Essays in Human Capital Development



Debbie Blair

Oriel College

University of Oxford

A thesis submitted for the degree of

Doctor of Philosophy

Michaelmas 2019

All chapters in this thesis are single authored.

None of the chapters in this thesis are published, or forthcoming as of date of submission.

Acknowledgements

I am grateful to my supervisors, Abigail Adams and Michael Keane for their words of encouragement and support over the last 3 years.

I could not have done this (and stayed sane) without my colleagues and friends at the Institute for Fiscal Studies. I very much valued the research chats, the tea breaks and the walking meetings over the past 2 years.

I am so grateful to all my friends, of which there are too many to name in London, Dublin, Chicago and scattered around the world. You helped make sure I had a fulfilling life outside of Economics.

For financial support I am indebted to the Economic and Social Research Council for their funding over the past four and a half years. I am also indebted to Michael Keane for funding a research trip to UNSW in Sydney.

I am particularly grateful for the academic support from researchers in many institutions. These include professors from University College London, University of Chicago, University of New South Wales, Deakin University, Trinity College Dublin and of course, University of Oxford. These include, but are not limited to, Orazio Attanasio, Sonya Krutikova, Craig Olsson, Chris Greenwood, Brent Hickman, Steve Bond and Chris Bowlder. I would also like to thank Lesley Darcy for fielding all my questions and supplying much needed support in getting me to the end of the process.

I thank my parents for all their support and encouragement - I told you I wouldn't be a student forever!

I'd like to thank the soles of my feet for all of their literal and figurative support during my PhD. Turns out a long walk can solve most problems.

Abstract

Human capital is the term used to describe the skills, experience, attitudes, aptitudes of an individual. It encompasses a wide array of skills that are contribute to the macroeconomic performance of an economy and the successful functioning of an individual. It is important for productivity, per capita incomes and sustaining growth. Insights from other disciplines such as psychology, child development and education can inform economic models. These disciplines have a long history of research on human capital, albeit using different labels. Overall, this thesis incorporates both constructs and methods from other disciplines, to help examine important research questions through an economic framework. These chapters contribute to our understanding of the development of human capital and socio-economic position.

Chapter 2 and 3 examine the role of specific inputs in the human capital process. Both of these chapters focus on the earliest years of a childs' life, recognising their importance as critical periods of development. Chapter 2 expands the existing literature of human capital production function estimation by including preschool as an important input for explaining cognitive and health skills at age 5 and 8. It compares these estimates for four lower-middle income countries; Ethiopia, India, Peru and Vietnam. Chapter 3 examines if the existing understanding of human capital production functions can be improved by including a measure of an infants' disposition - temperament - using a dataset from Ireland.

In contrast to the other two chapters, Chapter 4 focuses on the full period of childhood and adolescence up to early adulthood. It proposes that existing measures of socio-economic status, such as education or income, may not be the most appropriate. It proposes a more composite measure that accurately captures the complex socio-economic positions of young people in today's economy. It examines the role of distinct types of negative shocks that occur at different points in the lifespan and how these impact the likelihood of being advantaged or disadvantaged in adulthood. It also links this measure of SES to parenting behaviours and human capital at 9 months, providing some insight into intergenerational transmission of human capital.

Contents

1 Introduction **1**

2 Estimating the Effect of Preschool in the Production Function of Skills **6**
2.1 Introduction . . . 8
2.2 Literature Review . . . 12
2.3 The preschool context . . . 20
2.4 Data . . . 27
2.5 Theoretical methodology . . . 35
2.6 Results . . . 43
2.7 Discussion . . . 51

3 Temperament, Investment and Skill Development **84**
3.1 Introduction . . . 86
3.2 Literature Review . . . 89
3.3 Temperament . . . 94
3.4 Theoretical Framework and Estimation Strategy . . . 102
3.5 Data . . . 111
3.6 Results . . . 122
3.7 Implications of the point estimates: money or time? . . . 133
3.8 Discussion . . . 136

4 Risk Factors from Birth to Emerging Adulthood and their Impact on later Socio-Economic Status **160**
4.1 Introduction . . . 162
4.2 Literature Review . . . 166
4.3 Methodology . . . 182
4.4 Data . . . 192
4.5 Variable Creation and Descriptives . . . 194
4.6 Results . . . 203
4.7 Pathways to the next generation . . . 211
4.8 Discussion . . . 219

5 Conclusion **251**

1

Introduction

There is increased recognition that the performance of the macroeconomy is not just reliant on typical inputs such as capital and labour, but that the quality of that labour matters for growth. Having a well educated work force not only can increase the productivity of existing firms, but might also be a reason that foreign investment flows into a country. Economists have coined this factor *'human capital'*, and it plays an ever growing role in macro and micro economic analysis.

Human capital has not just been the purview of economics, however, with a large body of research in psychology and child development focusing on the developmental trajectory of different types of skills across the life span. Such research examines how individuals develop specific skills, for instance documenting how infants acquire and develop language, or how children become aware that they and other individuals have distinct mental states (beliefs, intents, desires, feelings) known as theory of mind. Child development specialists try understand how external influences interact with genetic endowments to produce skills, and how these skills are related to the underlying neurological and chemical structures of the brain.

The importance of cross-disciplinary knowledge sharing and the increased attention on how children develop skills originally motivated this thesis. It hopes to bring not only insights but also methods commonly used in psychology into the realm of economics to augment the understanding of skill development.

One of the main reasons we care about human capital is its link to later outcomes such as educational attainment and income. I suggest however that we can combine these and other information on employment, education and class in a way that provides a richer depiction of socio-economic status.

The economy is changing and measures of disadvantage and advantage need to accurately reflect the lived experiences of the population. There is less stability in employment, with people in the 2000s changing jobs on average twelve times in the US (2019*a*). People are entering the labour force at later ages, and reaching the typical adult milestones later and later. The average age of first time house buyers has increased to thirty three in England (2019*b*) from an average of 23 in 1960s, the age of first marriage is increasing (33.4 for men and 31.5 for women (2016) up from 28.3 and 25.3 respectively in 1960) and many people are choosing to delay childbirth (average age of first birth is 28.8 (2017*a*) up from around 24.8 in the 60s). Having a college degree is no longer the advantage in the labour market that it once was, with increased pressure to obtain further education. These changes not only suggest we might need to rethink how we measure advantage/disadvantage but that we need to think more carefully about the age that we measure outcomes at.

The second and third chapter of this thesis speak directly to the question of how human capital develops. The second chapter focuses on the impact of preschool and the fourth proposes that temperament may help explain heterogeneity in skills. The fourth chapter focuses on the timing and types of socio-economic risk factors and how they relate to a new measure of socio-economic status in adulthood. It also then looks at how this measure (and as a result those past shocks) impact the next generation's human capital.

Chapter 2 quantifies the effect of preschool on the cognitive and health outcomes of children at age 5 and age 8 in four different contexts. It examines the process of human capital formation in Ethiopia, India, Peru and Vietnam, using the same methodology and inputs in each country to try to understand if differences in preschool can explain observed differences in skills. Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017) estimate the human capital production function for health and cognition in India, and Ethiopia and Peru respectfully. They look at the impact of investment and past skills in explaining future skills at four points in time, age 5, age 8, age 12 and age 15. They allow the parameters of the production function to vary at each time point, as inputs

may be more or less productive at different ages. They find that investment substitutes for unobserved shocks, and that inputs are complements with low degrees of substitutability. This paper builds on this work in two main ways. Firstly, this paper focuses on preschool as a missing input in the production function. The original paper accounts for private investment from parents, but does not include any measure of public investment. There is both variability across- and within- country in the numbers of children attending preschool and the numbers of hours children typically spend in preschools. It was thought that preschool could potentially explain part of the differences in test scores. Secondly, it includes another LMIC country - Vietnam. Vietnam is a well known outlier amongst other LMICs, and outperforms the UK and the USA on PISA test scores. PISA tests in a comparable way the knowledge base of 16 year olds across a variety of domains in near to 80 countries worldwide. Cross-country comparisons help to validate if preschool is beneficial in all settings, and if not, what makes it helpful in some settings but not others.

Using a latent factor measurement system and non-linear least squares estimation of the production function I find that there is evidence of increases in cognitive scores at age 5 from attending school in Ethiopia. I also find evidence that spending more time at school may also increase cognitive scores at age 5 in both Peru and Vietnam. There seems to be little to no movement on health skills in relation to either measure of preschool, with the exception of hours attending school in Vietnam. I also looked at age 8 outcomes to see if there is a delayed effect of preschool attendance, via a school readiness channel. This channel proposes that preschool helps improve skills, by teaching children the skills needed to get the most out of their classes in school at later ages, rather than having a direct impact on skills now. There was some evidence for this in Ethiopia, Peru and Vietnam, but none in India.

Chapter 3 again focuses on the question of human capital development, addressing if a key measure from psychology, temperament, can help explain human capital formation. It analyses the impact of temperament, as well as time and money investment on outcomes of 3 year olds in a representative sample in Ireland. I consider different functional forms of the production function to allow for non-linearities of the key inputs, although recognising I lack clear identification of the main variables of interest. I propose three pathways through which temperament might affect cognitive and socio-emotional outcomes.

First, temperament might act as a fixed difference amongst infants that directly impacts the development of cognitive and socio-emotional skills. More difficult temperaments are thought to decrease cognitive and non-cognitive skills, with stronger effects on the latter. The second hypothesis is that investment by parents is likely to be less effective the more difficult the child is. This will change the productivity of the investment. The third pathway proposes that difficult temperaments might decrease the amount of investment any child receives. It is likely that parents could reinforce negative temperaments by investing less in their child. However this could go in the other direction: parents may realise that a difficult temperament puts their child at a disadvantage and may compensate for this by investing even more in the child.

I find that there is some evidence of lower levels of investment for those with more difficult temperaments. There is little evidence of direct or multiplicative effects of temperament on cognitive skills but some suggestion that it is strongly related to our measures of socio-emotional skills. However, problems of measurement make it hard to interpret such findings with confidence. We have a long way to go in measuring personality and other forms of socio-emotional skills, as well as thinking about how we include these in our models of child development.

Chapter 4 turns its attention to the impact of negative socio-economic risk factors throughout childhood, adolescence and emerging adulthood on later life outcomes. I look at a sample of 1055 individuals who were born in 1983 in Victoria, Australia. This sample was followed from birth up to age 28, with further sampling of those who have subsequently had a child - providing an unusually rich three-generational dataset. This paper defines a new measure of socio-economic status that combines numerous sources of information using a latent class analysis. This helps to classify the sample into a a threefold typology of socio-economic type at age 28. First, the typical advantaged group with high levels of education, income and skilled employment, secondly, a typical disadvantaged group with low levels of education and low skill jobs and a sizeable third group which I coin *'economically unstable'* who have high levels of education and skills, but with low incomes and a large amount of instability in their employment.

There are a number of potential ways that the socio-economic context from birth until young adulthood may matter. First, the presence of socio-economic

disadvantage in a formative period of the children's life may have long lasting implications, even if they are relatively well off in other periods of development. This is the sensitive period hypothesis: at certain times children are particularly vulnerable to external factors, both positive and negative. A second perspective suggests that socio-economic disadvantage is made up of multiple components, and that it is the simultaneous occurrence of multiple risk factors that is detrimental for outcomes. Any one risk factor on its own might not have a negative effect but when multiple risks co-occur it can create a sort of tipping point after which there are negative effects on child outcomes. Alternatively, it might not matter when the shocks occur, but instead it is the build up of reoccurring shocks over time that matters. The persistence of a particular type of shock could be damaging for future outcomes. I look at these in turn, and find that shocks that occur in childhood in addition to structural features of the household predict being in the typically disadvantaged group. Shocks at later time points are associated with being in the unstable class. Certain types of shock might be more risky for certain classes, with parental unemployment predicting type 2 and financial risk and a change in marital status predicting type 3. I then examine how these classes relate to the human capital of the next generation, for those remaining in the sample who have had a child. It seems that there is increased risk for problem behaviours at 9 months for those who were in the unstable class, even after controlling for parental behaviour.

Overall, this thesis contributes to the literature on human capital by examining the role of both preschool and temperament in producing cognitive, health and non cognitive skills. It also speaks to the intergenerational transmission of negative shocks, as well as how we measure socio-economic position.

By 2030, ensure that all girls and boys have access to quality early childhood development, care and pre-primary education so that they are ready for primary education

Sustainable Development Goal 4.2
The United Nations

2

Estimating the Effect of Preschool in the Production Function of Skills

A Comparison of 4 Lower Middle Income Countries

Abstract

Preschool availability and attendance has increased dramatically both in higher and lower middle income countries (LMICs). In particular, preschools in LMICs have seen a large increase in attention and in resources. However, there is limited research on the role that preschool plays in both increasing school readiness and increasing cognitive, socio-emotional and health skills. Typically, production functions of skills include one measure of investment, often a measure of parental involvement. This paper expands existing work on production function estimation by including both a measure of private investment and public investment from schools. I examine public investment both on the intensive margin using a measure of hours spent in preschool and then on the extensive margin, using a dummy of whether the child attended preschool. I also expand on previous research by using another LMIC, Vietnam, one that consistently scores highly on PISA educational standards. The productivity of preschool may be higher in Vietnam, which could explain why Vietnam outperforms other similar countries. I estimate a Constant Elasticity of Substitution production function for both health and cognition at age 5 and age 8, using non-linear least squares. I control for endogeneity of investment using a control function approach and use a latent factor measurement system to estimate key inputs and outputs. I compare findings across all four countries and find that attending preschool in areas with low attendance rates is linked to increases in cognition, but not health skills. An additional hour spent in school seems to be effective an increasing cognition contemporaneously in Ethiopia, Peru and Vietnam. There is some evidence of a preschool readiness channel in that preschool has a direct effect at later ages in Ethiopia. Further work should account for the endogeneity of public investment, and examine the importance of preschool quality in determining outcomes.

