment

Table 3.4 shows the estimates of our investment function parameters through childhood and adolescence. There is no strong evidence of reinforcement or compensation at any stage. Although there is a compensatory effect with respect to cognition in the first period, its 90% confidence interval marginally covers zero and so we fail to reject that it is equal to zero. The elasticities of investment with respect to cognitive and socio-emotional skill are small and are not statistically different from zero in any other period. It therefore appears that in our sample, parents do not invest in response to revealed human capital. This is broadly in line with findings in studies in similar settings, where there is limited evidence of household investment responding to child stocks of human capital. Attanasio et al. (2017, 2020b,c) find some evidence of investments' responsiveness to cognitive skill in childhood, but very little of any parental response to revealed health or socio-emotional capital. Whilst Attanasio et al. (2020b,c) focus mostly on earlier periods of childhood (until 12 and 4 years respectively), the results of Attanasio et al. (2017), who estimate investment functions up until the age of 15, overlap with the analysis in our earlier periods.

We do find that parental socio-emotional skill has a large impact on parental investment behaviours, particularly between the ages of 8-12 and 12-15. Their effect is similarly large but not statistically different from zero between the ages of 15 and 19. Although using data from the US, Agostinelli and Wiswall (2016a) find similarly large impacts on investment of parents' socio-emotional relative to cognitive skill, whereas Attanasio et al. (2020b) find the reverse in Colombia albeit at much younger ages. Family resources are estimated to strongly determine investments to an increasing degree in each period.[13] We also find that the variance of the production shock is decreasing over time, suggesting that in later adolescence, there are fewer external factors over and above income (and the other inputs) that explain household investments.

3.4.3 Skill Production in Childhood and Adolescence

We first present estimates of restricted Cobb-Douglas production functions for both socio-emotional and cognitive skill. In terms of Equations 3.2 and 3.3, this means estimating the production functions excluding the interaction of investments with human capital. We then estimate versions of the production function with interactions between skills and investment in order to test whether or not any complementarities exist between them.

[13] In the last period we use a wealth index, not family income, as a proxy for family resources. This is because Family income is not available for age 19 in the YL survey. We use income in the first two rounds due to its ease with which its elasticity can be interpreted. Using the wealth index in each period does not change the results of Table 3.4 qualitatively.

Table 3.4: Estimates of investment function parameters

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.023	0.028	-0.017
	(0.097)	(0.193)	(0.026)
	[-0.183,0.137]	[-0.290,0.345]	[-0.061,0.026]
$\ln H_{c,t-1}$	0.110	0.027	-0.021
	(0.077)	(0.132)	(0.275)
	[-0.017,0.238]	[-0.190,0.245]	[-0.474,0.432]
Parental human capital (fixed over time)			
$\ln P_s$	0.563**	0.398*	-0.022
	(0.241)	(0.220)	(0.212)
	[0.166,0.960]	[0.035,0.761]	[-0.371,0.327]
$\ln P_c$	-0.019	0.002	0.069
	(0.064)	(0.039)	(0.067)
	[-0.124,0.087]	[-0.061,0.066]	[-0.041,0.180]
Resources			
$\ln Y_t$	0.368***	0.545***	0.991***
	(0.130)	(0.199)	(0.341)
	[0.154,0.582]	[0.217,0.872]	[0.430,1.552]
$\sigma^2_{\pi_c}$	2.34	3.33	.0183
N	603	596	579

Notes: Standard errors are in parentheses and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 19 for the three columns respectively. The output in each column is investment. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and family income, respectively. In period 3 (ages 15-19) the we use the YL wealth index as a proxy for family income as this information is not available. The wealth index is a measure of the material resources of the family which ranges from 0 to 1, and is constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. See Briones (2017) for detail. All inputs except of family income are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3.3 are provided in Appendix C.2.

Socio-emotional skill

In table 3.5 we show estimates of the Cobb-Douglas production function for socio-emotional skill up to age 19. First focusing on the role of lagged human capital, we find some evidence of self-productivity in late childhood, between 15 and 19, but not in the earliest stage. We also find evidence of cross-productivity between cognitive skill and socio-emotional skill in all periods, however in period two, when it is at its largest, then it is estimated imprecisely. Although smaller in magnitude in the first period, cognition plays an important role on the development of socio-emotional skill given there is no evidence of self-productivity in this period. Together, these results suggest that cognition is a key factor in the development of socio-emotional skill across childhood. These findings are similar to those of Helmers and Patnam (2011), who use

YL data from India for ages 8 to 12 and find cognitive skills to influence socio-emotional skill accumulation to a greater extent than lagged stocks of themselves. However, they contrast slightly with Cunha et al. (2010), who use data from the US and find socio-emotional skill to be unaffected by cognitive skill in both early and late childhood, and to be increasingly self-productive over time between the birth and the age of 14.

It should be noted that Cunha et al. (2010) study human capital development in a sample of children in the US, whereas our sample is from Peru, a developing country. Given that, to our knowledge, there are no other studies that estimate socio-emotional production functions over an extended period similar to our study (Helmers and Patnam (2011) analysis overlaps only with period 1 in our model), it is conceivable that the developmental process differs in these two settings due to country and/or sample specific factors. It should also be considered throughout this section that Cunha et al. (2010), and indeed all other similar studies, do not necessarily use measures that identify an identical composite socio-emotional skill as here.

Moving to the role of parental human capital, there is not consistent evidence of their influence on socio-emotional development other than in the first period, between the ages of 8-12. We estimate that parents' cognitive skill has little effect on the production of socio-emotional skill except in the last period, between 15 and 19, where it is estimated they have a small negative impact on skills. In the first period, between 8 and 12, children's skill is highly malleable with respect to parental socio-emotional skill - its corresponding elasticity is estimated to be 0.58. The results in Table 3.5 also show that investments strongly, positively affect socio-emotional skill in all periods to roughly the same extent - the estimated elasticities are 0.21, 0.24, and 0.2 respectively. Only in the first period, however, is this effect estimated with real precision - the same period in which skills are being influenced by parents' socio-emotional skill and early cognition. In the second period, the estimated 90% confidence interval comfortably straddles zero, and in the last it does so marginally. We note here that throughout this section we do not necessarily interpret the estimates of large confidence intervals as strong evidence of absence of an effect for any input. Our sample size is relatively small in comparison with other similar studies, and, as Table 3.2 shows, our measures of socio-emotional skill are sometimes noisy. These two features of our data might then manifest in noisy parameter estimates.

To explore whether or not these effects differ across the distribution of cognitive and socio-emotional skill, Appendix Tables C9 and C10 show the estimated production function parameters when an interaction of cognitive and socio-emotional with investment is included respectively. We include the interactions separately rather than in the same equation due to the small size of our sample and the high-degree of collinearity between inputs induced by their inclusion, a common problem when estimating trans-log production functions.[14] We estimate that investments in the initial period are decreasing in children's cognitive skill in Table C9, but there is no evidence of any complementarity in any other period. There is a large negative interaction effect in the last

[14]Collinearity is also a concern due to the estimation method we use, which relies on instrumental variables. The estimation algorithm is outlined in detail in Appendix C.1

Table 3.5: Estimates of Cobb-Douglas socio-emotional production function parameters

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.062	0.028	0.073***
	(0.084)	(0.844)	(0.024)
	[-0.200,0.077]	[-1.360,1.415]	[0.034,0.112]
$\ln H_{c,t-1}$	0.233**	0.818	0.705***
	(0.114)	(0.745)	(0.207)
	[0.046,0.421]	[-0.407,2.044]	[0.365,1.046]
Parental human capital (fixed over time)			
$\ln P_s$	0.577***	-0.187	0.091
	(0.147)	(1.041)	(0.193)
	[0.335,0.820]	[-1.900,1.525]	[-0.226,0.408]
$\ln P_c$	0.039	0.104	-0.068*
	(0.076)	(0.201)	(0.041)
	[-0.086,0.164]	[-0.226,0.434]	[-0.136,-0.001]
Investments			
$\ln I_{t-1}$	0.212***	0.237	0.199
	(0.076)	(0.379)	(0.129)
	[0.087,0.338]	[-0.386,0.861]	[-0.013,0.410]
$\sigma^2_{\eta_n}$	1.5	13.9	.833
N	601	600	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment. All inputs are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3.3 are provided in Appendix C.2.

period, however we cannot reject that it is equal to zero. From Table C10, we infer that there are no strong interaction effects with respect to socio-emotional skill. This is in spite of there a being statistically significant interaction effect in the first period, as the point estimates and precision of the skill elasticities are sensitive to the inclusion of the interaction terms. This is unsurprising given the noise with which self-productivities were estimated, and the relatively low level of variation in socio-emotional measures relative to cognitive measures which leaves them more likely to introduce collinearities when used as interactions. We therefore do not draw any conclusions from Table C10.[15]

Turning finally to the estimated role of shocks to production, we find that their variance increases between the first two periods and then decreases significantly in late adolescence. This

[15]It is also caused by features of the estimation method that, in its present application, mean calculating the non-linear combinations of coefficients that have 1) been affected by the inclusion of the interaction and 2) are already estimated imprecisely.

suggests that factors other than the inputs in Table C10 impact the socio-emotional development most between the ages of 12-15 and that by the final period, between 15-19, there is relatively less external factors influencing socio-emotional development. In the middle period covering ages 12-15, however, the variance of the shocks increases substantially. Given the imprecision of the estimates between these ages, this is perhaps unsurprising. It is likely that socio-emotional skill development across this period is somewhat more malleable to external factors.

Cognitive skill

Table 3.6 shows analogous estimates to those in 3.5 for the production function of cognitive skill. In line with the much of the skill development literature, we find strong self-productivity in cognitive skill that is increasing over time (e.g. Cunha et al. (2010), Helmers and Patnam (2011),Agostinelli and Wiswall (2016a),Attanasio et al. (2017, 2020b,c)). We cannot reject zero cross-productivity in any period, however. Again, these results are comparable with studies that find little or small effects of socio-emotional skills on cognition (e.g. Cunha et al. (2010), Helmers and Patnam (2011) and Attanasio et al. (2020b)).

For parental human capital, we find a strong positive effect on socio-emotional skills in the initial period. The elasticity is estimated to be of roughly the same magnitude as in the production of socio-emotional skills, suggesting that parental socio-emotional skill plays a larger role in the early development of both skills in our sample. We do not estimate any large role for parental cognitive skill, however. We also find that investments influence cognitive development in all periods to a similar extent. The variance of production shocks is largest in the last period, however it is small and broadly similar in all periods, suggesting that cognitive production is influenced by little other than the inputs at any stage.

In Tables C11 and C12 we provide estimates of the production function with interactions of investment with cognition and socio-emotional skill respectively. There is a large, negative interaction effect between cognition and investments in the first and last periods in Table C11 , meaning that investments are more productive in children with low stocks of cognitive skill. In the last period, however, this effect is not statistically different from zero. In Table C12 there is a large positive interaction effect between investments and socio-emotional skill in the second period, which would suggest that across the period investments have higher returns in high-skilled children. The 90% confidence interval of this interaction contains zero, however.

3.4.4 The Implications of the Estimated Model

Together, the results of this section suggest that inequality in socio-emotional skill arises through the impact of family investments and its cross-productivity with cognition. To understand the implications of our results more concisely, we simulate the distribution of socio-emotional skills over time to analyse how they develop across the income distribution. To do so we first draw 100,000 synthetic observations from the estimated joint distribution of initial conditions,

Table 3.6: Estimates of Cobb-Douglas cognitive production function parameters

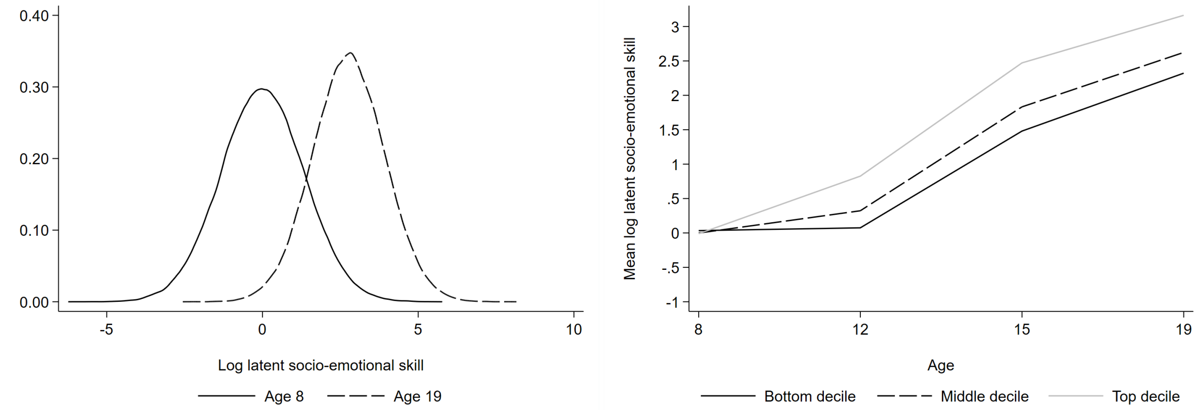
	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.048	-0.033	0.016
	(0.075)	(0.114)	(0.012)
	[-0.075,0.172]	[-0.220,0.154]	[-0.005,0.036]
$\ln H_{c,t-1}$	0.361***	0.595***	0.927***
	(0.089)	(0.079)	(0.095)
	[0.214,0.508]	[0.466,0.724]	[0.770,1.084]
Parental human capital (fixed over time)			
$\ln P_s$	0.366***	0.205	-0.039
	(0.133)	(0.143)	(0.079)
	[0.147,0.585]	[-0.031,0.440]	[-0.169,0.092]
$\ln P_c$	0.048	-0.016	-0.018
	(0.050)	(0.026)	(0.021)
	[-0.034,0.130]	[-0.058,0.026]	[-0.052,0.016]
Investments			
$\ln I_{t-1}$	0.177***	0.249***	0.114***
	(0.051)	(0.085)	(0.043)
	[0.093,0.260]	[0.109,0.390]	[0.043,0.185]
$\sigma^2_{\eta_c}$	.058	.0771	.142
N	597	594	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment. All inputs are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3.3 are provided in Appendix C.2.

estimates of which are shown in Appendix Tables C7 and C8. From the estimated investment parameters we then forward simulate household investment in the initial period and, subsequently, socio-emotional (and cognitive) skills in period 2. Repeating this process for periods 2 and 3 then simulates the full developmental path of skills between the ages of 8 and 19.

Figure 3.3 shows this simulated distribution of socio-emotional skill over time from two perspectives. Panel (a) plots its marginal distribution at the age of 8 and 19. Over time, the distribution becomes slightly narrower, suggesting the overall dispersion of socio-emotional skill declines with age. Panel (b) plots the mean level of log latent socio-emotional skill at each age, and shows that the relationship between income and skills strengthens over time, however. At age 8, the mean level of skill is approximately zero among those in the bottom, middle and top deciles of the income distribution, suggesting little-to-no relationship between income and skills. This is in line with the low correlations between the two presented in Figure 3.1. By age 12, however, a small gap opens up and those in the top decile of the income distribution have a higher level of

Figure 3.3: The Simulated Distribution of Socio-emotional Skill Over Childhood



(a) Marginal distribution of socio-emotional skills at age 8 and 19

(b) Mean stocks of socio-emotional skill over time across the income distribution

Note: Panel (a) the simulated distribution of socio-emotional skill at age 8 and 19, and panel (b) shows the simulated evolution of mean latent socio-emotional skill in the bottom, middle and top deciles of the income distribution. Both were estimated by simulating the developmental path of 100,000 observations randomly drawn from the estimated initial conditions.

skill on average than those in the bottom (or middle) decile. This then persists and widens slightly over time, and results in a clear income gradient in socio-emotional skills at age 19. Figure 3.3 makes it clear that whilst the overall dispersion of skills reduces over time in the sample, by age 19 they are strongly tied to income as a result of the estimated developmental process.

As we highlighted in Sections 3.2 and 3.3, we have attempted to increase the comparability of our latent concept of socio-emotional skill over time. It is important to bear in mind, however, that the trend we observe in the simulations in Figure 3.3 is likely affected by the fact the measures of socio-emotional skill used to estimate the model change over time.

3.5 Results Over Early Adulthood

With the results of the previous section in mind, we now move to estimates of how socio-emotional skills develop across early adulthood, and how they affect the likelihood of engagement in risky behaviour.

3.5.1 Production Function Estimates for Socio-emotional Skills

Table 3.7 shows estimates of the production functions of two disaggregated domains of socio-emotional skill between the ages of 19 and 22: social skills (column 1) and task effectiveness (column 2). The production functions estimated here - shown in Equation 3.4 - include TFP and allow the RTS to be freely estimated.

The estimates show that over early adulthood, the stock of socio-emotional skill accumulated by the end of adolescence has a strong, positive impact on both social skills and task effectiveness, to a similar extent. Cognition is cross-productive in the development of task effectiveness, however the opposite is true for social skills: over the period, a 1% increase in cognition associated with roughly a 0.41% *increase* in task effectiveness, but a 0.47% *decrease* in social skills. This suggests a level substitution for low cognition - individuals with lower levels of cognitive skills may develop higher social skills to compensate.

Moving to the vector of time-use included in TFP, we estimate that no allocation of time has an impact on the accumulation of social skills over early adulthood. However, in the case of task effectiveness, the coefficients on all of the time-use factors are estimated to be significantly different from zero, although in different directions. Specifically, the number of hours in paid work, caring for household members, and carrying out tasks related to home production negatively affects task effectiveness, whereas time spent studying outside of any formal education has a strong positive impact on its development over and above the effect of cognitive skill. The varying effect of skills and time-use highlights the importance of disaggregating skills along different domains. When aggregating measures of different facets of socio-emotional skills into one composite index, the effects of inputs will be either averaged across domains, or skewed to the sign and size of one domain that has a disproportionate signal. This would mean overlooking differences in the in the ways different domains of skill develop, such as those we find in Table 3.7.

There are also differences in the returns to scale of the skill production functions. For social skills, the technology is estimated as having decreasing returns to scale, suggesting, for example, that doubling socio-emotional skills and cognition at the end of adolescence would result in only around a 50% increase in social skills. The technology for task effectiveness, however is estimated to have a RTS of roughly 1.3, and its corresponding 90% confidence interval only marginally contains 1. This would suggest that that the same doubling of inputs would lead to a 130% increase in task effectiveness at age 22. The variance of the shocks is also larger for task effectiveness suggesting there are more external factors influencing its development relative to social skills and that task effectiveness is more malleable than social skills over early adulthood.

Table 3.7: Estimates of socio-emotional production functions in adulthood

	(1) *Social skills*	(2) *Task effectiveness*
Lagged human capital		
$\ln H_{s,t-1}$	0.933***	0.892***
	(0.136)	(0.199)
	[0.709,1.157]	[0.565,1.219]
$\ln H_{c,t-1}$	-0.473***	0.413**
	(0.123)	(0.196)
	[-0.675,-0.271]	[0.091,0.735]
Total Factor Productivity ($\ln A_T$)		
Hours studying	-0.070	0.707***
	(0.112)	(0.132)
	[-0.255,0.115]	[0.490,0.923]
Hours working	-0.015	-0.078**
	(0.028)	(0.032)
	[-0.061,0.031]	[-0.130,-0.026]
Hours caring	-0.019	-0.122***
	(0.030)	(0.044)
	[-0.068,0.031]	[-0.194,-0.049]
Hours home production	-0.009	-0.100***
	(0.036)	(0.030)
	[-0.069,0.051]	[-0.149,-0.051]
α_T	-0.095	-1.311***
	(0.477)	(0.470)
	[-0.879,0.690]	[-2.084,-0.538]
Returns to scale	0.460***	1.305***
	(0.143)	(0.185)
	[0.224,0.696]	[1.000,1.610]
$\sigma^2_{\eta^j_s}$	.555	1.2
N	550	550

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. T = age 19 in each column. The left column contains lagged child socio-emotional skill and cognitive skill; the variables included in $\ln A_T$; residual productivity α_T; and the estimates Returns to Scale (RTS). Lagged human capital is treated as unobservable. The observables used as measures for each are described in Appendix C.2. Appendix C.1 outlines the method used to obtain all estimates in the table.

3.5.2 Socio-emotional Skills and Risky Behaviour

The discussion of the estimated parameters of the investment and production functions to this point has necessarily been centred on relating the stocks of latent variables to one another over time. Even with the measurement system and normalizations, this discussion remains somewhat abstract. In order to provide a more socially or economically meaningful measure of the importance of human capital, we investigate the effect of skills on risky behaviours in early adulthood, given that many young people have not yet fully completed their education and begun earning. Risky behaviours are both predictive of future economic success, and may also reduce life-expectancy (Cawley and Ruhm, 2011). We define adult outcome O_{T+1} to be a function of our two $T+1$ socio-emotional domains (social skills and task effectiveness), cognitive skill at T and a vector of individual characteristics $\mathbf{x}_{T+1}$:

$$O_{T+1} = \mu_o + \gamma_1^o H^t_{s,T+1} + \gamma_2^o H^s_{s,T+1} + \gamma_3^o H_{c,T} + \mathbf{x}'_{T+1}\boldsymbol{\delta} + \eta^o_{T+1} \quad \text{for} \quad j \in \{t, s\} \tag{3.11}$$

We assume the error term, η^o_{T+1} is independent of the inputs, and that the outcome is measured without error. As outcomes, we use six indicators of risky behaviour collected as part of the YLS (in a self-administered questionnaire for sensitive items): smoked at least once a month; ever been drunk; ever taken illegal drugs; ever had unprotected sex; carried a weapon in the last month; been arrested for being part of a gang or carrying a weapon in the last month; or has a child or is pregnant (or has a partner who is pregnant) at age 22. As controls, included in $\mathbf{x}_{T+1}$, we use individuals' gender and wealth. Using cognitive skill as captured by measures at T is somewhat analogous to assuming that cognitive skill is fixed from age 18 onward. Given our estimates of the increasing self-productivity of cognitive skill, and the evidence that cognition is much less malleable than socio-emotional skills over the lifecourse, this assumption is not overly restrictive.[16]

All of the outcomes we use to estimate Equation 3.11 are binary. There are several possible ways to estimate its parameters for each outcome, however we use an IV linear probability model as it does not require us to make additional assumptions about the distribution of the measurement error, given the findings of Laajaj and Macours (2019), and it is robust to miss-specification of the first stage. Appendix C.1 discusses the estimation of Equation 3.11 in more detail. Table 3.8 reports the estimated marginal effects for each outcome. The marginal effect of task effectiveness is negative for every risky behaviour, and are marginally statistically different from zero for the likelihood of having smoked once a month (column 1), taken illegal drugs (column 3) and having been arrested for being part of a gang (column 6). Although the statistical evidence that the relationship between task effectiveness and these outcomes is marginal, the sample size and

[16] Kautz et al. (2014) discuss in detail how the development of socio-emotional and cognitive skills differs. Walsh and Walsh (2014) discuss how the slow-development of the pre-frontal cortex means personality traits are unstable over adolescence and later life stages.

Table 3.8: Estimates of the impact of age 22 socio-emotional skills on risky behaviours

	(1) Smoked	(2) Drank	(3) Drugs	(4) Unprotected sex	(5) Carried weapon	(6) Gang	(1) Child
$\ln H^{t}_{s,T+1}$	-0.084*	-0.007	-0.096*	-0.022	-0.019	-0.067*	-0.041
	(0.049)	(0.068)	(0.053)	(0.059)	(0.024)	(0.038)	(0.053)
$\ln H^{s}_{s,T+1}$	0.015	-0.050	0.016	-0.023	0.022	0.044	0.018
	(0.058)	(0.074)	(0.057)	(0.067)	(0.033)	(0.045)	(0.066)
$\ln H_{c,T}$	0.144	0.099	0.166*	0.046	0.021	0.081	-0.067
	(0.098)	(0.124)	(0.100)	(0.120)	(0.045)	(0.073)	(0.100)
Female	-0.253***	-0.293***	-0.106**	0.181***	-0.019	-0.082**	0.252***
	(0.050)	(0.063)	(0.044)	(0.059)	(0.020)	(0.037)	(0.047)
Wealth index	0.024	0.026	0.305	-0.267	-0.060	-0.033	-0.031
	(0.173)	(0.202)	(0.199)	(0.184)	(0.103)	(0.136)	(0.147)
Outcome mean	0.23	0.51	0.15	0.30	0.05	0.12	0.30
N	531	523	441	499	535	534	551

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. Standard errors in parentheses are calculated from 1,000 bootstrap replications. The outcomes in each column are whether not an individual has: smoked least once a month (1); ever been drunk (2); ever taken illegal drugs (3); ever had unprotected sex (4); carried a weapon in the last month (5); been arrested for being part of a gang or carrying a weapon in the last month (6); or has a child or is pregnant at age 22 (7). *Female* is a dummy indicating whether or not an individual is female, and the *wealth index* a measure of the material resources of the family which ranges from 0 to 1, constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. See Briones (2017) for detail. The number of observations differs in across columns due to missing responses.

methodology likely combine hear to limit out power to identify statistically strong correlations between the two.

The pattern is not as clear for social skills, and none of these effects are estimated with precision; we cannot reject that they are zero for every outcome. The marginal effects of cognition are positive and significant for having taken illegal drugs (column 3). Wealth also has a large, positive marginal effect on this outcome - a relationship that is perhaps unsurprising considering that illegal drugs include those that might be considered "recreational" - for example marijuana. These results are slightly different from those of Heckman et al. (2006), who find cognitive skills also decrease the probability of risky behaviour. Further, in their analysis, they measure latent socio-emotional skills by self-esteem and locus of control, which is a subset of our task effectiveness skill. Our results show that social skills do not have the same effect, highlighting that the definition of socio-emotional skills is important when drawing policy conclusions regarding skills and behaviour. The higher risk of drug taking for individuals with higher cognitive skills may also be related to the difference in context between US and Peru - but our results suggest that it is even more important to cultivate task effectiveness skills, if improved cognition does not reduce risky behaviour in this context.

The results in Table 3.8 highlight the complexity of the relationship between skills and outcomes. Firstly, they show again the importance if disaggregating socio-emotional skills along distinct domains. Not doing so, and treating socio-emotional skills as an aggregate, would mean overlooking how they affect outcomes differently - a key question for policy given the abstractness of aggregate "bundles" of skills. Secondly, the results show the potential interplay of skills in determining outcomes - even though being smarter is considered to be an improvement, it is likely that socio-emotional skills like task-effectiveness drive individuals to make life choices commensurate with social and economic success. Of course, we cannot know from this analysis the extent to which these skills are related to future social and economic outcomes, however evidence suggests risky behaviours are driven by the same factors that correlate with wages, employment and schooling attainment (Heckman et al., 2006).

3.6 Conclusion

In this paper we examined the accumulation of socio-emotional skills between the ages of 8 and 22 in Peru. We also estimate the developmental path of cognitive skill between 8 and 19, and the role it plays in this process (and vice-versa). To do so, we estimate a dynamic latent factor model of household investment and skill production using a framework developed by Agostinelli and Wiswall (2016a) that captures key aspects of the skill accumulation process.

We find that household investments are largely determined by family resources and parents' socio-emotional skills, and no evidence that parents invest in response to their children's revealed human capital. Our estimates of human capital production functions suggest that these investments positively affect socio-emotional skill accumulation in the early periods of our model, and that the impact varies across the distribution of skills. Our results also show that socio-emotional skills' self-productivity is increasing with age and that cognition is highly self-productive across all of adolescence. We also find that socio-emotional skills are determined by stocks of cognitive skills to a far greater extent than past socio-emotional skills at all stages. The result is the emergence of a socioeconomic gradient in socio-emotional skill between the ages of 8 and 12 that then persists over adolescence.

In early adulthood between the ages of 19 and 22, we disaggregate socio-emotional skills along two domains: social skills and task-effectiveness and relax some of the functional form restrictions required to estimate the technology of skill formation between 8 and 19. This portion of our analysis provides evidence that socio-emotional skills accumulated by the end of adolescence are important in building both these two domains in early adulthood, but there is a negative relationship between cognitive skill and the development of social skills, perhaps suggesting that individuals substitute low cognition with social skills. Over this period, we find that time spent studying positively affects the accumulation of task effectiveness, whereas the reverse is true for time in home production or caring for household members. Finally, we estimate the returns to scaling up the inputs of the socio-emotional skill functions are far greater for task effectiveness than for social skills. At age 22, we also find evidence that task-effectiveness is negatively correlated with the probability of individuals engaging in a range of risky behaviours, in particular smoking, taking drugs and engaging in gang related behaviour. Social skills on the other hand have no effect on these intermediate outcomes.

Together, these results suggest that gaps in socio-emotional skills arise and persist through differences in household investments and the cross-productivity of cognition in socio-emotional skill production. Socio-emotional skills are then highly self-productive across early adulthood, and lead to differences in engagement with a range of risk behaviours, this being predictive of likely lower economic success in future years. Gaining knowledge as to how human capital develops over childhood and adolescence is crucial in understanding the transmission of poverty and inequality across generations. The results of this paper offer several additions to the growing evidence base that has come from the literature on the economics of early skill accumulation over the past decade.

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Appendix A

Supplementary Material for Chapter 1

A.1 Additional Descriptive Results

A.1.1 Additional descriptive tables and figures

Table A1: Percent of families in each UK income quintile at age 14, by UK income quintile at age 9 months

		UK income quintile age 14					
		1	*2*	*3*	*4*	*5*	% Missing
UK Income quintile 9 months	*1*	46.90	28.75	15.50	6.34	2.52	49.72
	2	23.49	28.02	25.99	16.55	5.95	43.46
	3	5.13	14.17	28.67	34.27	17.75	38.43
	4	1.97	6.87	19.92	34.94	36.31	31.15
	5	0.97	3.52	11.63	26.21	57.67	28.77

Note: Each of the first 5 rows/columns indicates the income quintile a family was in when their child was aged 14 given their income quintile at 9 months for those present at both ages. The first 5 columns sum to 100% for each row. % Missing represents to proportion in each income quintile at 9 months who were not present at age 14. Income quintiles are defined out of sample relative the UK household income distribution.

Table A2: Percent of parents overweight or obese at age 11, by weight at age 9 months

		Parental weight at age 11				
		Normal range	*Overweight*	*Obese*	*Morbidly obese*	% Missing
Parental weight 9 months	*Normal range*	73.51	22.24	4.00	0.25	46.57
	Overweight	16.59	53.72	28.61	1.07	49.69
	Obese	2.74	21.80	65.18	10.27	54.18
	Morbidly obese	0	1.52	34.85	63.64	53.52

Note: Each of the first 4 rows/columns indicates the BMI range of parents' weight when their child was aged 11 given their category at 9 months for those present at both ages. The first 4 columns sum to 100% for each row. % Missing represents to proportion in each category at 9 months who were not present at age 11. Overweight is defined by having a BMI of between 25 and 30, obesity between 30 and 40, and morbid obesity above 40.

Table A3: The early predictors of obesity and overweight at age 14

	Weighted		Un-weighted	
	(1) Obese	(2) Overweight	(1) Obese	(2) Overweight
Main parent overweight at 9 months	0.047***	0.107***	0.043***	0.107***
	(0.000)	(0.000)	(0.000)	(0.000)
Main parent obese at 9 months	0.117***	0.186***	0.108***	0.213***
	(0.000)	(0.000)	(0.000)	(0.000)
Income quintiles				
Lowest quintile	0.044***	0.076***	0.034***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)
Second quintile	0.032***	0.043**	0.029***	0.026*
	(0.001)	(0.018)	(0.000)	(0.069)
Third quintile	−0.002	0.046***	0.013**	0.044***
	(0.728)	(0.005)	(0.039)	(0.001)
Fourth quintile	0.006	0.023	0.006	0.027**
	(0.444)	(0.107)	(0.286)	(0.030)
$\mathbb{E}[Pr(outcome)\|\boldsymbol{x}]$	0.043	0.169	0.043	0.163
N	8.663	8.142	8.664	8.143

Note: *, **, and *** denote statistical significance at 10%, 5% and 1% respectively. The effects reported are marginal effects from a logit regression with the outcomes being whether a child is obese (column 1 & 3) or overweight (column 2 & 4) at age 14. Family income is equivalised to adjust for household composition using the OECD equivalisation scales (Hansen et al., 2014). All observations in columns 1 and 2 are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted income category is the *fifth quintile*. Quintiles are relative to the distribution of income in the UK. The regression also controlled for gender, birthweight, weight gain between birth and 9 months, ethnicity, the number of siblings in the household and the parent's age at birth, level of education, and whether or not they have a long-term illness. All are fixed at their means in predicting the marginal effects reported. The *main parent* is the survey respondent, and is the mother for over 99% of children at 9 months. N differs between columns because the outcome in column 2 excludes obese children.

A.1.2 Constructing a healthy behaviour index

Tables A4a and A4b show how indicators of healthy behaviour were created from MCS variables in each round. From these measures we construct an overall index of healthy behaviour based on the number of healthy habits children are reported to have. As the number, type, and coding of measures differs across ages, so does our threshold for satisfying the index. We define children as having "healthy behaviour" if they have all three behaviours at age 3; four or more at ages 5, 7, and 14; and five at 11.

Table A4a: Notes on MCS variables used as measures of healthy behaviours

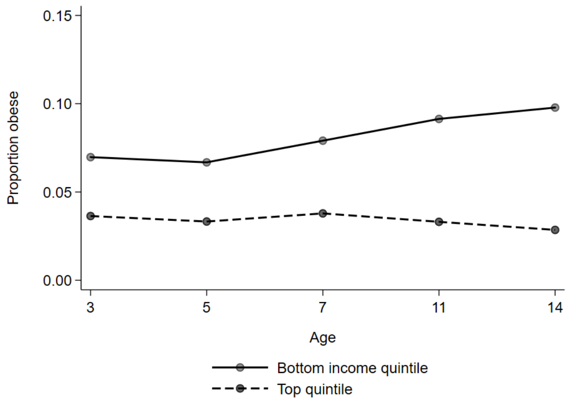
MCS variable	Responses	Indicator created
Age 3		
Child has fruit/vegetables once a day	0/1: no/yes	Variable used as it was
Child has regular meal times	1/2/3/4: never or almost never/sometimes/ usually/always	Child always has regular meals
Someone does sport with the child	0/1: no/yes	Variable used as it was
Age 5		
Portions of fruit/vegetables a day	0/1/2/3: none/one/two/three or more	Child has three portions of fruit/veg. a day
Child has regular meal times	See variable at age 3	Child always has regular meals
How often plays physically active games	1/2/3/4/5/6: not at all/less often/once or twice a month/once or twice a week/several times a week/every day	Plays physically active games with child once a week
Days per week child does sport/exercise	1/2/3/4/5/7: less often or not at all/one day/two days/three days/four days/five or more days	
How often child does sport/exercise with family	1/2/3/4/5/6/7: less often or never/once a year/every few months/once a month/once or twice a week/several times a week/every day	Parent does sport/exercise with child at least once a week
Age 7		
How often child eats fruit/vegetables	See variable at age 5	
Child has regular meal times	See variable at age 3	
How often plays physically active games	See variable at age 5	
Days per week child does sport/exercise	See variable at age 5	
How often parent does sport/exercise with child	1/2/3/4/5/6: not at all/less than once a month/once or twice a month/once or twice a week/several times a week/every day or almost every day	

Table A4b: Notes on MCS variables used as measures of healthy behaviours cont.

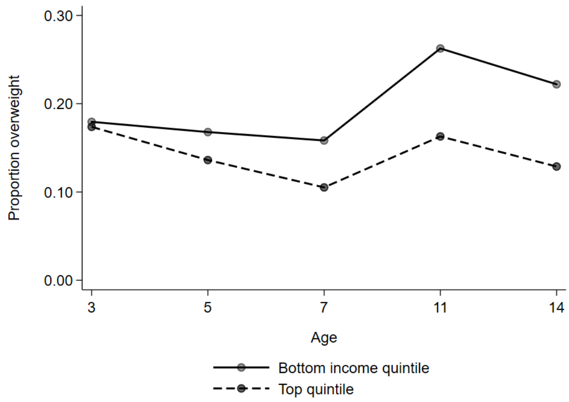
MCS variable	Responses	Indicator created
Age 11		
How often child eats fruit/vegetables	See variable at age 5	
How often parent does sport/exercise with child	See variable at age 7	
Days per week child does sport/exercise	See variable at age 5	
Days per week child does physical activities	1/2/3/4/5/6/7: not at all/less often than once a week/one day/two days/three days/four days/five or more days	Child plays physically active games at least once a week
Days per week child has breakfast	1/2/3/4/5/6/7	Child has breakfast every day
How often drinks sweetened drinks	1/2/3/4/5/6/7: more than once a day/once a day/3-6 days a week/1-2 days/once a month/less than once a month/never	Child drinks sweetened drinks less than once a day
How often drinks artificially sweetened drinks	1/2/3/4/5/6/7: more than once a day/once a day/3-6 days a week/1-2 days/once a month/less than once a month/never	Child drinks artificially sweetened drinks less than once a day
Age 14		
How often child two portions of fruit/vegetables	1/2/3: never/some days/every day	
Days per week child eats breakfast	1/2/3/4/5/6/7	
How often drinks sweetened drinks	See variable at age 11	
How often drinks artificially sweetened drinks	See variable at age 11	
How often has fast food	1/2/3/4/5/6/7: more than once a day/once a day/3-6 days a week/1-2 days/once a month/less than once a month/never	child has fast food less than once a month

A.1.3 Additional figures on height and weight across rounds of the MCS

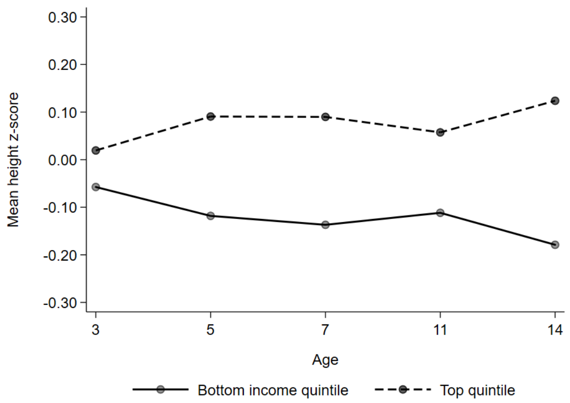
Figure A1: Obesity across waves in the MCS in the top and bottom income quintiles at age 9 months



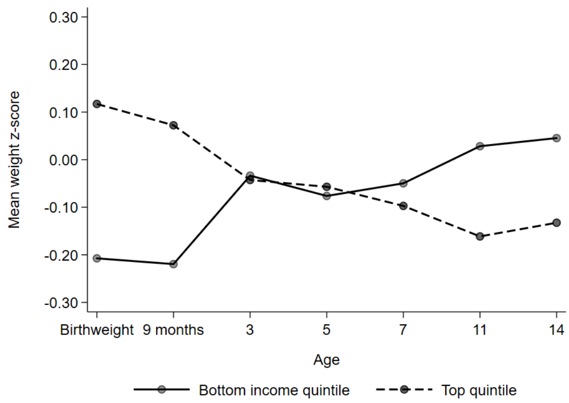
(a)



(b)



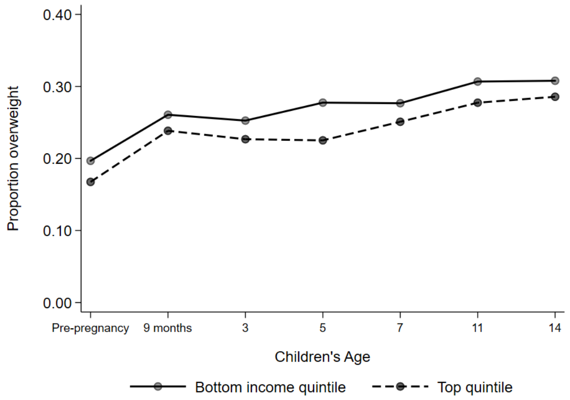
(c)



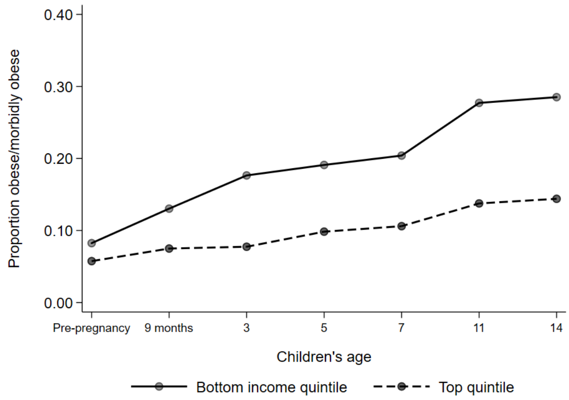
(d)

Note: Income quintiles are relative to the UK income distribution are defined in sample using households' equivalised income, calculated using the OECD equivalisation scales to adjust for family size and composition. Income is fixed at its level when children were 9 months old. Panel (a) shows the proportion of children at each age classified as obese and panel (b) the proportion classified overweight. Both definitions are based on the International Obesity Task Force age-specific BMI thresholds (see Table 1.1). Panel (c) shows the average height Z-score of children and panel (d) the average weight Z-score in each of these quintiles at each age. For comparability, the sample includes children who remained in the sample across all waves.