2.1 Introduction

Preschool attendance has significantly increased in higher income countries over the past few decades. There has been growing awareness from both an academic and policy perspective that early education is an important mechanism to promote positive life outcomes. Lower and middle income countries (hereafter **LMIC**) often don't have a well-developed preschool system and as such have an opportunity to design a system that optimises outcomes for children. Informed policy making requires an understanding of how preschool interacts with other inputs to produce skills. However, there are few robust estimates of the impact of preschool attendance on human capital, in particular a paucity of estimates that are comparable across different countries. This paper examines the effect of the internal and external margins of preschool attendance on measures of human capital. Is it enough to just get children to attend school or does the amount of time a child spends in school matter more?

Human capital is an important determinant of outcomes economists typically care about - labour market success, educational attainment, criminal and other anti-social activity, and savings behaviour among others (Heckman (2007), Heckman (2000)). Human capital is a multi-dimensional object, encompassing cognitive skills (maths, language), non cognitive (grit, determination, personality), and health (mental, physical). Cognitive skills are directly related to increased education achievement, both in terms of test scores, degree attainment and the number of years of education completed, as well as better labour market outcomes (skill level, income) (García et al. (2016), Hanushek et al. (2013)). Socio-emotional skills have also been related to labour market outcomes and educational participation decisions (Lindqvist and Vestman (2011*a*), Edin et al. (2018)). The two skills are likely to be interrelated, with some evidence of cross-complimentary between different types of skills. Not only does increased health allow an individual to function better in day-to-day tasks, it is also directly related to the development of cognitive and socio-emotional skills (Grantham-McGregor et al. (2007), Woldehanna, Behrman and Araya (2017)). While a three dimensional human capital object would have been preferable the quality of the socio-emotional measures was extremely low and its reliability and response rate was not consistent across country. As such the analysis was restricted to only cognition and health skills, with health being particularly important in these LMIC settings.

A wide body of research has examined how human capital develops over the lifespan with an increased focus on the early years. The brain is extremely malleable at young ages, undergoing vast neural development via synapse formation and pruning. Differences that emerge in the early years can be difficult to overcome. Research has attempted to dynamically estimate the way human capital develops, recognising the roles of parental investment, past levels of skills and parental endowments of skills in human capital accumulation. This research will attempt to expand the scope of inputs by including preschool attendance as an important determinant of skills.

I use data from Young Lives, a longitudinal cohort study - covering the four aforementioned countries. I examine the production function of cognition and health using the younger cohort of this dataset. This consists of 2000 children per country starting at 9 months, followed up at age 5 and age 8. This data gives us a rich set of demographic, social and community level factors that enable us to estimate the production function of skills at different ages. A production function is essentially the process through which inputs are transformed into outputs.

I estimate our main inputs - cognition, health, parental cognition, parental health, investment - as latent factors using a measurement model. I derive the full distribution of latent factors, instruments and controls using the EM algorithm. I then estimate a constant elasticity of substitution production functions using non-linear least squares, using a control function to account for endogeneity of investment. This procedure was developed initially by Cunha, Heckman and Schennach (2010), and further developed by Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017).

In the latter two papers, the production functions of health and cognition were estimated at age 5, 8, 12 and 15[1] in Ethiopia, India and Peru, focusing on the role of parental investment. This work builds on these papers in two

[1]The original papers estimate the production function at age 5 and 8 using data from the younger cohort, with the production function at age 12 and 15 using the older cohort of data. If we assume that the production function has not changed from one cohort to the next, they can be dynamically compared across ages. However, the questions available about preschool differed across the younger and older cohort, with the older cohort relying on recall on only if the child went to preschool, with no hours available. As such it did not feel valid to compare across samples as in Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017). The new waves of the younger cohort are now available at age 12 and 15, which may enable this work to be extended using all the same cohort to the full set of ages.

main ways - first it includes a fourth country, Vietnam which allows me to compare the human capital process to other settings. It is useful to compare results across different countries, as it should not just be assumed something that works in one setting will automatically translate to the next[2]. Second, it focuses attention on preschool - an important input at these ages that was omitted from the original analysis. I focus on the production functions at age 5 and age 8 as these represent the two most likely periods that preschool has an effect, age 5 representing the contemporaneous effect of preschool and age 8 to examine any effects that last after the child has begun formal schooling. I would expect that effects at age 12 and age 15 would be muted, and may also interact with later measures of schooling[3].

Preschool is hypothesised to affect cognition and health in multiple ways. First for cognition, both attending preschool and spending more hours in preschool would be expected to increase current stock of a child's cognitive skills. The extensive margin (attending preschool) and the intensive margin (increasing hours) are likely to be both important for increasing human capital. In different circumstances, it will be more appropriate to focus on one particular margin. For instance, in places where preschool enrolment is high, the intensive margin may be more informative about the usefulness of preschool. In places where preschool enrolment is low, simply attending a preschool may play a more prominent role. Overall, I expect both measures to increase current skills[4]. There may also be an additional effect of preschool at later ages, via a school readiness channel. This would be seen through an effect of preschool at later ages, that is not driven through contemporary changes in skills at the same age of attending preschool. Preschool can help children learn how to sit still, to not be distracted by other children and to learn how to concentrate. They would subsequently be better able to take in schooling investments when they begin primary school. This school readiness channel suggests an additional benefit to attending preschool, in addition to any contemporary increase in skills.

When it comes to health skills, the direction of effects are more ambiguous.

[2]Further work should explore what are the reasons behind any differences across country. It could be any number of quality differences, although these are not well understood and under-researched.

[3]As mentioned in an earlier footnote, the age 12 and 15 data came from the older cohort of individuals which did not have the same measures of preschool.

[4]Although there may be diminishing returns at higher levels of hours unexplored in this paper.

Preschools might offer health services directly such as supplying vaccinations, food or other services which would increase the stock of health. They also might teach good health practices as part of the curriculum which children would be able to adopt. Both of these would increase health of students in the short and medium run. However preschool could conceivably decrease health in the short run. Being exposed to lots of other children might expose children to pathogens and diseases which might decrease the current stock of health. However in the medium run this might help build up the immunity of the child against disease.

As well as the differential short and medium run effects of preschool, I examine the relationship between schooling and the other major inputs. Is schooling a complement to parental investment or a substitute? If inputs are complementary then more of one increases the productivity of the other. If instead inputs are substitutes then schooling may be able to overcome a lack of investment at home and vice versa.

Focusing first on the results from preschool attendance, we see that attending preschool in Ethiopia and Vietnam is significant at increasing cognition at age 8, with a small significant effect in Ethiopia at age 5. The effect at age 8 may be driven through a school readiness channel, in that preschool helps children be able to take in schooling inputs at later ages and produce higher skills. In India and Peru there is little to no effect of attendance on cognitive ability. We also see basically no effect on health, suggesting either preschool has no effect or perhaps the different channels mentioned earlier cancel each other out.

In comparison, an additional hour spent in preschool is effective at increasing cognitive ability. In Peru and Vietnam, we see current increases in cognition for an extra hour spent in preschool. Peru and Vietnam both have well developed preschools which may account for their effectiveness at increasing current measures of skills. In comparison in Ethiopia there is no current effect of time in school but there is an effect at age 8, suggesting that additional hours might be beneficial for the preschool readiness channel. There is a negative but insignificant effect of preschool in India, and across the board there seems to be no effects in India. This could reflect the low quality of the preschools in India, or potentially inaccurate measures of both time and attendance in India. There are again broadly no effects on health skills, except for in Vietnam with positive effects at both ages.

The elasticity of substitution is relatively low although imprecisely estimated, suggesting there is little to no evidence of high degrees of substitution between inputs. This suggests inputs are likely to be complements in all countries, with the elasticity typically increasing from age 5 to age 8 which suggests stronger complementarity at later ages. This broadly in keeping with findings from other contexts (Attanasio et al. (2015), Cunha, Heckman and Schennach (2010)).

These results support the main hypotheses of the paper. Attending preschool increases cognitive skills at later ages in Vietnam and Ethiopia. An extra hour in preschool increases your current cognitive ability in Vietnam and Peru. Preschool only seems to impact health in Vietnam at both ages, with no significant effects in the other countries. There are a number of mechanisms that could explain the positive effect of preschool on outcomes. First, the preschool curriculum, facilities and teachers themselves could improve children's skills directly. Second, it could be peer effects such that outcomes are improved through exposure to and interactions with other children. Third, it could be a selection issue, in that children that attend are fundamentally different than those that don't. This might be the case in Ethiopia, but somewhat unlikely in Vietnam and Peru which have very high attendance rates. These mechanisms behind the observed effects remain an avenue for further research.

2.2 Literature Review

2.2.1 Human Capital

The macro-economic literature has recognised that knowledge, or human capital, is an important component in producing goods and services, which contribute to GDP and as such is worthy of investment to boost a nation's productivity (Becker (1962)). Much of the early micro-economic research on the importance of schooling focused on high school and college age students to delineate what human capital (hereinafter **HC**) was and how it could be promoted. HC was modelled as a function of cognitive skills, captured by performance on standardised tests. This has since been expanded to include other attributes, namely non cognitive skills, that were also correlated with future positive outcomes (Almond and Currie (2011)). Skills such as motivation, perseverance, self-control and social competencies are some potential candidates that are

typically incorporated into non cognitive skills (Heckman (2006)). Central to this research area is the HC production function. Boardman and Murnane (1979) were among the first to model a cumulative production function of HC using panel data. Carneiro, Cunha and Heckman (2003) modelled the simultaneous development of cognitive and non-cognitive skills introducing concepts such as self-productivity (skills building on skills), cross-productivity (one skill increasing the amount of another) and dynamic complementarity (higher skills today increase the productivity of later investment).

Evidence from LMICs also suggests that health should be considered an important skill. Health of an individual is important in and of itself, in that individuals want to be fit and well. Health skills can include brain development and other core functions, that depend on nutrition and sanitation and other inputs. Neurodevelopment is vital for cognitive and non cognitive functions, allowing synapses and receptors in the brain to develop properly (Phillips and Shonkoff (2000)). Health is important to be able to function successfully, to achieve education and labour market success. Especially pertinent in LMICs are stunting and wasting, with stunting in particular being one of the main risk factors for child under development(Grantham-McGregor et al. (2007)). It has been shown that height-for-age z scores[5] at age 1 decrease cognitive skills directly, which has a subsequent negative indirect affect on non cognitive skills (Sánchez (2017)).

Evidence from neuroscience, biology and psychology has shown that the developmental process begins from the moment of fertilisation (Kolb (2009)). Early views adopted a static approach, believing that HC was innately endowed. However it was soon recognised that the human brain is plastic and malleable, being able to adapt to stimulation in the early years (Heckman (2007)). Environmental conditions interact with and alter gene expression to formulate skills (known as epigenetics). This increases the number of potential influences and time frames, as well as introducing the concept of critical periods. Nores and Barnett (2010) look at a range of developmental outcomes following interventions at early ages and conclude that *'children from different contexts and countries receive substantial cognitive, behavioural, health and*

[5]Height-for-age z scores are useful benchmarks for child anthropometrics, standardised relative to the median for children of the same age and gender in the WHO reference population

schooling benefits from early childhood interventions' and that these effects were sustained over time. There is also some evidence to suggest that early investment had higher returns than investment that occurred later, especially for disadvantaged groups (Barnett (2011)). Becker (2009) advocated that early investment was beneficial because there were longer periods to reap the returns. Further research suggests that early gains in skills have long-lasting effects - both because of skill multipliers (skills build on skills) and that investments are typically more productive.

There are many inputs in the HC production function, ranging from nutritional and health status of the parents, to their cognitive ability, and the levels of household stimulation.[6] A wide range of studies have focused on the potential impact of such variables which helps to inform the key inputs used in this analysis. This review focuses solely on the main variable of interest in this investigation: the early learning environment, specifically in the form of preschool.

2.2.2 Preschool

Evidence from higher income countries

A large amount of the research on preschool and early education centres has been conducted in higher income countries, namely in the U.S. and the UK. Camilli et al. (2010) conducted a comprehensive meta-analysis looking at the effects of early education interventions on cognitive and social skills. They examined 123 studies of high quality quasi-experiments and randomised control trials (RCTs) that focused on centre based interventions that only offered education services. They found the largest effect of preschool on cognitive skill development but there were positive effects on other outcomes. An earlier review by Currie (2001) on early childhood educations programmes points out that skill development incorporates cognitive skills, school readiness and socio-emotional development. Currie found short and medium term benefits of interventions on these three measures using a variety of studies from the U.S. A cost-benefit analysis of the nationwide Head Start programme suggested that

[6]There is a huge academic literature on the potential influences on child development that this review will not cover. For those interested I suggest Phillips and Shonkoff (2000) for a wide exploration of child development, as well as Almond and Currie (2011) chapter on early cognitive development.

the cost of the programme will be covered if only a quarter of long term gains seen in other more successful studies are achieved. Not only were there effects on initial skills but also increases in overall education attainment and earnings and reductions in welfare dependency and in crime.