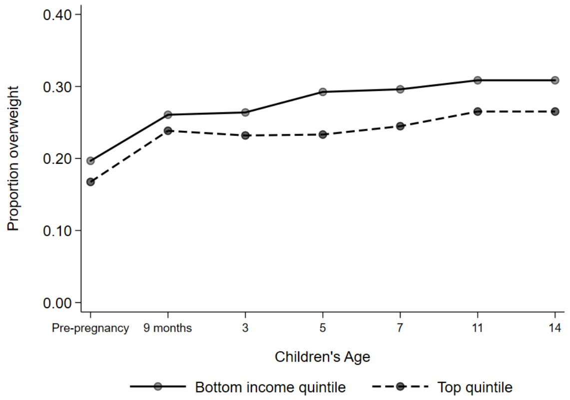
Figure A2: Overweight and obesity of parents across waves in the MCS, by income quintile



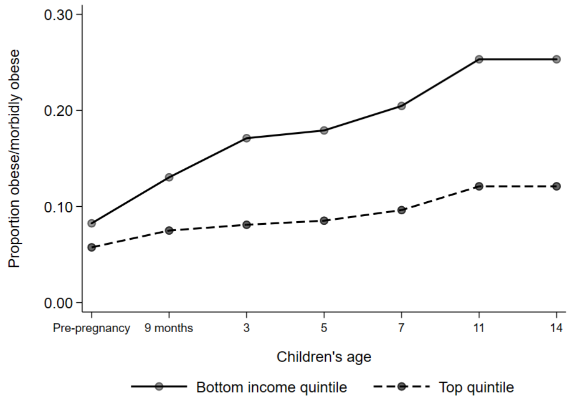
(a) Income varying over time



(b) Income varying over time



(c) Income fixed at 9 months



(d) Income fixed at 9 months

Note: Income quintiles are relative to the UK income distribution are defined in sample using households' equivalised income, calculated using the OECD equivalisation scales to adjust for family size and composition. In panels (a) and (b) quintiles are re-calculated at each age. In panels (c) and (d) they are fixed at their 9-months value. Panels (a) and (c) shows the proportion parents at each age that classified as obese and panel (b) and (d) the proportion classified morbidly obese. Overweight is defined by having a BMI of between 30 and 40, and obesity as a BMI above 40. For comparability, the sample includes parents of children who remained in the sample across all waves.

A.1.4 Predicting parents' weight at age 14

The MCS does not have weight or height information on parents when children are age 14. We therefore estimate how parents' weight evolves over childhood using the following equation:

$$MPW_{it} = \beta_0 + \beta_1 MPW_{it-1} + \beta_2 MPHeight_{it} + \beta_3 t + \beta_4 t^2 + \varepsilon_{it}\ , \tag{A2}$$

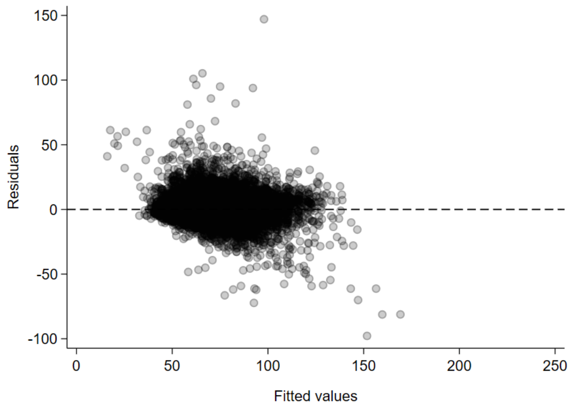
where MPW_{it} is the weight of the main parent in kilograms, MPW_{it-1} is lagged weight, $MPHeight_{it}$ is height in metres, t and t^2 represent a quadratic time-trend, and β_0 is a constant. We do not explicitly model individual heterogeneity here since we are not interested in strictly interpreting the parameters themselves. We estimate the parameters of this equation using information on parents' weight from pre-pregnancy to age 11 - the MCS asks respondents their BMI before pregnancy from which we are able to calculate their weight in kilograms pre-pregnancy, given that height is constant across rounds. Table A5 shows these estimates, and Figures A3(a)-A3(c) respectively show plots of the residuals versus fitted values, density of the residuals, and the correlation between actual and predicted values of parents' weight from this regression. We then use the parameters in Table A5 to predict parents' weight when children are aged 14.

Table A5: Determinants of parental weight across childhood

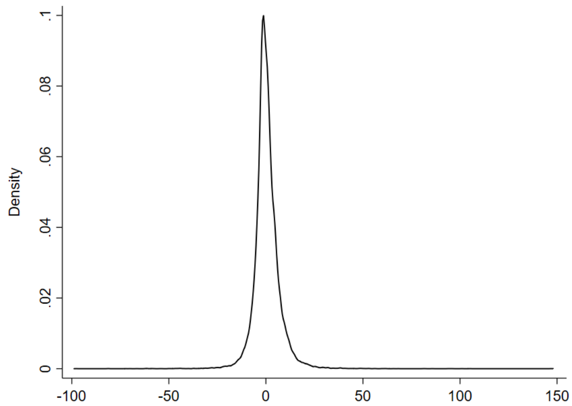
	β
Lagged weight	0.892***
	(0.007)
Height in metres	5.138***
	(0.669)
Linear trend	−2.267***
	(0.422)
Quadratic	0.307***
	(0.048)
Constant	3.216*
	(1.283)
Observations	19.245
R-Squared	0.770

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% respectively. Standard errors in parentheses are clustered at the individual level. The outcome is weight in kilograms.

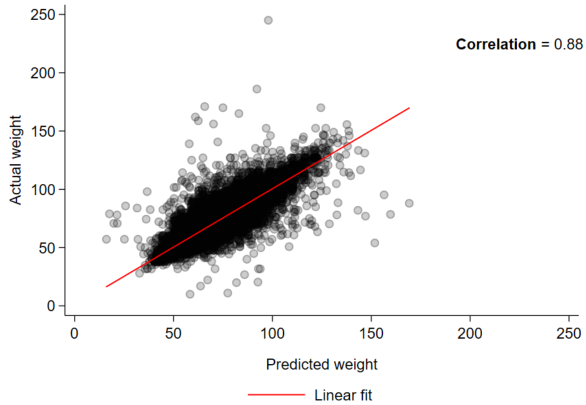
Figure A3: Properties of the residuals and fitted values from estimating the determinants of parental weight from pre-pregnancy to age 11



(a) Residuals versus fitted values



(b) Residual distribution



(c) Actual versus fitted values

Note: All panels use residuals and/or fitted values from estimating how lagged weight, height, and a quadratic time-trend explain parents' weight from pre-pregnancy to when children are aged 11 (Equation A2). Results of this regression are shown in Table A5.

A.2 Additional results

A.2.1 Additional tables on the determinants of overweight and obesity

Table A6: The determinants of child overweight and obesity across childhood, using a balanced panel and not adjusting for attrition or sample design

					(5)-(6) Age 14	
	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	Parental weight constant	Parental weight predicted
Panel A: Probability of overweight						
Main parent overweight	0.028***	0.058***	0.063***	0.113***	0.099***	0.074***
	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)
Main parent obese/morbidly obese	0.065***	0.100***	0.091***	0.184***	0.171***	0.169***
	(0.014)	(0.013)	(0.013)	(0.015)	(0.014)	(0.013)
Income quintiles						
Lowest quintile	0.026	0.033**	0.021	0.062***	0.083***	0.085***
	(0.017)	(0.016)	(0.016)	(0.023)	(0.023)	(0.023)
Second quintile	0.024	0.013	0.012	0.063***	0.040**	0.040**
	(0.015)	(0.014)	(0.014)	(0.018)	(0.017)	(0.017)
Third quintile	0.026*	0.003	0.003	0.060***	0.044***	0.046***
	(0.014)	(0.012)	(0.013)	(0.016)	(0.014)	(0.014)
Fourth quintile	0.024*	0.024**	−0.006	0.034**	0.015	0.014
	(0.013)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.162	0.138	0.125	0.199	0.153	0.154
N	7.203	7.775	7.462	6.848	6.674	6.674
Panel B: Probability of obesity						
Main parent overweight	0.014***	0.026***	0.026***	0.026***	0.023***	0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Main parent obese/morbidly obese	0.037***	0.054***	0.084***	0.081***	0.094***	0.092***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
Income quintiles						
Lowest quintile	0.021**	0.010	0.010	0.027**	0.075***	0.076***
	(0.010)	(0.009)	(0.010)	(0.013)	(0.015)	(0.015)
Second quintile	0.012	0.008	0.008	0.037***	0.036***	0.035***
	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.010)
Third quintile	−0.002	0.004	0.004	0.021**	0.021***	0.022***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)
Fourth quintile	0.007	0.001	−0.000	0.012	0.016**	0.016**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.039	0.038	0.042	0.046	0.038	0.038
N	7.589	8.193	8.023	7.296	7.067	7.067
Panel B: Probability of overweight or obesity						
Main parent overweight	0.036***	0.074***	0.079***	0.126***	0.114***	0.092***
	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)	(0.010)
Main parent obese/morbidly obese	0.087***	0.135***	0.152***	0.233***	0.234***	0.232***
	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)
Income quintiles						
Lowest quintile	0.044**	0.038**	0.029*	0.080***	0.134***	0.136***
	(0.017)	(0.016)	(0.017)	(0.024)	(0.023)	(0.023)
Second quintile	0.030*	0.020	0.016	0.087***	0.066***	0.065***
	(0.015)	(0.015)	(0.015)	(0.019)	(0.017)	(0.017)
Third quintile	0.024*	0.006	0.006	0.072***	0.058***	0.060***
	(0.014)	(0.013)	(0.014)	(0.016)	(0.014)	(0.014)
Fourth quintile	0.026*	0.024*	−0.006	0.039***	0.027**	0.026**
	(0.014)	(0.013)	(0.013)	(0.015)	(0.013)	(0.013)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.201	0.178	0.167	0.244	0.193	0.193
N	7.589	8.193	8.023	7.296	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is indicated by Panels A-C, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. The omitted income category is the highest quintile. All regressions also controlled for children's gender, birthweight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. Appendix Tables A8-A10 show full results. $\mathbb{E}[Pr(outcome)|\boldsymbol{x}]$ represents the estimated conditional expectation of each outcome. The *main parent* is the mother for 99% of children at 9 months. Ns differ in Panel A because these regressions exclude obese children. Ns differ across columns because of missing data.

Table A7: The difference in marginal effects of parental weight and income for those present in all waves of the MCS versus those who drop out at some point in the survey

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11
Panel A: Overweight				
Main parent Overweight	0.025	0.006	-0.001	-0.007
	(0.022)	(0.022)	(0.024)	(0.039)
Main parent obese/morbidly obese	0.010	-0.046	-0.046	-0.055
	(0.030)	(0.034)	(0.036)	(0.051)
Lowest quintile	-0.069	0.023	-0.004	0.188***
	(0.031)	(0.031)	(0.033)	(0.058)
Second quintile	-0.016	0.017	0.028	0.157***
	(0.029)	(0.031)	(0.032)	(0.056)
Third quintile	-0.027	0.036	-0.025	0.114*
	(0.029)	(0.030)	(0.033)	(0.059)
Fourth quintile	-0.027	0.015	-0.046	0.161***
	(0.028)	(0.031)	(0.034)	(0.054)
Panel B: Obese				
Main parent Overweight	-0.003	-0.002	-0.043*	-0.038
	(0.012)	(0.014)	(0.017)	(0.019)
Main parent obese/morbidly obese	-0.012	-0.029	-0.015	0.027
	(0.020)	(0.020)	(0.024)	(0.023)
Lowest quintile	0.012	-0.024	0.012	-0.036
	(0.017)	(0.019)	(0.022)	(0.028)
Second quintile	-0.012	-0.027	0.007	-0.012
	(0.016)	(0.019)	(0.021)	(0.024)
Third quintile	-0.026	-0.030	-0.022	-0.005
	(0.016)	(0.020)	(0.023)	(0.023)
Fourth quintile	-0.020	-0.034	-0.034	-0.025
	(0.017)	(0.020)	(0.025)	(0.026)
Panel C: Overweight or obese				
Main parent Overweight	0.023	0.006	-0.034	-0.036
	(0.023)	(0.023)	(0.026)	(0.039)
Main parent obese/morbidly obese	0.002	-0.060*	-0.051	-0.032
	(0.031)	(0.033)	(0.036)	(0.049)
Lowest quintile	-0.057*	0.003	0.002	0.158***
	(0.032)	(0.033)	(0.036)	(0.059)
Second quintile	-0.020	0.000	0.029	0.144***
	(0.030)	(0.033)	(0.034)	(0.056)
Third quintile	-0.042	0.012	-0.041	0.110**
	(0.030)	(0.033)	(0.035)	(0.059)
Fourth quintile	-0.040	-0.002	-0.067*	0.139**
	(0.030)	(0.033)	(0.037)	(0.056)

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is indicated by Panels A-C, defined using the IOTF cutoffs (Table 1.1). The effects reported are differences in marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean, and including an interaction of income quintiles and parental weight categories with an indicator of being present in all waves. The omitted income category is the highest quintile. All regressions also controlled for children's gender, birthweight, weight gain between birth and 9 months, whether they have a long-term illness and the number of health conditions reported, ethnicity, the number of siblings in the household, and the parent's level of education and whether they have a long-term illness. The *main parent* is the mother for 99% of children at 9 months. Ns differ in Panel A because these regressions exclude obese children. Ns differ across columns because of missing data.

Table A8: The determinants of child overweight across childhood with controls

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	 Parental weight predicted
Main parent overweight	0.022**	0.061***	0.065***	0.101***	0.105***	0.074***
	(0.010)	(0.010)	(0.010)	(0.012)	(0.014)	(0.012)
Main parent obese/morbidly obese	0.062***	0.126***	0.097***	0.197***	0.170***	0.172***
	(0.014)	(0.014)	(0.013)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.038**	0.025*	0.011	0.030	0.117***	0.122***
	(0.016)	(0.015)	(0.016)	(0.025)	(0.033)	(0.034)
Second quintile	0.035**	0.008	0.018	0.055***	0.055***	0.054***
	(0.015)	(0.014)	(0.015)	(0.021)	(0.021)	(0.021)
Third quintile	0.030**	−0.005	0.013	0.057***	0.041**	0.042***
	(0.013)	(0.012)	(0.013)	(0.018)	(0.016)	(0.016)
Fourth quintile	0.024*	0.023*	0.002	0.019	0.012	0.012
	(0.013)	(0.012)	(0.012)	(0.015)	(0.014)	(0.014)
Female	0.063***	0.092***	0.093***	0.069***	0.044***	0.045***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.013)	(0.013)
Child long-term illness	0.016	−0.016	−0.006	0.004	0.006	0.007
	(0.012)	(0.011)	(0.011)	(0.018)	(0.021)	(0.021)
Health conditions	0.004	0.006	0.003	0.001	0.006	0.005
	(0.004)	(0.004)	(0.004)	(0.005)	(0.010)	(0.010)
Main parent long-term illness	−0.015	−0.003	0.018*	0.007	−0.006	−0.003
	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)	(0.015)
No. of siblings	0.003	−0.005	−0.011**	−0.021***	−0.025***	−0.025***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
Birthweight	0.109***	0.090***	0.058***	0.033***	0.024**	0.028***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Weight gain 9 months-3 (kg)	0.077***	0.068***	0.041***	0.035***	0.023***	0.022***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
Main Parent's education						
NVQ level 1	0.008	0.019	−0.030	−0.016	−0.009	−0.014
	(0.021)	(0.020)	(0.020)	(0.027)	(0.033)	(0.034)
NVQ level 2	−0.004	−0.007	−0.007	−0.006	−0.003	−0.006
	(0.017)	(0.015)	(0.016)	(0.022)	(0.024)	(0.024)
NVQ level 3	−0.004	−0.000	−0.032*	−0.025	−0.025	−0.030
	(0.019)	(0.017)	(0.018)	(0.024)	(0.026)	(0.026)
NVQ level 4	0.001	0.004	−0.021	−0.016	−0.006	−0.011
	(0.018)	(0.016)	(0.017)	(0.024)	(0.025)	(0.025)
NVQ level 5	0.071**	0.004	−0.026	−0.024	−0.054	−0.058*
	(0.030)	(0.025)	(0.026)	(0.035)	(0.032)	(0.033)
Ethnicity						
Mixed	0.032	−0.009	−0.055	0.049	−0.030	−0.035
	(0.052)	(0.040)	(0.034)	(0.038)	(0.052)	(0.049)
Indian	−0.089***	0.017	0.047	0.059	0.094	0.098
	(0.026)	(0.038)	(0.037)	(0.041)	(0.091)	(0.096)
Pakistani and Bangladeshi	−0.021	−0.012	−0.000	0.065**	−0.001	−0.004
	(0.023)	(0.023)	(0.024)	(0.033)	(0.030)	(0.029)
Black or Black British	0.014	0.062**	0.073**	0.110***	0.043	0.041
	(0.032)	(0.031)	(0.035)	(0.041)	(0.037)	(0.038)
Other Ethnic group (inc. Chinese, Other)	−0.013	−0.042	−0.020	0.001	0.061	0.054
	(0.040)	(0.032)	(0.038)	(0.063)	(0.072)	(0.071)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.133	0.124	0.198	0.155	0.156
N	10.143	10.485	9.405	7.887	6.674	6.674

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents the estimated conditional probability a child is overweight at each age. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A9: The determinants of child obesity across childhood with controls

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent overweight	0.021***	0.026***	0.035***	0.037***	0.026***	0.025***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Main parent obese/morbidly obese	0.048***	0.065***	0.087***	0.084***	0.104***	0.098***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)	(0.010)
Income quintiles						
Lowest quintile	0.020**	0.018*	0.017*	0.039***	0.081***	0.082***
	(0.009)	(0.009)	(0.010)	(0.014)	(0.020)	(0.020)
Second quintile	0.013	0.012	0.012	0.042***	0.033***	0.034***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)	(0.012)
Third quintile	0.003	0.007	0.007	0.022**	0.019**	0.020**
	(0.007)	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)
Fourth quintile	0.015*	0.007	0.006	0.010	0.011	0.010
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Female	0.023***	0.017***	0.028***	0.023***	0.025***	0.025***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Child long-term illness	−0.012*	0.017**	0.003	0.003	0.009	0.010
	(0.006)	(0.007)	(0.007)	(0.009)	(0.012)	(0.012)
Health conditions	0.002	0.001	0.005**	0.005**	0.005	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Main parent long-term illness	−0.001	0.010*	0.006	0.016**	0.009	0.010
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)
No. of siblings	0.000	−0.007***	−0.006**	−0.010***	−0.010***	−0.010***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Birthweight	0.014***	0.026***	0.012***	0.020***	0.027***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Weight gain 9 months-3 (kg)	0.024***	0.018***	0.017***	0.014***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Main Parent's education						
NVQ level 1	0.007	−0.003	0.001	0.006	0.014	0.013
	(0.012)	(0.012)	(0.012)	(0.016)	(0.015)	(0.016)
NVQ level 2	−0.010	−0.007	0.004	−0.017	0.011	0.010
	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)
NVQ level 3	−0.014	−0.024**	0.001	−0.035***	0.007	0.006
	(0.010)	(0.010)	(0.011)	(0.012)	(0.014)	(0.014)
NVQ level 4	−0.008	−0.024***	−0.013	−0.025*	−0.007	−0.008
	(0.009)	(0.009)	(0.009)	(0.013)	(0.012)	(0.012)
NVQ level 5	0.006	−0.035**	−0.034**	−0.054***	−0.015	−0.016
	(0.018)	(0.013)	(0.012)	(0.016)	(0.018)	(0.018)
Ethnicity						
Mixed	0.047**	0.009	−0.030	0.037*	−0.008	−0.008
	(0.030)	(0.023)	(0.018)	(0.023)	(0.032)	(0.032)
Indian	−0.002	0.017	0.036	−0.032*	−0.011	−0.011
	(0.020)	(0.025)	(0.028)	(0.012)	(0.021)	(0.021)
Pakistani and Bangladeshi	0.004	0.039***	0.027**	0.028	0.008	0.008
	(0.011)	(0.016)	(0.016)	(0.020)	(0.017)	(0.017)
Black or Black British	0.049***	0.059***	0.081***	0.043**	0.016	0.017
	(0.020)	(0.022)	(0.022)	(0.023)	(0.021)	(0.021)
Other Ethnic group (inc. Chinese, Other)	0.019	0.018	0.026	−0.001	−0.010	−0.012
	(0.026)	(0.028)	(0.032)	(0.028)	(0.023)	(0.023)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.038	0.039	0.042	0.043	0.039	0.039
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is obese, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. $\mathbb{E}[Pr(obese)|\boldsymbol{x}]$ represents the estimated conditional probability a child is obese at each age. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A10: The determinants of child overweight or obesity across childhood with controls

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent overweight	0.036***	0.078***	0.087***	0.122***	0.121***	0.092***
	(0.011)	(0.010)	(0.010)	(0.013)	(0.014)	(0.013)
Main parent obese/morbidly obese	0.091***	0.166***	0.161***	0.246***	0.241***	0.238***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.054***	0.036**	0.026	0.060**	0.166***	0.171***
	(0.017)	(0.016)	(0.017)	(0.026)	(0.032)	(0.032)
Second quintile	0.042***	0.017	0.025	0.081***	0.077***	0.077***
	(0.015)	(0.014)	(0.015)	(0.021)	(0.021)	(0.022)
Third quintile	0.030**	0.000	0.019	0.070***	0.054***	0.056***
	(0.014)	(0.013)	(0.014)	(0.018)	(0.017)	(0.017)
Fourth quintile	0.031**	0.026**	0.007	0.025	0.019	0.019
	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)	(0.014)
Female	0.075***	0.098***	0.114***	0.080***	0.060***	0.061***
	(0.010)	(0.009)	(0.009)	(0.011)	(0.013)	(0.013)
Child long-term illness	0.007	−0.000	−0.002	0.007	0.011	0.011
	(0.013)	(0.012)	(0.012)	(0.018)	(0.022)	(0.022)
Health conditions	0.006	0.006	0.005	0.005	0.010	0.010
	(0.004)	(0.004)	(0.004)	(0.005)	(0.010)	(0.011)
Main parent long-term illness	−0.016	0.005	0.022**	0.017	0.002	0.005
	(0.011)	(0.010)	(0.011)	(0.014)	(0.015)	(0.015)
No. of siblings	0.003	−0.010**	−0.015***	−0.027***	−0.030***	−0.030***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Birthweight	0.114***	0.104***	0.063***	0.045***	0.043***	0.047***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Weight gain 9 months-3 (kg)	0.091***	0.077***	0.053***	0.043***	0.031***	0.031***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)
Main Parent's education						
NVQ level 1	0.010	0.013	−0.028	−0.011	0.001	−0.004
	(0.022)	(0.021)	(0.020)	(0.027)	(0.033)	(0.033)
NVQ level 2	−0.015	−0.011	−0.003	−0.019	0.004	0.000
	(0.017)	(0.016)	(0.017)	(0.022)	(0.024)	(0.024)
NVQ level 3	−0.017	−0.019	−0.028	−0.050**	−0.021	−0.026
	(0.019)	(0.018)	(0.019)	(0.024)	(0.026)	(0.026)
NVQ level 4	−0.008	−0.016	−0.028	−0.034	−0.012	−0.017
	(0.018)	(0.017)	(0.018)	(0.024)	(0.025)	(0.025)
NVQ level 5	0.067**	−0.021	−0.049*	−0.057	−0.064*	−0.068*
	(0.031)	(0.026)	(0.026)	(0.035)	(0.033)	(0.034)
Ethnicity						
Mixed	0.058	−0.005	−0.077*	0.069*	−0.033	−0.039
	(0.049)	(0.041)	(0.037)	(0.038)	(0.058)	(0.055)
Indian	−0.085**	0.031	0.074**	0.039	0.089	0.092
	(0.031)	(0.039)	(0.038)	(0.041)	(0.086)	(0.091)
Pakistani and Bangladeshi	−0.016	0.023	0.024	0.081***	0.005	0.001
	(0.023)	(0.025)	(0.026)	(0.033)	(0.030)	(0.030)
Black or Black British	0.058*	0.103***	0.125***	0.130***	0.051	0.050
	(0.033)	(0.033)	(0.034)	(0.040)	(0.038)	(0.039)
Other Ethnic group (inc. Chinese, Other)	0.000	−0.020	0.004	0.001	0.052	0.046
	(0.041)	(0.039)	(0.046)	(0.064)	(0.070)	(0.071)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.199	0.175	0.165	0.242	0.196	0.197
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight *or* obese, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. $\mathbb{E}[Pr(overweight \cup obese)|\boldsymbol{x}]$ represents the estimated conditional probability a child is overweight *or* obese at each age. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A11: The determinants of child overweight across childhood fixing income and parents' weight at their level when child was 9 months old

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent weight category at 9 months						
Overweight	0.045***	0.074***	0.073***	0.132***	0.110***	0.116***
	(0.012)	(0.011)	(0.012)	(0.015)	(0.016)	(0.016)
Obese/Morbidly obese	0.071***	0.139***	0.116***	0.255***	0.230***	0.240***
	(0.016)	(0.017)	(0.018)	(0.024)	(0.026)	(0.028)
Current weight						
Moved to lighter category	0.020	−0.008	0.011	−0.026	−0.015	−0.026
	(0.018)	(0.014)	(0.016)	(0.020)	(0.020)	(0.023)
Moved to heavier category	0.022	0.045***	0.040***	0.061***	0.078***	0.060***
	(0.015)	(0.013)	(0.013)	(0.014)	(0.017)	(0.014)
Income quintiles at 9 months						
Lowest quintile	0.055***	0.045***	0.050***	0.094***	0.114***	0.116***
	(0.019)	(0.017)	(0.018)	(0.025)	(0.029)	(0.029)
Second quintile	0.033**	0.032**	0.049***	0.073***	0.069***	0.069***
	(0.016)	(0.015)	(0.015)	(0.021)	(0.021)	(0.021)
Third quintile	0.015	0.025*	0.047***	0.066***	0.076***	0.077***
	(0.014)	(0.013)	(0.014)	(0.018)	(0.019)	(0.019)
Fourth quintile	0.019	0.030**	0.034***	0.048***	0.043***	0.043***
	(0.014)	(0.013)	(0.012)	(0.016)	(0.015)	(0.015)
Current income quintile						
Moved down	−0.009	−0.009	0.013	−0.006	0.003	0.004
	(0.012)	(0.011)	(0.011)	(0.016)	(0.018)	(0.018)
Moved up	−0.019*	−0.015	0.015	−0.008	−0.041***	−0.041***
	(0.011)	(0.010)	(0.011)	(0.014)	(0.016)	(0.016)
Female	0.062***	0.090***	0.091***	0.070***	0.043***	0.043***
	(0.010)	(0.009)	(0.009)	(0.012)	(0.014)	(0.014)
Child long-term illness	0.019	−0.012	−0.011	−0.002	−0.000	−0.000
	(0.013)	(0.012)	(0.012)	(0.018)	(0.022)	(0.022)
Health conditions	0.004	0.004	0.003	0.001	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.011)	(0.012)
Main parent long-term illness	−0.015	−0.006	0.017	0.003	0.002	0.004
	(0.011)	(0.010)	(0.011)	(0.014)	(0.016)	(0.016)
No. of siblings	−0.003	−0.008*	−0.014***	−0.020***	−0.022***	−0.022***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Birthweight	0.110***	0.087***	0.055***	0.025**	0.023**	0.024**
	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Weight gain 9 months-3 (kg)	0.077***	0.069***	0.041***	0.036***	0.022***	0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
Main Parent's education						
NVQ level 1	−0.004	0.009	−0.032	−0.011	−0.009	−0.013
	(0.023)	(0.021)	(0.020)	(0.029)	(0.037)	(0.038)
NVQ level 2	−0.011	−0.016	−0.003	0.001	−0.018	−0.020
	(0.018)	(0.017)	(0.017)	(0.023)	(0.027)	(0.027)
NVQ level 3	−0.011	−0.007	−0.028	−0.018	−0.043	−0.045*
	(0.020)	(0.019)	(0.019)	(0.025)	(0.028)	(0.029)
NVQ level 4	−0.007	−0.002	−0.007	−0.010	−0.017	−0.020
	(0.020)	(0.018)	(0.019)	(0.025)	(0.028)	(0.028)
NVQ level 5	0.047	−0.003	−0.005	−0.031	−0.050	−0.053
	(0.032)	(0.028)	(0.029)	(0.036)	(0.037)	(0.037)
Ethnicity						
Mixed	0.052	0.005	−0.038	0.056	−0.011	−0.009
	(0.058)	(0.045)	(0.042)	(0.038)	(0.059)	(0.059)
Indian	−0.094***	0.003	0.061	0.048	0.112	0.115
	(0.026)	(0.041)	(0.042)	(0.048)	(0.103)	(0.108)
Pakistani and Bangladeshi	−0.029	−0.027	0.009	0.044	−0.017	−0.017
	(0.025)	(0.024)	(0.029)	(0.035)	(0.030)	(0.030)
Black or Black British	0.030	0.063**	0.056*	0.113***	0.039	0.037
	(0.035)	(0.033)	(0.036)	(0.045)	(0.039)	(0.039)
Other Ethnic group (inc. Chinese, Other)	−0.011	−0.052	−0.032	0.004	0.071	0.069
	(0.044)	(0.033)	(0.039)	(0.066)	(0.076)	(0.076)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.159	0.132	0.123	0.195	0.153	0.154
N	9.207	9.514	8.566	7.178	6.089	6.089

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data does not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income at 9 months: highest quintile; current income quintile and weight category: stayed the same; parents' education: no qualifications; ethnicity: white. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents the estimated conditional expectation a child is overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A12: The determinants of child obesity across childhood fixing income and parents' weight at their level when child was 9 months old

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent weight category at 9 months						
Overweight	0.026***	0.026***	0.045***	0.050***	0.044***	0.045***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.008)
Obese/Morbidly obese	0.065***	0.085***	0.114***	0.127***	0.142***	0.147***
	(0.011)	(0.011)	(0.014)	(0.016)	(0.019)	(0.022)
Current weight						
Moved to lighter category	0.003	−0.005	−0.015*	−0.003	−0.014	−0.013
	(0.009)	(0.008)	(0.007)	(0.009)	(0.009)	(0.011)
Moved to heavier category	0.012	0.034***	0.027***	0.015*	0.033***	0.028***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.011)	(0.010)
Income quintiles at 9 months						
Lowest quintile	0.015*	0.022**	0.023**	0.044***	0.063***	0.063***
	(0.009)	(0.011)	(0.012)	(0.014)	(0.018)	(0.018)
Second quintile	0.019**	0.006	0.018*	0.038***	0.040***	0.040***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)	(0.012)
Third quintile	0.018**	0.001	0.001	0.020**	0.011	0.011
	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Fourth quintile	0.021***	0.009	0.005	0.018**	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Current income quintile						
Moved down	−0.000	0.007	−0.004	0.000	0.012	0.012
	(0.007)	(0.007)	(0.007)	(0.009)	(0.011)	(0.011)
Moved up	0.001	0.001	−0.006	−0.016**	−0.005	−0.005
	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)
Female	0.025***	0.019***	0.028***	0.021***	0.022***	0.022***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Child long-term illness	−0.010	0.016**	0.001	0.007	0.007	0.006
	(0.006)	(0.007)	(0.007)	(0.010)	(0.012)	(0.012)
Health conditions	0.002	0.001	0.004	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
Main parent long-term illness	−0.001	0.012*	0.004	0.012*	0.010	0.011
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)
No. of siblings	0.001	−0.008***	−0.007**	−0.012***	−0.004	−0.004
	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Birthweight	0.010**	0.024***	0.009*	0.016***	0.026***	0.027***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Weight gain 9 months-3 (kg)	0.024***	0.018***	0.017***	0.014***	0.014***	0.014***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Main Parent's education						
NVQ level 1	−0.003	0.004	0.003	0.015	0.012	0.011
	(0.013)	(0.012)	(0.012)	(0.017)	(0.016)	(0.016)
NVQ level 2	−0.017*	0.001	0.008	−0.014	0.013	0.012
	(0.010)	(0.010)	(0.010)	(0.013)	(0.012)	(0.013)
NVQ level 3	−0.021*	−0.017*	−0.003	−0.034***	0.003	0.002
	(0.011)	(0.010)	(0.011)	(0.013)	(0.013)	(0.014)
NVQ level 4	−0.013	−0.015	−0.010	−0.023*	−0.003	−0.003
	(0.011)	(0.010)	(0.010)	(0.014)	(0.013)	(0.013)
NVQ level 5	0.010	−0.023	−0.031**	−0.049**	−0.009	−0.010
	(0.021)	(0.015)	(0.013)	(0.016)	(0.019)	(0.019)
Ethnicity						
Mixed	0.085***	0.016	−0.023	0.037**	−0.006	−0.005
	(0.037)	(0.025)	(0.023)	(0.022)	(0.039)	(0.040)
Indian	−0.001	0.024	0.036	−0.031	−0.000	−0.000
	(0.022)	(0.030)	(0.031)	(0.014)	(0.023)	(0.023)
Pakistani and Bangladeshi	−0.001	0.042***	0.010	0.036*	0.025	0.025
	(0.013)	(0.018)	(0.015)	(0.023)	(0.024)	(0.025)
Black or Black British	0.040**	0.054***	0.067***	0.041**	0.026	0.025
	(0.021)	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)
Other Ethnic group (inc. Chinese, Other)	0.021	0.015	0.035	−0.015	−0.018	−0.018
	(0.027)	(0.030)	(0.035)	(0.023)	(0.019)	(0.018)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.036	0.037	0.041	0.039	0.036	0.036
N	9.718	10.065	9.271	7.662	6.435	6.435

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data does not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income at 9 months: highest quintile; current income quintile and weight category: stayed the same; parents' education: no qualifications; ethnicity: white. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents the estimated conditional expectation a child is overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A13: The determinants of child overweight and obesity across childhood fixing income and parents' weight at their level when child was 9 months old

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent weight category at 9 months						
Overweight	0.061***	0.089***	0.102***	0.163***	0.141***	0.147***
	(0.012)	(0.011)	(0.012)	(0.015)	(0.016)	(0.016)
Obese/Morbidly obese	0.112***	0.189***	0.192***	0.321***	0.311***	0.321***
	(0.016)	(0.017)	(0.018)	(0.022)	(0.025)	(0.026)
Current weight						
Moved to lighter category	0.028	−0.010	−0.006	−0.028	−0.027	−0.035
	(0.018)	(0.015)	(0.016)	(0.020)	(0.020)	(0.024)
Moved to heavier category	0.029*	0.066***	0.058***	0.067***	0.094***	0.075***
	(0.016)	(0.014)	(0.013)	(0.014)	(0.017)	(0.014)
Income quintiles at 9 months						
Lowest quintile	0.064***	0.061***	0.066***	0.121***	0.152***	0.155***
	(0.019)	(0.018)	(0.019)	(0.026)	(0.030)	(0.030)
Second quintile	0.046***	0.035**	0.062***	0.095***	0.096***	0.096***
	(0.017)	(0.016)	(0.016)	(0.022)	(0.022)	(0.022)
Third quintile	0.028*	0.026*	0.046***	0.077***	0.078***	0.079***
	(0.015)	(0.014)	(0.015)	(0.019)	(0.019)	(0.019)
Fourth quintile	0.034**	0.035***	0.037***	0.059***	0.045***	0.045***
	(0.014)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
Current income quintile						
Moved down	−0.010	−0.004	0.010	−0.006	0.010	0.012
	(0.012)	(0.011)	(0.012)	(0.016)	(0.018)	(0.018)
Moved up	−0.019	−0.013	0.009	−0.019	−0.041**	−0.041**
	(0.011)	(0.011)	(0.011)	(0.014)	(0.016)	(0.016)
Female	0.076***	0.098***	0.112***	0.079***	0.055***	0.056***
	(0.010)	(0.009)	(0.010)	(0.012)	(0.014)	(0.014)
Child long-term illness	0.011	0.001	−0.009	0.004	0.003	0.002
	(0.013)	(0.012)	(0.012)	(0.018)	(0.023)	(0.023)
Health conditions	0.005	0.004	0.005	0.003	0.007	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.012)	(0.012)
Main parent long-term illness	−0.015	0.002	0.021*	0.010	0.009	0.012
	(0.011)	(0.011)	(0.011)	(0.014)	(0.016)	(0.016)
No. of siblings	−0.002	−0.013***	−0.018***	−0.027***	−0.024***	−0.023***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Birthweight	0.114***	0.101***	0.057***	0.035***	0.041***	0.043***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
Weight gain 9 months-3 (kg)	0.092***	0.078***	0.052***	0.044***	0.031***	0.031***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Main Parent's education						
NVQ level 1	−0.009	0.008	−0.029	−0.004	−0.001	−0.004
	(0.023)	(0.022)	(0.021)	(0.029)	(0.036)	(0.037)
NVQ level 2	−0.027	−0.013	0.005	−0.011	−0.009	−0.011
	(0.019)	(0.017)	(0.018)	(0.023)	(0.027)	(0.027)
NVQ level 3	−0.028	−0.019	−0.027	−0.043*	−0.041	−0.043
	(0.021)	(0.019)	(0.020)	(0.025)	(0.028)	(0.028)
NVQ level 4	−0.020	−0.014	−0.012	−0.028	−0.019	−0.022
	(0.020)	(0.019)	(0.019)	(0.026)	(0.028)	(0.028)
NVQ level 5	0.047	−0.019	−0.028	−0.063*	−0.055	−0.058
	(0.033)	(0.029)	(0.029)	(0.037)	(0.037)	(0.038)
Ethnicity						
Mixed	0.098*	0.014	−0.054	0.074**	−0.014	−0.012
	(0.055)	(0.045)	(0.046)	(0.037)	(0.065)	(0.065)
Indian	−0.085**	0.022	0.088**	0.032	0.113	0.116
	(0.033)	(0.044)	(0.042)	(0.048)	(0.100)	(0.104)
Pakistani and Bangladeshi	−0.026	0.009	0.019	0.069**	0.005	0.005
	(0.025)	(0.026)	(0.029)	(0.035)	(0.034)	(0.034)
Black or Black British	0.066**	0.101***	0.102***	0.133***	0.055	0.053
	(0.036)	(0.035)	(0.036)	(0.045)	(0.040)	(0.040)
Other Ethnic group (inc Chinese,Other)	0.002	−0.034	−0.001	−0.006	0.060	0.058
	(0.044)	(0.041)	(0.048)	(0.068)	(0.076)	(0.077)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.196	0.172	0.163	0.237	0.193	0.193
N	9.718	10.065	9.271	7.662	6.435	6.435

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.2 fixing the independent variables at their sample mean. The MCS data does not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income at 9 months: highest quintile; current income quintile and weight category: stayed the same; parents' education: no qualifications; ethnicity: white. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents the estimated conditional expectation a child is overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

A.2.2 Additional tables on healthy behaviour and children's weight

Table A14: Index of healthy behaviours and overweight in children across ages with full controls

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Healthy lifestyle	−0.003	0.006	−0.008	−0.028**	−0.018	−0.019
	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)	(0.012)
Main parent overweight	0.022**	0.058***	0.061***	0.099***	0.102***	0.072***
	(0.010)	(0.009)	(0.010)	(0.013)	(0.014)	(0.012)
Main parent obese/morbidly obese	0.061***	0.124***	0.093***	0.197***	0.168***	0.169***
	(0.014)	(0.014)	(0.013)	(0.017)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.037**	0.024*	0.010	0.024	0.112***	0.116***
	(0.016)	(0.014)	(0.015)	(0.025)	(0.033)	(0.033)
Second quintile	0.034**	0.009	0.017	0.049**	0.051***	0.050**
	(0.014)	(0.013)	(0.014)	(0.021)	(0.021)	(0.021)
Third quintile	0.029**	−0.004	0.012	0.053***	0.038**	0.039**
	(0.013)	(0.011)	(0.013)	(0.018)	(0.016)	(0.016)
Fourth quintile	0.023*	0.022*	0.002	0.017	0.011	0.010
	(0.012)	(0.011)	(0.011)	(0.015)	(0.013)	(0.013)
Female	0.061***	0.087***	0.089***	0.069***	0.043***	0.043***
	(0.009)	(0.008)	(0.008)	(0.011)	(0.013)	(0.013)
Child long-term illness	0.015	−0.014	−0.005	0.004	0.005	0.007
	(0.012)	(0.010)	(0.011)	(0.018)	(0.020)	(0.021)
Health conditions	0.004	0.005	0.003	0.001	0.006	0.005
	(0.004)	(0.003)	(0.003)	(0.005)	(0.010)	(0.010)
Main parent long-term illness	−0.015	−0.003	0.017*	0.007	−0.006	−0.004
	(0.010)	(0.009)	(0.010)	(0.014)	(0.014)	(0.015)
No. of siblings	0.003	−0.005	−0.011**	−0.020***	−0.024***	−0.024***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Birthweight	0.106***	0.084***	0.055***	0.033***	0.024**	0.027***
	(0.008)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)
Weight gain 9 months-3 (kg)	0.075***	0.064***	0.039***	0.035***	0.022***	0.022***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
Main Parent's education						
NVQ level 1	0.008	0.018	−0.028	−0.016	−0.009	−0.014
	(0.021)	(0.019)	(0.019)	(0.027)	(0.032)	(0.033)
NVQ level 2	−0.004	−0.007	−0.006	−0.005	−0.003	−0.006
	(0.016)	(0.014)	(0.016)	(0.022)	(0.023)	(0.024)
NVQ level 3	−0.004	−0.001	−0.030*	−0.023	−0.023	−0.028
	(0.018)	(0.016)	(0.017)	(0.024)	(0.025)	(0.025)
NVQ level 4	0.001	0.003	−0.019	−0.011	−0.004	−0.008
	(0.017)	(0.015)	(0.017)	(0.024)	(0.024)	(0.025)
NVQ level 5	0.071**	0.002	−0.024	−0.016	−0.049	−0.052
	(0.031)	(0.024)	(0.024)	(0.035)	(0.031)	(0.032)
Ethnicity						
Mixed	0.031	−0.008	−0.051	0.049	−0.030	−0.034
	(0.052)	(0.037)	(0.030)	(0.039)	(0.049)	(0.046)
Indian	−0.083***	0.017	0.045	0.059	0.097	0.101
	(0.023)	(0.036)	(0.036)	(0.042)	(0.094)	(0.099)
Pakistani and Bangladeshi	−0.020	−0.011	−0.002	0.066**	−0.000	−0.003
	(0.022)	(0.021)	(0.023)	(0.034)	(0.029)	(0.029)
Black or Black British	0.014	0.062**	0.069**	0.114***	0.041	0.039
	(0.032)	(0.032)	(0.035)	(0.043)	(0.037)	(0.037)
Other Ethnic group (inc. Chinese, Other)	−0.013	−0.037	−0.019	0.002	0.063	0.056
	(0.038)	(0.028)	(0.035)	(0.063)	(0.073)	(0.072)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.133	0.124	0.198	0.155	0.156
N	10.143	10.485	9.405	7.887	6.674	6.674

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. Appendix Table A.1.2 describes how the index was constructed. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A15: Index of healthy behaviours and obesity in children across ages with full controls

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Healthy lifestyle	0.009**	−0.001	−0.001	−0.022***	−0.007	−0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
Main parent overweight	0.018***	0.023***	0.031***	0.031***	0.022***	0.021***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Main parent obese/morbidly obese	0.041***	0.057***	0.079***	0.071***	0.092***	0.086***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.011)	(0.010)
Income quintiles						
Lowest quintile	0.017**	0.014*	0.013*	0.026**	0.063***	0.063***
	(0.008)	(0.008)	(0.008)	(0.011)	(0.018)	(0.017)
Second quintile	0.011	0.010	0.010	0.028***	0.024***	0.024***
	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Third quintile	0.003	0.005	0.006	0.015*	0.014**	0.015**
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
Fourth quintile	0.012*	0.005	0.005	0.006	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female	0.019***	0.014***	0.022***	0.017***	0.018***	0.018***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Child long-term illness	−0.010*	0.014**	0.002	0.002	0.007	0.007
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
Health conditions	0.002	0.001	0.004**	0.004**	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Main parent long-term illness	−0.001	0.008*	0.005	0.012**	0.006	0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
No. of siblings	0.000	−0.006***	−0.005**	−0.008***	−0.007***	−0.007***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Birthweight	0.011***	0.021***	0.010***	0.015***	0.019***	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Weight gain 9 months-3 (kg)	0.019***	0.014***	0.014***	0.011***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Main Parent's education						
NVQ level 1	0.006	−0.002	0.001	0.005	0.010	0.009
	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
NVQ level 2	−0.008	−0.006	0.003	−0.012	0.008	0.007
	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
NVQ level 3	−0.012	−0.019**	0.001	−0.025***	0.005	0.004
	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
NVQ level 4	−0.007	−0.020***	−0.010	−0.015	−0.005	−0.005
	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)
NVQ level 5	0.006	−0.028**	−0.026**	−0.035**	−0.010	−0.010
	(0.015)	(0.011)	(0.010)	(0.013)	(0.013)	(0.013)
Ethnicity						
Mixed	0.041**	0.007	−0.023	0.028*	−0.006	−0.006
	(0.026)	(0.019)	(0.013)	(0.018)	(0.023)	(0.022)
Indian	−0.002	0.014	0.030	−0.022*	−0.007	−0.008
	(0.016)	(0.021)	(0.024)	(0.008)	(0.015)	(0.015)
Pakistani and Bangladeshi	0.004	0.032***	0.022*	0.021	0.006	0.006
	(0.009)	(0.014)	(0.013)	(0.015)	(0.013)	(0.013)
Black or Black British	0.044***	0.049***	0.069***	0.034**	0.012	0.012
	(0.018)	(0.019)	(0.020)	(0.019)	(0.016)	(0.016)
Other Ethnic group (inc. Chinese, Other)	0.017	0.015	0.021	−0.000	−0.007	−0.008
	(0.022)	(0.023)	(0.027)	(0.022)	(0.017)	(0.016)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.038	0.039	0.042	0.042	0.039	0.038
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is obese, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. Appendix Table A.1.2 describes how the index was constructed. $\mathbb{E}[Pr(obese)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being obese. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A16: Index of healthy behaviours and overweight and obesity in children across ages with full controls

					(5)-(6) Age 14	
	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	Parental weight constant	Parental weight predicted
Healthy lifestyle	0.005	0.005	−0.009	−0.049***	−0.025*	−0.026*
	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)	(0.013)
Main parent overweight	0.036***	0.077***	0.085***	0.122***	0.119***	0.090***
	(0.011)	(0.010)	(0.010)	(0.013)	(0.014)	(0.013)
Main parent obese/morbidly obese	0.094***	0.169***	0.159***	0.249***	0.241***	0.238***
	(0.015)	(0.015)	(0.014)	(0.017)	(0.018)	(0.018)
Income quintiles						
Lowest quintile	0.054***	0.037**	0.025	0.051**	0.165***	0.169***
	(0.017)	(0.016)	(0.016)	(0.026)	(0.033)	(0.034)
Second quintile	0.042***	0.017	0.023	0.074***	0.073***	0.073***
	(0.015)	(0.014)	(0.015)	(0.022)	(0.022)	(0.022)
Third quintile	0.030**	0.001	0.018	0.066***	0.052***	0.053***
	(0.014)	(0.013)	(0.014)	(0.019)	(0.017)	(0.017)
Fourth quintile	0.031**	0.026**	0.006	0.023	0.018	0.017
	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)	(0.014)
Female	0.077***	0.098***	0.112***	0.083***	0.060***	0.061***
	(0.010)	(0.009)	(0.009)	(0.012)	(0.013)	(0.013)
Child long-term illness	0.007	−0.000	−0.002	0.006	0.011	0.012
	(0.013)	(0.012)	(0.012)	(0.018)	(0.022)	(0.023)
Health conditions	0.006	0.006	0.005	0.005	0.010	0.010
	(0.004)	(0.004)	(0.004)	(0.005)	(0.011)	(0.011)
Main parent long-term illness	−0.016	0.005	0.022**	0.017	0.002	0.005
	(0.011)	(0.010)	(0.011)	(0.014)	(0.015)	(0.016)
No. of siblings	0.003	−0.010**	−0.014***	−0.028***	−0.030***	−0.030***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Birthweight	0.115***	0.104***	0.062***	0.047***	0.043***	0.048***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Weight gain 9 months-3 (kg)	0.092***	0.077***	0.052***	0.045***	0.031***	0.031***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)
Main Parent's education						
NVQ level 1	0.011	0.013	−0.028	−0.012	0.001	−0.005
	(0.022)	(0.021)	(0.020)	(0.028)	(0.033)	(0.034)
NVQ level 2	−0.015	−0.012	−0.003	−0.018	0.004	0.000
	(0.017)	(0.016)	(0.017)	(0.023)	(0.024)	(0.025)
NVQ level 3	−0.017	−0.019	−0.026	−0.047*	−0.020	−0.025
	(0.019)	(0.018)	(0.019)	(0.025)	(0.026)	(0.026)
NVQ level 4	−0.008	−0.017	−0.027	−0.027	−0.010	−0.014
	(0.018)	(0.017)	(0.018)	(0.025)	(0.025)	(0.025)
NVQ level 5	0.070**	−0.023	−0.047*	−0.045	−0.059*	−0.062*
	(0.033)	(0.026)	(0.026)	(0.037)	(0.033)	(0.034)
Ethnicity						
Mixed	0.061	−0.004	−0.073*	0.072*	−0.034	−0.039
	(0.052)	(0.040)	(0.033)	(0.040)	(0.057)	(0.054)
Indian	−0.082**	0.032	0.073**	0.039	0.097	0.100
	(0.028)	(0.040)	(0.039)	(0.043)	(0.093)	(0.098)
Pakistani and Bangladeshi	−0.016	0.024	0.022	0.084***	0.006	0.002
	(0.023)	(0.025)	(0.026)	(0.034)	(0.031)	(0.031)
Black or Black British	0.060*	0.109***	0.126***	0.140***	0.053	0.051
	(0.035)	(0.035)	(0.036)	(0.044)	(0.040)	(0.040)
Other Ethnic group (inc. Chinese, Other)	0.001	−0.019	0.003	0.001	0.056	0.050
	(0.042)	(0.038)	(0.045)	(0.067)	(0.074)	(0.075)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.199	0.175	0.165	0.241	0.196	0.197
N	10.714	11.119	10.186	8.426	7.067	7.067

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is overweight or obese, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. Appendix Table A.1.2 describes how the index was constructed. $\mathbb{E}[Pr(overweight \cup obese)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being overweight or obese. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A17a: Individual healthy behaviours and overweight in children across ages

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Main parent overweight	0.022**	0.061***	0.068***	0.100***	0.094***	0.067***
	(0.010)	(0.010)	(0.011)	(0.013)	(0.013)	(0.012)
Main parent obese/morbidly obese	0.061***	0.125***	0.093***	0.195***	0.167***	0.167***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.038**	0.026*	0.003	0.020	0.093***	0.095***
	(0.016)	(0.015)	(0.017)	(0.025)	(0.029)	(0.029)
Second quintile	0.036**	0.009	0.013	0.044**	0.052**	0.051**
	(0.015)	(0.014)	(0.016)	(0.021)	(0.021)	(0.021)
Third quintile	0.030**	−0.004	0.005	0.051***	0.039**	0.041**
	(0.013)	(0.012)	(0.014)	(0.018)	(0.017)	(0.017)
Fourth quintile	0.025*	0.024*	−0.000	0.018	0.008	0.008
	(0.013)	(0.012)	(0.013)	(0.015)	(0.014)	(0.014)
Healthy behaviours						
Fruit/veg once a day	0.014	0.010	0.003	0.007	0.012	0.012
	(0.025)	(0.008)	(0.009)	(0.011)	(0.013)	(0.013)
Regular meals	−0.004	0.003				
	(0.009)	(0.008)				
Physically active games once a week	−0.002	−0.004	−0.001	−0.030***		
	(0.011)	(0.009)	(0.009)	(0.011)		
Sport once a week		−0.001	−0.026*	−0.029		
		(0.009)	(0.016)	(0.020)		
Sport with child once a week		0.006	0.001	−0.010		
		(0.009)	(0.009)	(0.020)		
Breakfast every day				−0.035**	−0.037***	−0.038***
				(0.017)	(0.012)	(0.012)
Art. sweetened drinks less than once a week				−0.010	−0.074***	−0.077***
				(0.011)	(0.017)	(0.017)
Sweetened drinks less than once a week				−0.005	0.027*	0.026*
				(0.012)	(0.014)	(0.014)
Fast food less than once a week					0.021	0.023*
					(0.013)	(0.014)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.132	0.120	0.197	0.151	0.152
N	10.143	10.481	8.285	7.871	6.600	6.600

Table A17b: Individual healthy behaviours and overweight in children across ages cont.

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Female	0.063***	0.092***	0.097***	0.064***	0.043***	0.044***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)
Main parent's education						
NVQ level 1	0.008	0.018	−0.020	−0.011	−0.033	−0.039
	(0.021)	(0.020)	(0.022)	(0.026)	(0.028)	(0.029)
NVQ level 2	−0.004	−0.008	−0.013	−0.002	−0.014	−0.017
	(0.017)	(0.015)	(0.018)	(0.021)	(0.024)	(0.024)
NVQ level 3	−0.005	−0.002	−0.029	−0.020	−0.037	−0.041
	(0.019)	(0.017)	(0.020)	(0.024)	(0.026)	(0.026)
NVQ level 4	0.000	0.002	−0.024	−0.007	−0.017	−0.021
	(0.018)	(0.016)	(0.019)	(0.024)	(0.025)	(0.025)
NVQ level 5	0.070**	0.002	−0.030	−0.011	−0.064*	−0.068**
	(0.030)	(0.025)	(0.027)	(0.035)	(0.032)	(0.033)
Child long-term illness	0.016	−0.016	−0.004	0.000	0.005	0.007
	(0.012)	(0.011)	(0.012)	(0.017)	(0.021)	(0.021)
Health conditions	0.004	0.006	0.005	0.001	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.010)	(0.010)
Main parent long-term illness	−0.015	−0.003	0.016	0.005	−0.010	−0.008
	(0.010)	(0.010)	(0.011)	(0.013)	(0.014)	(0.014)
No. of siblings	0.003	−0.005	−0.011**	−0.019***	−0.022***	−0.022***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
Birthweight	0.109***	0.090***	0.058***	0.032***	0.024**	0.027***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Weight gain 9 months-3 (kg)	0.077***	0.068***	0.045***	0.036***	0.029***	0.029***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Ethnicity						
Mixed	0.032	−0.009	−0.019	0.048	−0.013	−0.019
	(0.052)	(0.040)	(0.046)	(0.038)	(0.054)	(0.051)
Indian	−0.090***	0.020	0.048	0.055	−0.010	−0.010
	(0.026)	(0.038)	(0.039)	(0.041)	(0.040)	(0.042)
Pakistani and Bangladeshi	−0.022	−0.011	−0.003	0.063**	0.002	−0.000
	(0.023)	(0.023)	(0.026)	(0.033)	(0.030)	(0.030)
Black or Black British	0.014	0.066**	0.078**	0.109***	0.044	0.043
	(0.032)	(0.032)	(0.037)	(0.041)	(0.038)	(0.038)
Other Ethnic group (inc. Chinese, Other)	−0.014	−0.041	−0.028	−0.000	0.056	0.049
	(0.040)	(0.032)	(0.040)	(0.064)	(0.067)	(0.067)
$\mathbb{E}[Pr(overweight)\|\boldsymbol{x}]$	0.161	0.132	0.120	0.197	0.151	0.152
N	10.143	10.481	8.285	7.871	6.600	6.600

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. Not all healthy behaviours on which we have measures are available at all ages so each columns include those that are. Appendix Table A4a describes how indicators of healthy behaviours were constructed. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A18a: Individual healthy behaviours and obesity in children across ages

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	(5)-(6) Age 14 Parental weight predicted
Main parent overweight	0.021*** (0.006)	0.026*** (0.006)	0.029*** (0.006)	0.035*** (0.007)	0.025*** (0.007)	0.025*** (0.006)
Main parent obese/morbidly obese	0.048*** (0.008)	0.065*** (0.009)	0.084*** (0.010)	0.080*** (0.010)	0.098*** (0.011)	0.093*** (0.010)
Income quintiles						
Lowest quintile	0.021** (0.010)	0.015 (0.009)	0.010 (0.010)	0.033** (0.014)	0.072*** (0.019)	0.073*** (0.019)
Second quintile	0.014* (0.008)	0.010 (0.009)	0.012 (0.009)	0.035*** (0.011)	0.027** (0.011)	0.028** (0.011)
Third quintile	0.004 (0.007)	0.005 (0.008)	0.002 (0.008)	0.018* (0.010)	0.017* (0.009)	0.018* (0.009)
Fourth quintile	0.015* (0.007)	0.006 (0.008)	0.003 (0.008)	0.008 (0.008)	0.007 (0.008)	0.007 (0.008)
Healthy behaviours						
Fruit/veg once a day	0.005 (0.014)	−0.004 (0.005)	0.007 (0.006)	−0.014** (0.006)	−0.000 (0.008)	−0.001 (0.008)
Regular meals	0.005 (0.005)	0.004 (0.005)				
Physically active games once a week	0.011* (0.006)	0.010* (0.005)	0.010* (0.006)	−0.014** (0.006)		
Sport once a week		−0.008 (0.005)	−0.016* (0.009)	−0.028*** (0.012)		
Sport with child once a week		−0.002 (0.005)	0.001 (0.006)	0.012 (0.013)		
Breakfast every day				−0.003 (0.008)	−0.029*** (0.007)	−0.029*** (0.007)
Art. sweetened drinks less than once a week				−0.029*** (0.007)	−0.018* (0.010)	−0.018** (0.010)
Sweetened drinks less than once a week				0.001 (0.006)	0.006 (0.008)	0.006 (0.008)
Fast food less than once a week					0.002 (0.008)	0.003 (0.008)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.038	0.039	0.039	0.040	0.037	0.037
N	10.714	11.115	8.942	8.408	6.985	6.985

Table A18b: Individual healthy behaviours and obesity in children across ages cont.

	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	(5)-(6) Age 14 Parental weight constant	Parental weight predicted
Female	0.023***	0.018***	0.029***	0.022***	0.019***	0.018***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Main parent's education						
NVQ level 1	0.006	−0.002	0.002	0.006	0.017	0.016
	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)	(0.015)
NVQ level 2	−0.011	−0.006	−0.000	−0.016	0.012	0.011
	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)	(0.012)
NVQ level 3	−0.015	−0.022**	−0.006	−0.031***	0.008	0.008
	(0.010)	(0.010)	(0.012)	(0.012)	(0.014)	(0.014)
NVQ level 4	−0.009	−0.022**	−0.019*	−0.017	−0.004	−0.004
	(0.009)	(0.009)	(0.011)	(0.013)	(0.012)	(0.012)
NVQ level 5	0.006	−0.033**	−0.040***	−0.044**	−0.013	−0.013
	(0.018)	(0.013)	(0.013)	(0.017)	(0.018)	(0.018)
Child long-term illness	−0.012*	0.017**	0.002	0.000	0.006	0.007
	(0.006)	(0.007)	(0.007)	(0.009)	(0.012)	(0.012)
Health conditions	0.002	0.001	0.005**	0.005**	0.005	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Main parent long-term illness	−0.001	0.010*	0.007	0.015**	0.009	0.010
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
No. of siblings	0.000	−0.007***	−0.004	−0.010***	−0.010***	−0.009**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Birthweight	0.014***	0.026***	0.013***	0.019***	0.029***	0.031***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Weight gain 9 months-3 (kg)	0.024***	0.018***	0.018***	0.014***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Ethnicity						
Mixed	0.047**	0.011	−0.021	0.039**	−0.030	−0.030
	(0.030)	(0.024)	(0.022)	(0.023)	(0.018)	(0.018)
Indian	−0.002	0.015	0.019	−0.031*	0.004	0.003
	(0.020)	(0.024)	(0.026)	(0.012)	(0.026)	(0.025)
Pakistani and Bangladeshi	0.005	0.038***	0.027*	0.028*	0.016	0.016
	(0.012)	(0.016)	(0.016)	(0.020)	(0.019)	(0.019)
Black or Black British	0.051***	0.058***	0.094***	0.052***	0.020	0.020
	(0.021)	(0.021)	(0.026)	(0.024)	(0.021)	(0.022)
Other Ethnic group (inc. Chinese, Other)	0.021	0.019	0.015	0.003	−0.014	−0.015
	(0.026)	(0.028)	(0.032)	(0.030)	(0.024)	(0.023)
$\mathbb{E}[Pr(obese)\|\boldsymbol{x}]$	0.038	0.039	0.039	0.040	0.037	0.037
N	10.714	11.115	8.942	8.408	6.985	6.985

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Table A19a: Individual healthy behaviours and overweight *or* obesity in children across ages

					(5)-(6) Age 14	
	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	Parental weight constant	Parental weight predicted
Main parent overweight	0.036***	0.078***	0.085***	0.120***	0.110***	0.084***
	(0.011)	(0.010)	(0.011)	(0.013)	(0.014)	(0.013)
Main parent obese/morbidly obese	0.091***	0.165***	0.155***	0.241***	0.232***	0.230***
	(0.014)	(0.014)	(0.015)	(0.016)	(0.018)	(0.017)
Income quintiles						
Lowest quintile	0.055***	0.035**	0.014	0.044*	0.138***	0.140***
	(0.017)	(0.016)	(0.018)	(0.026)	(0.029)	(0.029)
Second quintile	0.043***	0.016	0.020	0.065***	0.069***	0.068***
	(0.015)	(0.015)	(0.016)	(0.021)	(0.022)	(0.022)
Third quintile	0.030**	0.000	0.008	0.061***	0.050***	0.052***
	(0.014)	(0.013)	(0.015)	(0.018)	(0.018)	(0.017)
Fourth quintile	0.032**	0.026**	0.002	0.022	0.013	0.013
	(0.013)	(0.013)	(0.014)	(0.016)	(0.015)	(0.015)
Healthy behaviours						
Fruit/veg once a day	0.018	0.006	0.008	−0.003	0.012	0.011
	(0.025)	(0.009)	(0.009)	(0.011)	(0.014)	(0.014)
Regular meals	−0.000	0.007				
	(0.009)	(0.009)				
Physically active games once a week	0.006	0.004	0.007	−0.039***		
	(0.011)	(0.009)	(0.009)	(0.012)		
Sport once a week		−0.007	−0.036**	−0.051***		
		(0.009)	(0.017)	(0.020)		
Sport with child once a week		0.003	0.001	0.001		
		(0.010)	(0.010)	(0.021)		
Breakfast every day				−0.033**	−0.055***	−0.057***
				(0.017)	(0.013)	(0.013)
Art. sweetened drinks less than once a week				−0.031***	−0.081***	−0.084***
				(0.012)	(0.017)	(0.017)
Sweetened drinks less than once a week				−0.004	0.030**	0.029*
				(0.012)	(0.014)	(0.014)
Fast food less than once a week					0.022	0.023*
					(0.014)	(0.014)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.199	0.174	0.159	0.240	0.192	0.193
N	10.714	11.115	8.942	8.408	6.985	6.985

Table A19b: Individual healthy behaviours and overweight *or* obesity in children across ages cont.

					(5)-(6) Age 14	
	(1) Age 3	(2) Age 5	(3) Age 7	(4) Age 11	Parental weight constant	Parental weight predicted
Female	0.076***	0.099***	0.119***	0.075***	0.054***	0.055***
	(0.010)	(0.009)	(0.010)	(0.011)	(0.013)	(0.013)
Main parent's education						
NVQ level 1	0.010	0.013	−0.019	−0.007	−0.017	−0.023
	(0.022)	(0.021)	(0.023)	(0.026)	(0.029)	(0.029)
NVQ level 2	−0.015	−0.012	−0.012	−0.016	−0.004	−0.008
	(0.017)	(0.016)	(0.019)	(0.021)	(0.024)	(0.024)
NVQ level 3	−0.017	−0.019	−0.031	−0.042*	−0.030	−0.034
	(0.019)	(0.018)	(0.021)	(0.024)	(0.026)	(0.026)
NVQ level 4	−0.009	−0.017	−0.036*	−0.020	−0.018	−0.022
	(0.018)	(0.017)	(0.020)	(0.024)	(0.025)	(0.025)
NVQ level 5	0.066**	−0.023	−0.058**	−0.036	−0.070**	−0.074**
	(0.031)	(0.027)	(0.028)	(0.036)	(0.033)	(0.034)
Child long-term illness	0.007	−0.000	−0.002	0.001	0.010	0.011
	(0.013)	(0.012)	(0.013)	(0.017)	(0.022)	(0.022)
Health conditions	0.006	0.006	0.007*	0.005	0.008	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.010)	(0.010)
Main parent long-term illness	−0.016	0.005	0.022*	0.014	−0.002	0.000
	(0.011)	(0.010)	(0.011)	(0.013)	(0.014)	(0.014)
No. of siblings	0.003	−0.010**	−0.013***	−0.026***	−0.027***	−0.027***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Birthweight	0.114***	0.105***	0.065***	0.044***	0.044***	0.048***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)	(0.011)
Weight gain 9 months-3 (kg)	0.091***	0.077***	0.057***	0.044***	0.037***	0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ethnicity						
Mixed	0.059	−0.004	−0.036	0.070**	−0.039	−0.045
	(0.049)	(0.041)	(0.048)	(0.037)	(0.054)	(0.051)
Indian	−0.085**	0.032	0.063*	0.034	−0.004	−0.005
	(0.031)	(0.039)	(0.040)	(0.040)	(0.043)	(0.044)
Pakistani and Bangladeshi	−0.016	0.024	0.022	0.077**	0.013	0.011
	(0.023)	(0.025)	(0.028)	(0.032)	(0.031)	(0.031)
Black or Black British	0.058*	0.107***	0.138***	0.134***	0.055	0.054
	(0.033)	(0.033)	(0.037)	(0.040)	(0.038)	(0.039)
Other Ethnic group (inc. Chinese, Other)	0.000	−0.019	−0.010	−0.000	0.049	0.043
	(0.041)	(0.039)	(0.049)	(0.065)	(0.067)	(0.068)
$\mathbb{E}[Pr(overweight \cup obese)\|\boldsymbol{x}]$	0.199	0.174	0.159	0.240	0.192	0.193
N	10.714	11.115	8.942	8.408	6.985	6.985

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. The outcome in each column is whether or not a child is overweight, defined using the IOTF cutoffs (Table 1.1). The effects reported are marginal effects obtained after estimating Equation 1.3 fixing the independent variables at their sample mean. The MCS data do not contain parents' BMI at age 14, so columns 5 and 6 use BMI from age 11 or as predicted to define obesity. All observations are adjusted for the probability of attrition and being sampled, see (Hansen et al., 2014). The omitted categories are income: highest quintile; parents' education: no qualifications; ethnicity: white. *Female* is an indicator of whether a child is female. Not all healthy behaviours on which we have measures are available at all ages so each columns include those that are. Appendix Table A4a describes how indicators of healthy behaviours were constructed. $\mathbb{E}[Pr(overweight)|\boldsymbol{x}]$ represents estimated the conditional expectation of a child being overweight. The *main parent* is the mother for over 99% of children at 9 months. Ns differ across columns because of missing data.

Appendix B

Supplementary Material for Chapter 2

B.1 Estimation Algorithm

To estimate the human capital production and investment functions I follow the sequential algorithm developed by Agostinelli and Wiswall (2016a). The algorithm first requires identification of the measurement parameters and joint distribution of the initial conditions. Agostinelli and Wiswall (2016a) then show the restrictions on the measurement system or structural parameters under which the functions can be identified in the first and each subsequent period.

Given the restrictions/normalizations on the measurement system laid out in 2.2, estimation has four main steps: 1) Estimation of the joint distribution of the initial conditions; 2) Estimation of the investment function and investment measurement parameters in $t = 0$; 3) Estimation of the production function and measurement parameters for health and cognitive and socio-emotional skill in period t=1; 4) Repeat steps 2 and 3 for $t = 2, 3, 4, 5$. The next five subsections outline this process in full, focusing on the production function of health.

B.1.1 The joint distribution of initial conditions

The factor loading of each of the latent initial conditions can be retrieved by simply taking the ratio of covariances between different observed measurements. For example, for unobservable $\theta \in \{\ln H_{h,0}, \ln H_{c,0}, \ln H_{s,0}, \ln P_h, \ln P_s\}$:

$$\lambda_{\theta,m,0} = \frac{\mathrm{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\mathrm{Cov}(Z_{\theta,1,0}, Z_{\theta,m',})} \quad \forall m' \neq m \tag{B1}$$

Next, under the assumption that the initial conditions are mean zero the intercepts, $\mu_{\theta,m,0}$, can be estimated by $\mathbb{E}(Z_{\theta,m,0})$, and residual measures are constructed:

$$\tilde{Z}_{\theta,m,0} = \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} = \ln \theta_0 + \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} = \ln \theta_0 + \tilde{\varepsilon}_{\theta,m,0} \quad \forall m \tag{B2}$$

The latent variables are equivalent to:

$$\tilde{Z}^*_{\theta,m,0} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 \tag{B3}$$

The diagonal and off-diagonal elements of Σ_Ω can be estimated by

$$\frac{\mathrm{Cov}(Z_{\theta,1,0}, Z_{\theta,2,0})\mathrm{Cov}(Z_{\theta,1,0}, Z_{\theta,3,0})}{\mathrm{Cov}(Z_{\theta,2,0}, Z_{\theta,2,0})} = \frac{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\mathrm{Var}(\ln\theta_0)^2}{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\mathrm{Var}(\ln\theta_0)} = \mathrm{Var}(\ln\theta_0) \tag{B4}$$

and

$$\mathrm{Cov}(Z_{\theta,1,0}, Z_{\theta',1,0}) = \mathrm{Cov}(\ln\theta_0, \ln\theta'_0) \tag{B5}$$

respectively. Since $\ln Y_0$ and P_c are assumed to me measured without error, their mean and variance are easily computed, and their covariance with the latent initial conditions is simply:

$$\mathrm{Cov}(\ln Y_0, \ln\theta_0) = \mathrm{Cov}(\ln Y_0, Z_{\theta,1,0})$$
$$\mathrm{Cov}(\ln P_c, \ln\theta_0) = \mathrm{Cov}(\ln P_c, Z_{\theta,1,0})$$

Given the assumption that unobservables are mean zero in the initial period, the mean vector is

$$\mu_\Omega = (0, 0, 0, 0, \mu_{\ln P_c}, 0, \mu_{\ln Y,0})$$

B.1.2 Investment Functions

Substituting a structural investment equation in to one measurement equation for investment in human capital component $j \in \{c, h\}$ in period zero gives:

$$\begin{aligned} Z_{I_j,1,0} = \mu_{I_j,1,0} + \lambda_{I_j,1,0}(\beta^j_{1,0}\ln H_{c,t} &+ \beta^j_{2,0}\ln H_{s,0} + \beta^j_{3,0}\ln H_{h,0} + \beta^j_{4,0}\ln P_c \\ &+ \beta^j_{5,0}\ln P_s + \beta^j_{6,0}\ln P_h + \beta^j_7\ln Y_0 + \pi_{j,0}) + \varepsilon_{I_j,1,0} \end{aligned} \tag{B6}$$

Then, substituting the corresponding $\tilde{Z}^*_\theta = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0}$ in to this in place of the relevant θ Equation B6 can be re-written as:

$$\begin{aligned} Z_{I_j,1,0} = \mu_{I_j,1,0} + \lambda_{I_j,1,0}(\beta^j_{1,0}\tilde{Z}^*_{H_c,m,0} &+ \beta^j_{2,0}\tilde{Z}^*_{H_s,m,0} + \beta^j_{3,0}\tilde{Z}^*_{H_h,m,0} + \beta^j_{4,0}\ln P_c \\ &+ \beta^j_{5,0}\tilde{Z}^*_{P_s,m} + \beta^j_{6,0}\tilde{Z}^*_{P_h,m} + \beta^j_7\ln Y_0 + \pi_{j,0}) + \varepsilon_{I_j,1,0} \end{aligned} \tag{B7}$$

Expanding and rearranging this equation gives the following reduced form investment equation for $I_{j,0}$:

$$Z_{I_j,1,0} = \delta_0^j + \delta_{1,0}^j \tilde{Z}_{H_c,m,0} + \delta_{2,0}^j \tilde{Z}_{H_s,m,0} + \delta_{3,0}^j \tilde{Z}_{H_h,m,0} + \delta_{4,0}^j \ln P_c + \delta_{5,0}^j \tilde{Z}_{P_s,m} + \delta_{6,0}^j \tilde{Z}_{P_h,m} + \delta_{7,0}^j \ln Y_0 + \nu_{j,0} \tag{B8}$$

where

$$\begin{aligned}
\tilde{Z}_{\theta,m,0} =& \ln \theta_0 + \tilde{\varepsilon}_{\theta,m,0} \quad \text{for } \theta \in \{\ln H_{h,0}, \ln H_{c,0}, \ln H_{s,0}, \ln P_h, \ln P_s\} \\
\delta_0^j =& \mu_{I_j,1,0} \\
\delta_{i,0}^j =& \lambda_{I_j,1,0} \beta_{i,0}^j \quad \text{for} \quad i = 1, .., 7 \\
\nu_{j,0} =& \varepsilon_{I_j,1,0} + \lambda_{I_j,1,0}(\pi_{j,0} - \beta_{1,0}^j \tilde{\varepsilon}_{H_c,m,0} - \beta_{2,0}^j \tilde{\varepsilon}_{H_s,m,0} - \beta_{3,0}^j \tilde{\varepsilon}_{H_h,m,0} \\
& - \beta_{5,0}^j \tilde{\varepsilon}_{P_s,m,0} - \beta_{6,0}^j \tilde{\varepsilon}_{P_h,m,0})
\end{aligned}$$

In Equation B8, $\mathbb{E}(\tilde{Z}_{\theta,m,0}\nu_{j,0}) \neq 0$ since both contain $\tilde{\varepsilon}_{\theta,m,0}$. To consistently estimate the reduced form parameters in Equation B8 all other available measures of each latent input are used as instrumental variables for the error contaminated $\tilde{Z}$s. Under the assumption that measurement errors are independent of one another and all latent variables, the condition that $\mathbb{E}(Z_{\theta,m',0}\nu_{j,0}) = 0 \quad \forall \theta_0$ and $m' \neq m$ is satisfied and so these alternative measures are valid instruments. With the normalisation that $\lambda_{I_{j,0},m,0} = 1$ and $\mathbb{E}(\ln I_{j,0}) = 0$, the parameters of the investment function be recovered straightforwardly as:

$$\begin{aligned}
\beta_{i,0}^j &= \delta_{1,0}^j \quad \text{for} \quad i = 1, .., 7 \\
\delta_0^j &= \mu_{I_j,1,0}
\end{aligned}$$

A residual investment measure is then constructed as:

$$\tilde{Z}_{I_j,1,0} = Z_{I_j,1,0} - \mu_{I_j,1,0} = \ln I_{j,0} + \varepsilon_{I_j,1,0} \quad j \in \{c, h\} \tag{B9}$$

and latent investment is therefore equal to:

$$\tilde{Z}^*_{H_h,m,0} = \tilde{Z}_{I_j,1,0} - \varepsilon_{I_j,1,0} = \ln I_{j,0} \quad j \in \{c, h\} \tag{B10}$$