The medium and longer term effects have been further supported by Apps, Mendolia and Walker (2013). Using a cohort of English students born in 1990 they investigated the effects of attending day care facilities on cognitive skills at age 11, 14 and 16, as well as educational intentions at age 17 and economic activity at age 20-21. They also looked at a selection of other outcomes such as attitudinal variables and socialisation, health risk behaviours and problematic behaviours. Around 80% of their sample report retrospectively that they had attended preschool. The authors used both OLS estimation with a rich set of independent variables and propensity score matching techniques to compare a group of children who did not go to go preschool with a group of comparable children who did go. They found that preschool attendance had substantial positive effects on later cognitive outcomes. This positive effect was robust across a variety of models and different matching methods which reinforces the conclusion that preschool seemingly had important effects on cognitive outcomes. Duncan and Magnuson (2013) reviewed experimental and quasi-experimental studies in the last 50 years in the U.S. and found that across the 84 studies, the average impact of the treatment was 0.35SD on cognitive outcomes. This effect size decreased with time, and also varied depending on the starting age and duration of the early education environment.

There are number of key preschool studies from the US that have been extensively studied - such as Headstart and Carolina Abecederian Project - but the Perry Preschool Project has dictated much of the early years education policy. This intervention was targeted at disadvantaged, low IQ African-American children ages three to four, in which they took part in an early childhood school programme for two years. There were long run gains in education, employment, earnings, marriage, health, reductions in crime and increased participation in healthy behaviours at subsequent evaluations. Despite initial increases in IQ there was fade out over time, with no long run effects found on measures of cognition. There were however sustained changes in positive psychological skills, which are suggested to be the mechanisms behind the aforementioned long run effects on other outcomes (Heckman, Pinto and

Savelyev (2013)).

There is also evidence from other European countries on the benefits of preschool. For instance, Santín and Sicilia (2018) used a difference in difference design to analyse the effect of universal preschool expansion in Spain. They found that those who attended preschool had a 0.15SD gain in the PISA scores[7], as well as higher grade retention. Fessler and Schneebaum (2019) found strong and positive effects of preschool attendance on labour market and educational outcomes in Austria.

Evidence from lower-middle income countries

There has been a growing number of studies looking at the effect of preschool in LMICs. Children in LMICs are growing up in contexts that are often considerably different than HICs. They may have different needs from a preschool system, for instance with an increased focus on supplying appropriate nutrition in addition to stimulating atmospheres. There may be big quality differences across countries that could impact the productivity of preschool. In LMIC research there are fewer wide scale quasi-experimental and experimental designs but there are increased numbers of smaller RCTs looking at different aspects of preschool and early learning environments.

Martinez, Naudeau and Pereira (2012) analysed a randomised roll out of preschools in Mozambique. They found positive effects on cognition, subsequent school participation (children were 24% more likely to be at the appropriate grade of schooling) as well as effects on socio-emotional skills. However, they found no effects on health. The authors state that given 40% of children were already stunted, this would be hard to reverse within the short time frame (and in general it is very difficult to reverse stunting). A propensity score matching approach was used by Zhang (2017) in China. He found that attending preschool increased cognition amongst 7th graders but the effects had faded out by age 9.

Berlinski, Galiani and Gertler (2009) evaluated an early education programme in Argentina. They found that one year extra of preschool increases third grade test scores by 0.23 SD, as well reporting positive effects of atten-

[7]PISA is an international test of English, maths and science abilities of 15 year olds. It was designed to be comparable across country. For more information see .

dance on non cognitive measures such as attention, self control and classroom participation. Berlinski, Galiani and Manacorda (2008) used retrospective data from the Uruguayan household survey on preschool attendance and its subsequent impact on later outcomes. This analysis tracked outcomes up to age 15 and suggests that the benefits of preschool accumulate with time. They use both an IV approach and a within household estimator to substantiate their findings that preschool does indeed have both short and long term benefits. Behrman et al. (2014) used longitudinal data to look at the impact of preschool on life outcomes in Guatemala. They found that preschool had an effect on adult verbal skills, but no effects on measures of non verbal skills. They did find an indirect effect, in that preschool increased height-for-age scores at age 6 which impacted non verbal skills in adulthood, even after controlling for school attainment. This is further evidence that health is an important component of human capital production functions.

There is some evidence that preschool attendance may in fact have negative consequences. Specifically in Cambodia, Bouguen et al. (2018) found that there were small and insignificant effects of preschool construction on the entire sample. However for the most disadvantaged there were negative effects. They suggest it is important to consider the correct counterfactual - what is it that individuals are doing instead of going to preschool? In many LMICs preschools are not available, so instead children get sent early to primary school. In this scenario, poorer and less educated parents substituted away from primary to preschool. Other parents withdrew their children altogether, maybe not trusting the preschools. If countries are trying to promote preschool as a widespread policy, it is important to consider what preschool might be crowding out, and what the next best alternative might be.

There is relatively little known about the substitution between different education options, which in LMIC could be care in the home or in an informal preschool sector. There is also very little known about possible substitution between parental investment and early childhood education. In a context where the standard of preschool is poor then parents might compensate for the lack of preschool quality by increasing investment (parental investment here is a substitute). However, investment could also potentially be a compliment to preschool in that individuals who attend school may benefit more from parental investment, especially time spent at school makes the child more

receptive to parental investments and willing to learn. I hope to examine this substitution between investment and preschool by looking at elasticity of substitution between inputs.

These papers all attempt to answer the question of the importance of preschool, in very different contexts using a variety of methods. This can make it difficult to draw any firm conclusions - not knowing if it is a methodological difference driving different findings, or if the effects are actually different in different places and systems. This paper overcomes this by using the same methodology in four very different countries to examine the potential effects of preschool.

Evidence from Young Lives data

A number of different studies have used the Young Lives data-set to look at how skills develop. Woldehanna (2011) and Woldehanna and Gebremedhin (2012) look at the impact of attending preschool in Ethiopia on cognitive skills. They use OLS, IV and propensity score matching and find that there is a short run effect on cognitive skills at age 5, that is sustained at age 8. They do not use full production function estimation. Helmers and Patnam (2011) examined the production functions using both cohorts of the Indian data. They used both the OLS and IV estimation approaches to estimate the production functions of health, cognitive and non-cognitive skills[8]. They find strong evidence of self-productivity of cognitive skills and cross-productivity for non cognitive skills, health at age 1 is important for cognitive skill development. Health at age 1 also seems to be dependent on parental care in utero and the first year. Dercon and Sánchez (2013) found that height (which is often taken as a proxy for health) at age 8 predicted psycho-social competencies at age 12 in all four Young Lives countries.

Sánchez (2017) is similar to this chapter. He examines the human capital production function in all four countries, looking specifically at the role of early nutrition on later cognitive and socio-emotional skills. He constructs latent factors of the key skills as well as of investment and finds that investment increases both cognitive and non-cognitive skills. The effects are larger for cognitive skills than non-cognitive in Ethiopa and Peru, but larger for non-

[8]Again though, the measures of socio-emotional skills used are not very reliable across all four countries, which is the main reason I did not include non-cognitive skills in my analysis.

cognitive than cognitive in India, and being of similar magnitude in Vietnam. They also find evidence for cognitive self-productivity and cross-productivity onto non cognitive skills in all countries bar Ethiopia. They also find health as measured by height-for-age increases cognition at age 5 and at age 8, but has no direct effects on non-cognitive skills at age 8. There is an indirect effect through the increase in cognitive skills at age 5 which increases non-cognition at age 8. The process is similar in all countries, which is suggestive of a potentially consistent human capital function. One criticism is it relies on linear production functions, which have been shown to be poor fits of the process. They also do not consider preschool as an input.

One way to overcome the first criticism is to use a method that allows for more flexible functional forms such as constant elasticity of substitution, non-constant elasticity of substitution and translog specifications. The method I use borrows much of its structural estimation and identification strategies directly from previous work in three of the four Young Lives countries. Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017) estimate the production function of children's health and cognition in Peru and Ethiopia, and India respectively. They examine how lagged skills, parental skills and investment interact over time to produce different health and cognitive outcomes. They use an extensive measurement model to estimate latent factors for cognition, health, parental cognition, parental health and investment. This model is developed in Cunha, Heckman and Schennach (2010) using a non-linear dynamic factor model. Further details of this method is specifically given in the theoretical methodology section. This paper extends these work by including a new country - Vietnam - and directly comparing the production functions in all four countries as in Sánchez (2017) but proposes a new channel through which skills can develop that is often overlooked - preschool.

Preschool has not yet been included in a rigorous estimation of production functions. To date, I know of one paper that includes preschool as an input but it is included as a measure of investment as opposed to an input in addition to investment (see Aizer and Cunha (2012)). While it may be true that in some cases parents make a schooling decision and this could be viewed as an investment, I think there is value in analysing the two as separate inputs. The amount of hours spent at school, is a different form of investment then the other things typically thought of as investment such as money spent on food, clothes

and shelter or time spent by parents doing activities. It is also deserving of separate attention as it is a key mechanism through which government policy can try to improve childrens' outcomes.

Preschool can differ substantially from place to place and in the next section I provide details of the different economic and schooling environments in the four Young Lives countries.

2.3 The preschool context

2.3.1 General Country Comparison

Preschool attendance rates have been increasing globally over the past thirty or so years. More and more countries are trying to increase uptake of the available services by encouraging parents to send their children to preschools via informational campaigns[9]. Countries are also increasing offering free preschool places. This can vary on a number of dimensions, be it a full or part-time basis, for varying lengths of time and starting from different ages[10]. This is in part due to the growing awareness of the importance of early childhood education, but also due to the demands on parental labour force participation. No countries offer more than one year of parental leave after the birth of their child, with most offering much less. Without the financial means for childcare, or a close family/friend network nearby, the lack of preschool options may delay the return to work of one of the parents, typically the mother.

As figure 2.1 shows, the countries under investigation can be split into two groups based on the official statistics on preschool attendance. Both Peru and

[9]For instance overall uptake of preschool places in the UK was 94% for 3 and 4 year olds, but with significant group and regional variation. Local Authorities are in charge of provision of these services and thus can vary the type of messaging, information and recruitment strategies that to make families aware of the importance and existence of these services.

[10]Take, for example, the UK context. From 1996, parents of children in four local authorities in England were provided with vouchers for their children to attend nurseries. In 1997, this scheme was replaced with a entitlement for free part time nursery education place for all 4 year olds. The length of time provided was gradually increased, such that by 2015 it included all 3 year olds for 38 weeks of the year, for 15 hours a week. The current legislation, introduced in 2016, allows for 30 hours a week, for 38 weeks of the year for working parents of 3 and 4 year olds. If you are not working you can get 15 hours a week for 3 and 4 year olds, and disadvantaged groups can get an extra 15 hours a week for 2 year olds. Parents are not required to take up what they are eligible for, and can also engage with the private early childhood education market.

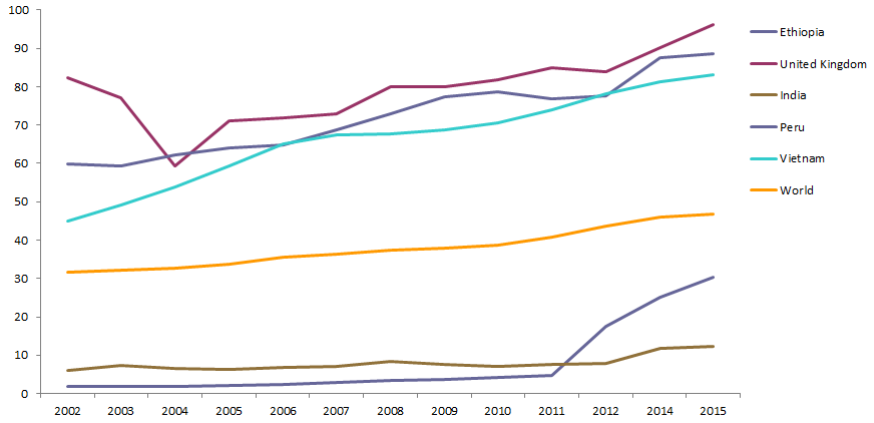


Figure 2.1: Preschool enrolment rate, gross percent

Notes *Gross enrolment ratio is the ratio of total enrolment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Preprimary education refers to programs at the initial stage of organised instruction, designed primarily to introduce very young children to a school-type environment and to provide a bridge between home and school. Downloaded from the World Bank, May 2019.*

Vietnam have high preschool attendance rates in 2015, similar rates to the UK. In contrast both India and Ethiopia have much lower rates of attendance, with a recent sharp uptake in Ethiopia. In India the actual attendance rates may be much higher, as will be seen in section 2.4.2, the proportion of individuals reporting attending preschool is more aligned with Peru and Vietnam. Most preschool provision in India occurs out of state-run Angadwadi Centre (AWCs) whose main purpose is community-wide health provision, amongst other services. The World Bank's statistics look at those attending institutions deemed specially designed for preschool. This may explain the observed differences in our sample and worldwide rates. Table 2.1 shows some other key differences amongst the four countries.