B.1.3 Production Functions

An identical procedure is then used to estimate the production functions health, cognition, and socio-emotional skill. Focusing on the production function of health, substituting Equation 2.3 in to an arbitrary measurement equation for period 1 stock of health gives:

$$\begin{aligned}
Z_{H_h,1,1} = \mu_{H_h,1,1} + \lambda_{H_h,1,1}\big(&\rho^h_{h,t}\ln H_{h,t} + \rho^h_{c,t}\ln H_{c,t} + \rho^h_{s,t}\ln H_{s,t} \\
&+\alpha^h_{h,t}\ln P_h + \alpha^h_{c,t}\ln P_c + \alpha^h_{s,t}\ln P_s \\
&+ \gamma^h_{h,t}\ln I_{h,t} + \kappa^h_{hh,t}(\ln I_{h,t}\ln H_{h,t}) + \eta_{h,t+1}\big) + \varepsilon_{H_h,1,1}
\end{aligned} \tag{B11}$$

Once more using the fact that $\tilde{Z}^*_{\theta,m,0} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0$ for $\theta_0 \in \{H_{c,0}, H_{s,0}, H_{h,0}, P_{c,0}, P_{s,0}, P_{h,0}, I_{c,0}, I_{h,0}\}$, this can be written as:

$$\begin{aligned}
Z_{H_h,1,1} = \mu_{H_h,1,1} + \lambda_{H_j,m,1}\big(&\rho^h_{k,0}\tilde{Z}^*_{H_h,m,0} + \rho^h_{c,0}\tilde{Z}^*_{H_c,m,0} + \rho^h_{s,0}\tilde{Z}^*_{H_s,m,0} \\
&+\alpha^h_{h,0}\tilde{Z}^*_{P_h,m} + \alpha^h_{c,0}P_c + \alpha^h_{s,0}\tilde{Z}^*_{P_s,m} \\
&+ \gamma^h_{h,0}\tilde{Z}^*_{I_h,m,0} + \kappa^h_{hh,0}\tilde{Z}^*_{H_h,m,0}\tilde{Z}^*_{I_h,m,0} + \eta_{h,1}\big) + \varepsilon_{H_h,1,1}
\end{aligned} \tag{B12}$$

Then expanding the $\tilde{Z}^*$s and rearranging gives the reduced form production function:

$$\begin{aligned}
Z_{H_h,1,1} = \omega_{h,0} &+ \tau^h_{h,0}\tilde{Z}_{H_h,m,0} + \tau^h_{c,0}\tilde{Z}_{H_c,m,0} + \tau^h_{s,0}\tilde{Z}_{H_s,m,0} \\
&+\sigma^h_{h,0}\tilde{Z}_{P_h,m} + \sigma^h_{c,0}P_c + \sigma^h_{k,0}\tilde{Z}_{P_s,m} \\
&+ \phi^h_{h,0}\tilde{Z}_{I_h,m,0} + \psi^h_{hh,0}\tilde{Z}_{H_h,m,0}\tilde{Z}_{I_h,m,0} + \upsilon_{j,1}
\end{aligned} \tag{B13}$$

where

$$\begin{aligned}
\tilde{Z}_{\theta,m,0} &= \ln\theta_0 + \tilde{\varepsilon}_{\theta,m,0} \quad \text{for } \theta \in \{\ln H_{h,0}, \ln H_{c,0}, \ln H_{s,0}, \ln P_h, \ln P_s, \ln I_{h,0}\} \\
\omega_{h,0} &= \mu_{H_h,1,1} + \ln A_t \\
\tau^h_{k,0} &= \lambda_{H_h,1,1}\rho^h_{k,0} \quad \text{for} \quad k \in \{h, c, s\} \\
\sigma^h_{k,0} &= \lambda_{H_h,1,1}\alpha^h_{k,0} \quad \text{for} \quad k \in \{h, c, s\} \\
\phi^h_{k,0} &= \lambda_{H_h,1,1}\gamma^h_{h,0} \\
\psi^h_{hh,0} &= \lambda_{H_h,1,1}\kappa^h_{hh,0}
\end{aligned}$$

and

$$\begin{aligned}
\upsilon_{h,1} =&\varepsilon_{H_h,1,1} + \lambda_{H_h,1,1}\Bigg[\eta_{h,1} - \sum_{k\in\{h,c,n\}} \rho^h_{k,0}\tilde{\varepsilon}_{H_k,m,0} - \sum_{k\in\{h,n\}} \alpha^h_{k,0}\tilde{\varepsilon}_{P_k,m,0} \\
&- \gamma^h_{h,0}\tilde{\varepsilon}_{I_h,m,0} - \kappa^h_{hh,0}\left(\tilde{Z}_{I_h,m,0}\tilde{\varepsilon}_{H_h,m,0} + \tilde{Z}_{H_h,m,0}\tilde{\varepsilon}_{I_h,m,0} - \tilde{\varepsilon}_{I_h,m,0}\tilde{\varepsilon}_{H_h,m,0}\right)\Bigg]
\end{aligned} \tag{B14}$$

As in estimation of the investment functions, all alternative measures of the inputs are used as instrumental variables with their validity implied by the assumption that measurement errors are fully independent. I assume that the measurement parameters of $Z_{H_h,1,1}$ are age-invariant, implying that $\lambda_{H_h,m,0} = \lambda_{H_h,m,1}$ and $\mu_{H_h,m,0} = \mu_{H_h,m,1}$. The structural parameters of the health production function can then be recovered as:

$$\begin{aligned}
\rho^h_{k,0} =&\frac{\tau^h_{k,0}}{\lambda_{H_h,1,0}} = \frac{\lambda_{H_h,1,1}\rho^h_{k,0}}{\lambda_{H_h,1,1}} \quad \text{for} \quad k \in \{h, c, s\} \\
\alpha^h_{k,0} =&\frac{\sigma^h_{k,0}}{\lambda_{H_h,1,0}} = \frac{\lambda_{H_h,m,1}\alpha^j_{k,0}}{\lambda_{H_h,1,0}} \quad \text{for} \quad k \in \{h, c, s\} \\
\gamma^j_{k,0} =&\frac{\phi^j_{k,0}}{\lambda_{H_h,1,0}} = \frac{\lambda_{H_h,m,1}\gamma^j_{k,0}}{\lambda_{H_h,1,0}} \\
\kappa^j_{hh} =&\frac{\psi^j_{hh}}{\lambda_{H_h,1,0}} = \frac{\lambda_{H_h,m,1}\kappa^j_{hh,0}}{\lambda_{H_h,1,0}}
\end{aligned}$$

Its TFP and RTS can then be backed out by:

$$\begin{aligned}
&RTS = \sum_k \frac{\tau^h_{k,0}}{\lambda_{H_h,1,0}} + \sum_k \frac{\sigma^h_{k,0}}{\lambda_{H_h,1,0}} + \frac{\phi^h_{h,0}}{\lambda_{H_h,1,0}} + \frac{\psi^h_{hh,0}}{\lambda_{H_h,1,0}} \\
&\ln A_t = \omega_{h,0} - \mu_{H_h,1,0}
\end{aligned}$$

These expressions simplify even further when the age-invariant measure is also the normalising measure, since $\lambda_{H_h,1,0} = \lambda_{H_h,1,1} = 1$ and $\mu_{H_h,1,0} = \mu_{H_h,1,1} = \mathbb{E}(Z_{H_h,1,0})$. A period 1 residual health measure can be constructed as:

$$\tilde{Z}_{H_h,1,1} = \frac{Z_{H_h,1,1} - \mu_{H_h,1,1}}{\lambda_{H_h,1,1}} = \ln H_{h,1} + \tilde{\varepsilon}_{H_h,1,1} \tag{B15}$$

This once more allows the following definition of latent health in the next period:

$$\tilde{Z}^{*}_{H_h,m,1} = \tilde{Z}_{H_h,m,1} - \tilde{\varepsilon}_{H_h,m,1} = \ln H_{h,1} \tag{B16}$$

The parameters of the socio-emotional skill measurement and production function parameters are estimated identically with one difference. I re-normalise socio-emotional skill in onto an age-invariant measure at $t = 1$. This means imposing $\mathbb{E}(\ln H_{s,1}) = 0$ and $\lambda_{H_s,1,1} = 1$ to fix the location and scale of latent socio-emotional skill to the age-invariant measure.

As outlined in the main body of the paper, the process for disentangling the structural production parameters from the measurement parameters is different in the case of cognitive skill. It is not possible to assume age-invariance for any of the measures available meaning restrictions have to be place on the structural cognitive production function parameters. The reduced form version of Equation B13 for cognitive skill production (with only one investment and interaction for simplicity) is given by:

$$\begin{aligned} Z_{H_c,m,1} = \omega_{c,0} + \tau^{c}_{h,0}\tilde{Z}_{H_h,m,0} + \tau^{c}_{c,0}\tilde{Z}_{H_c,m,0} + \tau^{c}_{s,0}\tilde{Z}_{H_s,m,0} \\ +\sigma^{c}_{h,0}\tilde{Z}_{P_h,m} + \sigma^{c}_{c,0}P_c + \sigma^{c}_{k,0}\tilde{Z}_{P_s,m} \\ + \phi^{c}_{h,0}\tilde{Z}_{I_c,m,0} + \psi^{c}_{cc,0}\tilde{Z}_{H_c,m,0}\tilde{Z}_{I_c,m,0} + \upsilon_{j,1} \end{aligned} \tag{B17}$$

where, again, the reduced form parameters can be written as a combination of the structural and measurement parameters of cognition in the next period:

$$\begin{aligned} \tilde{Z}_{\theta,m,0} &= \ln\theta_0 + \tilde{\varepsilon}_{\theta,m,0} \quad \text{for } \theta \in \{\ln H_{h,0}, \ln H_{c,0}, \ln H_{s,0}, \ln P_h, \ln P_s, \ln I_{h,0}\} \\ \omega_{c,0} &= \mu_{H_c,m,1} + \ln A_t \\ \tau^{c}_{k,0} &= \lambda_{H_c,m,1}\rho^{c}_{k,0} \quad \text{for} \quad k \in \{h, c, s\} \\ \sigma^{c}_{k,0} &= \lambda_{H_c,m,1}\alpha^{c}_{k,0} \quad \text{for} \quad k \in \{h, c, s\} \\ \phi^{c}_{k,0} &= \lambda_{H_c,m,1}\gamma^{c}_{c,0} \\ \psi^{c}_{cc,0} &= \lambda_{H_c,m,1}\kappa^{c}_{cc,0} \end{aligned}$$

In this case, however, it is not the case that $\lambda_{H_c,m,0} = \lambda_{H_c,m,1}$ or $\mu_{H_c,m,0} = \mu_{H_c,m,1}$, meaning the measurement parameters must be directly estimated. In order to do so, the restriction of CRS and no TFP must be imposed on the technology, which implies :

$$\lambda_{H_c,n,1} = \sum_k \tau^c_{k,0} + \sum_k \sigma^c_{k,0} + \phi^c_{c,0} + \psi^c_{cc,0}$$

$$\mu_{H_c,n,1} = \omega_{c,0}$$

$$\rho^c_{k,0} = \frac{\tau^c_{k,0}}{\lambda_{H_c,m,1}} \quad \text{for} \quad k \in \{h, c, s\}$$

$$\alpha^c_{k,0} = \frac{\sigma^c_{k,0}}{\lambda_{H_c,m,1}} \quad \text{for} \quad k \in \{h, c, s\}$$

$$\gamma^c_{k,0} = \frac{\phi^c_{c,0}}{\lambda_{H_c,m,1}}$$

$$\kappa^c_{k,0} = \frac{\psi^c_{cc,0}}{\lambda_{H_c,m,1}}$$

Once the parameters of the period 1 health, cognitive and socio-emotional production functions are estimated, $\tilde{Z}^*_{H_h,m,1}$, $\tilde{Z}^*_{H_c,m,1}$ and $\tilde{Z}^*_{H_s,m,1}$ can be used alongside $\tilde{Z}^*_{P_h,m}$, P_c and $\tilde{Z}^*_{P_s,m}$ to estimate the structural and measurement parameters of investment at $t = 1$, then the production functions of health and human capital in an identical manner. The same process is then followed in all subsequent periods.

B.1.4 Variance of shocks

The variance of the shocks to production and investment are estimated by the covariance between the residual from equations the reduced form investment ($\nu_{j,0}$) and production ($\upsilon_{j,1}$) functions (B8 and B13) and an alternative residual measure, $\tilde{Z}_{H_j,m',1}$ and $\tilde{Z}_{I_j,1',1}$. The assumption that measurement errors are independent means that:

$$\text{Cov}\left(\frac{\nu_{j,0}}{\lambda_{I_j,m,0}}, \tilde{Z}_{I_j,m',1}\right) = Var(\pi_{j,t}) = \sigma^2_{I_j,0} \quad \text{for} \quad j \in \{h, c\}, \tag{B18}$$

and

$$\text{Cov}\left(\frac{\upsilon_{j,0}}{\lambda_{H_j,m,1}}, \tilde{Z}_{H_j,m',1}\right) = Var(\eta_{j,1}) = \sigma^2_{\eta_j,1} \quad \text{for} \quad j \in \{h, c, s\} \tag{B19}$$

B.1.5 Signal to noise ratios

The variance of each measure of each latent variable can be easily decomposed into a portion caused by the latent variable - the signal - and a portion caused by measurement error. The signal of measure $Z_{\theta,m,t}$ is calculated by the ratio:

$$s_{\theta,m,t} = \frac{\lambda^2_{\theta,m,t}\mathrm{Cov}\left(\tilde{Z}_{\theta,m,t}, \tilde{Z}_{\theta,m',t}\right)}{V(Z_{\theta,m,t})} = \frac{\lambda^2_{\theta,m,t}V(\ln\theta_t)}{\lambda^2_{\theta,m,t}V(\ln\theta_t) + V(\varepsilon_{\theta,m,t})}\,, \tag{B20}$$

and the noise by $(1 - s_{\theta,m,t})$, where $\theta \in \{\ln H_{h,t}, \ln H_{c,t}, \ln H_{s,t}, \ln P_h, \ln P_s, \ln I_{h,t}, \ln I_{c,t}\}_{t=0}^{T}$.

B.2 Additional Data Description

B.2.1 Details of the child cognitive assessments used from the MCS

Denver Developmental Screening Test (DDST):

At 9 months of age, the MCS ask the main respondent 8 questions from the DDST aimed at assessing the level of gross (G) and fine (F) motor skill development in infants. The 8 questions have three possible responses: "Not Yet", "Once or Twice", and "Often" to questions about whether or not the child can

- Sit up with support (G);
- Stand up while holding onto something such as furniture (G);
- Walk a few steps on his/her own (G);
- Move around between places if placed on the floor (G);
- Put his/her hands together (F);
- Grab objects using the whole hand (F);
- Pick up small objects using forefinger and thumb only (F);
- Pass a toy back and forth between hands (F),

See Frankenburg and Dodds (1967) for full details of the development and purpose of the DDST.

MacArthur-Bates Communicative Development Inventory (CDI):

Also at 9 months of age, the MCS asks the main respondent 5 questions from the MacArthur-Bates CDI assessing the child's which assess the cohort members' development of receptive and productive vocabulary. The 5 questions have three possible responses: "Not Yet", "Once or Twice", and "Often" to questions about whether or not the child

- Smiles when smiled at;
- Reaches out to gives a toy or object he/she is holding;
- Waves bye-bye on his/her own when someone leaves;
- Extends his/her arms to show they want to be picked up;
- Nods his/her head for yes.

Fenson et al. (1986) provides full details of the MacArthur-Bates CDI.

Bracken School Readiness (BSR) Assessments:

At age 3 the MCS children are administered 6 BSR assessments of the following concepts:

- **Colours:** recognition of both primary colours and basic colour terms.
- **Letters:** recognition of both upper and lower case.
- **Numbers/Counting:** recognition of single- and double-digit numbers, and the ability to assign a number value to a set of objects
- **Sizes:** recognition of concepts describing one, two, and three dimensions
- **Comparisons:** the ability to match/differentiate objects based on salient characteristics
- **Shapes:** recognition of one-, two-, and three-dimensional shapes.

In total these 6 tests contain 88 questions, a child's answer to which is either correct or incorrect. Each assessment has two scores available: the raw total number of correct answers and the percent of questions answered correctly. I use the former in estimation production functions.

British Ability Scales (BAS) Assessments:

Table B1 shows the BAS assessments used at each age in the MCS and how they are administered. Each assessment has several scores available, including the raw total number of correct answers and the total number of correct answers adjusted for the specific question set administered - the *ability* score. I use the ability scores in estimation of the cognitive production functions.

National Foundation for Education Research (NFER) number skills:

At age 7 the National Foundation for Education Research (NFER) number skills test was administered as part of the MCS survey. All children were required to first complete an initial assessment that assigned them to an "easier", "medium", or "harder" test. The NFER number skills assessment is not normally administered in this two-step manner, however it was done so in the MCS to save survey and administration time. It also meant the cohort members answered half of the total number of questions in the full assessment.

The test to which they were routed based on this initial assessment comprised of various number problems, each of which was answered either correctly or incorrectly by the cohort members. Item Response Theory was used to scale the sub-set of questions administered in to an equivalent raw score from a fully administered test.

Cambridge Neurophysical Test Automated Battery (CANTAB) Tasks:

At ages 11 and 15 the computerised CANTAB Gambling Task was administered.

Table B1: British Ability Scales by age in the MCS

Assessment	Age	Test
Naming Vocabulary	3 & 5 years	Cohort members are shown coloured pictures one-by-one and asked to identify what they depict.
Picture Similarity	5 years	Cohort members are given a card and asked to place it underneath the picture to which it is most similar from a group of four images
Pattern Construction	5 & 7 years	Cohort members are given squares and asked to recreate a coloured pattern they are shown
Word Reading	7 years	Records how many words out of a group of ninety, arranged in nine blocks of ten in ascending order of difficulty, a cohort member can pronounce. If a child makes 8 errors in a block of 10 words, then the assessment stops
Verbal Similarities	11 years	The interviewer reads out three words to the child who must then say how the three things are similar. After 12 questions, the test stops unless the child has less than 3 failures on *all* questions until that point. If so they progress to answer 5 more questions.

In the gambling task, children are shown a row of ten boxes coloured either red or blue at the top of the screen and two rectangles containing the words "Red" and "Blue" at the bottom. They are told that there is a token hidden in one of these boxes. By pressing the corresponding rectangle, cohort members must indicate whether they think the token is in a red or blue box. Additionally, they are asked to gamble 5%, 25%, 50%, 75%, or 95% of an endowment of 100 points on their choice. The proportions were displayed on the right-hand side of the screen in either descending or ascending order. Six outcomes are measured:

- Overall proportional bet: mean proportion of points gambled across trials
- Deliberation time: mean time to respond to the questions
- Quality of decision making: proportion of trials in which the most likely option was chosen
- Risk taking: mean points bet on the most likely outcome
- Risk adjustment: the degree to which a cohort member alters their proportional bet in accordance with the odds of the token being in each colour of box.
- Delay aversion: a measure of the tendency to bet large proportions when the possible proportions were displayed in descending order, and vice versa.

At age 11 the CANTAB spatial working memory task was administered. This test was also computerised.

The spatial working memory task tested cohort members' ability to retain spatial information and manipulate remembered items in working memory, as well as their ability to us strategy. In the task, the children were shown a number of coloured boxes in the middle and an empty column on the right-hand side of the screen. They are asked to find a number of blue tokens in the coloured boxes and fill up the column with them. To do so, they must select a box by touching it and if a blue token is revealed move across and in to the column. Touching a box that has already been searched is an error, and the number of boxes is gradually increased from 3 to 8 with the colour and order of boxes altering between trials.

Three different aspects of performance are measured:

- **Errors:** the number of times a cohort member revisits a box
- **Strategy:** the order in which a cohort member searches the boxes
- **Latency:** mean time, in milliseconds, to first touch the screen, to touch the screen again after placing a token in the column, and to find the final token from the beginning of the trial.

Word Recognition:

At age 15 the cohort members' word recognition is assessed through testing their familiarity with words and their meaning. The cohort members were shown a list of 20 *target* words, each with 5 other words written next to them. From these 5 words, the children were asked to select that which was most like the target word. A child's score in this assessment indicates in how many of the 20 trials they correctly identified the most similar word from the group of 5 alternatives.

The words used were a subset of those from the standard vocabulary tests developed by the Applied Psychology Unit at the University of Edinburgh in 1976. A similar test was administered to the members of the 1970 British Cohort Study.

B.2.2 Details of the child socio-emotional assessments used from the MCS

Carey Infant Temperament Scales (CIT):

At 9 months of age the MCS administered 14 questions from CIT scale to the respondents. The questions were aimed at assessing 4 areas of cohort members' temperamental and behavioural development: regularity (R), approachability and withdrawal (AW), adaptability (A), and mood (M). The questions had 5 responses - "Almost never", "Rarely", "Usually does not", "Often", and "Always" - with regards to how often the cohort member:

- Makes happy sounds when having his/her nappy changed (M)
- Is pleasant (smiles, laughs) when he/she first arriving in unfamiliar places (M)
- Is pleasant (coos, smiles) during procedures like hair brushing (M)
- Is content (smiles, coos) during interruptions of milk or solid feeding (M)
- Remains pleasant or calm with minor injuries (M)
- Objects to being bathed in a different place of by a different person (AW)
- Is still wary or frightened of strangers after 15 minutes (AW)
- Is shy (turns away or clings) on you meeting another child for the first time (AW)
- Is fretful for the first few minutes in a new place (A)
- Appears bothered (cries/squirms) when first put down in a different sleeping place (A)
- Wants and takes milk feeds at about the same time (within one hour)from day to day (A)
- Gets sleepy about the same time (within 30 minutes) each evening (R)
- Naps are about the same length from day to day (R)
- Wants to take solid food at about the same time (within one hour) from day to day (R)

Carey and McDevitt (1978) provides details of the original CIT and outlines the revisions made that resulted in the questionnaire from which the questions asked in the MCS were taken.

Child Social and Behavioural Questionnaires (CSBQ):

Sub-sets of questions from the CSBQ were asked at 3, 5, 7, and 11 years of age. These questions aimed to measure the extent to which cohort members displayed Independence and Self-Regulation (ISR), Emotional Dysregulation (ED), and Cooperation (C). Table B2 shows the CSBQ items administered, the age at which they were asked, and which domain of child behaviour they measure.

Table B2: Child Social and Behavioural Questionnaire Items by age in the MCS

Item	Age	Domain
Likes to work things out for self	3,5 & 7 years	ISR
Does not need much help with tasks	3,5 & 7 years	ISR
Chooses activities on their own	3,5 & 7 years	ISR
Persists in the face of difficult tasks	3,5 & 7 years	ISR
Moves to a new activity after finishing a task	3,5& 7 years	ISR
Shows mood swings	3,5 & 7 years	ED
Gets over excited	3,5 & 7 years	ED
Easily frustrated	3,5 & 7 years	ED
Gets over being upset quickly	3,5& 7 years	ED
Acts impulsively	3,5 & 7 years	ED
Is calm and easy going	5 & 7 years	C
Works/plays easily with others	5 & 7 years	C
Says please and thank you when reminded	11 years	C
Waits his/her turn in games/activities	11 years	C
Co-operates with requests	11 years	C

Strengths and Difficulties Questionnaires (SDQ):

At ages 3, 7, 11, and 15, 25 questions from the SDQ were administered to cohort members' parents. The 25 questions asked questions regarding whether or not the children displayed behaviours indicative 0f 5 traits: emotional symptoms (E), conduct problems (C), hyperactivity/inattention (H), peer problems (P), and being pro-social (PS). Table B3 shows the SDQ questions administered and which of these traits the behaviour about which they ask is deemed to indicate.

Table B3: Strength and Difficulties Questions in the MCS

Item	Age	Trait
Complains of headaches/stomach-aches/sickness	3, 5, 7 & 11 years	E
Often seems worried	3, 5, 7 & 11 years	E
Often unhappy	3, 5, 7 & 11 years	E
Nervous or clingy in new situations	3, 5, 7 & 11 years	E
Many fears, easily scared	3, 5, 7 & 11 years	E
Often has temper tantrums	3, 5, 7 & 11 years	C
Generally obedient	3, 5, 7 & 11 years	C
Fights with or bullies other children	3, 5, 7 & 11 years	C
Often argumentative with adults	3, 5, 7 & 11 years	C
Can be spiteful to others	3, 5, 7 & 11 years	C
Restless, overactive, cannot stay still long	3, 5, 7 & 11 years	H
Constantly fidgeting	3, 5, 7 & 11 years	H
Easily distracted	3, 5, 7 & 11 years	H
Can stop and think before acting	3, 5, 7 & 11 years	H
Sees tasks through to the end	3, 5, 7 & 11 years	H
Has at least one good friend	3, 5, 7 & 11 years	P
Generally liked by other children	3, 5, 7 & 11 years	P
Tends to play alone	3, 5, 7 & 11 years	P
Picked on or bullied by other children	3, 5, 7 & 11 years	P
Gets on better with adults	3, 5, 7 & 11 years	P
Considerate of others' feelings	3, 5, 7 & 11 years	PS
Shares readily with others	3, 5, 7 & 11 years	PS
Helpful if someone is hurt, upset or ill	3, 5, 7 & 11 years	PS
Kind to younger children	3, 5, 7 & 11 years	PS
Often volunteers to help others	3, 5, 7 & 11 years	PS

In each of the five categories - emotional symptoms, conduct problems, hyperactivity/inattention, peer problems, and being pro-social - cohort members' scores were the total number of symptoms displayed. Johnson et al. (2015) gives details of all the socio-emotional assessments administered to the children of the MCS between the ages of 9 months and 11 years, and Fitzsimons et al. (2017) provides analogous descriptions for the age 15 survey

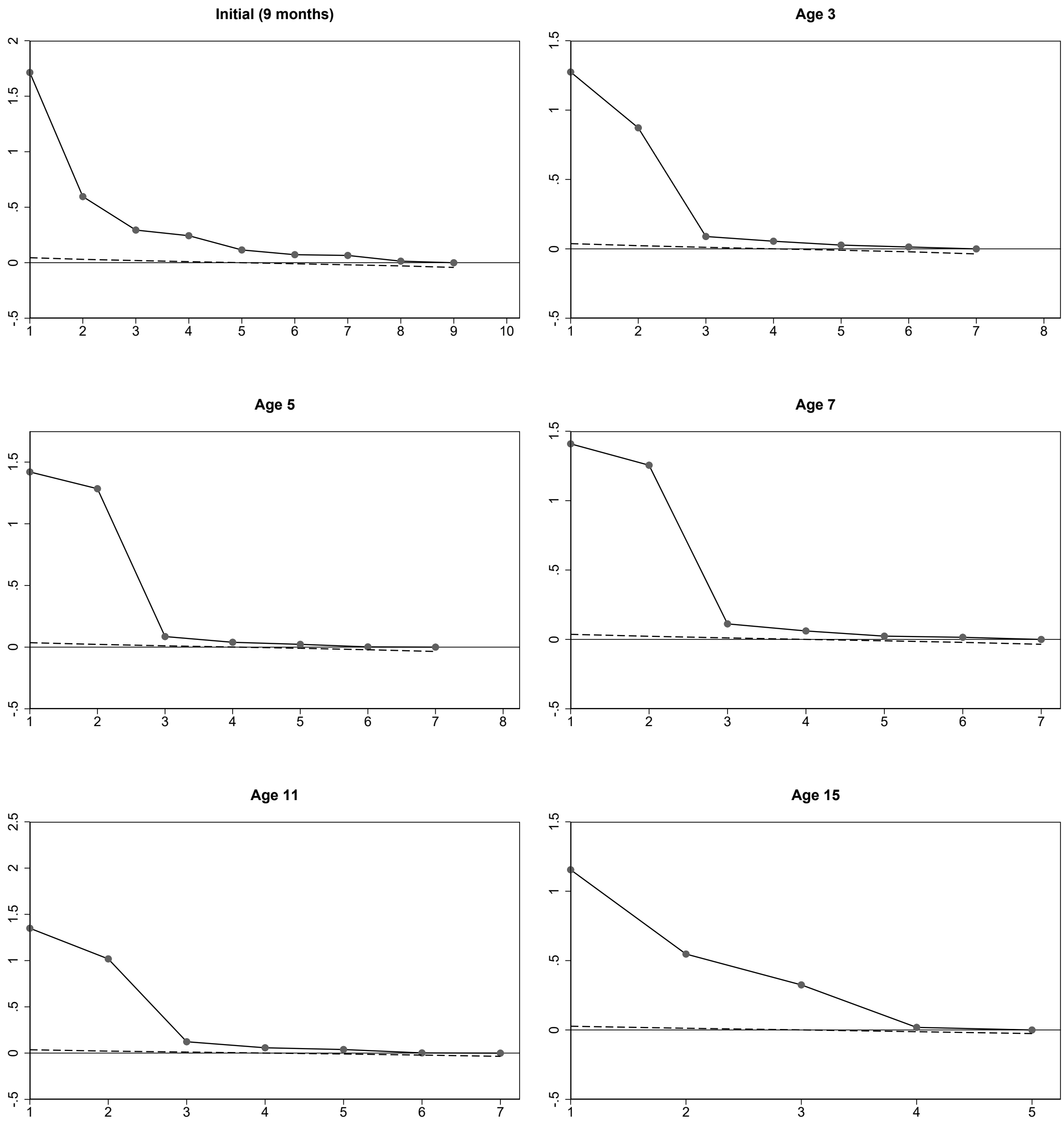
B.3 Exploratory Factor Analysis

B.3.1 Verifying and selecting the number of latent factors

The first step in "confirming" the structure of the measurement system was to verify that the observable measures shared enough variation to meaningfully exploit their correlations in estimating the investment and production functions. To do this, I use a similar approach to Attanasio et al. (2020b) in selecting their measures of skills an investments to estimate human capital production functions in a sample of Colombian children. First, I group the measures into four broad categories based on ex-ante beliefs about what they proxy: (1) health; (2) cognitive and socio-emotional skills; (3) Investments; and (4) endowments. I then examine how much variation they share and along how many dimensions - in others words, are the health measures highly correlated and, if so, is it only in one direction? Similarly, I would like to know if the cognitive and socio-emotional skill measures are highly correlated, and if this correlation is sufficiently strong along two dimensions. To do this, it is possible to simply examine the eigenvalues of the correlation matrix of the groups of observable measures and use some general rules of thumb as to what their magnitude imply about the number of latent variables underlying them. For example, Kaiser (1960) suggests only keeping a number of factors greater or equal to the number of eigenvalues greater than 1. Cattell (1966) on the other hand proposes a graphical solution, recommending that by plotting the latent factors against their eigenvalues the number of factors to be retained can be shown by the decrease in eigenvalues begins to smooth. I consider both these criteria, while at the same time using a parallel analysis (Horn, 1965). This analysis involves generating correlation matrices from randomly generated data of the same dimension as the actual data (hence *parallel*), and calculating and comparing their eigenvalues. Horn (1965) suggests keeping factors whose eigenvalues are larger than that of its randomly generated counterpart.

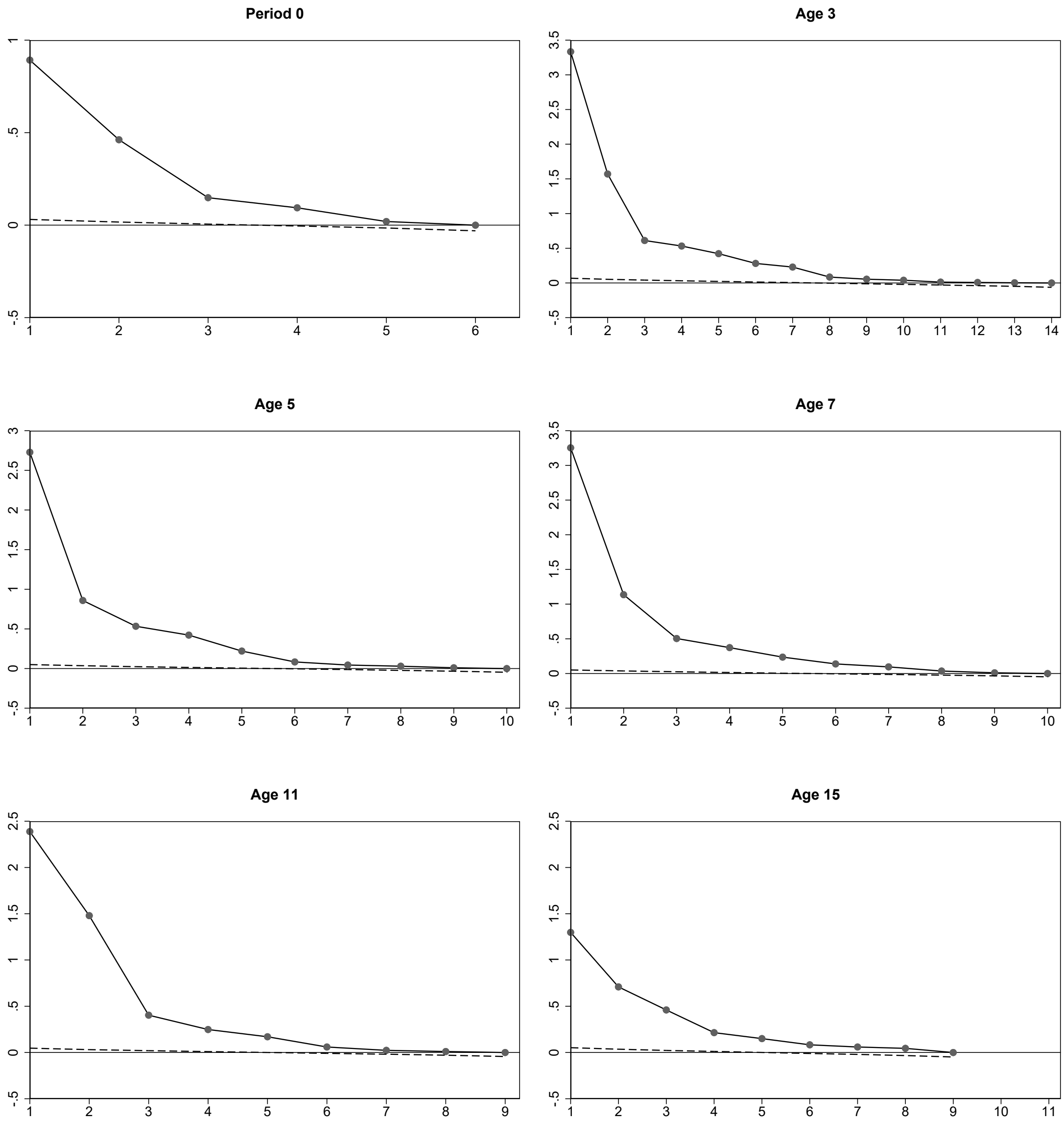
To combine these three rules of thumb, Figures B1, B2, B3, and B4 plot the eigenvalues of the correlation matrices of the four groupings of observable variables listed above in order of size, alongside their counterparts from randomly simulated data. They show that using a combination of the rules described above, the data supports extracting between 1 and 3 latent health (Figure B1) and skill (Figure B2) factors in each period, and somewhere between 1 and 4 investment factors in each period. For parental human capital the data similarly support the extraction of up to 3 factors. With this considered, it appears the data are rich enough to estimate a model with latent health, cognition, socio-emotional skill, parents' human capital and two types of investment. However, because there appear to be more latent factors underlying the data, I retain up to three factors across periods, and next analyse the extent to which different measures are correlated with the various latent factors.

Figure B1: Scree Plots of factors and their eigenvalues from an exploratory factor analysis of health measures in each period



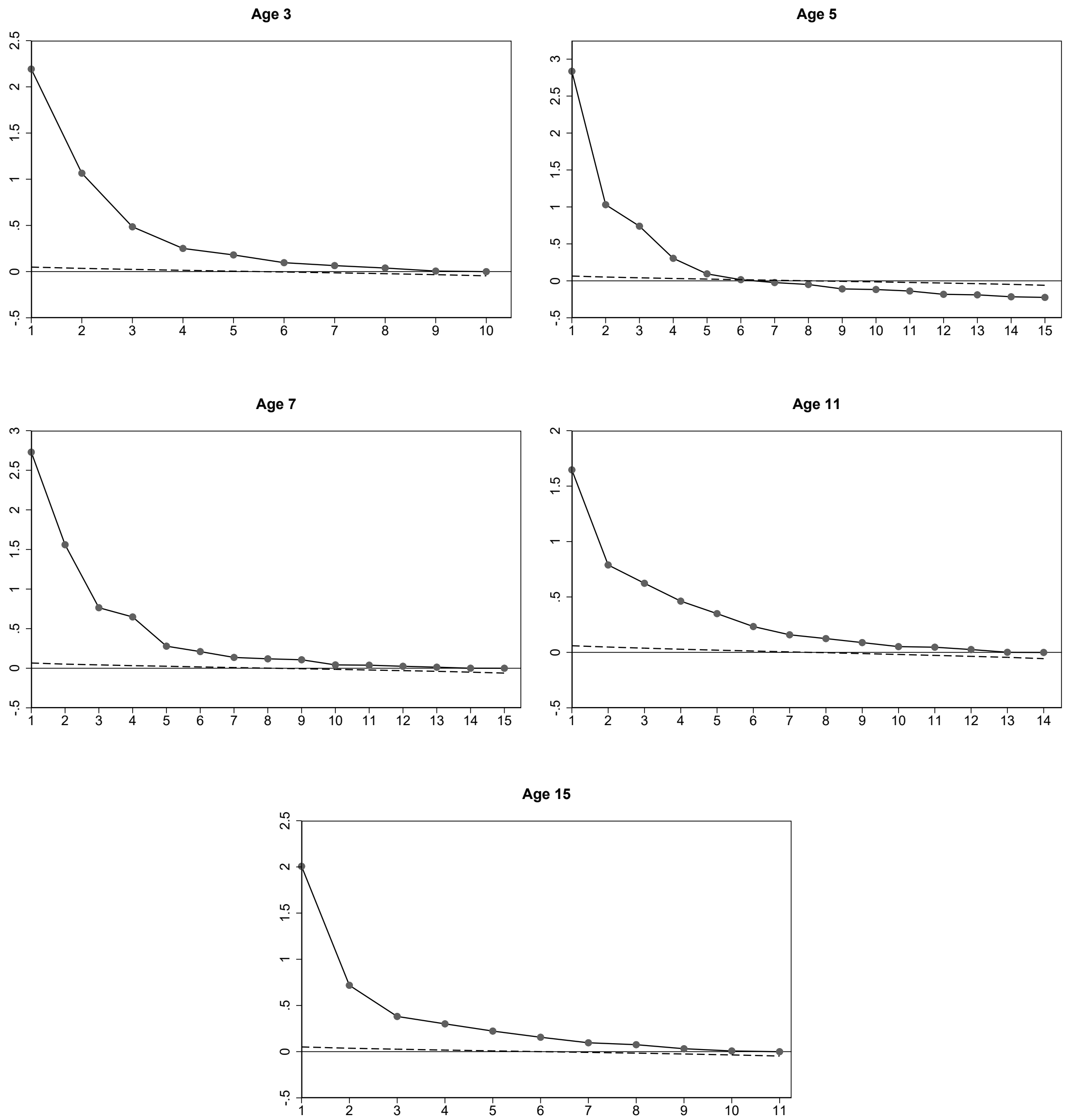
Note: The solid line connects the eigenvalues of the factors underlying k measures of health at each age. The dotted line connects the eigenvalues of the factors underlying randomly simulated data of the same dimension (i.e. $N \times k$). This figure was generated using Philip B. Ender's -*fapra*- package in Stata.

Figure B2: Scree Plots of factors and their eigenvalues from an exploratory factor analysis of both cognitive and socio-emotional skill measures in each period



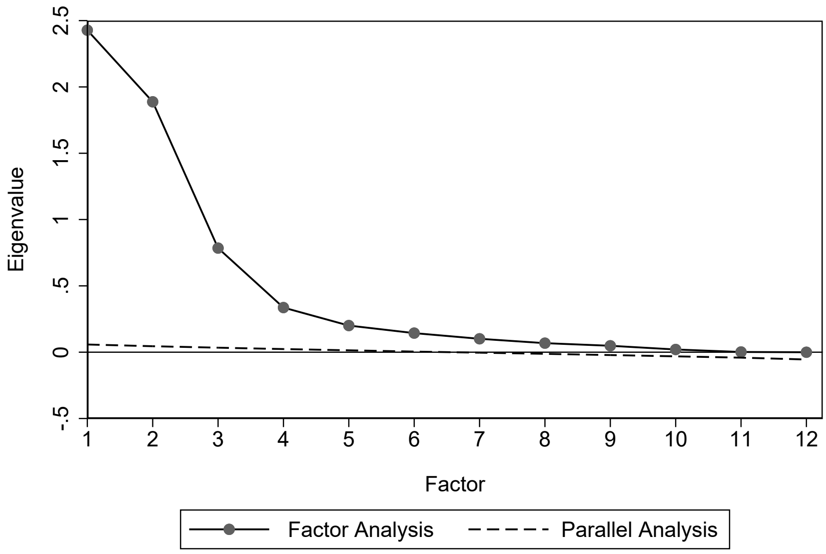
Note: The solid line connects the eigenvalues of the factors underlying k measures of cognitive and socio-emotional skill at each age. The dotted line connects the eigenvalues of the factors underlying randomly simulated data of the same dimension (i.e. $N \times k$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

Figure B3: Scree Plots of factors and their eigenvalues from an exploratory factor analysis of both cognitive and health investment measures in each period



Note: The solid line connects the eigenvalues of the factors underlying k measures of health and cognitive investments at each age. The dotted line connects the eigenvalues of the factors underlying randomly simulated data of the same dimension (i.e. $N \times k$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

Figure B4: Scree Plots of factors and their eigenvalues from an exploratory factor analysis of parent human capital measures in the initial period



Note: The solid line connects the eigenvalues of the factors underlying k measures of each parent's health and socio-emotional skill. The dotted line connects the eigenvalues of the factors underlying randomly simulated data of the same dimension (i.e. $N \times k$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

B.3.2 Selecting and excluding individual measures

Given the initial analysis of the shared variation in measures showed there to be numerous factors underlying the data, it was then necessary to exclude measures that were correlated with either more than one factor, or with the "wrong" factor based on their purpose. For example, after retaining two latent health factors, if one health measure was correlated strongly with both - either in the same or opposite directions - then it was excluded from the analysis. Similarly if a socio-emotional skill measure appeared to measure cognitive skill then it was not used, nor was a health investment measure if it was highly correlated with a cognitive investment measure. I then retained measures based on the extent of their signal - how much of their variation is explained by variation in the latent variable. Excluding or retaining measures in this manner is important given the methodology employed to estimate the investment and production functions. It maximises the likelihood that the measures used as instruments have two features: they predominantly explain variation in the measure used as an input/output, and that they do not only do so weakly. The former of these two qualities is important to reduce the incidence of cross-correlations between measures giving misleading results, and the latter so that estimates of the structural parameters are not biased by using weak instruments in the first stage of the methodology.

Tables B4, B5a and B5b, and B6a and B6b show the results of an exploratory factor analysis of the measures of health, cognitive and socio-emotional skills and investments respectively. The factor loadings presented are obtained through an *oblique quartimin* rotation, to allow for factors to be correlated and to accurately depict the how measures load on common factors. In each table, the highlighted rows (either in grey or red) show the measures selected to be used in estimating the investment and production functions. Looking at Table B4 highlights the process of measure selection, and the importance of ex-ante establishing the loadings of measures. For example, at 9 months, the number of health conditions, and complications during pregnancy and first week of life load heavily on a different factor to birthweight. At the same time, gestation length loads heavily on both factors and complications during labour load negatively on the factor associated with birthweight but positively on that associated with health conditions. I choose to select the measures of health conditions, and complications during pregnancy and the first week of life for two reasons. Firstly, and most importantly, health conditions arguably measures health in a cardinal way, and it is available at each age. I use it as an age-invariant measure which enables me to estimate flexible production functions with limited restrictions on their parameters Agostinelli and Wiswall (2016a). Second, complications during pregnancy and the first week of life are the only measures that load heavily on the factor on which the measure of health conditions loads and none other. In each subsequent period, the choice of measures comes down to a similar choice of which measures load most strongly on the factor associated with health conditions. In some periods I don't retain measures that meet this criteria simply because they are relatively noisy. For example, at ages 5, 7 and 11 I do not use a measure of non-regular hospital visits despite them loading heavily only on the relevant factor because it is consistently less than 10% signal.

I follow an identical process for selecting measures of cognitive and socio-emotional skill. In Table B5a and B5b the rows highlighted in grey indicate the measures retained for cognition and those in red the measures retained for socio-emotional skill. The table shows that the process of selection is straightforward at all ages in that all variables, with only one or two exceptions, load on the factor they were ex-ante assumed to measure. There is one caveat here in that I do not include all measures of cognition at age 15. This is because when doing so, there are two measures that skew the correlations between variables to be somewhat misleading. For example if considering all cognitive measures available at this age, four of the six load heavily on socio-emotional skill, and two load negatively on the factor I assume to be latent cognition. This is undoubtedly due in part to the nature of the measures. The CANTAB gambling task is meant to measure both problem solving *and* risk aversion. It is perhaps intuitive then that some of these measures be correlated with a bundle of socio-emotional skills. Two measures strongly load on what might be labelled the cognitive factor, however, and have almost 100% of their variance shared with the latent variables. These are measures of a children's overall proportional bet and their risk taking. Respectively, these two measures are of the overall average bet a child makes and the average bet the child makes when they have selected the most likely outcome. It is not possible to say with that these two strictly measure cognition, and they likely capture some aspect of risk attitudes. They are also highly correlated by construction given that the latter is contained within the former. I therefore present results of the EFA in Table B5b excluding these measures. The cognitive measure with the least noise in this last period is the *risk adjustment* measure, which records how children adjust their bets when they the odds are highly in their favour. I take this as measure of their problem solving skills, and less so as a measure of risk attitudes.

Moving to investments, the pattern in loadings differs somewhat from what was expected ex-ante based on assumptions about the type of investments variables measure. For example, in all periods many measures load on both or the "wrong" latent factors - at age 3 helping a child playing a sport is highly correlated with measures defined as proxies of cognitive investment, and a measure of the frequency with which a parent reads to the child loads heavily on both investments. Similarly, while measures of helping children with writing and maths load heavily on the latent cognitive investment factor at age 5, they are also highly negatively correlated with the health investment factor. As a result, although they are intuitively appealing measures of cognitive investment, I exclude them in this period. The results in Table B6b also show that it is more difficult to separate investments from one another in later period, between 11 and 15. For example, three measures defined as proxies of health investment in the other periods load on the cognitive investment factor at age 15, and the majority of measures are correlated to the same extent with both types of latent investment. The same is true at age 11, meaning at these ages it is more difficult to make a clear cut selection of measures. Instead I select measures in order to minimize the extent to which these cross-correlations occur.

Table B4: EFA of observable health measures at each age

	Factor 1	Factor 2	Factor 3	Uniqueness
Initial (9 months)				
Health conditions	-0.130	0.219		0.960
First week complications	0.047	0.510		0.716
Pregnancy complications	-0.047	0.317		0.910
Birthweight (Kilos)	0.888	-0.014		0.223
Length of gestation	0.509	0.319		0.495
Complications during labour	-0.188	0.333		0.909
Age came home from hospital	0.132	0.351		0.818
Weight z-score	0.441	-0.151		0.842
Non-regular hospital visits	-0.011	0.150		0.979
N	10,525			
Age 3				
Health conditions	-0.034	0.580		0.664
Long-term illnesses	0.039	0.554		0.690
Non-regular hospital visits	-0.007	0.351		0.877
Accidents	-0.037	0.097		0.990
Emergency health problems	0.027	0.245		0.939
Weight z-score	0.834	-0.020		0.305
Height z-score	0.751	0.028		0.433
N	9,848			
Age 5				
Health conditions	-0.028	0.601		0.639
Long-term illnesses	-0.005	0.724		0.477
General health	0.048	0.550		0.694
Non-regular hospital visits	-0.003	0.308		0.905
Accidents	0.001	0.078		0.994
Weight z-score	0.921	-0.024		0.152
Height z-score	0.746	0.046		0.439
N	10,724			
Age 7				
Health conditions	-0.032	0.582		0.663
Long-term illnesses	0.007	0.719		0.482
General health	0.023	0.554		0.691
Non-regular hospital visits	-0.004	0.248		0.939
Accidents	-0.014	0.056		0.997
Weight z-score	0.761	-0.049		0.423
Height z-score	0.900	0.030		0.187
N	10,450			
Age 11				
Health conditions	-0.003	0.502		0.748
Long-term illnesses	0.041	0.577		0.668
General health	-0.049	0.560		0.681
Non-regular hospital visits	0.003	0.242		0.941
Accidents	-0.039	0.069		0.993
Weight z-score	1.152	-0.014		-0.329
Height z-score	0.569	0.113		0.671
N	10,606			
Age 14				
Health conditions	-0.004	0.359		0.871
Long-term illnesses	0.002	0.579		0.665
General health	-0.059	0.164		0.969
Weight z-score	3.373	-0.000		-10.374
Height z-score	0.150	0.089		0.970
N	10,655			

Note: The columns represent the observable measures of health, their factor loadings on retained factors, and their unique variance respectively. All we obtained from an exploratory factor analysis using an oblique quartimin rotation of the factor loading matrix. The number of factors retained was determined as outlined in Appendix B.3.1. The rows highlighted in grey represent the variables selected as measures of health to be used in estimating the production and investment functions.

Table B5a: EFA of observable cognitive and socio-emotional skill measures at each age

	Factor 1	Factor 2	Factor 3	Uniqueness
Initial (9 months)				
Denver Developmental Screening Test	0.771	-0.018		0.407
Communicative Development Inventories	0.505	0.064		0.736
Number of developmental concerns	0.188	0.021		0.964
Carey Infant Temperament: Mood	0.000	0.738		0.455
Cary Infant Temperament: Regularity	-0.030	0.176		0.969
Cary Infant Temperament: Adaptability and Withdrawal	0.001	0.223		0.950
N	10,791			
Age 3				
Bracken School Readiness: Numbers	0.617	-0.097		0.653
Bracken School Readiness: Colours	0.640	0.075		0.551
Bracken School Readiness: Letters	0.473	-0.116		0.802
Bracken School Readiness: Sizes	0.610	0.028		0.615
Bracken School Readiness: Comparisons	0.518	-0.004		0.733
Bracken School Readiness: Shapes	0.765	-0.010		0.419
British Ability Scales: Naming Vocabulary score	0.612	0.081		0.584
SDQ: Conduct Problems	-0.017	0.727		0.480
SDQ: Emotional regulation	0.037	0.396		0.831
SDQ: Hyperactivity/Inattention	0.032	0.652		0.558
SDQ: Peer problems	0.035	0.408		0.822
SDQ: Pro-sociality	-0.027	0.444		0.811
CSR: Independence	0.049	0.278		0.910
CSBQ: Emotional Dysregulation	-0.003	0.595		0.648
N	8,783			
Age 5				
British Ability Scales: Picture Similarities	-0.043	0.601		0.656
British Ability Scales: Naming Vocabulary	0.051	0.545		0.680
British Ability Scales: Pattern construction	0.013	0.622		0.607
SDQ: Conduct Problems	0.752	-0.045		0.457
SDQ: Emotional regulation	0.421	0.029		0.813
SDQ: Hyperactivity/Inattention	0.678	0.064		0.504
SDQ: Peer problems	0.452	0.047		0.778
SDQ: Pro-sociality	0.488	-0.004		0.763
CSR: Independence	0.407	0.127		0.780
CSBQ: Emotional Dysregulation	0.659	-0.043		0.585
N	10,302			

Note: The columns represent the observable measures of cognitive and socio-emotional skill, their factor loadings on retained factors, and their unique variance respectively. All we obtained from an exploratory factor analysis using an oblique quartimin rotation of the factor loading matrix. The number of factors retained was determined as outlined in Appendix B.3.1. The rows highlighted in grey and red represent the variables selected as measures of cognitive and socio-emotional skill to be used in estimating the production and investment functions.

Table B5b: EFA of observable cognitive and socio-emotional skill measures at each age (cont.)

	Factor 1	Factor 2	Factor 3	Uniqueness
Age 7				
NFER Maths score	-0.030	0.865		0.269
British Ability Scales: Word Reading	0.092	0.575		0.623
British Ability Scales: Pattern construction	0.033	0.550		0.683
SDQ: Conduct Problems	0.770	-0.052		0.432
SDQ: Emotional regulation	0.470	0.036		0.766
SDQ: Hyperactivity/Inattention	0.698	0.092		0.460
SDQ: Peer problems	0.495	0.033		0.743
SDQ: Pro-sociality	0.521	-0.060		0.747
CSR: Independence	0.442	0.188		0.711
CSBQ: Emotional Dysregulation	0.788	-0.035		0.398
N	9,903			
Age 11				
BAS verbal similarities	0.242	0.149		0.905
CANTAB Spatial working Memory: Strategy	0.010	0.594		0.644
CANTAB Spatial working Memory: Four-box errors	0.014	0.472		0.774
CANTAB Spatial working Memory: Eight-box errors	-0.003	1.103		-0.215
SDQ: Conduct Problems	0.735	-0.021		0.466
SDQ: Emotional regulation	0.561	-0.006		0.686
SDQ: Hyperactivity/Inattention	0.693	0.057		0.500
SDQ: Peer problems	0.580	-0.016		0.667
SDQ: Pro-sociality	0.507	-0.060		0.752
N	9,980			
Age 14				
Word activity score	0.095	0.274		0.906
CANTAB gambling: Risk adjustment	-0.015	0.648		0.584
CANTAB gambling: decision quality	0.054	0.332		0.880
CANTAB gambling: delay aversion	-0.007	-0.385		0.850
SDQ: Conduct Problems	0.479	0.075		0.751
SDQ: Emotional Symptoms	0.711	-0.015		0.498
SDQ: Hyperactivity/Inattention	0.309	0.004		0.904
SDQ: Peer Problems	0.431	-0.037		0.819
SDQ: Pro-sociality	0.199	0.025		0.958
N	8,262			

Note: The columns represent the observable measures of cognitive and socio-emotional skill, their factor loadings on retained factors, and their unique variance respectively. All we obtained from an exploratory factor analysis using an oblique quartimin rotation of the factor loading matrix. The number of factors retained was determined as outlined in Appendix B.3.1. The rows highlighted in grey and red represent the variables selected as measures of cognitive and socio-emotional skill to be used in estimating the production and investment functions.

Table B6a: EFA of observable health and cognitive investment measures at each age

	Factor 1	Factor 2	Factor 3	Uniqueness
Age 3				
Regular bed times	-0.061	0.682		0.551
Regular meal times	-0.010	0.614		0.626
Portions of fruit	0.133	0.325		0.856
Someone helps child learn sport	0.287	0.043		0.910
S2 MAIN How often do you read to the child C1	0.317	0.404		0.676
How often helps child learn alphabet	0.545	-0.044		0.713
How often helps child with numbers/counting	0.776	-0.061		0.416
How often child visits library	0.107	0.284		0.894
How often helps child with songs/poems/rhymes	0.663	0.093		0.522
How often paints/draws with the child	0.397	-0.001		0.842
N	10,569			
Age 5				
Days per week child eats breakfast	-0.042	0.558		0.698
Portions of fruit	0.102	0.400		0.810
Regular bed times	-0.030	0.550		0.705
Regular meal times	0.031	0.498		0.743
How often plays sports with child	0.286	0.210		0.846
How often child plays non-club/class sports	0.081	0.343		0.862
How often plays active games with child	0.468	0.183		0.708
How often helps child learn reading	0.467	0.081		0.758
How often helps child with writing	0.646	-0.102		0.603
How often helps child with maths	0.653	-0.123		0.596
How often child visits library	0.131	0.236		0.913
How often helps child with songs/poems/rhymes	0.460	0.098		0.758
How often draws/paints with child	0.564	0.033		0.672
How often tells the child stories	0.465	0.041		0.773
How often plays games/toys with child	0.552	0.103		0.658
N	10,686			
Age 7				
Days per week child eats breakfast	0.218	-0.029		0.955
Portions of fruit	0.285	-0.043		0.924
Regular bed times	0.188	-0.026		0.967
How often plays sport with child	0.546	-0.045		0.713
How often child does physical activity	0.249	-0.092		0.942
How often plays active games with child	0.659	-0.038		0.578
How often helps child learn alphabet	0.048	0.710		0.475
How often helps child with writing	-0.022	0.893		0.213
How often helps child with numbers/counting	0.000	0.783		0.387
How often child visits library	0.172	0.048		0.964
How often sings songs/plays music with child	0.466	-0.003		0.783
How often paints/draws with child	0.546	0.085		0.669
How often reads/tells stories to child	0.405	0.095		0.806
How often plays games with child	0.649	0.010		0.575
Hours per week doing homework	0.123	0.031		0.982
N	10,310			

Note: The columns represent the observable measures of health and cognitive investment, their factor loadings on retained factors, and their unique variance respectively. All we obtained from an exploratory factor analysis using an oblique quartimin rotation of the factor loading matrix. The number of factors retained was determined as outlined in Appendix B.3.1. The rows highlighted in grey and red represent the variables selected as measures of health and cognitive investments to be used in estimating the production and investment functions.

Table B6b: EFA of observable health and cognitive investment measures at each age (cont.)

	Factor 1	Factor 2	Factor 3	Uniqueness
Age 11				
Days per week child eats breakfast	0.177	0.212		0.908
Portions of fruit	0.267	0.108		0.905
How often drinks artificially sweetened drinks	0.066	0.112		0.980
How often drinks artificially sweetened drinks	0.036	0.022		0.998
How often child has regular bed times	0.071	0.225		0.938
How often plays sport with child	0.730	-0.030		0.474
Days per week child does non-club sport/exercise	0.169	0.110		0.952
How often plays active games with child	0.174	0.138		0.941
Hours per week doing homework	0.006	0.262		0.931
How often does someone check homework before other activities	-0.011	0.782		0.391
How often does someone help child with homework	0.007	0.366		0.865
How often talks to child about important topics	0.186	0.234		0.893
How often child visits library	0.142	0.059		0.973
How often plays games with child	0.622	0.028		0.605
N	10,791			
Age 14				
Days per week child has breakfast	0.462	0.104		0.738
Portions of fruit per day	0.424	0.185		0.724
How often child has regular bed times	0.440	0.041		0.790
How often drinks sweetened drinks	0.026	0.677		0.527
How often drinks artificially sweetened drinks	-0.135	0.400		0.864
How often eats fast food	0.058	0.575		0.640
Hours per week child does homework	0.394	0.201		0.742
How often does someone help child with homework	0.525	-0.213		0.767
How often talks to child about things important to them	0.225	-0.045		0.955
How often does child visit museums, libraries, galleries etc.	0.342	0.121		0.836
School absences	0.146	0.183		0.924
N	10,973			

Note: The columns represent the observable measures of health and cognitive investment, their factor loadings on retained factors, and their unique variance respectively. All we obtained from an exploratory factor analysis using an oblique quartimin rotation of the factor loading matrix. The number of factors retained was determined as outlined in Appendix B.3.1. The rows highlighted in grey and red represent the variables selected as measures of health and cognitive investments to be used in estimating the production and investment functions.

B.4 Additional Figures and Tables

B.4.1 Additional sample descriptive statistics

Table B7: Percent of families in each UK income quintile at age 14, by UK income quintile at age 9 months

		UK income quintile age 14					
		1	*2*	*3*	*4*	*5*	% Missing
UK Income quintile 9 months	*1*	46.90	28.75	15.50	6.34	2.52	49.72
	2	23.49	28.02	25.99	16.55	5.95	43.46
	3	5.13	14.17	28.67	34.27	17.75	38.43
	4	1.97	6.87	19.92	34.94	36.31	31.15
	5	0.97	3.52	11.63	26.21	57.67	28.77

Note: Each row/column indicates the income quintile a family was in when their child was aged 9 months/14 for those present at both ages. *% Missing* represents to percent in each income quintile at 9 months who were not present at age 14. Numbers represent the percent of each row that were in each column. Income quintiles are defined out of sample relative the UK household income distribution.

Table B8: Health investment measures in period 1 (ages 9 months-3 years) across income quartiles

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
Fresh fruit/veg once a day	0.94	0.96	0.98	0.99
Anyone help child with sport	0.74	0.76	0.81	0.83
Child has regular meals				
Never or almost never	0.04	0.03	0.01	0.01
Sometimes	0.12	0.10	0.06	0.04
Usually	0.38	0.41	0.45	0.46
Always	0.46	0.46	0.49	0.49
Child has regular bed times				
Never or almost never	0.13	0.10	0.06	0.03
Sometimes	0.20	0.16	0.12	0.08
Usually	0.31	0.35	0.41	0.42
Always	0.36	0.38	0.41	0.46
Observations	3,243	3,489	3,724	3,975

Note: The table provides a statistical description of the health investment measures used between 9 months and 3 years of age. Measures are in bold, and where appropriate answers are italicised. Where there are no answers, the measures are binary, with a value of one representing a positive response. All numbers are proportions. Income quartiles are relative to the sample income distribution.

Table B9: Cognitive investment measures in period 1 (ages 9 months-3 years) across income quartiles

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
How often does maths with child				
Not at all	0.06	0.04	0.03	0.03
Occasionally or less than once a week	0.06	0.05	0.05	0.05
1 - 2 days per week	0.14	0.14	0.14	0.12
3 times a week	0.11	0.11	0.11	0.10
4 times a week	0.07	0.08	0.08	0.08
5 times a week	0.06	0.07	0.06	0.06
6 times a week	0.04	0.04	0.04	0.04
7 times a week constantly	0.44	0.47	0.50	0.51
How often reads to/with child				
Not at all	0.07	0.04	0.01	0.00
Less often	0.04	0.03	0.01	0.00
Once or twice a month	0.05	0.03	0.02	0.01
Once or twice a week	0.23	0.20	0.14	0.08
Several times a week	0.20	0.21	0.20	0.16
Every Day	0.41	0.49	0.62	0.74
How often practices the alphabet child				
Not at all	0.18	0.20	0.20	0.18
Occasionally or less than once a week	0.12	0.12	0.13	0.13
1-2 days per week	0.24	0.20	0.22	0.21
3 times a week	0.13	0.13	0.12	0.12
4 times a week	0.07	0.08	0.07	0.08
5 times a week	0.05	0.05	0.04	0.05
6 times a week	0.02	0.02	0.03	0.02
7 times a week/constantly	0.19	0.19	0.18	0.20
Observations	3,243	3,489	3,723	3,975

Note: The table provides a statistical description of the cognitive investment measures used between 9 months and 3 years of age. Measures are in bold, and where appropriate answers are italicised. All numbers are proportions. Income quartiles are relative to the sample income distribution.

B.4.2 Summaries of observable measures used in estimations

Table B10: Summary statistics of observable health measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
9 months					
Health conditions	-0.406	0.612	0	-5	6
Complications during labour	-0.423	0.704	0	-5	6
Complications during pregnancy	-0.541	0.858	0	-7	8
Non-regular hospital visits	-0.198	0.876	0	-84	14
Age 3					
Long-term illnesses	-0.183	0.466	0	-5	6
Health conditions	-0.976	1.038	0	-6	7
Non-regular hospital visits	-0.191	0.393	0	-1	2
Age 5					
Long-term illnesses	-0.252	0.577	0	-7	8
General health	4.285	0.884	5	1	5
Health conditions	-1.182	1.203	0	-7	8
Age 7					
Long-term illnesses	-0.241	0.568	0	-5	6
General health	4.425	0.813	5	1	5
Health conditions	-1.283	1.279	0	-8	9
Age 11					
Long-term illnesses	-0.207	0.673	0	-8	8
General health	4.420	0.822	5	1	5
Health conditions	-1.294	1.306	0	-6	7
Age 14					
Long-term illnesses	-0.246	0.743	0	-9	10
General health	3.470	0.917	5	1	5
Health conditions	-0.586	0.812	0	-5	6

Note: The measures in this table are those of health used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of health the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table B11: Summary statistics of observable cognitive skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
9 months					
Denver Developmental Screening Test	2.653	0.196	3	1	23
Communicative Development Inventory	2.115	0.349	3	1	16
Developmental concerns	-0.018	0.140	0	-3	4
Age 3					
BSR shapes	6.231	4.078	20	0	21
BAS naming vocabulary	73.198	17.983	141	10	31
BSR numbers	2.902	3.699	19	0	20
Age 5					
BAS pattern construction	87.271	19.582	152	10	47
BAS picture similarity	82.098	11.923	119	10	30
BAS naming vocabulary	107.349	16.425	170	10	35
Age 7					
NFER score	18.406	5.834	28	0	21
BAS reading	106.498	30.899	222	10	91
BAS pattern construction	116.154	17.238	211	10	79
Age 11					
CANTAB SWM: errors 8 boxes	-35.664	18.748	0	-173	108
CANTAB SWM: errors 4 boxes	-1.207	2.109	0	-23	23
CANTAB SWM: strategy	-34.307	5.962	0	-48	45
Age 14					
CANTAB gambling: Risk adjustment	1.203	0.834	5	0	423
CANTAB gambling: decision quality	0.518	0.148	1	0	91
Word activity score	7.055	2.623	15	0	20

Note: The measures in this table are those of cognitive skill used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of cognitive skill the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table B12: Summary statistics of observable socio-emotional skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
9 months					
CIT: Mood	3.842	0.689	5	1	39
CIT: Emotional regulation	4.243	0.786	5	1	25
CIT: Adaptability/withdrawal	3.997	0.785	5	1	41
Age 3					
SDQ: Conduct problems	-2.834	2.077	0	-10	11
SDQ: Hyperactivity	-3.932	2.372	0	-10	11
SDQ: Emotional regulation	-1.384	1.522	0	-10	11
SDQ: Peer relationships	-1.563	1.600	0	-10	11
SDQ: Pro-sociality	7.356	1.889	10	0	11
CSR: Emotional regulation	-1.500	0.516	-1	-3	3
Age 5					
SDQ: Conduct problems	-1.522	1.519	0	-10	11
SDQ: Hyperactivity	-3.327	2.382	0	-10	11
SDQ: Emotional regulation	-1.396	1.604	0	-10	11
SDQ: Peer relationships	-1.179	1.463	0	-10	11
SDQ: Pro-sociality	8.372	1.681	10	0	11
CSR: Emotional regulation	-1.357	0.494	-1	-3	3
Age 7					
SDQ: Conduct problems	-1.396	1.551	0	-10	11
SDQ: Hyperactivity	-3.378	2.523	0	-10	11
SDQ: Emotional regulation	-1.538	1.774	0	-10	11
SDQ: Peer relationships	-1.236	1.559	0	-10	11
SDQ: Pro-sociality	8.578	1.648	10	0	11
CSBQ: Emotional regulation	-1.728	0.475	-1	-3	21
Age 11					
SDQ: Conduct problems	-1.390	1.577	0	-10	11
SDQ: Hyperactivity	-3.130	2.472	0	-10	11
SDQ: Emotional regulation	-1.873	1.993	0	-10	11
SDQ: Peer relationships	-1.377	1.692	0	-10	11
SDQ: Pro-sociality	8.781	1.571	10	0	11
Age 14					
SDQ: Conduct problems	-2.463	1.172	0	-10	11
SDQ: Hyperactivity	-4.021	1.454	0	-10	11
SDQ: Emotional regulation	-2.050	2.141	0	-10	11
SDQ: Peer relationships	-1.377	1.692	0	-10	11
SDQ: Pro-sociality	8.781	1.571	10	0	11

Note: The measures in this table are those of socio-emotional skill used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of socio-emotional skill the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table B13: Summary statistics of observable health investment measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 3					
Regular bed times	3.109	0.922	4	1	4
Fruit or veg. once a day	0.968	0.176	1	0	2
How often child has regular meals	3.352	0.716	4	1	4
Age 5					
Days per week eats breakfast	6.697	1.128	7	0	8
Portions of fruit per day	2.228	0.891	3	0	4
How often child has regular meals	3.492	0.720	4	1	4
Regular bed times	3.109	0.922	4	1	4
Age 7					
How often plays active games with child	3.288	1.396	6	1	6
Portions of fruit per day	2.214	0.915	3	0	4
How often plays sports with child	4.169	1.369	6	1	6
How often child has regular bed times	3.459	0.773	4	1	4
Days per week child has breakfast	6.764	0.984	7	0	8
Age 11					
How often plays sports with child	2.683	1.347	6	1	6
Portions of fruit per day	2.028	0.970	3	0	4
Days per week child has breakfast	6.501	1.426	7	0	8
How often child plays non-club/class sports	5.343	1.935	7	1	7
Age 14					
How often drinks artificially sweetened drinks	3.818	1.751	7	1	7
How often eats fast food	4.939	1.012	7	1	7
How often drinks artificially sweetened drinks	4.247	1.899	7	1	7

Note: The measures in this table are those of health investment used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of health investment the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table B14: Summary statistics of observable cognitive investment measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 3					
How often helps child with maths/counting	4.905	2.345	7	0	8
How often helps child with alphabet	2.989	2.461	7	0	8
How often sing songs/rhymes with child	5.119	2.323	7	0	8
Age 5					
How often helps child with reading	5.368	0.986	6	1	6
How often plays games with child	4.491	1.208	6	1	6
How often sings songs/plays music with child	4.773	1.302	6	1	6
How often paints/draws with child	3.869	1.222	6	1	6
How often reads/tells stories to child	3.609	1.563	6	1	6
Age 7					
How often helps child with writing	3.314	1.895	6	1	6
How often helps child with maths	2.867	1.829	6	1	6
How often helps child with reading	3.715	2.015	6	1	6
Age 11					
How often checks child's homework	3.405	0.894	4	1	4
How often helps child with homework	2.592	0.950	4	1	4
Hours per week doing homework	2.199	1.911	30	0	100
Age 14					
How often helps child with homework	3.031	1.013	7	1	7
How often talks to child about important topics	5.497	0.817	6	1	6
How often child visits museum/library/gallery	2.204	1.015	6	1	6
Hours per week doing homework	2.401	0.833	5	1	5

Note: The measures in this table are those of cognitive investment used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of cognitive investment the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table B15: Summary statistics of observable parental human capital measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Health					
Health conditions	-1.192	1.263	0	-8	9
Has a long term illness	-0.211	0.408	0	-1	2
Subjective health	3.096	0.744	4	1	4
Socio-emotional skill					
Rosenberg self-esteem scale	4.963	1.450	6	0	7
Rutter Malaise psychological Inventory	7.290	1.801	9	0	10
Locus of control	2.429	0.880	3	0	4
Cognitive skill (measured without error)					
Main parent's highest NVQ	2.353	1.467	5	0	6

Note: The measures in this table are those of parental human capital used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of parental human capital the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

B.4.3 Measurement system estimates

Table B16: Measurement system estimates for observed health

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (9 months)				
No. of long-term illnesses	0.418	1.000	0.052	0.948
Labour complications	0.427	0.895	0.0.032	0.988
Pregnancy complications	0.542	1.488	0.062	0.938
Non-regular hospital visits	0.188	0.786	0.013	0.987
Age 3				
No. of long-term illnesses	0.418	1.000	0.280	0.720
Hospital admissions	0.367	2.606	0.368	0.632
No. of health conditions	0.408	0.574	0.125	0.875
Age 5				
No. of long-term illnesses	0.418	1.000	0.555	0.445
Hospital admissions	4.963	1.111	0.295	0.705
No. of health conditions	0.494	1.674	0.361	0.639
Age 7				
No. of long-term illnesses	0.418	1.000	0.571	0.429
Subjective health	5.092	1.027	0.289	0.711
No. of health conditions	0.605	1.695	0.324	0.676
Age 11				
No. of long-term illnesses	0.418	1.000	0.341	0.659
Subjective health	5.054	1.196	0.323	0.677
No. of health conditions	0.669	1.646	0.241	0.759
Age 14				
No. of long-term illnesses	0.418	1.000	0.354	0.646
Subjective health	4.133	0.303	0.021	0.979
No. of health conditions	0.077	0.622	0.114	0.886

Note: From left to right the columns represent the observable measure of health and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

Table B17: Measurement system estimates for observed cognitive skill

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (9 months)				
Communicative development inventories scale	2.109	1.000	0.254	0.746
Denver Developmental screening test	2.653	0.852	0.611	0.389
Parents' developmental worries	0.017	0.140	0.035	0.965
Age 3				
BAS: vocabulary	66.054	26.889	0.479	0.521
BSR: numbers	1.193	2.366	0.179	0.821
BSR: shapes	3.824	6.346	0.515	0.485
Age 5				
BAS: picture similarity	80.764	7.331	0.295	0.705
BAS: naming vocabulary	100.060	18.830	0.537	0.463
BAS: pattern construction	81.255	14.809	0.455	0.545
Age 7				
NFER score	88.640	25.753	0.498	0.502
BAS: word reading	110.057	12.650	0.406	0.594
BAS: pattern construction	15.634	5.115	0.551	0.449
Age 11				
CANTAB SWM: errors 4 boxes	1.109	0.634	0.286	0.714
CANTAB SWM: Strategy	34.015	2.201	0.431	0.569
CANTAB SWM: errors 8 boxes	34.225	10.643	1.009	-0.009
Age 14				
CANTAB gambling: Risk adjustment	2.095	1.677	0.221	0.779
CANTAB gambling: decision quality	0.391	0.400	0.124	0.876
Word activity score	0.785	0.047	0.158	0.842

Note: From left to right the columns represent the observable measure of cognitive skill and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

Table B18: Measurement system estimates for observed socio-emotional skill

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (9 months)				
CIT mood	3.829	1.000	0.377	0.623
CIT: self-regulation	4.266	0.376	0.042	0.958
CIT: adaptation and withdrawal	4.013	0.485	0.071	0.929
Age 3				
CSR: emotional regulation	2.768	1.000	0.644	0.356
SDQ: hyperactivity	4.049	0.193	0.486	0.514
SDQ: emotional regulation	1.680	1.010	0.634	0.366
SDQ: peer relationships	4.185	0.458	0.325	0.675
SDQ: pro-sociality	4.014	0.545	0.406	0.594
SDQ: conduct problems	12.883	0.540	0.284	0.716
Age 5				
CSR: emotional regulation	2.768	1.000	0.609	0.391
SDQ: hyperactivity	2.891	0.287	0.618	0.382
SDQ: emotional regulation	1.002	1.428	0.655	0.345
SDQ: peer relationships	2.857	0.711	0.355	0.645
SDQ: pro-sociality	3.103	0.736	0.470	0.530
SDQ: conduct problems	12.620	0.683	0.300	0.700
Age 7				
CSR: emotional regulation	2.768	1.000	0.620	0.380
SDQ: hyperactivity	2.392	0.320	0.809	0.191
SDQ: emotional regulation	0.815	1.494	0.634	0.366
SDQ: peer relationships	2.580	0.796	0.363	0.637
SDQ: pro-sociality	2.909	0.771	0.447	0.553
SDQ: conduct problems	12.701	0.671	0.301	0.699
Age 11				
SDQ: hyperactivity	2.768	1.000	0.575	0.425
SDQ: emotional regulation	1.033	1.514	0.583	0.417
SDQ: peer relationships	2.249	1.042	0.420	0.580
SDQ: pro-sociality	3.883	1.342	0.632	0.368
SDQ: conduct problems	12.914	0.662	0.280	0.720
Age 14				
SDQ: emotional regulation	2.768	1.000	0.665	0.335
SDQ: hyperactivity	1.210	0.391	0.071	0.929
SDQ: peer relationships	3.182	2.156	0.997	0.003
SDQ: pro-sociality	3.883	1.342	0.632	0.368
SDQ: conduct problems	13.547	0.700	0.141	0.859

Note: From left to right the columns represent the observable measure of socio-emotional skill and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

Table B19: Measurement system estimates for observed health investments

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Age 3				
Fruit or veg. once per pay	3.125	1.173	0.240	0.760
Has regular meals	0.972	0.039	0.016	0.984
Has regular bedtimes	3.354	0.898	0.447	0.553
Age 5				
Portions of fruit and veg. per day	6.711	1.000	0.120	0.880
Has regular meals	2.253	0.807	0.122	0.878
Has regular bed times	3.497	0.829	0.199	0.801
Days per week has breakfast	3.125	1.173	0.240	0.760
Age 7				
Portions of fruit and veg. per day	3.283	1.000	0.065	0.935
How often plays sport with child	2.239	0.930	0.133	0.867
Has regular bedtimes	4.163	0.922	0.058	0.942
Days per week has breakfast	3.462	0.562	0.067	0.933
How often plays physically active games	6.772	0.848	0.095	0.905
Age 11				
Portions of fruit and veg. per day	2.688	1.000	0.361	0.639
Days per week has breakfast	2.052	0.790	0.433	0.567
Days per week does non-club physical activity	6.531	0.562	0.105	0.895
How often plays sport with child	5.342	0.409	0.029	0.971
Age 14				
How often has fast food	3.818	1.000	0.534	0.466
How often drinks artificially sweetened drinks	4.939	0.405	0.262	0.738
How often drinks sweetened drinks	4.247	0.481	0.105	0.895

Note: From left to right the columns represent the observable measure of health investment and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

Table B20: Measurement system estimates for observed cognitive investments

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1-s_{\theta,m,t}$
Age 3				
How often practices alphabet	4.929	1.000	0.684	0.316
How often plays music or sings	2.998	0.646	0.258	0.742
How often practices maths	5.144	0.620	0.271	0.729
Age 5				
How often plays games	5.370	1.000	0.075	0.925
How often sings	4.486	3.279	0.530	0.470
How often practices paints	4.750	2.957	0.365	0.635
How often tells stories	3.849	3.221	0.494	0.506
How often practices reading	3.590	3.252	0.314	0.686
Age 7				
How often practices maths	3.293	1.000	0.700	0.300
How often practices reading	2.860	0.814	0.499	0.501
How often practices writing	3.698	0.861	0.453	0.547
Age 11				
How often practices homework	3.410	1.000	0.605	0.395
Tie spent doing homework	2.591	0.481	0.123	0.877
How often checks homework	2.205	0.591	0.045	0.955
Age 14				
How often talks about important topics	3.031	1.000	0.192	0.808
How often visits museum/gallery/historical place	5.497	0.505	0.075	0.925
Time spent doing homework	2.204	1.094	0.228	0.772
How often helps with homework	2.401	1.434	0.582	0.418

Note: From left to right the columns represent the observable measure of cognitive investment and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

Table B21: Measurement system estimates for observed parental human capital

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1-s_{\theta,m,t}$
Health				
Health conditions	1.205	1.000	0.231	0.769
Long term illness	0.214	0.482	0.511	0.489
Subjective health	3.114	0.630	0.269	0.731
Socio-emotional skill				
Rosenberg self-esteem	4.976	1.000	0.541	0.459
Rutter-Malaise psychological distress inventory	7.783	1.043	0.398	0.602
Locus of control	2.465	0.600	0.542	0.458

Note: From left to right the columns represent the observable measure of parental human capital and its estimated mean, factor loading, signal and noise respectively. All parameters are estimated as outlined in Appendix B.1, and all measures are described in detail in Appendix B.2.