There are likely to be large quality differences within and between countries in preschool provision. This could arise due to natural variation within government-run preschools, depending on how tightly the government regulates and monitors preschools. There will also be differences in the numbers attending non-government preschools - supplied by either the private market or NGOs/charities. If there is a high quality public option, then the majority of children will attend public preschools, as there will be less need for NGOs to set up their own alternatives or for parents to pay to send their child to a private preschool.

Table 2.1: Key Country Facts

	Ethiopia	India	Peru	Vietnam
Free state-run formal preschool	No	No	Yes	Yes
Gross preschool enrolment rate (2015)	30.23	12.24	88.7	82.98
Age to start primary school	7	6	6/7	6
GDP per capita (2017) (International) $	1,899	7,056	13,434	6,775
Spending on education (%GDP)	4.5	3.8	3.8	5.7

Notes *All statistics taken from world bank group online. For India it is hard to define whether there is an official state run preschool. State run Angadwadi Centres provide education services, but their primary objective is nutrition and health.*

In this case selection issues will only occur at the very top end of the income distribution. If instead there is a limited or poorly-run government preschool system then there would be more concern about selection into preschools, and the varying quality amongst types. I abstract from any of these debates in this paper but recognise that there are important distinctions to be made in terms of preschool provider, and similarly preschool quality.

Measures of quality are often hard to come by, even in higher-income countries. While attributes like class size, pupil teacher ratio and numbers of materials might be available and measurable, there are likely to be a large number of unobservable quality differences, often thought to be due to teacher quality. The literature typically tries to look at quality via teacher value added measures which requires within-student test scores. More work needs to be done to uncover the aspects of quality that really matter for effective preschool in all types of environments, as well as how to measure such attributes.

2.3.2 Specific Country Specific Details

Details where possible are accurate for the period during the 2000s, given the sample were 5 years old in 2006. Many of the countries have since expanded or reformed their preschool education policy, and as such this overview should not be taken as current conditions (unless otherwise noted) but rather those faced during the study period.

2.3.2.1 Ethiopia

Ethiopia does not provide a public preschool option and attendance at preschools are strictly optional. Early childhood education is structured in the form of

kindergartens and predominantly provided by the private sector, Non Governmental Organisations (NGO), communities and faith-based organisations (Hoot, Szente and Mebratu (2004)). In it's 2007 report, the Ministry of Education (MOE) states that the government does not run preschools for two main reasons. The first, is to enhance the involvement of the private sector in the education sector, the second justification is to maximise the government's effort in the other levels of the sector (Woldehanna (2016)).

This has resulted in a lack of preschools in more rural parts of the country, as well as preventing poorer families from accessing preschools. This led to parents sending their children to primary school early, despite an official starting age of 6. Potentially due to the lack of government involvement, the preschools that did exist had many problems. The following issues have been highlighted within the Ethiopian system: *"high payment that is requested to attend the preschool, lack of proper training of preschool teachers; lack of standard curriculum and guidelines; lack of culturally relevant story books; quasi non-existence of alternative care and education services for the majority of the children population in the rural areas; lack of access to early childhood education for almost all children and especially children from low socio-economic backgrounds; lack of awareness about the value and type of care and education of young children; low salary for teachers, causing high staff turnover; lack of early childhood education professionals; misconception about teaching children 'because they are children' and the use of foreign languages (mainly English) as a medium of instruction"* (Hagos and Hoddinott (2018)).

It should be noted that since 2010, Ethiopia has made strides to reform its preprimary education sector with a national policy framework for early childhood care and education. This states that a the government would set up a *"comprehensive, integrated, quality, developmentally appropriate and culturally responsive service for the holistic development of all childre"*. It has introduced an 'O class', that is a reception year available to all children prior to entering first grade. The goal was for by 2020 that all children receive at least one year of preschool education.

2.3.2.2 India

The Indian government's 86*th* amendment to the constitution provided children aged 6-14 the right to free and compulsory education. However, there does

remain some services provided by the Indian government through the ICDS (Integrated Child Development Service). This includes preschooling or ECE (early childhood education) for children aged 3 to 6 through Anganwadi centres. There is also a growing private sector for preschools, with growth in recent years in low fee paying private preschools that reach rural and tribal areas (Kaul and Sharma (2017)).

However, despite increases in access, there remains large quality concerns. The quality of ECE available to children is often not developmentally appropriate across both private and public schools. It varies from a minimal provision of songs and rhymes in most Anganwadis, to an extension of the primary curriculum, delivered in a didactic and teacher-centred fashion in the private preschools. Neither offers children the environment and inputs they need for their optimal development. Specifically, opportunities for planned play, a critical component of a lot of successful ECE programmes, are almost entirely absent, with a focus on formal teaching of reading, writing and arithmetic (UNICEF (2017)).

Anganwadi centres also provide nutrition, health and day care facilities, in addition to their role in delivering preschool services. There is quite a lot of instability in children's participation in preschool and early primary grades with little attention paid to linear age trajectories prescribed by policy. This is combined with a school structure, curricula and process that is designed based on age-based development milestones, which in reality are rarely met in the classroom. As such the materials and lessons are often inappropriate to the varying needs within the classroom. For instance, AWCs are meant to be attended by those aged 3 to 6, but often have a disproportionate number of 2-to 4-year olds compared to 5-to 6-year olds.

Again, like in the other contexts the period after 2010 has seen substantial policy reforms focused on preschool access and quality. India's 12th Five Year Plan (2012 - 2017) highlighted the preprimary and early primary period (aged 4 to 8 years old) as *'an integrated early learning unit'* to ensure a solid foundation for all children. It also made strides in regulating both private and public preschools to try to increase quality as well as developing a national curriculum. Concerns remain about the implementation of such policy, and whether children are actually benefiting from these goals.

2.3.2.3 Peru

The Peruvian government has provided preschools in two many ways: a formal preschool (also known as kindergartens/Jardines/Centros de Educación Inicial (CEIs)) and a non-formal community based programme (known as PRONOI). These provide preschool services to children aged 3 to 5, with one year being compulsory and the other year optional (but all years are free) (Ames, Rojas and Portugal (2009)). There is a significant private sector for preschools, but these are the typically quite expensive with little government oversight.

Under Peruvian General Education Law 2003 Law NO. 28044, *"Early education is the first level in regular basic education. It serves children under the age of six and is provided in formal or non-formal settings under the terms set out in the regulations. The State also undertakes to provide for children's health and nutritional needs within a framework of intersectoral action. Early education is coordinated with primary education, ensuring educational and curricular consistency and preserving identity, specificity and administrative and management autonomy."* (Cueto et al. (2016)) . The National Curriculum Design (NCD) focuses on four main domains: personal social, science environment, logic and mathematics, and integrated communication.

The main difference between the two preschool services is that while preschools have a certified preschool teacher (requiring basic pedagogical training), PRONOEIs have an 'animator', usually a woman from the community who is trained by a preschool teacher who is in charge of about five to ten animators. The community provides the building and furniture for this programme. PRONOEIs are located in smaller villages where there are less than 30 children enrolled at preschool, although they are can also be found in poor urban areas.

For a time the Peruvian government tried to integrate the compulsory one year of preschool as an extension of primary education, aligning the curriculum and teaching methods. In reality however, this rarely occurred in any setting and this practise was discontinued in 2008. Preschools are typically 5 days a week, with at least 4 and half hours of schooling. There are more highly regulated in terms of time spent compared to the other countries in this study.

2.3.2.4 Vietnam

Vietnam has very high preschool enrolment rates, with a small uptake of private preschool in comparison to the other countries. This is largely due to the lack of socialisation within communities of private preschool but also a concentrated effort of the Vietnamese government to provide education for all.

Early childhood education typically consists of creches, kindergartens and sprout schools, depending on the age of the child. Creches are for children from 3 months to 3 years and as such are not the focus of this work. Instead, kindergartens (3 years to 6 years) and sprout schools (educational facilities combining creches and kindergartens) are focused on. Article 22 in the Vietnamese education law (2005*a*) states that *"The objectives of preschool education are to help children develop physically, emotionally, intellectually and aesthetically, in order to shape the initial elements of personality and to prepare children for the first grade."* Article 23.2 goes on to say that *"The major method in preschool education is to help children develop comprehensively through playing activities while attaching importance to praising, encouraging and stimulating good examples."*

Nearly all teachers are women, and new preschool teachers must possess an upper secondary pedagogical diploma. Some of the existing staff did not possess this educational requirement, and as such the Vietnamese government worked to upgrade staff through in-service training courses. However, the extent to which this has been successful remains questionable. For instance, in 2004-2005 school year the percentage of qualified teachers in the ECE sub-sector was 75.8% ((2005*b*)).

Despite these stated goals of education policy, and with high enrolment rates, there seemed to remain quality problems. A report by YoungLives found that only 3% of ECD classrooms seemed able to met the Vietnamese national standard, with hardly any schools employing quality teaching methods in a child friendly environment (Lan et al. (2007)). Some 60% of children received private tutoring under the age of 5 while attending preschool ((2005*b*)).

The 2005 law also laid out the basic uniform national curriculum, but one that failed to acknowledge the potential different life experiences, languages, and local contexts. Many policy makers and education experts have criticised the Vietnamese ECE sector for being too focused on scholastic achievement,

which may help explain their success on aptitude tests like PISA. Preschools are not compulsory, nor are the length of days regulated, with most kindergartens being open for at least 10 hours a day.

2.4 Data

2.4.1 Young Lives study

This paper uses the Young Lives dataset. Young Lives is an international longitudinal cohort study funded primarily by the UK government that ran from 2001 - 2017. It follows two cohorts of children in four countries: Ethiopia, India (in the provinces of Andhra Pradesh and Telangama), Peru and Vietnam[11].

This research focuses on the younger cohort, in all four countries using the first three rounds of data collected in 2002, 2006 and 2009. Round one (R1) was collected when the child was one year old, round two (R2) refers to children typically around age 5 and the children were age 8 at round three (R3). These rounds were chosen as in R2 most children are not in primary school whereas in R3 the entire sample will have started primary school. I look both at the immediate impact but also at any delayed effects.

The entire survey covers approximately 12,000 children, 2,000 per younger cohort and 1,000 per older cohort in each of the four countries. In each country children were sampled from twenty sentinel sites, which were defined specifically for each country. The site was chosen to represent a certain type of the population, in order to expose trends facing this subgroup or area. Within each cluster children were randomly selected. Poorer families were over-sampled, as this study was particularly focused on disadvantaged communities. The different sites covered a mix of urban and rural areas, with differing religious, economic and geographical features.

The study itself is extremely detailed, consisting of multiple surveys for the household, carer, individual child and community. The household survey has extensive socio-economic data, demographic data on all household members as well as information about expenditure and income. The carer-specific survey includes details about the main carer and the child themselves, focusing on issues such as health, socio-emotional skills, cognitive skills, amongst other

[11]This data is freely available from www.younglives.org.

items. In most rounds, there was a child survey which included anthropometrics such as weight and height measurements; as well as some cognitive tests.

One of the key advantages of Young Lives is the extremely low levels of attrition over time. The survey administrators in each country worked closely with the field supervisors who maintained close relationships with the families over time. This resulted in very low attrition rates. Any attrition that did exist was mainly due to child death or families moving extremely far away. If families moved a large amount of effort went into finding them. The following were the attrition rates from round 1 to round 3 : Ethiopia - 5.7%, India - 3.9%, Peru - 5.3% and Vietnam with 1.95%. It can be shown that there were no systematic differences between those who left the sample compared to those who stayed. As such, we do not have to worry about sampling biases due to differential drop-out. There were also low levels of item non response limited mainly by those who did not answer the preschool module but as can be seen in Table 2.2 the sample sizes are still quite large.

2.4.2 Preschool

The surveys contain a number of questions on preschool attendance. I define preschool as any 'school' the parent reports the child is in at age 5 i.e.at round two of the data collection. In all countries of this study official school does not start till age 6 or 7, although some children seem to have started at younger ages. To circumvent the concern that hours reported might in fact be from official school rather than preschool, I use a measure of hours taken directly from the preschool question.[12] In the main household survey, parents are asked if the child attended preschool or child care since the age of 3. If the parents answered yes, they were then asked a number of follow up questions[13]: the age when the child first attended, how many months the child attended, who ran it, the cost, quality, how many days per week and importantly for this study, the hours they attended per day. I construct both a binary attend/not attend measure of preschool, and a more granular measure of the number of hours attended (which is equal to zero for non-attenders). In the case that the child

[12]As mentioned in the literature review, I might be concerned that children from richer parents may attend school instead of preschool. This analysis is not able to address the issue raised as to the appropriate counterfactual, which in some cases may be attending school, as opposed to not attending anything. This is a direction for further research.

[13]Although they were differing levels of responsiveness to the follow-up questions.

attended multiple preschools, I take the most recent preschool for the measure of hours. When people report the child does not attend preschool, I set hours equal to zero.[14]

As can be seen in Table 2.2, there is extremely high preschool attendance rates in India, Peru and Vietnam, with much lower preschool attendance in Ethiopia.[15] There are differences in mean time spent in preschool across countries. On average, people spent the most time in school in Ethiopia, conditional on going to school. This was followed by Vietnam, India and lastly Peru. Looking at the unconditional hours, Ethiopia drops down significantly, given the large number of children who spent zero hours in preschool. The ordering of Vietnam, followed by India and then Peru is maintained.