B.4.4 Additional production estimates of initial conditions and production functions with interacted investments and human capital

Table B22: Variance covariance matrix of the initial conditions

	$\ln H_{h,0}$	$\ln H_{c,0}$	$\ln H_{c,0}$	$\ln P_h$	$\ln P_c$	$\ln P_s$	$\ln Y_0$
$\ln H_{h,0}$	0.020	0.006	0.005	0.078	-0.063	0.024	-0.024
$\ln H_{c,0}$	0.006	0.022	0.003	-0.002	0.018	0.012	0.001
$\ln H_{c,0}$	0.005	0.003	0.176	-0.006	-0.021	0.088	0.009
$\ln P_h$	0.078	-0.002	-0.006	0.371	0.007	0.255	0.036
$\ln P_c$	-0.063	0.018	-0.021	0.007	2.105	0.227	0.508
$\ln P_s$	0.024	0.012	0.088	0.255	0.227	1.132	0.153
$\ln Y_0$	-0.024	0.001	0.009	0.036	0.508	0.153	0.466

Table B23: Mean vector of the initial conditions

$$\begin{array}{ccccccc} \ln H_{h,0} & \ln H_{c,0} & \ln H_{c,0} & \ln P_h & \ln P_c & \ln P_s & \ln Y_0 \\ \end{array}$$
$$\begin{pmatrix} 0, & 0, & 0, & 0, & 2.522, & 0, & 9.473 \end{pmatrix}$$

Table B24: Estimates of health production functions with interacted health and health investment

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.678***	1.222***	0.796***	0.527***	0.777***
	(0.148)	(0.081)	(0.037)	(0.043)	(0.062)
	[0.435,0.921]	[1.089,1.356]	[0.736,0.857]	[0.456,0.598]	[0.675,0.879]
$\ln H_{c,t-1}$	0.014	0.050	0.001	0.104***	0.009
	(0.122)	(0.036)	(0.019)	(0.017)	(0.009)
	[-0.187,0.215]	[-0.009,0.108]	[-0.031,0.033]	[0.076,0.131]	[-0.007,0.024]
$\ln H_{s,t-1}$	0.077	-0.003	0.003	0.060***	0.068***
	(0.067)	(0.008)	(0.008)	(0.010)	(0.017)
	[-0.033,0.188]	[-0.017,0.011]	[-0.010,0.017]	[0.042,0.077]	[0.040,0.095]
Parental human capital (fixed over time)					
$\ln P_h$	0.031*	0.057***	0.026	0.069***	0.034
	(0.017)	(0.022)	(0.017)	(0.020)	(0.023)
	[0.003,0.059]	[0.021,0.094]	[-0.001,0.053]	[0.035,0.103]	[-0.004,0.071]
$\ln P_c$	0.038*	-0.005	-0.008	-0.049***	-0.007
	(0.021)	(0.023)	(0.014)	(0.018)	(0.018)
	[0.004,0.072]	[-0.043,0.033]	[-0.030,0.014]	[-0.079,-0.020]	[-0.038,0.023]
$\ln P_s$	0.010	-0.007	-0.001	-0.021*	0.006
	(0.011)	(0.012)	(0.009)	(0.011)	(0.013)
	[-0.007,0.028]	[-0.026,0.013]	[-0.015,0.013]	[-0.039,-0.003]	[-0.014,0.027]
Investments					
$\ln I_{h,t-1}$	0.012	0.023	-0.015	-0.027	-0.025
	(0.024)	(0.054)	(0.013)	(0.035)	(0.017)
	[-0.027,0.052]	[-0.065,0.112]	[-0.036,0.005]	[-0.085,0.030]	[-0.053,0.004]
$\ln I_{h,t-1} \times \ln H_{h,t-1}$	-0.341	0.067	0.055	0.180	0.175**
	(0.330)	(0.243)	(0.048)	(0.125)	(0.076)
	[-0.883,0.202]	[-0.332,0.467]	[-0.024,0.134]	[-0.026,0.386]	[0.050,0.299]
$\ln A_t$	0.217***	0.148***	0.172***	0.206***	0.157***
	(0.022)	(0.026)	(0.016)	(0.019)	(0.020)
	[0.181,0.253]	[0.104,0.191]	[0.145,0.199]	[0.175,0.237]	[0.124,0.189]
RTS	0.520**	1.405***	0.857***	0.842***	1.036***
	(0.234)	(0.262)	(0.048)	(0.121)	(0.071)
	[0.135,0.904]	[0.974,1.837]	[0.778,0.935]	[0.643,1.041]	[0.919,1.153]
$\sigma^2_{\eta_h}$	0.015**	0.056***	0.032***	0.037***	0.031***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.011)
	[0.005,0.026]	[0.047,0.065]	[0.024,0.039]	[0.027,0.048]	[0.013,0.049]
N	8,300	7,012	7,947	7,716	7,823

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's health measured by the observables in Appendix Table B16. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; health investment; and an interaction of health investment and health, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

Table B25: Estimates of cognitive production function parameters with interacted cognitive skill and health investment

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.191**	0.120	-0.033	-0.060	0.206*
	(0.082)	(0.093)	(0.055)	(0.076)	(0.114)
	[0.056,0.326]	[-0.033,0.273]	[-0.123,0.058]	[-0.184,0.064]	[0.019,0.394]
$\ln H_{c,t-1}$	0.083	0.700***	0.978***	0.825***	0.181***
	(0.120)	(0.202)	(0.067)	(0.124)	(0.033)
	[-0.114,0.280]	[0.367,1.032]	[0.868,1.087]	[0.621,1.030]	[0.127,0.235]
$\ln H_{s,t-1}$	0.122*	0.036**	0.026*	0.011	-0.034
	(0.069)	(0.016)	(0.015)	(0.022)	(0.034)
	[0.010,0.235]	[0.010,0.063]	[0.001,0.051]	[-0.026,0.047]	[-0.089,0.021]
Parental human capital (fixed over time)					
$\ln P_h$	-0.010	0.021	-0.008	-0.042	-0.024
	(0.018)	(0.031)	(0.028)	(0.042)	(0.050)
	[-0.040,0.019]	[-0.030,0.071]	[-0.054,0.038]	[-0.112,0.027]	[-0.106,0.057]
$\ln P_c$	0.206***	0.053*	0.136***	0.079*	0.288***
	(0.059)	(0.030)	(0.029)	(0.044)	(0.056)
	[0.109,0.303]	[0.005,0.102]	[0.089,0.184]	[0.007,0.151]	[0.196,0.381]
$\ln P_s$	0.011	-0.025	0.013	0.034	0.028
	(0.009)	(0.017)	(0.016)	(0.025)	(0.021)
	[-0.004,0.026]	[-0.053,0.002]	[-0.013,0.039]	[-0.008,0.076]	[-0.008,0.063]
Investments					
$\ln I_{h,t-1}$	0.056*	0.141	0.031	0.119	0.137***
	(0.029)	(0.102)	(0.027)	(0.106)	(0.035)
	[0.009,0.104]	[-0.027,0.309]	[-0.014,0.075]	[-0.055,0.293]	[0.079,0.196]
$\ln I_{c,t-1}$	0.049***	-0.074	-0.028***	-0.190**	0.143
	(0.014)	(0.084)	(0.010)	(0.080)	(0.094)
	[0.026,0.073]	[-0.212,0.065]	[-0.044,-0.012]	[-0.322,-0.057]	[-0.011,0.297]
$\ln I_{h,t-1} \times \ln H_{c,t-1}$	0.292	0.028	-0.115	0.224	0.075***
	(0.205)	(0.243)	(0.071)	(0.149)	(0.027)
	[-0.046,0.629]	[-0.373,0.428]	[-0.231,0.001]	[-0.021,0.470]	[0.030,0.120]
$\sigma^2_{\eta_c}$	0.228	0.102	0.052***	1.030**	0.105***
	(4.412)	(0.089)	(0.016)	(0.478)	(0.029)
	[-7.029,7.485]	[-0.045,0.249]	[0.025,0.078]	[0.243,1.817]	[0.058,0.152]
N	7,998	6,898	7,853	7,373	7404

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's cognitive skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; health and cognitive investment; and an interaction of health investment and cognitive skill, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

Table B26: Estimates of cognitive production function parameters with interacted cognitive skill and cognitive investment

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.258***	0.123	-0.046	-0.051	0.254**
	(0.099)	(0.108)	(0.055)	(0.090)	(0.129)
	[0.096,0.420]	[-0.054,0.300]	[-0.137,0.045]	[-0.199,0.097]	[0.042,0.466]
$\ln H_{c,t-1}$	0.139	0.558***	0.883***	0.973***	0.164***
	(0.144)	(0.151)	(0.050)	(0.155)	(0.033)
	[-0.098,0.375]	[0.310,0.807]	[0.801,0.966]	[0.717,1.228]	[0.110,0.218]
$\ln H_{s,t-1}$	0.175**	0.041**	0.026	0.012	-0.044
	(0.075)	(0.016)	(0.017)	(0.027)	(0.038)
	[0.052,0.298]	[0.014,0.068]	[-0.002,0.053]	[-0.033,0.057]	[-0.106,0.018]
Parental human capital (fixed over time)					
$\ln P_h$	-0.015	0.026	-0.004	-0.043	-0.044
	(0.025)	(0.033)	(0.027)	(0.049)	(0.051)
	[-0.056,0.026]	[-0.028,0.080]	[-0.049,0.040]	[-0.124,0.037]	[-0.129,0.040]
$\ln P_c$	0.287***	0.065*	0.129***	0.102**	0.317***
	(0.045)	(0.035)	(0.027)	(0.043)	(0.073)
	[0.212,0.362]	[0.008,0.123]	[0.085,0.173]	[0.032,0.173]	[0.197,0.437]
$\ln P_s$	0.013	-0.028	0.013	0.036	0.032
	(0.011)	(0.020)	(0.017)	(0.031)	(0.025)
	[-0.006,0.031]	[-0.060,0.005]	[-0.014,0.040]	[-0.016,0.088]	[-0.010,0.073]
Investments					
$\ln I_{h,t-1}$	0.083***	0.160*	0.011	0.240**	0.170***
	(0.025)	(0.089)	(0.023)	(0.112)	(0.042)
	[0.041,0.125]	[0.014,0.307]	[-0.026,0.049]	[0.056,0.424]	[0.102,0.239]
$\ln I_{c,t-1}$	0.069***	-0.119	-0.037**	-0.232**	0.152
	(0.014)	(0.113)	(0.014)	(0.098)	(0.114)
	[0.046,0.092]	[-0.305,0.066]	[-0.061,-0.013]	[-0.393,-0.070]	[-0.035,0.340]
$\ln I_{h,t-1} \times \ln H_{c,t-1}$	-0.008	0.172	0.026	-0.037	0.000
	(0.090)	(0.228)	(0.028)	(0.119)	(0.136)
	[-0.156,0.140]	[-0.203,0.547]	[-0.020,0.071]	[-0.232,0.158]	[-0.223,0.223]
$\sigma^2_{\eta_c}$	1.897	0.098***	0.065***	1.717**	0.118***
	(228.502)	(0.034)	(0.018)	(0.749)	(0.037)
	[-373.955,377.750]	[0.042,0.154]	[0.036,0.095]	[0.485,2.948]	[0.057,0.178]
N	7,998	6,898	7,853	7,373	7,404

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's cognitive skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; health and cognitive investment; and an interaction of health investment and cognitive skill, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

Table B27: Estimates of socio-emotional production function parameters with interacted socio-emotional skill and health investment

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.274	0.107	0.131*	0.020	0.114
	(0.292)	(0.143)	(0.071)	(0.081)	(0.073)
	[-0.207,0.755]	[-0.128,0.341]	[0.014,0.248]	[-0.112,0.153]	[-0.007,0.234]
$\ln H_{c,t-1}$	0.246	0.053	-0.002	0.078**	0.021
	(0.430)	(0.077)	(0.049)	(0.037)	(0.014)
	[-0.461,0.953]	[-0.074,0.180]	[-0.082,0.078]	[0.018,0.138]	[-0.002,0.044]
$\ln H_{s,t-1}$	0.437*	0.412***	0.793***	0.677***	0.307***
	(0.227)	(0.015)	(0.021)	(0.022)	(0.023)
	[0.063,0.811]	[0.387,0.436]	[0.758,0.828]	[0.642,0.713]	[0.269,0.346]
Parental human capital (fixed over time)					
$\ln P_h$	0.011	-0.018	-0.004	0.050	0.042
	(0.069)	(0.045)	(0.034)	(0.040)	(0.032)
	[-0.102,0.124]	[-0.092,0.057]	[-0.061,0.053]	[-0.017,0.116]	[-0.011,0.095]
$\ln P_c$	0.529***	0.041	0.142***	0.079*	0.084***
	(0.073)	(0.048)	(0.035)	(0.040)	(0.029)
	[0.409,0.649]	[-0.038,0.121]	[0.083,0.200]	[0.013,0.145]	[0.036,0.133]
$\ln P_s$	0.391***	0.097***	0.053**	0.044*	0.036*
	(0.041)	(0.026)	(0.024)	(0.026)	(0.020)
	[0.323,0.459]	[0.055,0.139]	[0.014,0.092]	[0.001,0.087]	[0.003,0.069]
Investments					
$\ln I_{h,t-1}$	0.712***	0.181	0.060*	0.303***	0.040*
	(0.085)	(0.112)	(0.032)	(0.083)	(0.023)
	[0.571,0.852]	[-0.002,0.365]	[0.007,0.112]	[0.166,0.440]	[0.003,0.078]
$\ln I_{c,t-1}$	0.063***	0.436***	-0.010	0.054	0.061
	(0.020)	(0.093)	(0.012)	(0.064)	(0.082)
	[0.030,0.096]	[0.283,0.589]	[-0.030,0.009]	[-0.052,0.160]	[-0.074,0.196]
$\ln I_{h,t-1} \times \ln H_{s,t-1}$	-0.078	-0.033	-0.048	0.013	-0.038
	(0.661)	(0.060)	(0.032)	(0.065)	(0.025)
	[-1.166,1.010]	[-0.132,0.066]	[-0.100,0.005]	[-0.094,0.119]	[-0.080,0.003]
$\ln A_t$	-0.473***	1.090***	1.130***	1.136***	0.166***
	(0.066)	(0.055)	(0.049)	(0.046)	(0.038)
	[-0.581,-0.364]	[1.000,1.180]	[1.050,1.211]	[1.061,1.211]	[0.104,0.228]
RTS	2.584***	1.277***	1.114***	1.319***	0.668***
	(0.749)	(0.158)	(0.078)	(0.121)	(0.097)
	[1.352,3.817]	[1.017,1.536]	[0.985,1.244]	[1.120,1.518]	[0.509,0.826]
$\sigma^2_{\eta_s}$	0.920***	0.343***	0.383***	0.384***	0.154***
	(0.085)	(0.031)	(0.034)	(0.029)	(0.011)
	[0.780,1.060]	[0.292,0.394]	[0.328,0.438]	[0.337,0.432]	[0.135,0.173]
N	8,195	6,908	7,892	7,578	7619

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's socio-emotional skill measured by the observables in Appendix Table B18. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; health and cognitive investment; and an interaction of health investment and socio-emotional skill, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

Table B28: Estimates of socio-emotional production function parameters with interacted socio-emotional skill and cognitive investment

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{h,t-1}$	0.360	0.129	0.126*	0.038	0.068
	(0.269)	(0.145)	(0.070)	(0.074)	(0.071)
	[-0.082,0.803]	[-0.109,0.367]	[0.012,0.241]	[-0.084,0.161]	[-0.049,0.186]
$\ln H_{c,t-1}$	0.215	0.038	0.009	0.077**	0.015
	(0.403)	(0.051)	(0.040)	(0.036)	(0.011)
	[-0.447,0.878]	[-0.046,0.123]	[-0.057,0.075]	[0.019,0.136]	[-0.003,0.034]
$\ln H_{s,t-1}$	0.425**	0.410***	0.788***	0.679***	0.300***
	(0.201)	(0.015)	(0.021)	(0.021)	(0.025)
	[0.095,0.756]	[0.385,0.435]	[0.753,0.823]	[0.643,0.714]	[0.259,0.342]
Parental human capital (fixed over time)					
$\ln P_h$	-0.000	-0.008	-0.008	0.042	0.056*
	(0.057)	(0.046)	(0.034)	(0.039)	(0.033)
	[-0.094,0.093]	[-0.083,0.068]	[-0.064,0.048]	[-0.022,0.107]	[0.003,0.110]
$\ln P_c$	0.534***	0.039	0.140***	0.080**	0.070**
	(0.071)	(0.048)	(0.034)	(0.040)	(0.031)
	[0.417,0.652]	[-0.040,0.119]	[0.084,0.197]	[0.015,0.145]	[0.020,0.120]
$\ln P_s$	0.397***	0.091***	0.058**	0.045*	0.034*
	(0.037)	(0.025)	(0.023)	(0.025)	(0.020)
	[0.336,0.457]	[0.050,0.132]	[0.020,0.096]	[0.003,0.087]	[0.001,0.067]
Investments					
$\ln I_{h,t-1}$	0.714***	0.146	0.047	0.288***	0.021
	(0.082)	(0.118)	(0.030)	(0.088)	(0.017)
	[0.579,0.848]	[-0.048,0.339]	[-0.001,0.096]	[0.143,0.434]	[-0.007,0.050]
$\ln I_{c,t-1}$	0.066***	0.475***	-0.007	0.039	0.091
	(0.019)	(0.128)	(0.016)	(0.067)	(0.079)
	[0.033,0.098]	[0.264,0.686]	[-0.033,0.019]	[-0.071,0.149]	[-0.039,0.221]
$\ln I_{c,t-1} \times \ln H_{s,t-1}$	0.098	-0.070	-0.008	-0.011	-0.131*
	(0.154)	(0.074)	(0.015)	(0.042)	(0.067)
	[-0.156,0.353]	[-0.192,0.052]	[-0.033,0.017]	[-0.081,0.059]	[-0.242,-0.021]
$\ln A_t$	-0.487***	1.095***	1.129***	1.137***	0.186***
	(0.070)	(0.057)	(0.049)	(0.046)	(0.042)
	[-0.602,-0.372]	[1.002,1.188]	[1.048,1.210]	[1.061,1.212]	[0.117,0.255]
RTS	2.810***	1.251***	1.146***	1.278***	0.525***
	(0.362)	(0.157)	(0.071)	(0.116)	(0.138)
	[2.214,3.406]	[0.993,1.509]	[1.029,1.262]	[1.087,1.470]	[0.298,0.752]
$\sigma^2_{\eta_s}$	0.915***	0.342***	0.385***	0.385***	0.154***
	(0.086)	(0.032)	(0.033)	(0.029)	(0.011)
	[0.774,1.057]	[0.289,0.395]	[0.330,0.440]	[0.338,0.432]	[0.136,0.173]
	[0.774,1.057]	[0.289,0.395]	[0.330,0.440]	[0.338,0.432]	[0.136,0.173]
N	8,195	6,908	7,892	7,578	7,619

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's cognitive skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child health, cognitive skill and socio-emotional skill; parental health, cognitive skill and socio-emotional skill; health and cognitive investment; and an interaction of cognitive investment and socio-emotional skill, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

B.4.5 Estimates of the investment and production functions of cognitive and socio-emotional skill excluding health

Table B29: Estimates of cognitive investment function parameters, excluding health

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{c,t-1}$	1.505***	0.058***	-0.174***	-0.050***	-0.025***
	(0.459)	(0.022)	(0.027)	(0.012)	(0.005)
	[0.749,2.261]	[0.022,0.095]	[-0.219,-0.129]	[-0.069,-0.030]	[-0.033,-0.016]
$\ln H_{s,t-1}$	0.954***	0.037***	0.049*	0.060***	0.054***
	(0.218)	(0.010)	(0.026)	(0.011)	(0.016)
	[0.596,1.312]	[0.020,0.053]	[0.007,0.092]	[0.042,0.079]	[0.028,0.080]
Parental human capital (fixed over time)					
$\ln P_c$	0.137**	0.054	0.052	0.007	-0.018
	(0.068)	(0.033)	(0.053)	(0.032)	(0.030)
	[0.025,0.248]	[-0.001,0.108]	[-0.035,0.139]	[-0.045,0.059]	[-0.068,0.031]
$\ln P_s$	-0.059	0.060***	-0.054*	0.048***	0.032**
	(0.037)	(0.015)	(0.028)	(0.014)	(0.015)
	[-0.120,0.001]	[0.036,0.084]	[-0.100,-0.008]	[0.024,0.071]	[0.007,0.057]
Income					
$\ln Y_t$	0.146***	0.047**	0.013	0.066**	0.044
	(0.044)	(0.022)	(0.039)	(0.034)	(0.034)
	[0.074,0.219]	[0.011,0.082]	[-0.050,0.077]	[0.011,0.122]	[-0.012,0.100]
$\sigma^2_{\pi_c}$	3.347***	0.044***	1.965***	0.412***	0.066***
	(0.100)	(0.005)	(0.032)	(0.019)	(0.010)
	[3.183,3.511]	[0.035,0.053]	[1.914,2.017]	[0.381,0.444]	[0.049,0.083]
N	8239	6904	7821	7710	8098

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is cognitive investment measured by the observables in Appendix Table B20. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child cognitive and socio-emotional skill; parental cognitive and socio-emotional skill; and family income, respectively. All with the exception of parental cognitive skill and family income are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

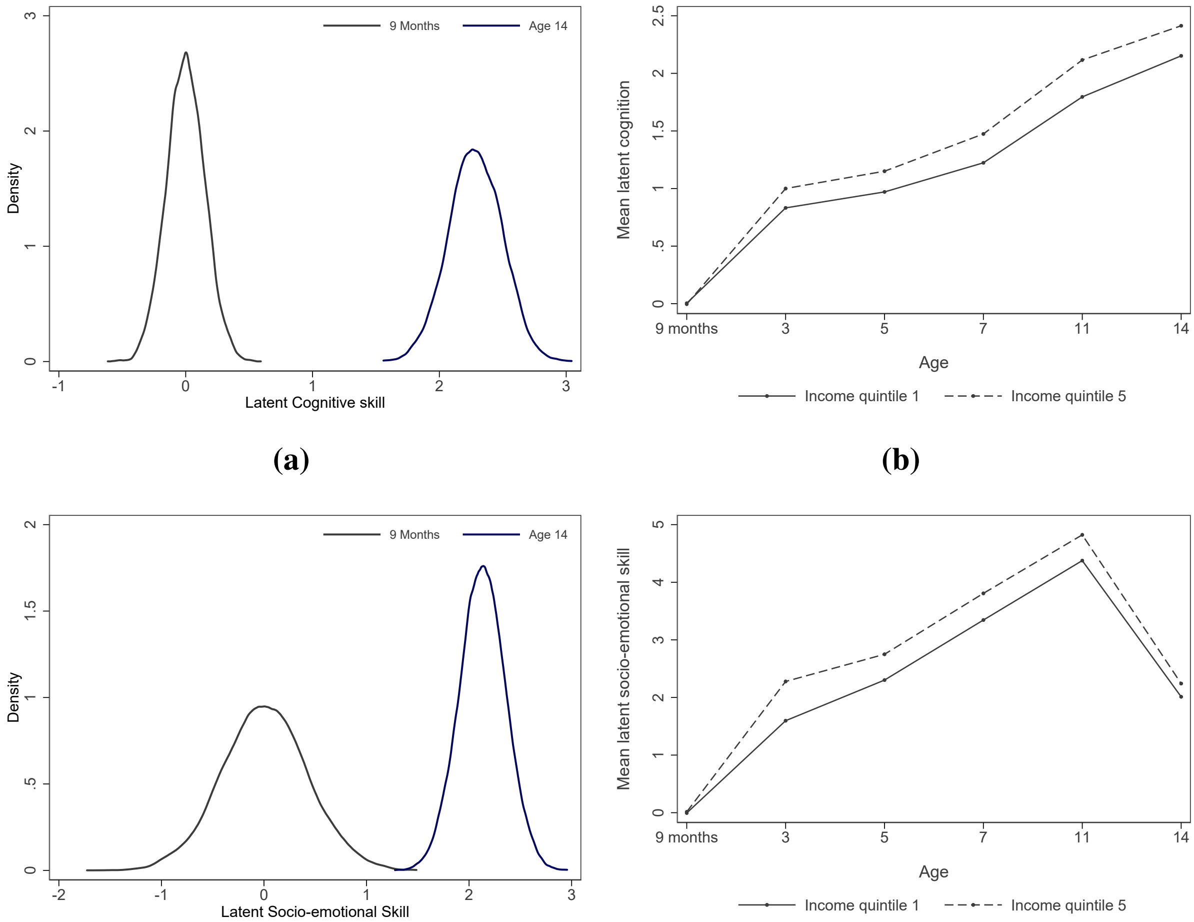
Table B30: Estimates of Cobb-Douglas socio-emotional skill production function, excluding health

	Period 1 *Ages 9 months-3*	Period 2 *Ages 3-5*	Period 3 *Ages 5-7*	Period 4 *Ages 7-11*	Period 5 *Ages 11-14*
Lagged human capital					
$\ln H_{c,t-1}$	-0.603*	0.036	0.007	0.036**	0.013**
	(0.351)	(0.038)	(0.017)	(0.015)	(0.006)
	[-1.180,-0.025]	[-0.027,0.098]	[-0.021,0.034]	[0.011,0.060]	[0.004,0.022]
$\ln H_{s,t-1}$	1.000***	0.411***	0.792***	0.695***	0.338***
	(0.176)	(0.017)	(0.021)	(0.019)	(0.021)
	[0.710,1.291]	[0.384,0.439]	[0.758,0.826]	[0.664,0.726]	[0.303,0.373]
Parental human capital (fixed over time)					
$\ln P_c$	0.740***	0.052	0.143***	0.110***	0.087***
	(0.057)	(0.041)	(0.032)	(0.039)	(0.027)
	[0.646,0.834]	[-0.016,0.119]	[0.091,0.196]	[0.045,0.174]	[0.043,0.132]
$\ln P_s$	0.423***	0.108***	0.073***	0.082***	0.052***
	(0.034)	(0.022)	(0.021)	(0.024)	(0.016)
	[0.368,0.479]	[0.072,0.145]	[0.039,0.108]	[0.043,0.122]	[0.025,0.078]
Investments					
$\ln I_{c,t-1}$	0.073***	0.529***	-0.003	0.073	0.097
	(0.021)	(0.109)	(0.011)	(0.055)	(0.089)
	[0.038,0.108]	[0.350,0.709]	[-0.021,0.014]	[-0.018,0.163]	[-0.050,0.244]
$\ln A_t$	-0.652***	1.009***	1.061***	1.062***	0.116***
	(0.058)	(0.052)	(0.044)	(0.051)	(0.036)
	[-0.747,-0.556]	[0.923,1.094]	[0.990,1.133]	[0.978,1.146]	[0.056,0.176]
RTS	1.634***	1.136***	1.012***	0.995***	0.587***
	(0.317)	(0.090)	(0.037)	(0.067)	(0.085)
	[1.113,2.156]	[0.987,1.285]	[0.950,1.073]	[0.885,1.106]	[0.447,0.727]
$\sigma^2_{\eta_n}$	0.973***	0.358***	0.389***	0.401***	0.161***
	(0.078)	(0.039)	(0.032)	(0.032)	(0.012)
	[0.845,1.101]	[0.294,0.421]	[0.336,0.443]	[0.347,0.454]	[0.141,0.181]
N	8199	6915	7905	7596	7690

Notes: Standard errors in parentheses and 90% confidence intervals in square brackets are calculated using 100 bootstrap replications. The outcome in each equation column is children's socio-emotional skill measured by the observables in Appendix Table B17. $t-1$ = ages 9 months and ages 3, 5, 7, and 11 years for the five columns respectively. The inputs in the left column are lagged child cognitive and socio-emotional skill; parental cognitive and socio-emotional skill; and cognitive investment, respectively. All with the exception of parental cognitive skill are treated as unobservable. Section 2.2.5 describes the observables used as measures of each input, and their estimated measurement parameters are shown in Tables B16-B21.

B.4.6 Additional simulation results

Figure B5: The estimated developmental path of cognitive and socio-emotional skill



(a) **(b)**

(c) **(d)**

Note: Panel (a) and (c) show the simulated distribution of cognitive and socio-emotional skill at 9 months and age 14, and panels (b) and (d) shows the simulated evolution of mean latent cognitive and socio-emotional skill in the top and bottom quintiles of the income distribution. Both were estimated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions.

The effects of income transfers

Table B31: Short- and long-term human capital impacts of a £5,000 increase in income across childhood

Transfer period	**Health**		**Cognition**		**Socio-emotional**	
	Short-term	*Long-term*	*Short-term*	*Long-term*	Short-term	Long-term
Age 9 months-3	0.0298	0.1027	0.4082	0.0609	1.7316	0.1579
	(0.0109)	(0.0376)	(0.1495)	(0.0223)	(0.6344)	(0.0579)
Age 3-5	0.0120	0.0991	0.3625	0.0623	0.8946	0.1766
	(0.0028)	(0.0229)	(0.0839)	(0.0144)	(0.2071)	(0.0409)
Age 5-7	-0.0141	-0.0015	0.0048	0.0000	0.0476	0.0103
	(0.0020)	(0.0002)	(0.0007)	(0.0000)	(0.0069)	(0.0015)
Age 7-11	-0.1885	-0.0527	1.0232	0.1203	1.6638	0.5316
	(0.0172)	(0.0048)	(0.0932)	(0.0110)	(0.1515)	(0.0484)
Age 11-14	-0.1134	-0.1134	2.2019	2.2019	0.3748	0.3748
	(0.0065)	(0.0065)	(0.1255)	(0.1255)	(0.0214)	(0.0214)
N	10,000	10,000	10,000	10,000	10,000	10,000

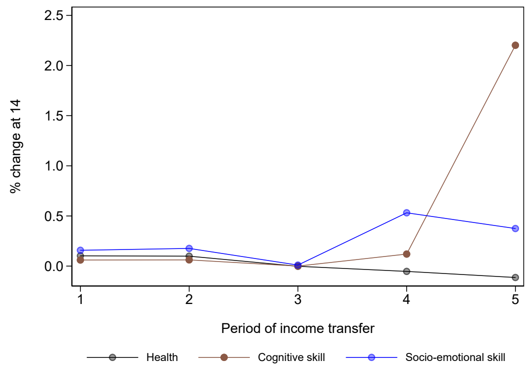
Note: Each cell shows $100 * E[\ln H^{Y}_{j,t} - \ln H_{j,t}]$ - the average change in human capital component j - indicated by the column - given an income transfer, Y, in the period indicated by the row. The differences are calculated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions, with and without a one-time £5,000 increase in income in the corresponding period. Standard errors of the difference are in parentheses.

Table B32: Short- and long-term human capital impacts of a £5,000 increase in income across childhood for these in the bottom quartile of the income distribution

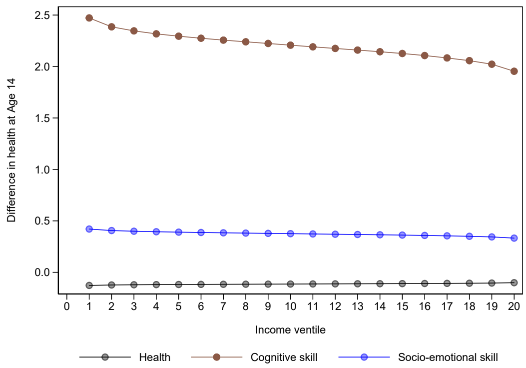
Transfer period	**Health**		**Cognition**		**Socio-emotional**	
	Short-term	*Long-term*	*Short-term*	*Long-term*	Short-term	Long-term
Age 9 months-3	0.0446	0.1538	0.6111	0.0912	2.5924	0.2364
	(0.0082)	(0.0281)	(0.1117)	(0.0167)	(0.4738)	(0.0432)
Age 3-5	0.0157	0.1297	0.4744	0.0815	1.1707	0.2311
	(0.0018)	(0.0151)	(0.0554)	(0.0095)	(0.1366)	(0.0270)
Age 5-7	-0.0168	-0.0018	0.0058	0.0000	0.0567	0.0122
	(0.0012)	(0.0001)	(0.0004)	(0.0000)	(0.0042)	(0.0009)
Age 7-11	-0.2108	-0.0589	1.1440	0.1345	1.8602	0.5944
	(0.0096)	(0.0027)	(0.0523)	(0.0061)	(0.0851)	(0.0272)
Age 11-14	-0.1217	-0.1217	2.3631	2.3631	0.4023	0.4023
	(0.0035)	(0.0035)	(0.0674)	(0.0674)	(0.0115)	(0.0115)
N	2,500	2,500	2,500	2,500	2,500	2,500

Note: Each cell shows $100 * E[\ln H^{Y}_{j,t} - \ln H_{j,t}]$ - the average change in human capital component j - indicated by the column - given an income transfer, Y, in the period indicated by the row. The differences are calculated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions, with and without a one-time £5,000 increase in income in the corresponding period. Standard errors of the difference are in parentheses.

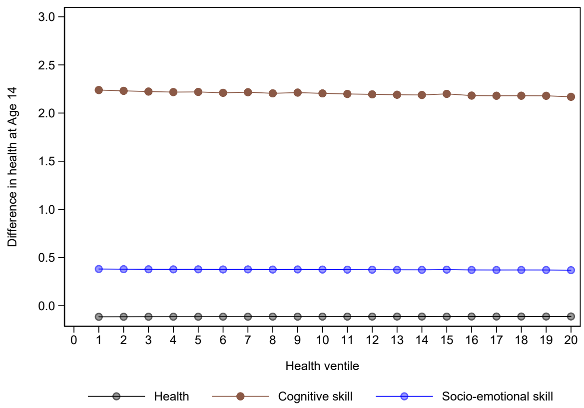
Figure B6: Long-term human capital impacts of a £5,000 increase in income across childhood



(a) Long-term effects by round of transfer



(b) Effects of an income transfer at age 11 by income ventile



(c) Effects of an income transfer at age 11 by health ventile

Note: Panel (a) shows the % increase in health and cognitive and socio-emotional skill at 14 given an income transfer of £5,000 at the age shown on the x-axis. panel (b) shows the % increase in each component of human capital at 14 given an income transfer at age 11 across ventiles of the income distribution. panel (c) shows the same change across ventiles of the health distribution. The effects were calculate by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without income transfers in each period. It is assumed that the transfers are spent fully in the period they are given.

The effects of health improvements

Table B33: The short- and long-term impacts on human capital of health improvements across childhood

Transfer period	Health		Cognition		Socio-emotional	
	Short-term	*Long-term*	*Short-term*	*Long-term*	Short-term	Long-term
Age 9 months-3	6.6389	3.3289	2.2678	0.8966	2.2504	0.9729
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age 3-5	11.7997	4.4938	1.6398	0.9354	0.3149	0.9821
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age 5-7	12.2654	5.5817	-0.6797	0.8964	1.9143	1.1114
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age 7-11	7.3225	6.0391	-0.7162	1.0929	0.1902	0.7726
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age 11-14	9.9570	9.9570	1.9886	1.9886	1.1921	1.1921
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	10,000	10,000	10,000	10,000	10,000	10,000

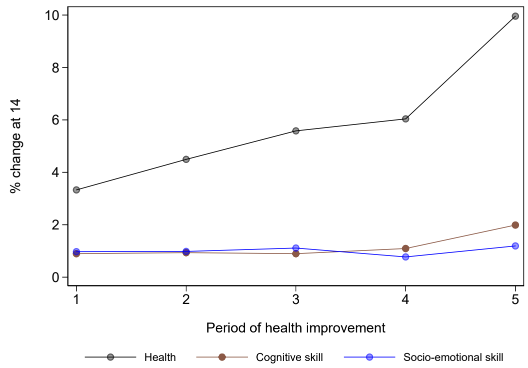
Note: Each cell shows $100 * E[\ln H_{j,t}^{H_h} - \ln H_{j,t}]$ - the average change in human capital component j - indicated by the column - given an improvement in health, H_h, in the period indicated by the row. The differences are calculated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions, with and without a one-time 10% increase in health capital in each period. Standard errors of the difference are in parentheses.

Table B34: The short- and long-term impacts on human capital of health improvements across childhood for those in the bottom quartile of the health distribution

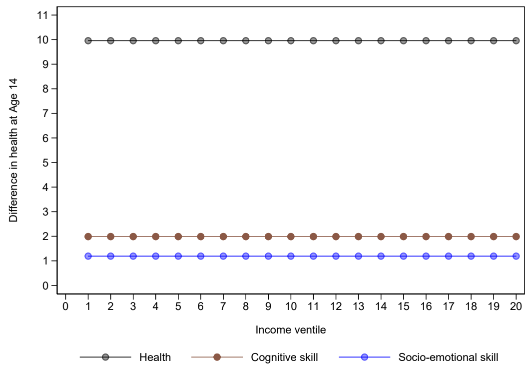
Transfer period	**Health**		**Cognition**		**Socio-emotional**	
	Short-term	*Long-term*	*Short-term*	*Long-term*	Short-term	Long-term
Age 9 months-3	5.4705	2.7430	1.8687	0.7388	1.8543	0.8017
	(2.5287)	(1.2680)	(0.8638)	(0.3415)	(0.8572)	(0.3706)
Age 3-5	11.2900	4.2997	1.5690	0.8950	0.3013	0.9396
	(2.3994)	(0.9138)	(0.3335)	(0.1902)	(0.0640)	(0.1997)
Age 5-7	12.0054	5.4633	-0.6653	0.8774	1.8738	1.0878
	(1.7672)	(0.8042)	(0.0979)	(0.1292)	(0.2758)	(0.1601)
Age 7-11	6.8597	5.6575	-0.6709	1.0239	0.1782	0.7238
	(1.7821)	(1.4698)	(0.1743)	(0.2660)	(0.0463)	(0.1880)
Age 11-14	9.0250	9.0250	1.8025	1.8025	1.0806	1.0806
	(2.9008)	(2.9008)	(0.5793)	(0.5793)	(0.3473)	(0.3473)
N	2,937	2,937	2,937	2,937	2,937	2,937

Note: Each cell shows $100 * E[\ln H_{j,t}^{H_h} - \ln H_{j,t}]$ - the average change in human capital component j - indicated by the column - given an improvement in health, H_h, in the period indicated by the row. The differences are calculated by simulating the developmental path of 10,000 observations randomly drawn from the estimated initial conditions, with and without a one-time 10% increase in health capital in each period. Standard errors of the difference are in parentheses.

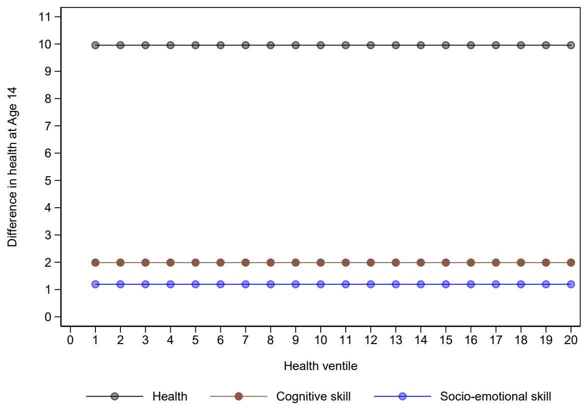
Figure B7: Long-term human capital impacts of a one standard deviation improvement in health across childhood



(a) Long-term effects by round of improvement



(b) Effects of an improvement at age 11 by income ventile

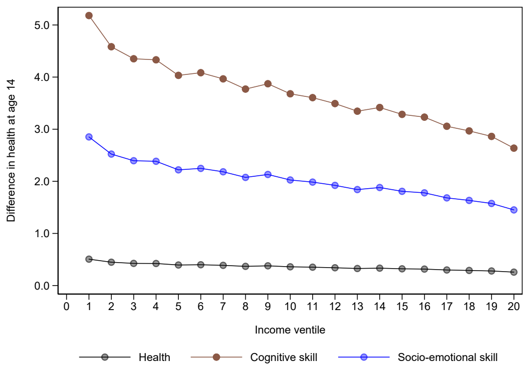


(c) Effects of an improvement at age 11 by health ventile

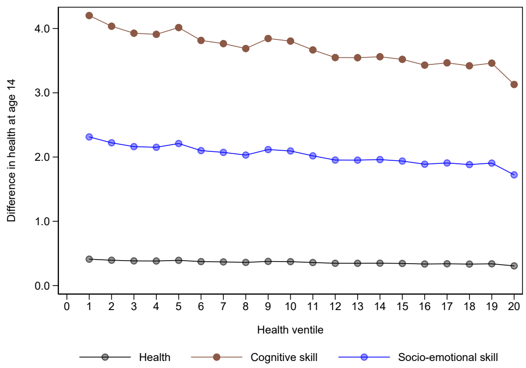
Note: panel (a) shows the % increase in health and cognitive and socio-emotional skill at 14 given a one standard deviation improvement in health at the age shown on the x-axis. panel (b) shows the % increase in each component of human capital at 14 given a health improvement at age 11 across ventiles of the income distribution. panel (c) shows the same change across ventiles of the health distribution. The effects were calculate by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without health improvements in each period.

The effect of increases in parents' human capital

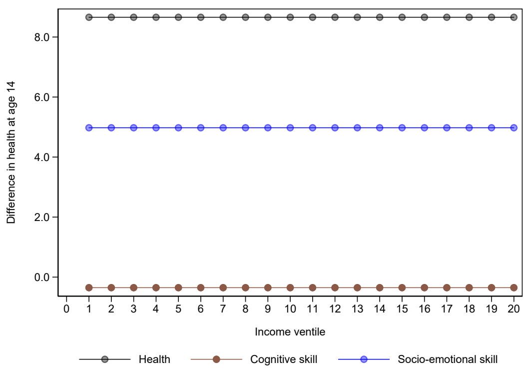
Figure B8: Long-term increases in health and cognitive and socio-emotional skills due to increases in parents' education and health, by position in the health and income distributions



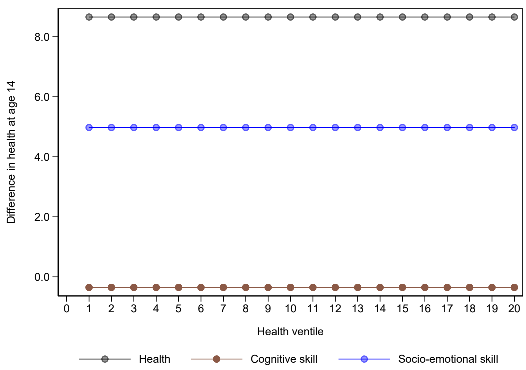
(a) % increase due to increased parental education by income ventile



(b) % increase due to increased parental education by health ventile



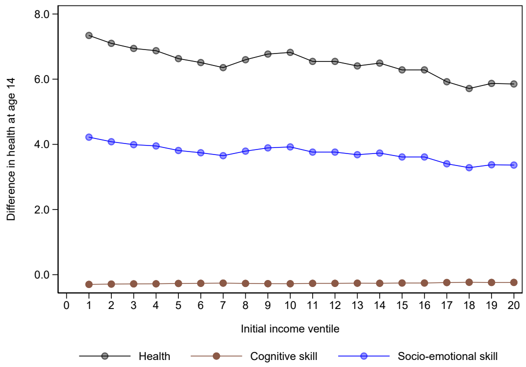
(c) % increase due to increased parental health by income ventile



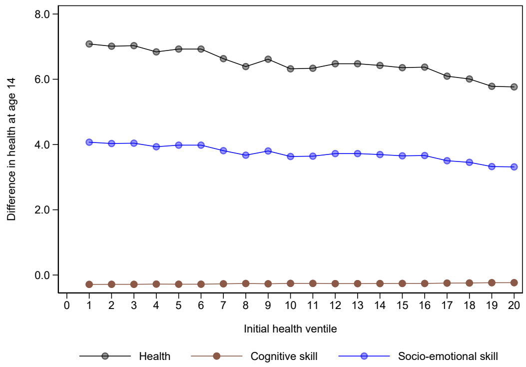
(d) % increase due to increased parental health by health ventile

Note: Panels (a) and (c) show the % increase in health and cognitive and socio-emotional skill at 14 given an increases in parents' education and health respectively for all children at age 9 months by ventile of the income distribution. Panels (b) and (d) show the % increase in each component of human capital at 14 given an improvement in parents' education and health for all children at age 9 months across ventiles of the health distribution. The effects were calculate by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without increases to parents' education and health at 9 months of age.

Figure B9: Long-term changes in the health and skill composition across the health and income distributions due to increases in parents' education and health for the 25% poorest and least healthy parents



(a) Increase in parents' health for the unhealthiest 25% of children



(b) Increase in parents' health for the poorest 25% of families

Note: Panels (a) and (b) show the % increase in health and cognitive and socio-emotional skill at 14 given an increases in parents' education for children in the poorest and unhealthiest 25% of families at age 9 months by ventiles of the health and income distributions respectively. The effects were calculated by drawing 10,000 observations from the estimated initial conditions and forward simulating the child development path with and without increases to parents' education and health at 9 months of age for children in the poorest and unhealthiest 25% of families.

Appendix C

Supplementary Material for Chapter 3

C.1 Identification and Estimation

We estimate equations 3.2 and 3.1 in between the ages of 8-12, 12-15, and 15-19 following Agostinelli and Wiswall (2016a). The starting point in estimating this system is the identification of the initial period measurement parameters and the joint distribution of the initial conditions. Given that we have three measures of each of the latent variable in the initial period and have assumed full independence of the measurement errors, we are able to identify and estimate both. With the initial period measurement parameters and the joint distribution of the initial conditions recovered, Agostinelli and Wiswall (2016a) show that the technologies in Equations 3.2 and 3.1 can be sequentially identified in each subsequent period.

Estimation of the model of human capital accumulation between the ages of 8 and 19 laid out in Section 3.2 consists of four main steps:

1. First, we estimate of the joint distribution of the initial conditions.
2. We then estimate of the investment function of Equation 3.1 and recover the investment measurement parameters in the first period.
3. Next, we estimate of the production function and measurement parameters for socio-emotional and cognitive skill in period 1.
4. We then repeat of steps 2 and 3 for in periods 2 and 3.

We then estimate the measurement system of three domains of socio-emotional skill at age 22: relationships, wellbeing, and agency. We impose normalisations on this measurement system that all us to identify and estimate the flexible production functions - shown in Equation 3.4 - of these skills between the ages of 19 and 22.

C.1.1 The Joint Distribution Of Initial Conditions

The factor loadings of to the measures of the initial conditions are retrieved by taking the ratio of the covariances of observed measures. For example:

$$\lambda_{\theta,m,0} = \frac{\text{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,m',})} \quad \forall m' \neq m \tag{C1}$$

Imposing the normalisation that the initial period latent variables all have a mean of zero, the measurement intercepts $\mu_{\theta,m,0}$, can be estimated by $\mathbb{E}(Z_{\theta,m,0})$. We the residualise measures as follows:

$$\tilde{Z}_{\theta,m,0} = \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} = \ln\theta_0 + \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 + \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} \quad \forall m \tag{C2}$$

The latent variables are then equivalent to:

$$\tilde{Z}^*_{\theta,m,0} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 \tag{C3}$$

Having identified and estimated the factor loadings, the theorem of Kotlarski (1967) can be applied to the set of residual measures, $\{\tilde{Z}_{\theta,m,0}\}_{m=1}^{M_{\theta,0}}$, to identify the distributions of $\ln\theta_0$ and $\varepsilon_{\theta,m,0}$ conditional on $\mathbf{I}_0$. This then allows identification of the joint distribution of the initial conditions and investments at t= 0. Agostinelli and Wiswall (2016a) show that the production technologies are sequentially identified in each of the following periods $t = 0, ..., T$.

The diagonal and off diagonal elements of the covariance matrix of the initial conditions can be estimated by

$$\frac{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,2,0})\text{Cov}(Z_{\theta,1,0}, Z_{\theta,3,0})}{\text{Cov}(Z_{\theta,2,0}, Z_{\theta,2,0})} = \frac{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\text{Var}(\ln\theta_0)^2}{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\text{Var}(\ln\theta_0)} = \text{Var}(\ln\theta_0) \tag{C4}$$

and

$$\text{Cov}(Z_{\theta,1,0}, Z_{\theta',1,0}) = \text{Cov}(\ln\theta_0, \ln\theta'_0) \tag{C5}$$

respectively. Since $\ln Y_0$ and $\ln Size_0$ are measured without error, their respective variance is easily computed, and their covariances with a given unobservable initial condition, θ_0, are:

$$\text{Cov}(\ln Y_0, \ln\theta_0) = \text{Cov}(\ln Y_0, Z_{\theta,1,0})$$

Given the assumption that unobservables are mean zero in the initial period, the mean vector is

$$\mu_\Omega = (0, 0, 0, 0, 0, 0, \mu_{Y,0})$$

C.1.2 Investment Functions

Substituting Equation 3.1 in to one measurement equation for investment in the first period gives the following expression:

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \lambda_{I_0,m,0}(\beta_{1,0} \ln H_{s,0} &+ \beta_{2,0} \ln H_{c,0} + \beta_{3,0} \ln P_s \\ &+ \beta_{4,0} \ln P_c + \beta_{5,0} \ln Y_0 + \pi_0) + \varepsilon_{I_0,m,0} \end{aligned} \tag{C6}$$

Substituting the corresponding proxies of latent inputs in to the investment equations - $\tilde{Z}^*_{\theta,m,0}$ for each $\theta_0 \in \{H_{s,0}, H_{c,0}, P_s, P_c\}$ - in to Equation C6 in place of the unobservables this can be re-written as

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \lambda_{I_0,m,0}(\beta_{1,0}\tilde{Z}^*_{H_s,m,0} &+ \beta_{2,0}\tilde{Z}^*_{H_c,m,0} + \beta_{3,0}\tilde{Z}^*_{P_s,m} \\ &+ \beta_{4,0}\tilde{Z}^*_{P_c,m} + \beta_{5,0} \ln Y_0 + \pi_0) + \varepsilon_{I_0,m,0} \end{aligned} \tag{C7}$$

and so

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \delta_{1,0}\tilde{Z}_{H_s,m,0} + \delta_{2,0}\tilde{Z}_{H_c,m,0} &+ \delta_{3,0}\tilde{Z}_{P_s,m} \\ &+ \delta^j_{4,0}\tilde{Z}_{P_c,m} + \delta_{5,0} \ln Y_0 + \nu_0 \end{aligned} \tag{C8}$$

where

$$\begin{aligned} \delta_{i,0} =& \lambda_{I_0,m,0}\beta_{i,0} \quad \text{for} \quad i = 1, .., 5 \\ \nu_0 = \varepsilon_{I_0,m,0} + \lambda_{I_0,m,0}(\pi_0 &- \beta_{1,0}\tilde{\varepsilon}_{H_s,m,0} - \beta_{2,0}\tilde{\varepsilon}_{H_c,m,0} - \beta^j_{3,0}\tilde{\varepsilon}_{P_s,m,0} - \beta^j_{4,0}\tilde{\varepsilon}_{P_c,m,0}) \end{aligned}$$

Since we are using error contaminated proxies for the latent inputs persists of Equation C8,, $\mathbb{E}(\tilde{Z}_{\theta,m,0}\nu_{j,0}) \neq 0$. We therefore use, all other measures of each latent variable as instruments to estimate of the reduced form parameters in Equation C8. Given the assumptions on the measurement errors, $\mathbb{E}(Z_{\theta,m',0}\nu_{j,0}) = 0 \quad \forall\, \theta_0$ and $m' \neq m$ and so these alternative measures are valid instruments. With the CRS assumption we can recover the measurement and structural parameters of the investment equation as:

$$\beta_{i,0} = \frac{\delta_{i,0}}{\sum_{i=1}^{6} \delta_{i,0}} = \frac{\lambda_{I_0,m,0}\beta_{i,0}}{\sum_{i=1}^{6} \lambda_{I_0,m,0}\beta_{i,0}^{j}} \quad \text{for} \quad i = 1, .., 5$$

We then construct residual investment measures as:

$$\tilde{Z}_{I,m,0} = \frac{Z_{I,m,0} - \mu_{I,m,0}}{\lambda_{I,m,0}} = \ln I_0 + \tilde{\varepsilon}_{I,m,0} \,,$$

and investment is equal to:

$$\tilde{Z}^{*}_{I_j,m,0} = \tilde{Z}_{I_0,m,0} - \tilde{\varepsilon}_{I,m0} = \ln I_0 \tag{C9}$$

C.1.3 Production Functions

The parameters of Equation 3.2 are estimated in an identical manner. Again, we start by substituting Equation 3.2 in to that of an observable measurement of period 1 stock of socio-emotional skill, giving:

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} + \lambda_{H_s,m,1}\big(&\rho^{s}_{1,0} \ln H_{s,0} + \rho^{s}_{2,0} \ln H_{c,0} + \alpha^{s}_{1,0} \ln P_s + \alpha^{s}_{2,0} \ln P_c \\ &+ \gamma^{s}_{0} \ln I_0 + \kappa^{s}_{0}(\ln H_{s,0} \ln I_0) + \eta^{s}_{0}\big) + \varepsilon_{H_s,m,1} \end{aligned} \tag{C10}$$

Once again using the fact that, based on the measurement system laid out in Equation 3.6, $\tilde{Z}^{*}_{\theta,m,0} = \ln \theta_0$ for $\theta_0 \in \{H_{s,0}, H_{c,0}, P_s, P_c, I_0\}$, Equation C10 can be written as

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} + \lambda_{H_s,m,1}\big(&\rho^{s}_{1,0}\tilde{Z}^{*}_{H_{s,0},m,0} + \rho^{s}_{2,0}\tilde{Z}^{*}_{H_{c,0},m,0} + \alpha^{s}_{1,0}\tilde{Z}^{*}_{P_s,m,0} + \alpha^{s}_{2,0}\tilde{Z}^{*}_{H_c,m,0} \\ &+ \gamma^{s}_{0}\tilde{Z}^{*}_{I_0,m,0} + \kappa^{s}_{0}\big(\tilde{Z}^{*}_{H_{s,0},m,0}\tilde{Z}^{*}_{I_0,m,0}\big) + \eta^{s}_{0}\big) + \varepsilon_{H_s,m,1} \,, \end{aligned} \tag{C11}$$

which can be re-arranged as:

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} &+ \phi^{s}_{1,0}\tilde{Z}_{H_{s,0},m,0} + \phi^{s}_{2,0}\tilde{Z}_{H_{c,0},m,0} + \chi^{s}_{1,0}\tilde{Z}_{P_s,m,0} + \chi^{s}_{2,0}\tilde{Z}_{H_c,m,0} \\ &+ \tau^{s}_{0}\tilde{Z}_{I_0,m,0} + \psi^{s}_{0}\big(\tilde{Z}_{H_{s,0},m,0}\tilde{Z}_{I_0,m,0}\big) + \upsilon^{s}_{1} \end{aligned} \tag{C12}$$

where

$$\phi_{i,0}^s = \lambda_{H_s,m,1}\rho_{i,0}^s \quad \text{for} \quad i = 1, 2$$

$$\chi_{i,0}^s = \lambda_{H_s,m,1}\alpha_{i,0}^s \quad \text{for} \quad i = 3, 4$$

$$\tau_0^s = \lambda_{H_s,m,1}\gamma_0^s$$

$$\psi_0^s = \lambda_{H_s,m,1}\kappa_0^s$$

and

$$\upsilon_1^j = \varepsilon_{H_s,m,1} + \lambda_{H_j,m,1}\Big[\eta_0^s - \rho_{1,0}^s\tilde{\varepsilon}_{H_{s,0},m,0} - \rho_{2,0}^s\tilde{\varepsilon}_{H_{c,0},m,0} - \alpha_{1,0}^s\tilde{\varepsilon}_{P_s,m,0} - \alpha_{2,0}^s\tilde{\varepsilon}_{P_c,m,0} - \gamma_0^s\tilde{\varepsilon}_{I_0,m,0}$$
$$- \kappa_0^s(\tilde{Z}_{H_{s,0},m,0}\tilde{\varepsilon}_{I_0,m,0} + \tilde{Z}_{I_0,m,0}\tilde{\varepsilon}_{H_{s,0},m,0} + \tilde{\varepsilon}_{H_{s,0},m,0}\tilde{\varepsilon}_{I_0,m,0})\Big] \tag{C13}$$

As in estimation of the production functions, all alternative measures of the inputs are used as instrumental variables with their validity implied by assumptions regarding the joint distribution of the unobservables and measurement errors. The assumption of CRS again allows the structural parameters of Equation 3.2 to be calculated as

$$\rho_{i,0}^s = \frac{\phi_{i,0}^s}{\phi_{1,0}^s + \phi_{2,0}^s + \chi_{1,0}^s + \chi_{2,0}^s + \tau_0^s + \psi_0^s} \quad \text{for} \quad i = 1, 2$$

$$\alpha_{i,0}^s = \frac{\chi_{i,0}^s}{\phi_{1,0}^s + \phi_{2,0}^s + \chi_{1,0}^s + \chi_{2,0}^s + \tau_0^s + \psi_0^s} \quad \text{for} \quad i = 3, 4$$

$$\gamma_0^s = \frac{\tau_0^s}{\phi_{1,0}^s + \phi_{2,0}^s + \chi_{1,0}^s + \chi_{2,0}^s + \tau_0^s + \psi_0^s}$$

$$\kappa_0^s = \frac{\psi_0^s}{\phi_{1,0}^s + \phi_{2,0}^s + \chi_{1,0}^s + \chi_{2,0}^s + \tau_0^s + \psi_0^s}$$

The denominator in each of the above equations gives the factor loading relating period 1 stock of socio-emotional skill to the observable measure $Z_{H_s,m,1}$. That is,

$$\lambda_{H_s,m,1} = \phi_{1,0}^s + \phi_{2,0}^s + \chi_{1,0}^s + \chi_{2,0}^s + \tau_0^s + \psi_0^s$$

Again, a residual measure of socio-emotional skill in period 1 can than be constructed as:

$$\tilde{Z}_{H_s,m,1} = \frac{Z_{H_s,m,1} - \mu_{H_s,m,1}}{\lambda_{H_s,m,1}} = \ln H_{s,1} + \tilde{\varepsilon}_{H_s,m,1} \,,$$

and latent socio-emotional skill can be defined as being equal to:

$$\tilde{Z}^*_{H_j,m,1} = \tilde{Z}_{H_j,m,1} - \tilde{\varepsilon}_{H_j,m,1} = \ln H_{j,1}$$

The parameters of the cognitive production function and measurement system are estimated, and a residual measure of cognitive skill constructed, in the same way. An identical process for estimating the investment and production functions is then used in each subsequent period.

C.1.4 Variance of Investment and Production Shocks

The variance of shocks to investment and production are estimated by as the covariance between the residual from equations C8 and C12 with an alternative measure of their output respectively. Alternative residual measures are constructed by estimating equations C8 and C12 using $Z_{H_j,m',0}$ for $j \in \{s, c\}$ and $Z_{I_s,m',0}$ as outcomes and retrieving their measurement parameters. Given the assumptions on the measurement errors the variance of shocks can be estimated in each t as:

$$\text{Cov}\left(\frac{\nu_t}{\lambda_{I,m,t}}, \tilde{Z}_{I,m',t}\right) = Var(\pi_t) = \sigma^2_{\pi,t} \,,$$

and

$$\text{Cov}\left(\frac{\upsilon^j_t}{\lambda_{H_j,m,t}}, \tilde{Z}_{H_j,m',t}\right) = Var(\eta^j_t) = \sigma^2_{H_j,t}$$

C.1.5 Signal to Noise Ratios

The proportion of the variance in an observable measure attributable to the latent variable it proxies as opposed to measurement error is estimated as a function of its measurement parameters and the variance of the unobservable. In the initial period, these are calculated as in Section C.1.1. In subsequent periods, they are recovered by estimating Equations C8 and C12 using each measure of investment and human capital as the dependent variable. The signal in, for example, a measure of socio-emotional skill at time t is then given by

$$s_{H_{s,1},m,t} = \frac{\lambda^2_{H_{s,1},m,t} V(\ln H_{s,1})}{\lambda^2_{H_{s,1},m,t} V(H_{s,1}) + V(\varepsilon_{H_{s,1},m,t})} = \frac{\lambda^2_{H_{s,1},m,t} \text{Cov}\left(\tilde{Z}_{H_{s,1},m,t}, \tilde{Z}_{H_{s,1},m',t}\right)}{V(Z_{H_{s,1},m,t})} \tag{C14}$$

C.1.6 Socio-emotional Skills in Early Adulthood

For the measures of three domains of socio-emotional skill - task-effectiveness (t) and social skills (s) - at age 22 ($T+1$), we estimate the measurement system laid out in Equation 3.6 imposing the following normalizations for $j \in \{t, s\}$:

$$E(\ln H^j_{s,T+1}) = 0$$
$$\lambda_{H^j_{s,1,T+1}} = 1$$

These normalisations fix the location and scale of each of these latent socio-emotional skills to one of their observable measures. They also allow us to estimate the measurement means as $E(Z_{H_s,m,T+1}) = \mu_{H_s,m,T+1}$. Given these measurement parameters, we take one measurement equation for socio-emotional skill $Z_{H^j_s,m,+T+1}$ and substitute in to it Equation 3.4, giving:

$$Z_{H^j_s,m,T+1} = \mu_{H^j_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}(\ln A_T + \rho^{s,j}_{1,T} \ln H_{s,T} + \rho^{s,j}_{2,T} \ln H_{c,T} + \eta^{s,j}_T) + \varepsilon_{H^j_s,m,T+1}$$

After substituting in to this equation residual measures of period T socio-emotional and cognitive skill and rearranging, we arrive at an expression similar to Equations C8 and C12:

$$Z_{H^j_s,m,T+1} = \mu_{H_s,m,T+1} + \phi^{s,j}_{1,T+1}\tilde{Z}^*_{H_s,m,T} + \phi^{s,j}_{2,T+1}\tilde{Z}^*_{H_c,m,T} + \lambda_{H^j_{s,m,T+1}} \ln A_T + \upsilon^{s,j}_{T+1} \tag{C15}$$

Substituting in our expression of $\ln A_T$, this can be re-written as:

$$Z_{H^j_s,m,T+1} = \phi^{s,j}_{0,T+1} + \phi^{s,j}_{1,T+1}\tilde{Z}_{H^s,m,T} + \phi^{s,j}_{2,T+1}\tilde{Z}_{H_c,m,T} + \mathbf{x}'_T\omega^{s,j}_{T+1} + \upsilon^{s,j}_{T+1} \tag{C16}$$

Where:

$$\phi^{s,j}_{0,T+1} = \mu_{H_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}\alpha_T$$
$$\phi^{s,j}_{i,T+1} = \lambda_{H^j_{s,m,T+1}}\rho^{s,j}_{i,T} \qquad \text{for} \quad i = 1, 2$$
$$\omega^{s,j}_{T+1} = \lambda_{H^j_{s,m,T+1}}\boldsymbol{\beta}$$
$$\upsilon^{s,j}_{T+1} = \varepsilon_{H^j_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}(\eta^{s,j}_T - \rho^{s,j}_{1,T}\tilde{\varepsilon}_{H_s,m,T} - \rho^{s,j}_{2,T}\tilde{\varepsilon}_{H_c,m,T})$$

Given the normalisations on the period T measurement system, both $\mu_{H_s,m,T+1}$ and $\lambda_{H^j_{s,m,T+1}}$

are known, and the location and scale of socio-emotional skill j is anchored in one of its measures. Using the same instrumental variables strategy as om estimating the investment and production functions of periods 1-3, we can then recover α_T, $\boldsymbol{\beta}$ and $\rho^{s,j}_{i,T}$, for $i = 1, 2$ without the restriction of CRS. We estimate the returns to scale (RTS) as:

$$\frac{\phi^{s,j}_{2,T+1} + \phi^{s,j}_{1,T+1}}{\lambda_{H^j_{s,m,T+1}}} = \frac{\lambda_{H^j_{s,m,T+1}}(\rho^{s,j}_{1,T} + \rho^{s,j}_{2,T})}{\lambda_{H^j_{s,m,T+1}}}$$

C.1.7 The Parameters of the Adult Outcome Equation

Substituting a residual measure of $T+1$ task effectiveness and social skills, and a time T measure of cognition in to equation 3.11 gives:

$$O_{T+1} = \mu_o + \gamma^o_1 \tilde{Z}^*_{H^t_s,m,T+1} + \gamma^o_2 \tilde{Z}^*_{H^s_s,m,T+1} + \gamma^o_3 \tilde{Z}^*_{H_c,m,T} + \mathbf{x}'_{T+1}\boldsymbol{\delta} + \eta^o_{T+1} \tag{C17}$$

As in estimating the production and investment equations across period 1-4, this can be rearranged as:

$$O_{T+1} = \mu_o + \gamma^o_1 \tilde{Z}_{H^t_s,m,T+1} + \gamma^o_2 \tilde{Z}_{H^s_s,m,T+1} + \gamma^o_3 \tilde{Z}_{H_c,m,T} + \mathbf{x}'_{T+1}\boldsymbol{\delta} + \nu^o_{T+1} \quad , \tag{C18}$$

where

$$\nu^o_{T+1} = \eta^o_{T+1} + \gamma^o_1 \varepsilon_{H^p_s,m,T+1} + \gamma^o_2 \varepsilon_{H^l_s,m,T+1} + \gamma^o_3 \varepsilon_{H_c,m,T} \tag{C19}$$

Although we do not have to disentangle the factor loadings from the parameters of the outcome equation, we have an identical measurement error problem as in estimating Equations C8, C12 and C16.

Given we use indicators of risky behaviours as outcomes, we use a similar instrumental variable strategy and estimate a linear probability model using alternative measures of the two socio-emotional skill domains and cognition as instruments - but for binary outcomes with endogenous, continuous independent variables. We favour this method over maximum likelihood or control function methods for two main reasons. Firstly, consistency estimators based on these methods relies on full specification of the first stage equations and having continuously distributed endogenous variables (Blundell and Powell, 2004). The variables we use as proxies are not truly continuous (although we assume that the latent variables are), and we know we do not have a complete set of relevant instruments on the latent variables, so these assumptions are not satisfied. An estimator of a LPM using 2SLS will not be inconsistent, however, and only on standard IV assumptions i.e. that $\mathbb{E}(Z_{H^k_s,m',T+1}\nu_{j,0}) = 0 \quad \forall H^k_s$ and $m' \neq m$,

Secondly, an IV LPM makes no assumptions about the distribution of the measurement error, where ML/control function methods rely on joint normality of v^o_{T+1} and in the error term in the first stage regressions. Given v^o_{T+1} is an additive function of the measurement error and outcome equation error, this amounts to assuming that the measurement errors, outcome equation errors, and the errors in the first stage regressions are jointly normally distributed. As alluded to in the main body of this study, the methodology we use to estimate the investment and human capital production functions is robust to non-normal measurement errors (Agostinelli and Wiswall, 2016a), an added benefit given Laajaj and Macours (2019) find evidence that measurement error in socio-emotional skill measures is non-classical among samples in Kenya and Colombia.

C.2 Additional description of child assessments

The observable measures of child and parental human capital and investment in the Young Lives data are derived from both caregivers' and children's responses to survey questions across waves. In the case of cognitive skill, all measures are scores on tests administered as part of the survey. Below, we provide more detail on the types of measures used for each of the inputs in to and outputs of the human capital development process.

Socio-emotional Skill Measures

We do not use all of the socio-emotional measures available in the YL survey. Instead, where possible, we focus on those that can be described as reflecting children's Core Self-Evaluation (CSE) - those that predominantly ask questions about the children themselves, and their evaluation of aspects of their personality. For example, we excluded commonly used measures of subjective wellbeing such as Cantril's ladder (Cantril et al., 1965), and measures of children's trust in others or their social networks. We also use measures in some rounds but not in others because their sub-items had change over time. This is the case, for example, with measures of pride and self-esteem, which change substantially after age 15

Strengths and Difficulties Questionnaire (SDQ)

In the initial period at age 8, the children are not asked questions so we used caregivers' responses to the 25 question SDQ. Detailed information on the structure and purpose of the SDQ can be found at https://www.sdqinfo.com/. These 25 questions are designed to measure 5 aspects of the children's socio-emotional skills: emotional symptoms, conduct problems, hyperactivity/inattention, peer/relationship problems, and pro-social behaviour. Each of these sub-scales contains 5 questions about whether a child exhibits certain behaviours, and, traditionally, responses from parents can be *not true*, *somewhat true*, or *certainly true*. If assigned the values of one, two, and three respectively, the responses to these questions can be summed within each sub-scale to give an indication of the extent to which a child is experiencing difficulties.

In the survey administered as part of the Young Lives survey in Peru, the possible responses caregivers could provide were *yes*, *sometimes*, and *no*. Although slightly different in wording, these responses are observationally equivalent, and so we assign them analogous numerical values and sum responses within the 5 sub-scales, giving us 5 measures of socio-emotional skill. Goodman (2001) and Muris et al. (2003) discuss the validity and reliability of the SDQ in measuring these 5 underlying socio-emotional characteristics.

Young Lives Psychosocial Scales

Across its rounds, the Young Lives survey has adapted several commonly used scales designed to measure specific psychosocial characteristics. At ages 12, 15, 19, and 22 we use a measure of *pride and self-esteem*, based on Rosenberg (1965) scale. This scale poses statements to children about their self-confidence as it relates to their belongings, home, abilities, work, and achievements. For example, the following statements are contained in the scale:

- *I feel proud the show my friends or other visitors where I live*;
- *I am often proud because I do have the right books, pencils, and other equipment for school*;
- *I am proud of my achievement at school*; and
- *The job I do makes me feel proud*.

The children are then asked to what degree these statements represent their beliefs. At age 12, possible responses are on a 3-point scale of *no*, *yes*, or *more or less* respectively. At ages 15, 19, and 22 possible responses were on a 5-point scale from *strongly agree* to *strongly disagree*. After being assigned a numeric value, responses were summed to give each child a pride/self-esteem "score".

We also use a scale measuring agency at ages 12, 15, 19, and 22. This scale is based on Rotter (1966) and Bandura (1993), and poses a number of statements to children about the degree of control they have over their life. For example, the scales includes statements such as:

- *If I try hard I can improve my situation in life*;
- *I like to make plans for my future studies and work*; and
- *If I study hard at school I will be rewarded by a better job in the future.* .

The possible responses across ages are the same as in the case of the pride and self-esteem scale. Again, once assigned a numeric value, these responses are summed to give each child a agency/self-efficacy score. More information on the selection, construction, and validity of all of these scales can be found in Yorke and Ogando (2018).

General Self-efficacy

At ages 19 and 22 we utilise a newly added self-efficacy measure from the Young Lives data. This measure is based on the *general self-efficacy* scale of Jerusalem and Schwarzer (1979), which is designed to measure individuals' belief in their self-determination and ability to cope with adversity. Again, the scale consists of statements that children are asked to agree/disagree with. It contains statements such as:

- *I can always manage to solve difficult problems if I try hard enough*;
- *It is easy for me to stick to my aims and accomplish my goals*; and
- *I can solve most problems if I invest the necessary effort*.

Responses to these statements are on a 4-point scale from *strongly agree* to *strongly disagree*. These responses are assigned numeric values and then summed to prove a general self-efficacy "score" which we use as a measure of socio-emotional skill. Yorke and Ogando (2018) provides more detailed information on the selection and construction of this scale in the Young Lives data.

Marsh Self Description

At ages 19 and 22 we also use sub-scales of the Marsh Self-description Questionnaires measuring general self-esteem, peer relations, and parent relations. Each sub-scale is comprised of eight statements about self-concept in the respective domain. They sub-scales are based heavily on the proposed multi-dimensional structure of self-concept of Shavelson et al. (1976). These statements are presented to children, who are then asked to what extent they agree or disagree with them. As examples, the general self-esteem scale includes the statement *a lot of things about me are good*; the peer relations scale a statement that *I get along with other kids easily*; and the parent relations scale that *my parents understand me*. Once again, the possible responses to these statements range from *strongly agree* to *strongly disagree*, which we assign numeric values and sum within sub-scales to derive scores for each. Yorke and Ogando (2018) provides more detailed information on theoretical concepts underpinning the Marsh Self-description questionnaires and the validity of their structure.

Duckworth and Quinn Grit Scale

At age 22, we use measures of two aspects of "grit" as designed by Duckworth and Quinn (2009). These sub-scales are shortened versions of those first proposed in Duckworth et al. (2007) and are designed to measure what they define as *consistency of interest* and *perseverance of effort*. As with the vast majority of the psychometric measures we use, these assessments involve presenting children with several statements - in this case four - about the relevant aspect of grit, then asking them the extent to which they agree the statements describe themselves. Respectively, the consistency of interest and perseverance of effort scales contain statements such as *I often set a goal but choose to pursue a different one*, and *I finish whatever I begin*. Responses to the statements are on a 5-point scale, from *not like me at all* to *very much like me*. We sum responses within each group to construct scores for each aspect of grit.

Review of Personal Effectiveness with Locus of Control (ROPELOC)

At age 22 we also make use of two, three-question sub-scales from the ROPELOC measuring their leadership and cooperative teamwork abilities (Richards et al., 2002). The two scales contain questions statements such as *I am seen as a capable leader* and *I am good at cooperating with team members* respectively. Children are asked to what extent they agree these statements describe themselves, with possible responses being on a 4-point scale from *strongly agree* to *strongly disagree*. After being assigned numeric values, we use the sum of responses within each sub-scale as measure of their ability in each domain.

Big Five Inventory

Also at age 22, we use two components of the Big Five Inventory - conscientiousness and neuroticism. The sub-scales are part of the larger inventory which also seeks to measures openness, agreeableness, and extraversion. They contain eight and nine statements respectively and respondents are asked the extent to which they agree that these statements describe them. For example, the statements representing conscientiousness include:

- *I am someone who does a thorough job*;
- *I am someone who tends to be organised*; and
- *I am someone who makes plans and follows through with them.*

Similarly, the statements indicating neuroticism include:

- *I am someone who is relaxed, handles stress well*;
- *I am someone who is emotionally stable, not easily upset*; and
- *I am someone who gets nervous easily.*

Responses are on a 5-point scale from *strongly agree* to *strongly disagree* and are assigned a numeric value. The responses are summed within each of the two components to give children a score for conscientiousness and neuroticism.

C.2.1 Cognitive Skill

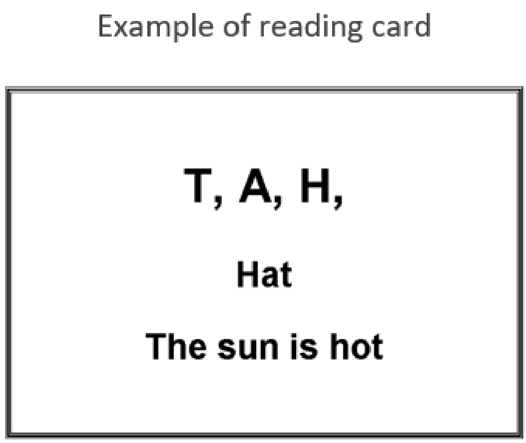
The YL data contains cognitive assessments at every age except 22. As with the socio-emotional skill measures, the assessments administered differ across ages based on suitability, however the measures cover the same three broad domains of cognitive skills: language ability and fluid intelligence, or reasoning.

Reading and Writing Levels

At ages 8 and 12, the writing level of children in the older cohort was assessed by asking them to read from aloud from cards containing three lines, the first containing individual letters, the second a word, and the third a simple sentence. Figure C1 shows what one of these cards looks like. The children were give a score of 1 if they could read the sentence, 0.66 if they could read the word, and 0.33 if they could read the letters, and 0 if they could not read anything.