One other concern is that the reporting between preschool attendance (either concurrent or in the past) does not align with hours reported. There are two main issues - people who report attending preschool but log zero hours as the time spent there, and then those who report that they don't/haven't attended preschool but record positive hours. This is shown in table Table 2.3.

However, these discrepancies can be explained by a number of features of the data. Firstly, what a parent considers preschool may differ from than that of the interviewer. Some parents might answer that their child is not attending a preschool, when in fact they are receiving positive hours of instruction from a preschool-like institution. For this analysis, I want to include this in our measure of hours, and thus I take it as hours spent in preschool, which are

[14]There is another option for a preschool time measure. This comes from the time-use component of the survey. This is somewhat unique for studies in LMICs, detailing the time spent in a number of activities on an average day. One such activity is parent-reported hours spent in school (excluding commuting time) in each country. This category includes commuting time to school in Ethiopia. One concern is that the time-use variables were only asked of children who were older than 5 at the time of collection, so in some cases there is no measure for children who were under 5 but who did attend preschool. There are also doubts about the accuracy of measurement of time spent in each activity, in that they often did not sum to twenty four hours. A robustness check showed that the results did not differ depending on which measure was used, with the estimation from the time use questionnaire in Appendix D.

[15]As mentioned earlier one discrepancy between our data and the worldbank statistics in the difference in attendance rates. This is due to the way the worldbank define preschool, which is as 'an institution whose primary function is to provide schooling services'. In India, a lot of preschool services are run out of Anganwadi Centre's (AWCs) which are primarily set up to provide healthcare to the local community. This typically includes contraceptive counselling and supply, nutrition education and supplementation, and preschool activities. These however will not be classified as preschools in worldbank statistics.

Table 2.2: Summary statistics of attendance and hours

	Ethiopia	India	Peru	Vietnam
	Preschool Attendance (0,1)			
Mean	.275	.915	.920	.898
SD	(.446)	(.278)	(.270)	(.301)
N	1872	1,929	1,952	1,924
	Hours Preschool Conditional			
Mean	6.796	5.006	4.251	5.973
SD	(1.380)	(1.658)	(.871)	(2.471)
N	476	1,692	1,639	1,784
	Hours Preschool Unconditional			
Mean	1.857	4.86	3.954	5.791
SD	(3.114)	(1.838)	(1.371)	(2.641)
N	1,742	1,743	1,762	1,840

Notes *Preschool attendance is a binary variable indicating if parents say the child is attending preschool. Conditional hours are hours for those who are attending preschool. Unconditional hours includes those who do not attend preschool and thus have a mean zero.*

Table 2.3: Attendance/Hours discrepancies

	Ethiopia	India	Peru	Vietnam
Attend=0 & Hours >0	90	111	32	139
	5.16%	6.36%	1.8%	7.55%
Attend=1 & Hours =0	0	1	3	0
	0.00%	0.05%	0.17%	0.00%
Total sample	1742	1743	1762	1,840

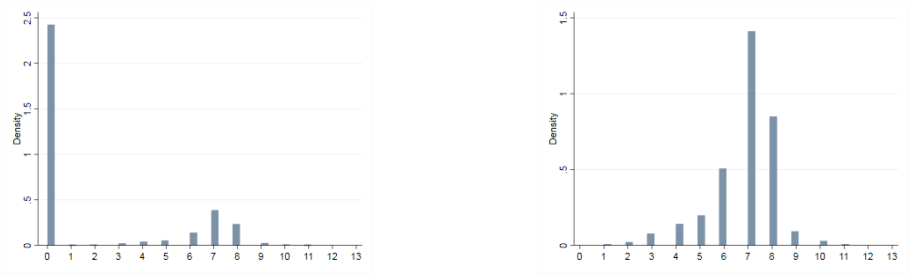
Notes *The first two row indicates the number (and percentage of sample) who report not going to preschool, but subsequently report some level of positive hours in preschool. These hours were included in the hours estimation. The latter two rows indicate the number (and percentage) for those who say they are attending preschool but report zero hours of attendance. These were included in the hours estimation as if they did not attend preschool, but the result were robust to dropping these observations.*

recorded even if the parents don't consider it a preschool.[16] Second, the numbers of zero hours reported when they say the child actually did attend a preschool. In this incidence, especially for the time-use category variable, the parent might

[16]I conduct a sensitivity analysis in which I set the measure of preschool equal to preschool attendance, when there are any positive hours recorded. The results are robust to this re-categorisation.

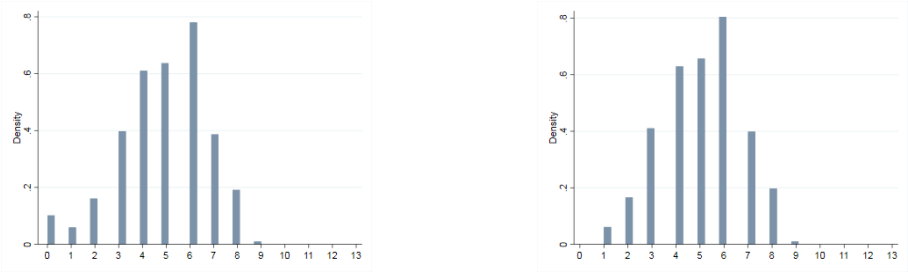
be remembering the recent past when the child may have not been attending preschool for some reason and thus record zero. The number of cases when this occurs is low and the results were robust to dropping these observations.

We can see that the distribution of hours varies by country, both unconditionally and conditional on attending. In Ethiopia (figure 2.2), there is a large mass point at zero in the unconditional hours, representing the large proportion of children who don't attend preschool. In India (Figure 2.3) both the unconditional and conditional hours are normally distributed.



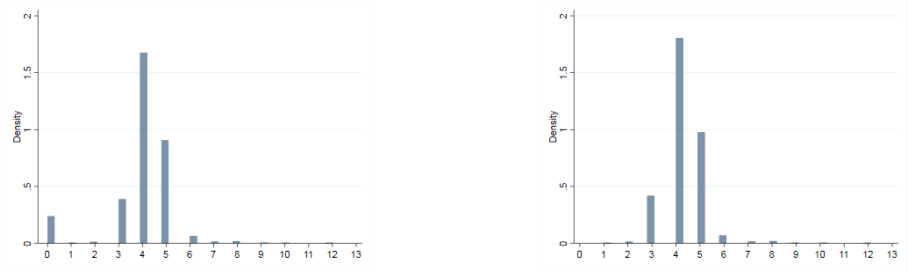
(a) Unconditional Hours (b) Conditional Hours

Figure 2.2: Time in Preschool, Ethiopia



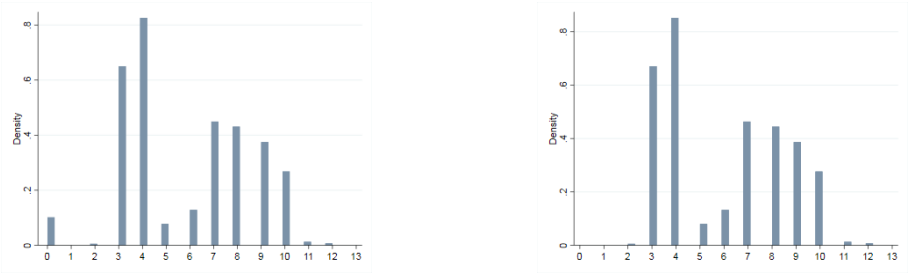
(a) Unconditional Hours (b) Conditional Hours

Figure 2.3: Time in Preschool, India



(a) Unconditional Hours (b) Conditional Hours

Figure 2.4: Time in Preschool, Peru



(a) Unconditional Hours (b) Conditional Hours

Figure 2.5: Time in Preschool, Vietnam

In comparison, Peru (Figure 2.4) the distribution is much narrower, with most of the mass between 3 and 5 hours. In Vietnam (Figure 2.5) it is bimodal, with a large proportion spending 3 or 4 hours at preschool, but likewise a lot of other children spending around 8 hours in preschool. This suggests that there are very different patterns of hours spent in preschool.

2.4.3 Other key inputs

As outlined above I specify a number of latent factors in the estimation. Each latent factor is estimated using a number of measures, the exact measures can vary by by round. This varies due to age appropriate tests, with the measures used listed in Table 2.4. For children's cognition, a variety of different tests were used. First, there is PPVT, which stands for Peabody Picture Vocabulary Test and is used to test a child's language skills. Then there is CDA which is Child Development Assessment, designed to evaluate early numeracy, vocabulary and socio-emotional skills. The third is EGRA, Early Grade Reading Assessment and used to test early reading skills. Height-for-age and weight-for-age Z scores are useful benchmarks for child anthropometrics which are standardised relative to the median for children of the same age and gender in the WHO reference population. The investment measures were a mix of the proportion of money spent on each child on books, clothing, shoes and a school uniform; as well as the number of meals for an average day that they had and the diversity of those meals. I attempted to construct measures of each that were transferable across country as to make the results as comparable as possible.

In each country I use the same set of controls, that is gender of the child, number of children in the household and the number of older siblings. Appendix A contains the full descriptive statistics of all inputs for each country. In addition

to the main inputs and the control variables, a set of instruments is needed to account for the endogeneity of investment. The instruments used for investment are community prices and household resources. The price of food, of clothes, of notebook and of two types of drugs are included in this set. I assume that differences in prices reflect supply factors, not demand. I also use household resources, which is considered a latent factor (measured by income and wealth quintile), as an instrument.

Both prices and resources affect the households' budget constraint. A shift in the budget constraint will change parent's choice of investment, without directing affecting the cognition or health skills of the child. Of course, to be valid we need these changes in the budget constraint to come from the supply side, as opposed to the demand side. If the prices are instead changing due to demand effects, then parents are changing investment themselves independently of prices and this causes the price changes (i.e. less demand for certain 'investment' goods). Here, our prices are measured at a local level, being constructed as the average from multiple vendors who are asked in the community survey from the local market. We collect these at each round and there is sufficient variation faced by individuals in the sample for them to be valid. These markets supply whole neighbourhoods and as such no individual household is likely to be able to cause a change in prices. We use prices on goods we believe parents would buy that could impact development of the child, but that aren't too suspect to seasonal variation. Given they are collected at different time points in different villages, we want differences to reflect actual differences in constraints as opposed to seasonal variations. The chosen prices were food, notebooks, clothes and drugs. These (asides from drugs) are also the items used to construct the investment measure, reflecting the quantity of such goods invested in the child.

There is enough variation in the prices at a local level that are seemingly unrelated to households investment decision for us to be confident in their validity as instruments. However, there is more concern about the use of household resources as an instrument. To be valid, it is assumed that conditional on background characteristics of the parent, the changes in resources reflect liquidity shocks and not inputs in the production function. The main risk is that income is actually correlated with unobserved shocks or child development. I include children's initial conditions and parental human capital (as measured

both by education level and literacy). Conditional on their inclusion, resources are plausibly exogenous. There is sufficient power from just using the prices to estimate the model without relying on income as an instrument, and the results remained unchanged from including or excluding it.

Table 2.4: Latent Factors

Round1	**Round2**	**Round3**
	Cognition	Cognition
	PPVT	PPVT
	CDA	Maths
	n/a	EGRA
Health	Health	Health
Z height for age	=	=
Z weight for age	=	=
Self-report health	=	=
	Investment	Investment
	Books	=
	Clothing	=
	Shoes	=
	Uniform	=
	Food (meals)	=
	Food (diversity)	=
Parental Cognition		
Mother education		
Father education		
Literacy Mother		
Parental Health		
Mother Weight		
Mother Height		

Notes *The equals sign is used to indicate when the same measure is used as in the round before. Parental endowments of health and cognition are measured in round one only and taken as constant over time. There is no measure of cognition or investment at round one. PPVT measures vocabulary skills, CDA measures early numeracy, vocabulary and socio-emotional skills, EGRA measures early reading skills and Maths measures maths skills. Z scores are measures which are standardized by median for children of same age and gender in the WHO reference population.*

2.5 Theoretical methodology

2.5.1 Human capital formation

In our context human capital is considered a bi-dimensional function of health and cognition at the start of adult life:

$$HC_a = HC(\theta^H, \theta^C)\,. \tag{2.1}$$

Children are born with a set of endowments of health and cognition. In other settings, the set of human capital dimensions might be different, typically including non-cognitive skills[17], or disaggregating cognition into different types such as language and maths ability. In LMIC, health deficits at birth are very common, many children do not reach their full development potential[18] and are frequently exposed to negative environmental toxins that can lead to morbidity and in some cases mortality. Negative health effects have been shown to significantly hamper the ability to work and to learn.

Parents make investment decisions throughout childhood which can impact the developmental process. These investment decisions can include a wide range of behaviours, such as time spent with the child doing certain activities and using monetary resources used to buy things like medicine, food and clothes that are vital for investment. Parents maximise their own welfare function which contains personal consumption and children's human capital subject to a budget constraint.

Production functions are used to examine the dynamics of human capital formation as well the relative importance of different inputs both at any point in time and over different time points.