For the writing assessment, interviewers read aloud a sentence which children were asked to transcribe. For example, children might have been asked to write down the sentence "*the sun is hot*". Sentences were adapted based on the country in which the test was administered to ensure comprehension. If children could write the sentence down easily they were awarded 1 point, and

Figure C1: Example of a YL reading card used to assess children's reading level at ages 8 and 12



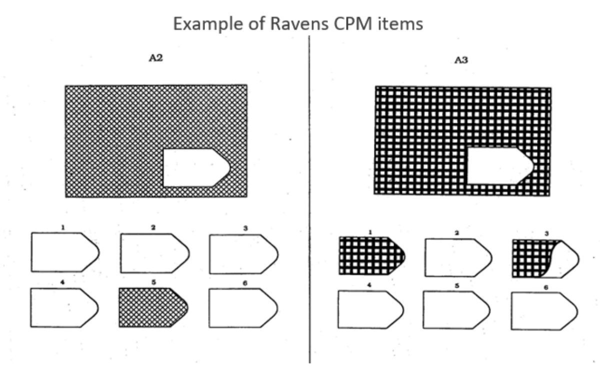
Source: Revollo (2018)

were awarded 0.5 or 0 points respectively if they wrote it down with errors or could not write it at all.

Raven's Coloured Progressive Matrices

At age 8 children are administered the Raven's coloured progressive matrices test Raven (1958). This assessment involves showing children patterns with missing blocks, and asking them to identify which block from a choice of six completes it. The test as administered in the YL survey has 36 items, asked in order of difficulty. A child's raw score in the test is calculated as the total number of correct responses.

Figure C2: Examples of straightforward a Raven's matrices at age 8

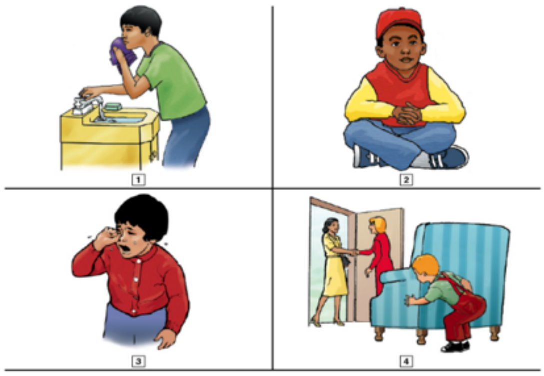


Source: Revollo (2018)

Peabody Picture Vocabulary Test (PPVT)

The PPVT was administered to children in age ages 12 and 15, and is designed to measure receptive vocabulary in children as young as 2.5 years old. The test involves presenting children with cards depicting four different scenarios, and asking them which picture best shows a sentence or word read aloud by the examiner. For example, an examiner might say "point to the picture that shows crying" whilst showing them the card in Figure C3. The questions become increasingly difficult, with the starting point of the test determined by the child's age.

Figure C3: Example of a PPVT picture card at ages 12 and 15



Source: Revollo (2018)

YL Maths Test

The YL also contains a maths test to measure "mathematical achievement". For the older Peruvian cohort, this test was administered at ages 12, 15, and 19. At age 12 it consisted of 10 mathematics questions from the International Association for the Evaluation of Educational Achievement's (IEA) 2003 Trends in International Mathematics and Science Study Reddy et al. (2003). Children's raw score were simply the total number of correct answers.

At age 15 the test was expanded to include 30 questions in two sections, one with 20 questions on mathematics (addition, division etc.) and another with 10 problem solving questions. At age 19 the test was further altered to account for differences in competencies across countries. Questions were grouped into three "booklets" of increasing difficulty, and children started on the second, intermediate booklet. If they performed well on intermediate skills they then answered questions on advanced skills, whereas if they performed poorly they moved on to answer questions on basic skills. Revollo (2018) describes the tests and their internal and external validity in detail.

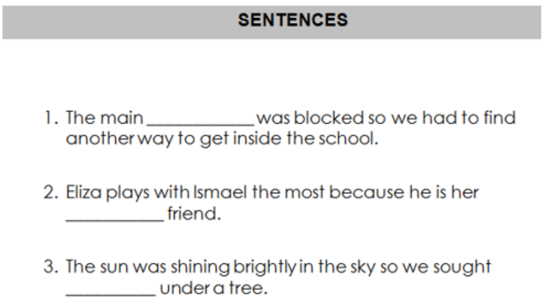
YL Reading Comprehension/Language Test

At age 19, children's reading comprehension was tested in a similar manner to their mathematical achievement ate the same age, described above. Comprehension questions were grouped into three booklets: (1) basic comprehension, (2) intermediate comprehension and (3) advanced comprehension. Children started with questions in booklet 2, and progressed to booklets 1 or 3 depending on their performance. The items administered were country specific in that they described or asked about day-to-day activities or situations that commonly occur in Peru. Revollo (2018) describes the design of the reading comprehension test in detail.

Cloze Language Test

At age 15, the children were administered the Cloze reading comprehension test, developed by the Development Analysis Group in Peru (GRADE - Grupo de Análisis para el Desarrollo). It was made up of 24 items, of increasing difficulty that asked children to fill in missing words in a sentence. Figure C4 shows an example of an item on the test. Ra scores were the total correct answers.

Figure C4: Example of a Cloze test card at age 15



SENTENCES

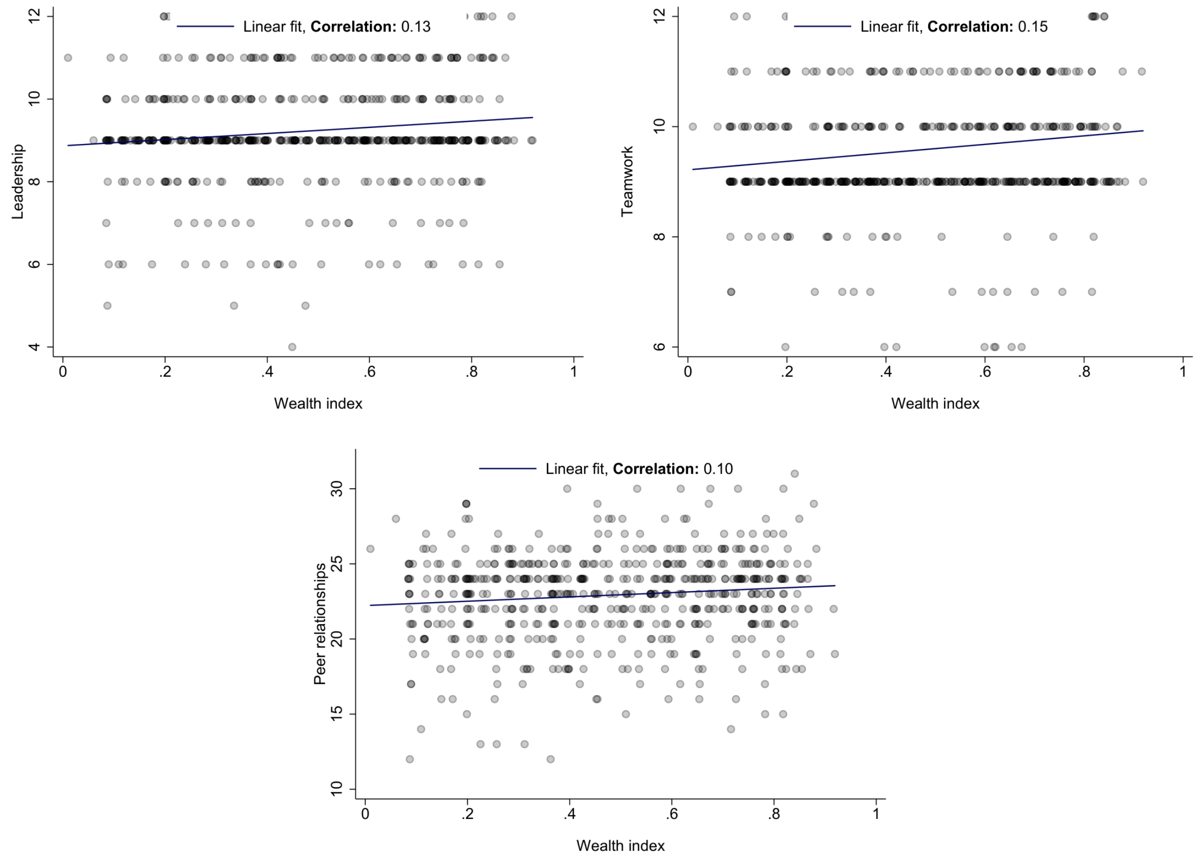
1. The main ___________ was blocked so we had to find another way to get inside the school.
2. Eliza plays with Ismael the most because he is her __________ friend.
3. The sun was shining brightly in the sky so we sought _________ under a tree.

Source: Revollo (2018)

C.3 Additional Tables and Figures

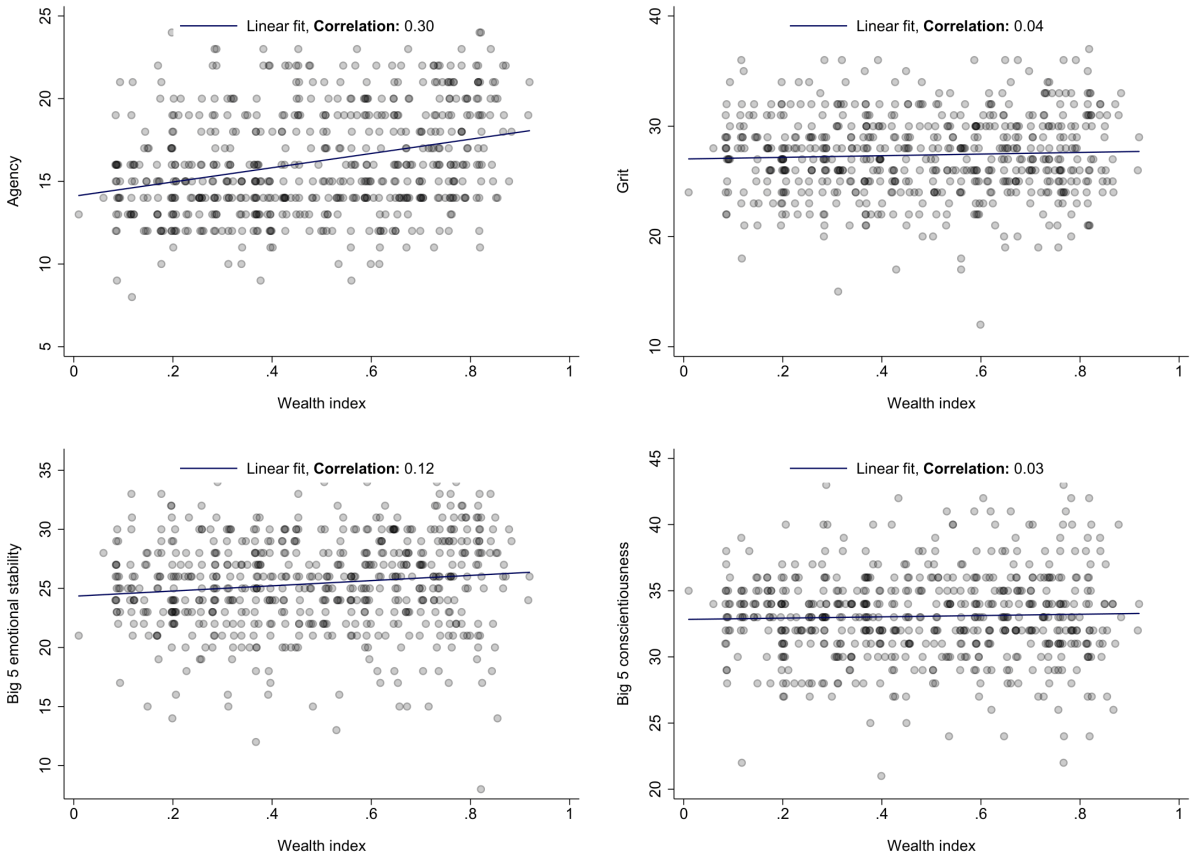
C.3.1 Additional Descriptive Figures and Tables

Figure C5: The correlation between measures of social skills at age 22 and household wealth at age 8



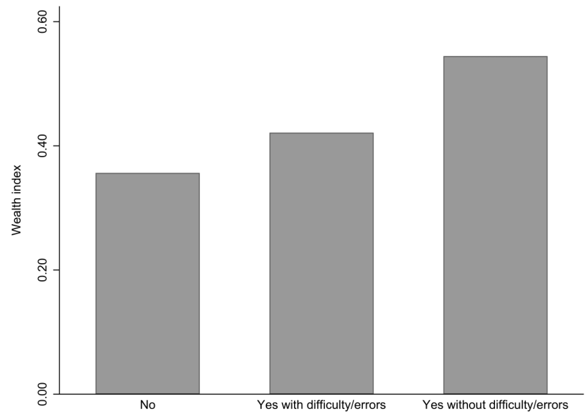
Note: The measures, clockwise from top left, are of leadership qualities, ability to work in a team, and quality of relationships with peers, and are described in detail in Appendix C.2. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

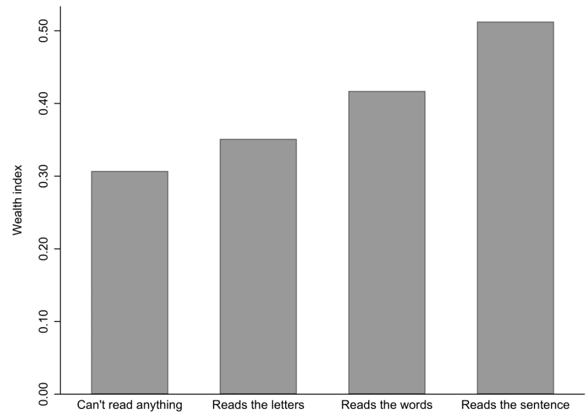
Figure C6: The correlation between measures of Task Effectiveness skills at age 22 and household wealth at age 8

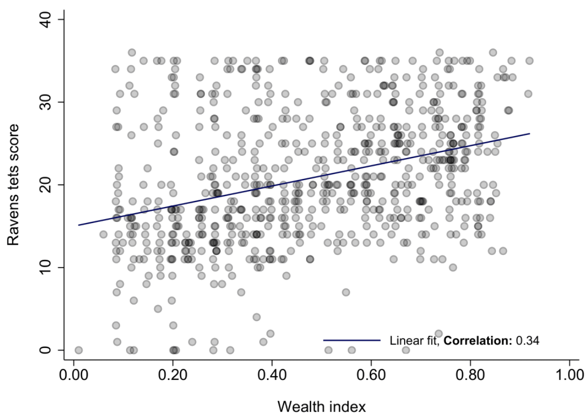


Note: The measures, clockwise from top left, are of agency, grit, emotional stability, and conscientiousness, and are described in detail in Appendix C.2. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

Figure C7: The correlation between cognitive skill measures and household wealth at Age 8







Note: The measures, clockwise from top left, are of the child's writing ability, reading ability, and score on the Ravens progressive matrices test, and are described in detail in Appendix C.2. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

C.3.2 Summaries of Observable Measures Used in Estimations

Table C1: summary statistics of observable socio-emotional skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 8					
SDQ: conduct problems*	12.263	2.210	15	5	11
SDQ: hyperactivity*	9.752	2.469	15	5	11
SDQ: pro-sociality	14.013	1.587	15	5	10
SDQ: emotional regulation*	10.513	3.080	15	5	11
SDQ: peer problems*	11.815	2.212	15	5	11
Age 12			11		
Pride & self-esteem	12.415	2.646	16	2	14
Agency	6.911	1.364	10	2	9
Age 15					
Pride & self-esteem	22.936	2.905	30	14	17
Agency	18.168	2.054	25	11	14
Age 19					
Agency	18.865	2.088	25	12	14
Self-esteem	24.778	2.335	32	16	17
Self-efficacy	30.205	3.274	40	8	21
Peer relationships	22.748	3.255	32	10	21
Age 22: task effectiveness					
Agency	16.181	3.275	25	8	18
Grit	27.393	3.730	40	12	25
Big 5 emotional stability	25.428	4.002	36	8	26
Big 5 conscientiousness	33.064	3.323	44	21	23
Age 22: social skills					
Leadership	9.228	1.281	12	4	9
Teamwork	9.586	1.172	12	6	7
Peer relationships	22.921	3.124	32	12	21

Note: The measures in this table are those of socio-emotional skill used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of socio-emotional skill the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table C2: summary statistics of observable cognitive skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 8					
Ravens score	20.822	8.062	36	0	37
Writing level	2.418	0.709	3	1	3
Reading level	3.582	0.968	4	1	4
Age 12					
Math score	5.754	1.774	8	0	9
PPVT score	72.025	15.554	106	10	71
Writing level	2.845	0.394	3	1	3
Reading level	3.934	0.387	4	1	4
Age 15					
Math score	13.139	5.722	29	0	29
PPVT score	96.924	17.300	125	13	72
Cloze score	14.706	5.658	24	0	25
Age 19					
Math score	16.960	5.611	28	1	28
Language score	15.926	3.718	24	3	20

Note: The measures in this table are those of cognitive skill used to estimate the human capital production and investment functions. From left to right, the columns contain either the name of the test through which skill was measured of the aspect of cognition the test captured, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample.

Table C3: summary statistics of observable investment and parental skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 12					
Per-child expenditure on books	1.341	2.822	65	0	.
Per-child expenditure on uniforms	1.028	3.135	76	0	.
Hours studying	2.950	1.282	8	0	9
Hours in school	4.776	1.585	12	0	10
Age 15					
Per-child expenditure on books	1.670	1.821	20	0	,
Per-child expenditure on uniforms	1.302	1.841	27	0	.
Food groups	22.436	4.038	32	3	27
Hours studying	2.079	1.168	7	0	8
Hours in school	5.908	1.966	11	0	10
Age 19					
Educational expenditure	0.537	1.729	36	0	.
Per-child non-food expenditure	4.502	6.517	55	0	.
Food groups	8.914	1.923	14	3	12
Hours in school	3.565	3.645	15	0	16
Hours studying	1.473	1.852	12	0	11
Parental socio-emotional skill					
Agency	12.974	2.030	15	7	9
Pride & self-esteem	14.458	1.154	15	8	8
Cantril's ladder	4.848	2.044	9	1	9
Parental cognitive skill					
Education	7.251	4.539	18	0	17
Can read newspaper	2.604	0.713	3	1	3
Can understand things written in Spanish	2.502	0.787	3	1	3

Note: The measures in this table are those of investment and parental human capital used to estimate the human capital production and investment functions. From left to right, the columns contain a descriptions of the investment or human capital measures, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. Variables with missing number of unique values are continuous.

C.3.3 Results of Initial Exploratory Factor Analysis (EFA) Across Ages 8-19

As part of our EFA, we first examine whether our observable measures have enough variation to capture sufficient variation in the latent variables we use as inputs/outputs of the production and investment functions. To do so, we first analyse the extent of the shared variation in the observable measures, and retain/discard their underlying factors based on their eigenvalues and a parallel analysis as proposed by Horn (1965). The measures we use in this EFA at each age described in the previous Section of this Appendix, and were those that best met the principal of Core Self-Evaluation (CSE).

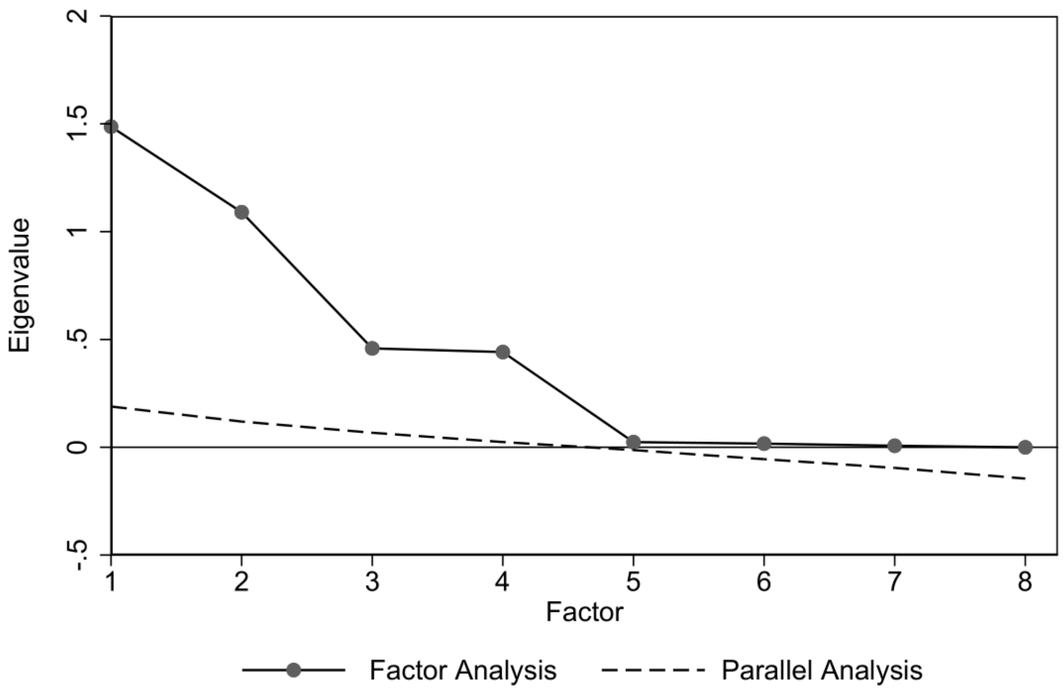
The parallel analysis first involves randomly simulating data of the same dimension as that being analysed. For example, if preforming an EFA on 6 variables measuring characteristics of N individuals, the resulting simulated dataset would be $N \times 6$. The eigenvalues of the correlation matrix among the randomly simulated data are the calculated and compared with those from the factors underlying the actual data. Horn (1965) suggests retaining factors from the actual data as long as their eigenvalues are larger than those from the randomly generated correlation matrix. To complement this we generate scree plots as proposed by Cattell (1966), plotting the eigenvalues of factors in order of magnitude.[1]

Figure C8 shows one of these plots for initial cognitive and socio-emotional skill. Using Horn (1965)'s rule-of-thumb, the figure would suggest these measures have enough variation to retain at most 4 factors. Cattell (1966) suggests retaining only the factors whose eigenvalues are larger than that of the factor at which the first large drop in eigenvalue occurs. In Figure C8 the first major drop in eigenvalue occurs at factor 3. Additionally, Kaiser (1960) suggests keeping only a number of factors greater or equal to the number of eigenvalues greater than 1, which is true for only 2 latent factors in Figure C8. Together, these criteria suggest that these measures are rich enough to capture at least the two underlying factors we ex-ante believe to be underlying the measures. We repeat this analysis in each round, grouping observables as those measuring child human capital, investments, or parental skills.

Having verified the measures share meaningful variation with which to capture their underlying factor, we then establish the relationship between each measure and retained factor by estimating their factor loadings. Tables C4 and C5 show the rotated factor loadings and unique variance associated with each measure of human capital and investment respectively in each period. We rotate the factor loadings obtained from an EFA using the *oblique quartimin* rotation, which enables us to obtain a vector of factor loadings allowing for underlying factors to be correlated and so the loadings accurately capture the extent to which observables group around factors. For children's human capital (Table C4) there is a clear divide between those we ex-ante believed to measure socio-emotional versus cognitive skill. For example, in the initial period the SDQ

[1] To conduct this analysis we use Philip B. Ender's *-fapra-* package in Stata.

Figure C8: Eigenvalues from EFA and parallel analysis of initial (Age 8) child socio-emotional and cognitive skill measures



Note: The solid line connects the eigenvalues of the factors underlying 8 measures of socio-emotional (5 measures) and cognitive skill (3) at age 8 in the YL survey. The dotted line connects the eigenvalues of the 8 factors underlying randomly simulated data of the same dimension (i.e. $N \times 8$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

measures load heavily on Factor 2 - which we define as the socio-emotional factor - whereas the cognitive assessments load heavily on Factor 1 - the cognitive factor. There are a couple of slight exceptions to this, however. Agency appears to load on both factors in periods 2 and 3, albeit to a much larger extent on the socio-emotional factors. The same is true for self-efficacy in period 3. This is perhaps unsurprising given the relationship between measures of this type and cognitive skill. We retain these measures given that they are highly correlated with cognition, and are measures of particular interest to the questions of this paper.

Although, informed by the data, we only retain one factor for investments, Table C5 shows the estimated rotated factor loadings and unique variance associated with each measure of investment across periods. These are useful in that they provide an ex-ante approximation to the extent of signal in each measure.

Table C4: Factor loadings and unique variance of observable cognitive and socio-emotional skill measures

	Factor 1	Factor 2	Uniqueness
Age 8			
SDQ conduct problems	0.019	0.605	0.630
SDQ emotional symptoms	0.055	0.450	0.788
SDQ hyperactivity	-0.035	0.620	0.621
SDQ peer problems	-0.007	0.274	0.925
SDQ prosociality	0.026	0.185	0.964
Ravens test score	0.389	-0.063	0.852
Writing level	0.790	-0.048	0.385
Reading level	0.750	0.067	0.418
N	606		
Age 12			
Agency	-0.011	0.316	0.904
Pride	0.002	0.853	0.270
Current position on ladder	0.023	0.096	0.988
Maths test score	0.618	0.068	0.568
PPVT score	0.904	-0.020	0.202
N	630		
Age 15			
Agency	0.106	0.326	0.875
Pride	-0.002	1.201	-0.442
Cantril's ladder	0.100	0.114	0.975
SDQ: Emotional	0.279	0.078	0.911
Maths test score	0.711	-0.048	0.499
PPVT score	0.821	0.025	0.321
Cloze test score	0.875	0.002	0.233
N	614		
Age 19			
Agency	0.197	0.325	0.830
Self-efficacy	0.683	0.148	0.473
Self-esteem	0.788	-0.057	0.393
Peer relationships	0.667	-0.061	0.567
Cantril's ladder	0.304	-0.030	0.910
SDQ: Emotional	0.205	0.124	0.933
Maths test score	-0.006	0.821	0.327
Language test score	-0.004	0.839	0.297
N	584		

Note: The table contains rotated factor loadings and the proportion of variance in each cognitive and socio-emotional skill measure not shared with all others after retaining two factors from an initial exploratory factor analysis. Two factors were retained based on the assumption the measures proxy two latent concepts, socio-emotional and cognitive skill and the rules-of-thumb for factor retention proposed by Kaiser (1960), Horn (1965), and Cattell (1966). Factor loadings were obtained through an oblique quartimin rotation.

Table C5: Factor loadings and unique variance of observable investment measures

	Factor 1	Uniqueness
Age 12		
Per child book expenditure	0.584	0.659
Per child uniform expenditure	0.285	0.919
Per child non-food expenditure	0.332	0.890
Hours studying	0.155	0.976
Hours in school	0.327	0.893
Food groups	0.543	0.705
N	593	
Age 15		
Per child book expenditure	0.734	0.462
Per child uniform expenditure	0.419	0.824
Per child non-food expenditure	0.338	0.886
Hours studying	0.405	0.836
Hours in school	0.416	0.827
Food groups	0.427	0.818
N	526	
Age 19		
Education expenditure	0.319	0.898
Non-food expenditure (soles)	0.051	0.997
Hours studying	0.626	0.609
Hours in school	0.881	0.223
Food groups	0.080	0.994
N	618	

Note: The table contains rotated factor loadings and the proportion of variance in each investment measure not shared with all others after retaining one factors from an initial exploratory factor analysis. One factor was retained based on the assumption the measures proxy one latent investment and the rules-of-thumb for factor retention proposed by Kaiser (1960), Horn (1965), and Cattell (1966). Factor loadings were obtained through an oblique quartimin rotation.

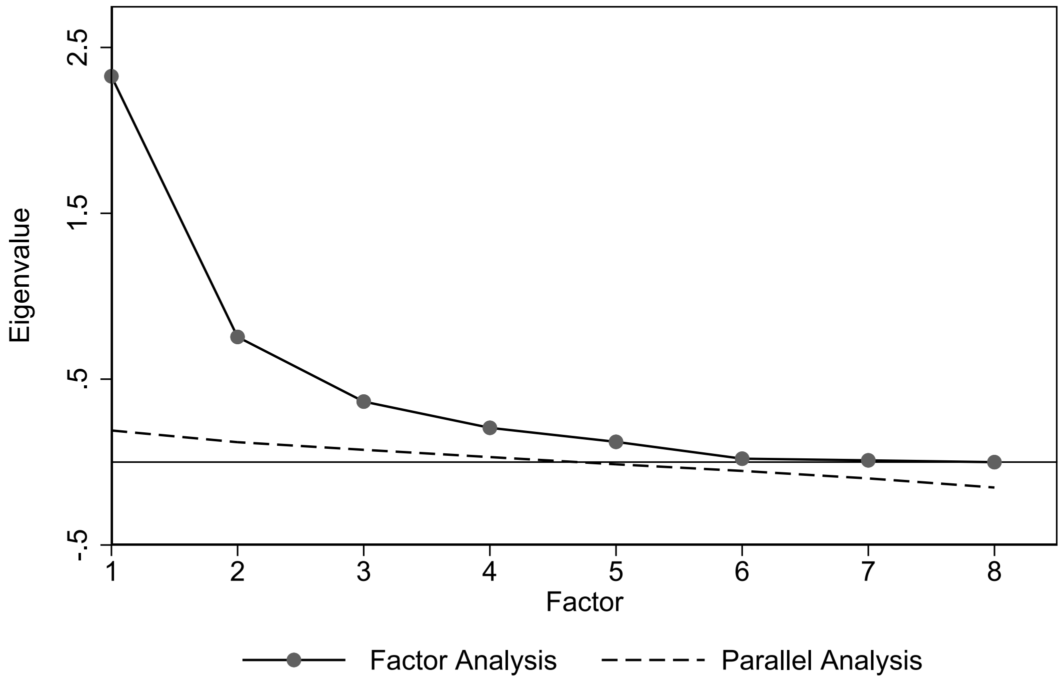
C.3.4 Results of EFA on Age 22 Socio-emotional Skill Measures

At age 22, as was the case between ages 8-19, we again first used the principal of CSE to select measures, excluding those that were measuring subjective wellbeing or relied on assessments of their feelings/reactions to the behaviour of others. This meant, for example, excluding Cantril's ladder (Cantril et al., 1965) and measures of trust and respondents' relationship with their parents, as well as measures of pride and self-esteem that had changed substantially from earlier rounds.

We were then left with 8 measures of leadership qualities, quality of relationships with peers, ability to work in a team, self-efficacy, agency, grit, and the Big 5 emotional stability and conscientiousness scales. Ex-ante, we divided these into two groups, with the former 3 seemingly best representing social skills, and the latter 5 task effectiveness. With these measures we first confirmed they shared sufficient variation to extract as in the preceding periods - Figure C9 plots the eigenvalues of the factors underlying the measures alongside those from a parallel analysis as outlined in the previous subsection. It shows that, using the same rules-of-thumb as in the EFA of measures at previous ages the data supports extracting either 1 or 2 factors. Although the eigenvalue of the second factor is below 1 - another commonly used threshold to decide upon extraction (Kaiser, 1960) - we chose to extract 2 factors in order to disaggregate socio-emotional skills into 2 domains.

Table C6 then shows the estimated rotated factor loadings and unique variance that correspond to each retained measure and factor at age 22. It shows that, with the exception of self-efficacy, our ex-ante beliefs about the groupings of the skill measures is borne out in the data - leadership qualities, quality of relationships with peers and ability to work in a team load heavily on the first factor, whereas agency, grit, and the Big 5 emotional stability and conscientiousness scales load heavily on the second.

Figure C9: Eigenvalues from EFA and parallel analysis of age 22 socio-emotional skill measures



Note: The solid line connects the eigenvalues of the factors underlying 8 measures of socio-emotional skill at age 22 in the YL survey. The dotted line connects the eigenvalues of the 8 factors underlying randomly simulated data of the same dimension (i.e. $N \times 8$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

Table C6: Factor loadings and unique variance of observable socio-emotional skill measures at age 22

	Factor 1	Factor 2	Factor 3	Uniqueness
Social skills				
Leadership	0.668	0.004		0.551
Peer relationships	0.648	-0.091		0.648
Teamwork	0.583	0.062		0.609
Task effectiveness				
Agency	0.106	0.364		0.807
Self-efficacy	0.703	0.054		0.454
Grit	-0.040	0.643		0.617
Big 5 neuroticism	-0.047	0.498		0.780
Big 5 conscientiousness	0.161	0.512		0.607
N	596			

C.3.5 Additional Production Function Estimates

Table C7: Variance covariance matrix of the initial conditions

	$\ln H_{s,0}$	$\ln H_{c,0}$	$\ln P_s$	$\ln P_c$	$\ln Y_0$
$\ln H_{s,0}$	1.774				
$\ln H_{c,0}$	0.663	8.762			
$\ln P_s$	0.135	2.737	0.037		
$\ln P_c$	-0.373	9.500	1.930	12.870	
$\ln Y_0$	-0.0188	0.621	0.114	0.590	1.141

Table C8: Mean vector of the initial conditions

$\ln H_{s,0}$	$\ln H_{c,0}$	$\ln P_s$	$\ln P_c$	$\ln Y_0$
(0	0	0	0	6.25)

Table C9: Estimates of socio-emotional production function parameters with interacted investment and cognitive skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.006	0.175	0.173***
	(0.057)	(0.682)	(0.063)
	[-0.100,0.087]	[-0.946,1.296]	[0.069,0.277]
$\ln H_{c,t-1}$	0.534***	0.683	0.508*
	(0.107)	(0.599)	(0.272)
	[0.358,0.711]	[-0.302,1.668]	[0.060,0.955]
Parental human capital (fixed over time)			
$\ln P_s$	0.190	0.023	0.124
	(0.154)	(0.652)	(0.273)
	[-0.063,0.443]	[-1.049,1.095]	[-0.325,0.572]
$\ln P_c$	0.012	0.092	-0.050
	(0.025)	(0.151)	(0.034)
	[-0.030,0.054]	[-0.157,0.340]	[-0.106,0.005]
Investments			
$\ln I_{t-1}$	0.481***	0.058	0.382
	(0.085)	(0.378)	(0.233)
	[0.340,0.621]	[-0.564,0.680]	[-0.001,0.764]
$\ln I_{t-1} \times \ln H_{c,t-1}$	-0.210***	-0.030	-0.135
	(0.064)	(0.343)	(0.171)
	[-0.315,-0.106]	[-0.595,0.534]	[-0.417,0.147]
$\sigma^2_{\eta_n}$	3.75	5.22	.893
N	602	601	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix Tables C.2. Appendix C.1 outlines the method used to obtain all estimates in the table.

Table C10: Estimates of socio-emotional production function parameters with interacted investment and socio-emotional skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.394**	0.524	0.162***
	(0.194)	(0.841)	(0.062)
	[-0.713,-0.074]	[-0.858,1.907]	[0.059,0.265]
$\ln H_{c,t-1}$	0.198*	0.416	0.452**
	(0.102)	(0.862)	(0.194)
	[0.031,0.366]	[-1.002,1.835]	[0.134,0.770]
Parental human capital (fixed over time)			
$\ln P_s$	0.397***	-0.069	0.195
	(0.134)	(0.492)	(0.198)
	[0.176,0.618]	[-0.878,0.740]	[-0.131,0.521]
$\ln P_c$	-0.043	0.074	-0.039
	(0.028)	(0.128)	(0.027)
	[-0.088,0.003]	[-0.137,0.285]	[-0.084,0.005]
Investments			
$\ln I_{t-1}$	0.683***	0.145	0.219
	(0.207)	(0.536)	(0.138)
	[0.343,1.023]	[-0.736,1.027]	[-0.008,0.446]
$\ln I_{t-1} \times \ln H_{n,t-1}$	0.158**	-0.091	0.012
	(0.076)	(0.213)	(0.075)
	[0.034,0.283]	[-0.442,0.260]	[-0.111,0.135]
$\sigma^2_{\eta_n}$	2.4	11.4	.902
N	602	601	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t - 1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix Tables C.2. Appendix C.1 outlines the method used to obtain all estimates in the table.

Table C11: Estimates of cognitive production function parameters with interacted investment and cognitive skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.048	-0.039	0.048*
	(0.039)	(0.166)	(0.029)
	[-0.016,0.113]	[-0.312,0.234]	[0.001,0.095]
$\ln H_{c,t-1}$	0.572***	0.623***	0.874***
	(0.080)	(0.120)	(0.207)
	[0.440,0.703]	[0.425,0.821]	[0.533,1.215]
Parental human capital (fixed over time)			
$\ln P_s$	0.121	0.210	-0.026
	(0.108)	(0.159)	(0.159)
	[-0.057,0.299]	[-0.051,0.471]	[-0.287,0.236]
$\ln P_c$	0.011	-0.002	-0.043**
	(0.019)	(0.014)	(0.020)
	[-0.020,0.042]	[-0.025,0.022]	[-0.076,-0.010]
Investments			
$\ln I_{t-1}$	0.437***	0.196**	0.312*
	(0.065)	(0.078)	(0.189)
	[0.330,0.544]	[0.068,0.324]	[0.001,0.624]
$\ln I_{t-1} \times \ln H_{c,t-1}$	-0.189***	0.012	-0.166
	(0.051)	(0.083)	(0.128)
	[-0.272,-0.105]	[-0.125,0.149]	[-0.377,0.045]
$\sigma^2_{\eta_c}$	.105	.681	.843
N	598	595	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 15 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix C.2. Appendix C.1 outlines the method used to obtain all estimates in the table.

Table C12: Estimates of cognitive production function parameters with interacted investment and socio-emotional skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.043	-0.518	0.028
	(0.152)	(0.854)	(0.027)
	[-0.208,0.293]	[-1.922,0.887]	[-0.016,0.072]
$\ln H_{c,t-1}$	0.356***	1.047	0.882***
	(0.080)	(0.695)	(0.169)
	[0.224,0.488]	[-0.096,2.191]	[0.604,1.160]
Parental human capital (fixed over time)			
$\ln P_s$	0.404***	0.277	-0.042
	(0.139)	(0.271)	(0.144)
	[0.174,0.633]	[-0.169,0.724]	[-0.279,0.195]
$\ln P_c$	-0.023	-0.001	-0.030*
	(0.023)	(0.021)	(0.018)
	[-0.061,0.015]	[-0.036,0.034]	[-0.059,-0.001]
Investments			
$\ln I_{t-1}$	0.219	0.072	0.189**
	(0.163)	(0.240)	(0.093)
	[-0.049,0.487]	[-0.323,0.466]	[0.035,0.342]
$\ln I_{t-1} \times \ln H_{n,t-1}$	0.002	0.122	-0.028
	(0.061)	(0.207)	(0.044)
	[-0.099,0.102]	[-0.219,0.463]	[-0.100,0.044]
$\sigma^2_{\eta_c}$	.0619	.494	.878
N	598	595	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 15 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix C.2. Appendix C.1 outlines the method used to obtain all estimates in the table.