2.5.2 Production functions

Consider our human capital production function:

$$\theta^k_{i,t} = f_t(\theta^k_{i,t-1}, \theta^{k'}_{i,t-1}, I_{i,t}, P^k_i, P^{k'}_i, S_i, X_{i,t}, A^k_t, \epsilon^k_{i,t})\,. \tag{2.2}$$

[17] Due to data reliability in all four countries we did not use the socio-emotional skill measures as advised by Young Lives researchers.

[18] Walker et al. (2005) estimate that over 200 million children suffer from linear growth faltering i.e. stunting and wasting.

Here θ is our skill, k specifies which type of skill, which in this case are cognitive skills and health skills. The skills for individual i, at time t are a time varying function of a variety of inputs. The inputs included lagged skill θ^k_{t-1} and the lag of the other type of skill $\theta^{k'}_{t-1}$. I can examine the dynamics across both time in the same skill and in different skills. I can look at self-(skill k on skill k) and cross-productivity (skill k' on skill k). I examine self-productivity by looking at the partial effect:

$$\frac{\partial \theta^k_{i,t}}{\partial \theta^k_{i,t-1}}\,, \tag{2.3}$$

and cross-productivity denoted by:

$$\frac{\partial \theta^k_{i,t}}{\partial \theta^{k'}_{i,t-1}}\,. \tag{2.4}$$

The next input is parental investment I_t. I do not let the type of investment vary by type of skill, however its effectiveness can vary across skills. Investment is seen as a particularly important input, as is perhaps the most easy to change compared to parental income or parental cognitive ability. Investment also poses a lot of estimation problems, namely endogeneity which I will return to later. The dynamics between investment and skills are also an important feature of production functions. Theory suggests that the higher the level of current skills, the more effective future investment will be, a concept known as dynamic complimentarity.

I pay particular attention to these interactions as they help to understand the persistence of skills and their dynamic formation. By allowing the marginal effects of inputs to vary over time, I examine the idea of sensitive periods of development in which an input such as investment might be at its most effective at increasing the stock of human capital.

The level of skills also depend on the level of parental skills. These could impact the endowment the child receives at birth, a sort of genetic transmission mechanism, or enables the parent to engage in behaviours that promote skill development.

Then I also include a set of controls, X_{it} that might impact human capital. These can include variables such as gender of the child, the number of older siblings, and the total number of siblings. Gender is included as the process of human capital may be different for boys and girls. The more siblings any child

has, the less attention and resources they will receive from parents. However, sibling-to-sibling learning could potentially boost human capital development.

The A_i^t term captures Total Factor Productivity (TFP), which flexibly captures growth over time and with age. This is particularly important in the context of human capital development when skills naturally increase with age. I also include an error term to capture unobservable shocks to human capital.

The main input of interest is preschool, denoted S_i. Preschool might impact skills in a number of ways. First, it might directly impact the accumulation of skills at the age at which the child is attending. Second, it might have long-term sleeper effects, in which it has an additional effect at later ages, through a 'school readiness' channel. Preschool attendance might help the child to learn how to concentrate and sit still, without being distracted by other children. These are useful skills to learn before starting primary school, and will allow them to be more effective at turning later school inputs into outputs. Here I do not let the measure of schooling to vary over time, focusing purely on preschool attendance. One extension of this work would be to include schooling inputs at different ages to examine how these interact.

To estimate this equation, I will impose some functional form restrictions. A fully non-parametric form can be identified under certain conditions, as demonstrated in Cunha, Heckman and Schennach (2010). However by imposing some structure I can look at different dynamics over time, and complimentary/substitution patterns between inputs at different times.

2.5.3 Functional form

The main specification used in this paper is that of Constant Elasticity of Substitution, (hereinafter **CES**), which has been shown to fit the HC accumulation process reasonably well (Attanasio et al. (2017)). This form allows some degree of flexibility over how inputs interact. Different inputs can be viewed as substitutes or compliments. One limitation of this approach is that the elasticity of substitution is the same across any two pairs of inputs. The CES functional form in our case looks like:

$$\theta_{i,t}^{k} = \left[\gamma_{1}^{k} \theta_{i,t-1}^{C\rho_{tk}} + \gamma_{2t}^{k} \theta_{i,t-1}^{H\rho_{tk}} + \gamma_{3t}^{k} I_{i,t}^{\rho_{tk}} + \gamma_{4t}^{k} P_{i}^{C\rho_{tk}} + \gamma_{5t}^{k} P_{i}^{H\rho_{tk}} + \gamma_{6t} S_{i}^{\rho tk} \right]^{\frac{1}{\rho_{tk}}} \times e^{\phi_{tk}^{'} X_{i,t} + A_{t}^{k} + \epsilon_{i,t}^{k}}, \quad k \in \{C, H\}. \quad (2.5)$$

The γ_{it}'s capture the degree the marginal benefit of each input and are constrained to sum to 1 in each period (homogeneity). The degree of substitution between any two inputs is captured by ρ_t; CES assumes that elasticity of substitution is the same among any two pairs of inputs (**P1**). If ρ_t is equal to 1 it is a linear production function; if equal to 0 then the production function is Cobb Douglas.

A more flexible specification is Nested CES (hereinafter **NCES**). This relaxes assumption **P1** by allowing different degrees of substitution between different subsets of inputs. For instance you might believe that the initial conditions for child skills, that is the lagged skills, are combined by one CES (governed by ρ_*) which is then nested inside another CES.

$$\theta_{i,t}^{k} = \left[\gamma_{1t}^{k} P_{i}^{C\rho_{tk}} + \gamma_{2t}^{k} P_{i}^{H\rho_{tk}} + \gamma_{3t}^{k} I_{i,t}^{\rho_{tk}} + \gamma_{4t}^{k} \left(\delta_{1t}^{k} \theta_{i,t-1}^{C\rho_{*,tk}} + (1 - \delta_{1t}^{k}) \theta_{i,t-1}^{H\rho_{*,tk}} \right)^{\frac{\rho_{tk}}{\rho_{*,tk}}} + \gamma_{6t} S_{i}^{\rho tk} \right]^{\frac{1}{\rho_{t}k}} \times e^{\phi_{tk}^{'} X_{i,t} + A_{t}^{k} + \epsilon_{i,t}^{k}}, \quad k \in \{C, H\}. \quad (2.6)$$

In theory, you can examine multiple nestings by grouping inputs into different sets and each set has a different degree of substitution, ρ. This allows for different possible dynamics between subsets of inputs. I do not explore these potential interactions, and how they may vary at different ages, but suggest this is an avenue for future research.

2.5.4 Measurement models

One of the problems with estimating production functions is that a number of the key inputs and outputs are inherently unobservable. Cognition, health,

investment are not easily measurable and often there are multiple different ways to measure any of these underlying factors. Specifically, any one measure is an error-ridden indicator of a latent factor. Using one measure could lead to biased results. To mitigate this, I use a measurement model to estimate the latent factors. Cunha and Heckman (2008) and Cunha, Heckman and Schennach (2010) developed a measurement system for childrens' skills, linking the observed measurable tests to the underlying latent factors.

By way of exposition, suppose I have μ^{θ}_{kt} measures of a child's skill θ^{k}_{t} of type k (for instance cognitive or health skill) at time t. I also have μ^{I}_{kt} measures of parental investment I_t at time t. I assume there is a dedicated measurement system in which each measure only proxies for one factor. I also assume that each measure is additively separable in the log of the latent factor it is proxying. Thus the following system of equations holds, which is formally known as our 'measurement system':

$$
\begin{aligned}
m^{\theta}_{kjdt} &= \mu^{\theta}_{kjt} + \alpha^{\theta}_{kjt} ln\theta^{k}_{dt} + \epsilon^{\theta}_{kjt}\,, \\
m^{\theta}_{k'jdt} &= \mu^{\theta}_{k'jt} + \alpha^{\theta}_{k'jt} ln\theta^{k'}_{dt} + \epsilon^{\theta}_{k'jt}\,, \\
m^{I}_{jdt} &= \mu^{I}_{jt} + \alpha^{I}_{jt} lnI_{dt} + \epsilon^{I}_{jt}\,,
\end{aligned}
$$

where μ^{θ}_{kjt}, $\mu^{\theta}_{k'jt}$, μ^{I}_{jt} are intercepts and the terms α^{θ}_{kjt}, $\alpha^{\theta}_{k'jt}$ and α^{I}_{jt} are factor loadings, the terms ϵ^{θ}_{kjt}, $\epsilon^{\theta}_{k'jt}$and ϵ^{I}_{jt} are mean zero measurement error terms that are assumed to be independent of the latent factors and of each other.

I assume that the measurement system is the unchanged whether or not the child is attending preschool. This implies that any differences seen in the distribution of the factors result from differences in the distribution of the latent factor only and not other variables. As the latent factors are unobserved, identification requires normalisation to set both their scale and location. Following the norm of the literature, I set the scale of factors by setting the factor loading of one measure of each latent factor to 1, specifically that $\alpha^{\theta}_{k1t} = \alpha^{I}_{1t} = 1, \forall\ t\ , k = \{C, S\}$. This sets the scale of the latent factor to that measure, which is important for interpretation.

Where possible I use the same measurement in each wave of data to fix

the loading factor. This allows valid inference across time periods. I set the location of all the factors by fixing the mean of the latent factor in logs to 0. Cunha, Heckman and Schennach (2010) show that with these assumptions and using Kotlarski theorem, the latent factor distribution is identified as long as there are at least three measures with nonzero factor loadings corresponding to each latent factor. I also assume here that measures only load onto one factor but this assumption can be relaxed if necessary. An alternative identification procedure has been shown in Agostinelli and Wiswall (2016) where they set the normalisations in the first period and can identify each latent factor. This suggests the full set of restrictions may well lead to an overly restricted model. However, Monte Carlo simulations suggest that this approach performs well in samples of similar sizes to this (Attanasio et al. (2017)).

In this paper, cognition, health, investment, parental health, parental cognition, as well as household resources are specified as unobserved latent factors. The details of what measures are used are listed in the data section and more details on the estimation results of the measurement are in the appendix.

2.5.5 Control functions

Parental investment is determined by the lifetime of parental resources, parents' expectations about returns to investment and the prices of investment goods. I follow exactly the approach taken in Attanasio et al. (2017) in regard to how I measure investment. Here I give a short exposition of their approach. Parents select investment taking into account children's skill levels, as this may determine the return to investment. The type and amount of investment may also vary by the level of parental skills. The amount of investment chosen may vary by gender, number of siblings, birth order and potentially other characteristics. This process can be conceptualised as a parent attempting to maximise a welfare function that consists of child human capital and parental consumption, subject to a budget constraint and technology constraint (which is the production function of human capital).

In order for estimates of investment to be unbiased, all the determinants of human capital investment need to be captured by the inputs already included. This is difficult to achieve in practice, especially given unobserved shocks to the child's human capital stock. Parents may react differently to a positive or

negative shock. They may over-invest in the child if they receive a negative shock (compensatory behaviour). Alternatively they might reinforce shocks, for example decreasing investment in response to a negative shock. This potential source of endogeneity requires some form of adjustment to get unbiased estimates of the effect of investment.

I use a control function approach, as is used in Attanasio et al. (2015). I use household resources and community level prices to act as instruments. To be valid, these instruments must only affect future skills via their influence on investment. For prices, this requires that shifts in prices reflect only supply side effects, such as cost differences, as opposed to changes in demand. For resources to be a valid instrument, I assume that conditional on parental health and cognition, any changes in resources are liquidity shocks, reflecting shorter term differences. A longer discussion of the instruments used is found in the data section of this paper.

Investment is a function of the log of prices, the log of resources and all of the variables included in the main production function. In the control function approach I take the error term from this first stage and I include this residual in the second stage estimation of skills. The investment equation is given by:

$$lnI_{it} = d_o + d_1 ln\theta_{it}^C + d_2 ln\theta_{it}^H + d_3 lnP_i^C + d_4 lnP_i^H + d_5 lnS_i + d_6^{'} X_{i,t} + d_7^{'} lnq_{t,k} + d_8 lnY_{i,t} + v_{i,t}\,. \quad (2.7)$$

Taking logs of equation 2.5 gives us equation 2.8, which we can estimate using non-linear least squares. The production function is thus given by:

$$ln\theta_{t+1}^k = ln\left(g(\theta_{it}^C, \theta_{it}^H, I_{it}, P_i^C, P_i^H)\right) + \phi_t^k X_{it} + A_t^k + \epsilon^k v_{i,t} + \epsilon_{i,t}^{*,k}, \quad k \in \{C, H\}\,, \quad (2.8)$$

where g is our CES specification. Here I assume that schooling is independent conditional on all included inputs schooling. There were no available instruments that could be used to assess the plausibility of this assumption. Conditional on the inputs that I do include in the main specification, the decision of whether to send the child to preschool (and for how long) is plausibly exogenous.

Future work should examine the plausibility of this assumption, and attempt to overcome it if exogeneity does not hold.

2.5.6 Three step estimator

The identification of the non-linear factor model is shown in Cunha, Heckman and Schennach (2010). The use of multiple measures in a non-linear context to deal with measurement error and latent factors lies at the basis of this approach.

The estimation procedure used here follows that of Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017) that directly estimates the production functions in Ethiopia and Peru, and India respectively. These papers do not include preschool as an important input into the human capital production function, but otherwise I follow their estimation procedure quite closely. The three step procedure is as follows:

1. Estimate the joint distribution of the measurements. In this step I include not only all the measurements of the latent factors but all other variables used in the production function estimation (i.e. all controls and instruments). This is to recover the underlying relationship with the latent factors accurately, as it depends on the relationships between all variables used in the estimation.

2. Then I use the subsequent measurement system to recover the joint distribution of the latent factors, as well as estimates of the factor loading and the measurement error distribution. Here I use the restrictions implied by all the normalizations and zero restrictions (which sets out which measures are related to which factors).

3. I then generate a synthetic data set by drawing 10,000 observations from the joint distribution of factors, controls and instruments. I use this synthetic data set to estimate the investment equations and production functions of different functional forms using non-linear least squares.

A key assumption of this estimation in the first step is that the joint distribution of measurements is a mixture of two normal distributions. This implies the joint distribution of the latent factors is also a mixture of two normal distributions. If I do not assume a mixture (but instead assume

one normal distribution), I cannot estimate non-linear production functions. Linear production functions impose constraints on the substitutability between elasticities and scaling of inputs. More flexible production functions do not impose these especially restrictive assumptions on the interaction between inputs. The production function can be interpreted as the conditional mean of an output in period *t+1* given inputs at *t*. If a normal distribution was assumed, then this conditional mean is linear. Thus I can only estimate either linear production functions or a Cobb Douglas production function (which is linear in logs). However, given I do not think such a specification would accurately capture the production function of skills, I make the assumption of two normal distributions.

The first step requires the EM algorithm (expectation maximisation). This algorithm is typically credited to Dempster, Laird and Rubin (1977), although it had been used many times before. The application of EM to models like this one is laid out in Arcidiacono and Jones (2003). I begin by guessing the starting values for vectors of means, covariance matrices and mixture weights. In the E step, I estimate the probability that any given observation is drawn from each of the two possible normal distributions, conditional on observables. In the M step, I then maximise the conditional likelihood function and update the parameter estimates specified at the beginning for each of the two normal distributions. I iterate over these two steps until convergence is reached.

This gives the full structure of dependence between all factors, including controls and instrument as a joint mixture of normals. After drawing the synthetic dataset of factors (as if they were observable), I then run the estimation using non-parametric bootstrapping over all three steps in order to obtain accurate confidence intervals and critical values of the test statistics.

2.6 Results

The main focus of this work is the effect of preschool on outcomes at different ages. I will concentrate the results and subsequent discussion on these parameters as opposed to the full specification of the production function . The appendices have the full estimates of the measurement system parameters, the production functions and the investment equations for the three cases: the preferred hours variable (Appendix B), when preschool is a binary indicator

(Appendix C), and for robustness using the hours variable from the time-use survey component (Appendix D).

The results shown use the CES specification, with a control function to account for the endogeneity of investment. The CES specification was also estimated without the control function to give some indication of the bias in results when endeogeneity is not accounted for. However, including the control function results in a better fit and it is thus preferred. This follows Attanasio, Meghir and Nix (2015) and Attanasio et al. (2017).

Table 2.5: Preschool Cross Country Comparison - Attendance

	Cognition		Health	
Age	5	8	5	8
Ethiopia	0.045 [0,0.12]	**0.063** [0.02,0.13]	0.027 [−0.03,0.07]	−0.033 [−0.07,0.01]
India	0.024 [−0.06,0.05]	0.047 [−0.04,0.09]	−0.024 [−0.12,0.01]	−0.042 [−0.07,0.01]
Peru	0.022 [−0.17,0.09]	0.076 [−0.04,0.16]	−0.017 [−0.16,0.03]	−0.023 [−0.04,0.04]
Vietnam	−0.005 [−0.04,0.03]	**0.043** [0.01,0.07]	−0.032 [−0.05,0.01]	0.019 [0,0.04]

Notes *The coefficient on preschool from the CES estimation is reported. Bold indicates when a coefficient is significant. 95% confidence intervals based on 100 bootstrap replications in square brackets.*

Table 2.5 shows the effect of attending preschool on cognition and health in all four countries at age 5 and age 8. This is γ_6 in equation 2.5. In both cases this measures the impact of preschool. At age 5, it is thus the contemporaneous effect of preschool, whereas at age 8 it is the lagged effect (i.e it is the measure of preschool at age 5). Bootstrapped confidence intervals are shown in square brackets underneath the point estimates.

First we look at the effect on cognition. The point estimates are nearly all positive (and are in bold when significant), which suggests that just attending preschool is effective at increasing cognitive skills. However, they are not significantly different from zero except for in two cases. Ethiopia is an interesting context, as approximately only 30% of people in the sample report attending preschool. Thus it seems that attending preschool gives you an added bonus, even after controlling for investment by parents and parental endowments of skills. The effect exists at both ages, although zero is part of the confidence interval at age 5. There is also an effect of preschool attendance in Vietnam

that emerges at age 8. Here, potentially preschool is preparing children for later schooling by teaching skills such as sitting still, concentrating, managing their emotions, and developing appropriate relationships with other children and the teacher. This is the aforementioned school-readiness channel.

Table 2.6: Preschool Cross Country Comparison - Hours

	Cognition		Health	
Age	5	8	5	8
Ethiopia	0.028 [−0.06,0.13]	**0.086** [0.04,0.17]	−0.082 [−0.11,0.02]	0.034 [−0.03,0.07]
India	−0.002 [−0.03,0.06]	0.021 [−0.05,0.07]	−0.015 [−0.06,0.01]	−0.019 [−0.05,0]
Peru	**0.05** [0.03,0.1]	0.029 [−0.01,0.05]	0.026 [−0.01,0.06]	0.003 [−0.02,0.03]
Vietnam	**0.216** [0.16,0.25]	−0.094 [−0.11,0.03]	**0.041** [0.01,0.07]	**0.05** [0.01,0.08]

Notes *The coefficient on preschool hours from the CES estimation is reported. Bold indicates when a coefficient is significant. 95% confidence intervals based on 100 bootstrap replications in the square brackets.*

In comparison, Table 2.6 shows the effect of an additional hour of preschool in the four countries. In contrast to the pure attendance measure there are now positive and significant effects in Peru and Vietnam at age 5. There is also a slight negative effect in India but this could be due to data issues with the hours measure in India or the difficulty in separating out time spent in AWCs receiving many services compared to time in AWCs receiving just preschool instruction. There is still a lagged effect at age 8 in Ethiopia, again suggestive of the preschool readiness channel.

In Figure 2.6 and Figure 2.7 I plot the marginal product of an each additional hour of preschool on cognitive outcomes at age 5 and at age 8. I use the mean value of all other inputs when calculating the marginal product. In the age 8 figure I only include the direct effect of preschool (that is preschool measured at age 5) on age 8 cognition, and do not account for the increase in cognition and health that might occur at age 5 which then enter into the age 8 equations via the lagged values. Again, this exercise does not account for the (sometimes quite large) standard errors and so we should be cautious when interpreting the magnitudes shown in the following figures.

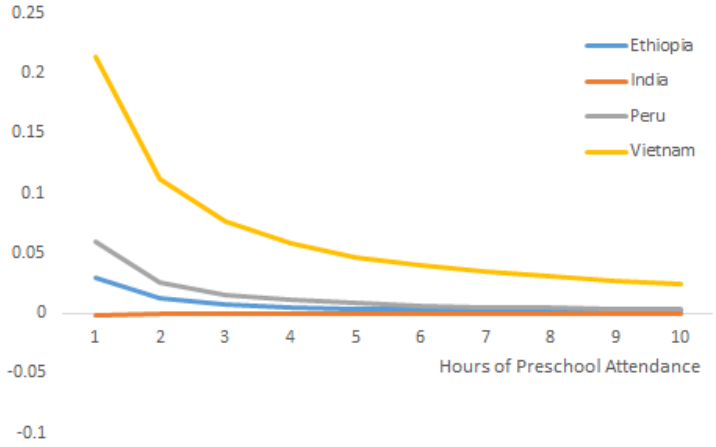


Figure 2.6: Marginal Product of Hours of Preschool Attendance at Age 5 on Cognition at Age 5

The benefit of additional preschool hours is highest in Vietnam, with the rate of decay over time the least steep, with gains still to be made going from nine to ten hours. In contrast, in Ethiopia and Peru there does not seem to be any additional benefit after attending four or five hours a day. There seems to be basically no impact in India, again likely to be reflecting either measurement issues or the low quality AWCs that currently provide preschool.

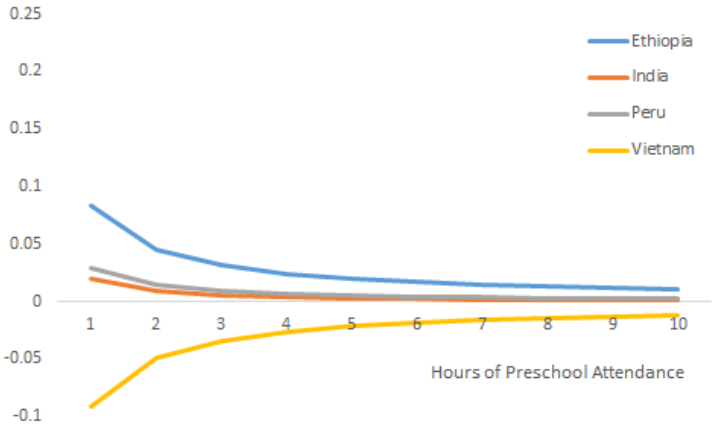


Figure 2.7: Marginal Product of Hours of Preschool Attendance at Age 5 on Cognition at Age 8

When we look at the results at age 8, they are quite starkly different. There are still delayed benefits of going to preschool in Ethiopia with gains that are actually greater than the gains at age 5. This suggests that the preschool

readiness channel may be important in Ethiopia. There are negligible effects in India and Peru. In keeping with the results from Table 2.6, there does seem to be a negative effect on cognition at age 8 from attending preschool, with negative marginal products. This warrants further investigation.

Looking at the estimation results for health, we see little evidence of either attendance or hours on health at either age in any country. The exception is Vietnam where there are significant positive effects at both age 5 and age 8. Unfortunately we do not know the causal mechanisms between such effects without better quality data. I cannot determine if there is simply no effect of preschool on health in the other countries, or if the different possible routes that it might affect health simply cancel each other out - resulting in a null effect.

Tables 2.7-2.10 show the full estimation results for cognition and health at age 5 and 8 in Ethiopia, India, Peru and Vietnam. This estimation uses hours of preschool, but the results do not vary much between including hours or attendance. The results from the attendance models are in Appendix C. In all cases we use lags of cognition and health where available. At age 5 there is no lag of cognition due to a lack of an age 1 cognitive measure. We do have age 1 health indicators (created using Z height- and weight-for-age scores and self reported health to construct a health latent factor). At age 8, we use the outcomes at age 5 (health and cognition) for our lagged measure of skills in each estimation. Significant coefficients from the production functions are indicated with bold. Gender is one for female, zero for male.

First we look at the elasticity of substitution, which in the CES case is restricted to be constant between any two inputs. The elasticity of substitution between two factor inputs measures the percentage response of relative marginal products of the two factors to a percentage change in the ratio of their quantities. It is a function of ρ, given by $\frac{1}{1-\rho}$. Under this parameterization, as $\rho \to -\infty$ the inputs are perfect complements, whereas as $\rho \to 1$, inputs become perfect substitutes. The higher the levels of the elasticity of substitution the more substitutable inputs are.

We see that elasticities are reasonably low and with the elasticity being quite imprecisely estimated at some points. It is broadly close to one for both cognition and health in all countries, suggesting inputs are compliments

Table 2.7: Ethiopia

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	**0.331** [0.25,0.45]	NA [NA,NA]	−0.006 [−0.06,0.05]
Health	0.089 [0,0.17]	**0.074** [0.04,0.16]	**0.555** [0.51,0.62]	**1.004** [0.93,1.05]
Parental Cognition	0.016 [−0.04,0.17]	0.005 [−0.08,0.09]	**-0.105** [−0.17,−0.02]	−0.015 [−0.05,0.04]
Parental Health	−0.023 [−0.05,0.05]	−0.044 [−0.1,0.00]	**0.117** [0.08,0.25]	0.009 [−0.02,0.04]
Investment	**0.89** [0.57,1.08]	**0.548** [0.3,0.65]	**0.514** [0.27,0.57]	−0.025 [−0.12,0.12]
Complementarity ρ	−0.322 [−0.73,0.88]	0.112 [−0.07,0.38]	−0.127 [−0.27,−0.02]	−0.295 [−0.45,0.38]
Elasticity of Substitution	0.756 [0.51,5.06]	1.126 [0.94,1.63]	0.887 [0.79,0.98]	0.772 [0.69,1.63]
Log TFP	0.009 [−0.05,0.05]	0.02 [−0.02,0.05]	0.072 [0.04,0.11]	0.004 [−0.03,0.02]
Investment Residual υ	−0.828 [−1.05,−0.49]	−0.562 [−0.72,−0.34]	−0.478 [−0.53,−0.22]	−0.028 [−0.18,0.08]
Number of Children	−0.018 [−0.05,0]	**-0.038** [−0.07,−0.02]	**-0.082** [−0.11,−0.04]	−0.017 [−0.03,0.01]
Older Siblings	**0.022** [0.01,0.06]	0.021 [0.00,0.04]	**0.055** [0.02,0.08]	0.024 [0.00,0.03]
Gender	−0.001 [−0.01,0.01]	−0.001 [−0.01,0.02]	−0.012 [−0.02,0.00]	−0.007 [−0.01,0.00]
Preschool	0.028 [−0.06,0.13]	**0.086** [0.04,0.17]	−0.082 [−0.11,0.02]	0.034 [−0.03,0.07]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. TFP stands for total factor productivity and allows for growth in latent factors over time. The preschool measure is the hours variable from the preschool question.*

Table 2.8: India

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	**0.297** [0.19,0.36]	NA [NA,NA]	−0.059 [−0.09,0.00]
Health	**0.188** [0.14,0.28]	**0.223** [0.16,0.28]	**0.685** [0.6,0.75]	**0.85** [0.78,0.91]
Parental Cognition	**0.332** [0.25,0.42]	0.018 [−0.05,0.1]	0.002 [−0.04,0.06]	**0.057** [0.01,0.09]
Parental Health	0.074 [−0.01,0.2]	**-0.115** [−0.24,−0.04]	**0.291** [0.19,0.41]	0.032 [−0.02,0.1]
Investment	**0.408** [0.19,0.54]	**0.557** [0.42,0.74]	0.037 [−0.07,0.18]	**0.138** [0.06,0.2]
Complementarity ρ	−0.142 [−0.37,−0.02]	−0.18 [−0.23,0.06]	−0.019 [−0.14,0.08]	0.07 [−0.03,0.16]
Elasticity of Substitution	0.876 [0.73,0.98]	0.848 [0.81,1.07]	0.981 [0.88,1.09]	1.076 [0.97,1.19]
Log TFP	−0.015 [−0.05,0.03]	−0.028 [−0.08,−0.01]	0.03 [0,0.06]	−0.002 [−0.02,0.03]
Investment Residual υ	−0.229 [−0.43,−0.01]	−0.608 [−0.88,−0.45]	0.023 [−0.15,0.15]	−0.102 [−0.18,0.01]
Number of Children	0.007 [−0.01,0.03]	0.001 [−0.01,0.02]	0.001 [0.00,0.02]	−0.002 [−0.02,0.01]
Older Siblings	0.002 [−0.01,0.02]	−0.007 [−0.02,0.01]	**-0.018** [−0.04,−0.01]	−0.004 [−0.01,0.01]
Gender	0.015 [0.00,0.03]	**0.041** [0.02,0.05]	0.00 [−0.01,0.01]	0.004 [−0.01,0.01]
Preschool	−0.002 [−0.03,0.06]	0.021 [−0.05,0.07]	−0.015 [−0.06,0.01]	−0.019 [−0.05,0.00]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. TFP stands for total factor productivity and allows for growth in latent factors over time. The preschool measure is the hours variable from the preschool question.*

and perhaps more similar to a Cobb Douglas production function. This is

Table 2.9: Peru

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	**0.431** [0.37,0.55]	NA [NA,NA]	−0.037 [−0.1,0.00]
Health	0.001 [−0.05,0.08]	0.055 [−0.04,0.11]	**0.682** [0.62,0.73]	**1.08** [1.01,1.13]
Parental Cognition	−0.023 [−0.13,0.19]	**0.195** [0.1,0.29]	0.045 [−0.01,0.13]	0.02 [−0.03,0.04]
Parental Health	−0.138 [−0.27,0.04]	**-0.104** [−0.21,−0.02]	**0.182** [0.11,0.25]	−0.039 [−0.08,0.01]
Investment	**1.11** [0.77,1.24]	**0.394** [0.26,0.53]	0.065 [−0.09,0.19]	−0.028 [−0.09,0.12]
Complementarity ρ	−0.247 [−0.48,0.44]	−0.034 [−0.15,0.11]	0.045 [−0.3,0.2]	−0.2 [−0.27,0.2]
Elasticity of Substitution	0.802 [0.67,1.35]	0.967 [0.87,1.12]	1.047 [0.77,1.24]	0.833 [0.79,1.25]
Log TFP	−0.061 [−0.09,0]	−0.014 [−0.05,0.01]	−0.02 [−0.05,0.01]	0.015 [0.01,0.04]
Investment Residual υ	−1.144 [−1.26,−0.77]	−0.358 [−0.49,−0.23]	0.009 [−0.14,0.2]	0.037 [−0.11,0.14]
Number of Children	0.037 [0.00,0.06]	−0.017 [−0.04,0.01]	−0.014 [−0.02,0.01]	−0.017 [−0.03,0.00]
Older Siblings	−0.015 [−0.03,0.02]	0.019 [0.00,0.05]	0.00 [−0.02,0.01]	0.014 [0.00,0.03]
Gender	0.002 [−0.01,0.02]	0.01 [0.00,0.02]	**0.024** [0.01,0.03]	−0.009 [−0.02,0.00]
Preschool	**0.05** [0.03,0.1]	0.029 [−0.01,0.05]	0.026 [−0.01,0.06]	0.003 [−0.02,0.03]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. TFP stands for total factor productivity and allows for growth in latent factors over time. The preschool measure is the hours variable from the preschool question.*

Table 2.10: Vietnam

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	**0.904** [0.24,0.92]	NA [NA,NA]	−0.003 [−0.07,0.08]
Health	−0.009 [−0.06,0.07]	0.052 [−0.02,0.1]	**0.587** [0.49,0.65]	**0.918** [0.77,0.96]
Parental Cognition	**0.18** [0.03,0.3]	**0.188** [0.15,0.35]	**0.099** [0.07,0.17]	0.005 [−0.04,0.04]
Parental Health	−0.016 [−0.18,0.05]	−0.05 [−0.08,0.02]	**0.231** [0.19,0.31]	0.00 [−0.01,0.06]
Investment	**0.629** [0.5,0.89]	0.00 [−0.11,0.37]	0.041 [−0.1,0.15]	0.029 [−0.03,0.13]
Complementarity ρ	0.077 [−0.1,0.14]	0.095 [−0.23,0.26]	−0.042 [−0.1,0.05]	0.087 [−0.16,0.36]
Elasticity of Substitution	1.084 [0.91,1.16]	1.105 [0.81,1.35]	0.96 [0.91,1.05]	1.095 [0.86,1.57]
Log TFP	−0.017 [−0.06,0.01]	0.069 [0,0.1]	0.041 [0.01,0.07]	0.01 [0,0.04]
Investment Residual υ	−0.49 [−0.78,−0.2]	−0.092 [−0.79,0.07]	0.321 [0.1,0.67]	−0.208 [−0.43,−0.15]
Number of Children	0.004 [−0.01,0.03]	−0.045 [−0.07,−0.02]	**-0.035** [−0.05,−0.01]	−0.003 [−0.01,0.01]
Older Siblings	−0.004 [−0.02,0.02]	0.019 [0.00,0.05]	−0.004 [−0.02,0.01]	0.005 [−0.01,0.01]
Gender	0.006 [−0.01,0.02]	−0.013 [−0.02,0.00]	**0.019** [0.01,0.03]	−0.011 [−0.02,0.00]
Preschool	**0.216** [0.16,0.25]	−0.094 [−0.11,0.03]	**0.041** [0.01,0.07]	**0.05** [0.01,0.08]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. TFP stands for total factor productivity and allows for growth in latent factors over time. The preschool measure is the hours variable from the preschool question.*

typically what has been found in other estimates of production functions.

Elasticity somewhat increases from age 5 to age 8 for cognition, which would imply stronger degrees of substitution at later ages - a finding that has been substantiated in other contexts (Cunha, Heckman and Schennach (2010)). Again, the caveat is that the estimates are imprecise.

Another parameter of particular interest is the coefficient on the investment residual. This stems from the first stage of the control function approach. This parameter captures the responsiveness of parental investment to unobserved shocks. A negative coefficient is seen across the board for cognition, implying that parents compensate for negative shocks to cognition (a positive coefficient would imply reinforcing behaviour). There is less of a pattern for health, sometimes negative and sometimes positive, varying across both countries and ages. The fact that parents seem to compensate for unobserved shocks is backed up by the coefficient on investment in the OLS estimations, which is broadly lower than that in the control function. This suggests that investment is downward biased in the OLS estimates.

Other patterns to note are related to investment. Investment by parents has larger effects on cognition than on health. The effects are also typically larger at age 5 than age 8. This suggests that children's cognitive abilities are more malleable at younger ages. On health, investment is either having non significant negative/zero effects or slightly positive and significant. For cognition, there are large lagged effects of cognition from age 5. There is some suggestion of cross productivity with positive and significant effects of lagged health on cognition in Ethiopia and India. For health, there is no evidence of an effect of lagged cognition on health outcomes. Instead there is a large lagged effect of health on health, which becomes more persistent with age.

We can also look at the determinants of investment, with the full investment equations in Appendix B for our preferred measure of preschool hours (as opposed to attendance). Prices typically decrease investment, whereas parental cognition and health increase investment. There are inconclusive effects of lagged health and lagged cognition on investment, except for in Vietnam where lagged health increases investment. The number of siblings and number of older siblings are significant only where they decrease investment. Income is a strong determinant of investment at both ages in all countries. Attending preschool for more hours also seems to increase investment in children.

The estimation assuming exogenous investment is in Appendix B.3 and C.3. In every case the coefficient on investment is significantly lower. This suggests that OLS systematically underestimates the effect of investment on skills. This is additional evidence that parents play a compensatory role against shocks received by children.

2.7 Discussion

The results suggest that attending preschool where not many people attend preschool has large benefits for cognitive skills both immediately and at later ages. In countries when the majority of people attend preschool, attendance seems to have little impact on outcomes. However, spending additional hours in preschool in these places (such as Peru and Vietnam) is immediately beneficial at increasing cognitive skills. I found some evidence of negative effects in India, although with the caveat that the hours variable used may be highly inaccurate for capturing the actual time spent in preschool. It is more likely to reflect the time spent in AWCs which would be an upper bound given they provide multiple services.

This supports the main hypothesis of the paper that additional time at preschool is effective at contemporaneously increasing skills. There is little evidence of a preschool readiness effect of hours spent in school in Peru or Vietnam - both of which have well-developed schooling systems. However, in Ethiopia I see evidence on both attendance and hours on cognitive outcomes at age 8. This suggests that attending preschool gives additional advantages when the child starts regular schooling.

Aside from in Vietnam, there were neglible effects on health using either measure of preschool at either age in any country. However, it is unknown if this is because there are no effects of preschool on health outcomes, or if the proposed channels outlined in the introduction cancel each other out. More work could be done to try to disentangle these possible mechanisms, perhaps by collecting data on peers or on other services offered at the schools.

One caveat in interpreting these results in Ethiopia is selection into preschool. While I am controlling for parental cognition and health, as well as income via the investment function, those who attend preschool could be a highly selected

group. Thus it may not be purely preschool attendance that is increasing skills, but some other variable that affects cognition and attendance at the same time.

One major limitation of this paper is the potential for preschool decisions to be endogenous, which would lead to biased estimates. I would argue that conditional on the included covariates the decision to send the child to school and how many hours to spend in school is plausibly exogenous. The average time spent in preschool by children is unlikely to respond to temporary shocks to the child's cognition or health. I am also controlling for past levels of cognition or health which might influence the schooling decision by parents. However, this conditional independence argument is open to criticism. Preschool decisions could be dependent on a host of factors that are not included such as the mother's labour supply decision,[19] subsequent child care needs, as well as their knowledge of potential benefits of preschool. Future work could address these concerns by including a control function for preschool. There were two reasons why I was unable to do so in this circumstance.

First, there were no strong instruments available for preschool. One option might have been to use the distance to current school (asked in terms of time to commute), but in many cases this was for a normal school, not their preschool. It also did not take into consideration mode of transport used which could influence the commuting time, and thus not be an accurate distance measure. Preliminary first stage regressions suggested it would not be a good instrument. Second, and more importantly is that the theory of how to deal with two control functions using this estimation procedure is unclear, as well as how to construct control functions for a binary variable.

A remaining question, and one that is under researched in the literature, is what makes a preschool effective. It is highly unlikely that every hour is equally productive for a variety of reasons. First, an additional hour from the second to the third hours a day is likely to be more productive than an additional hour from the ninth to tenth hour a day. Second, the quality of that hour will matter - or more specifically the quality of preschool facilities and teaching. There are big differences within countries as to the quality of preschools, not just in

[19]The majority of care-givers in this setting do not have formal work, but as these countries develop with the associated rise in female employment it is likely to be a more important feature of the child development process.

terms of resources and teachers, but also in their approach to preschool. Some systems believe preschools should focus on play and soft skills, whereas others see them as an opportunity for school to start earlier and should follow the same structure as regular schools. These ideological differences could result in different estimates of preschool outcomes on cognition and health. This might make it look like preschools are ineffective, but is just reflecting differences in the aims of preschools, which might show up as increases in soft skills rather than cognition and health. There was a lack of good quality comparable measures of softer skills in these surveys and therefore I focused only on cognition and health.

Future work could address some of these caveats and expand production function estimation to age 12 and 15, the data for which has recently become available for the Younger Cohort of Young Lives. This work could also be extended to include schooling inputs, particularly the hours spent in school, throughout the life cycle. Given it seems that preschool mainly has a concurrent positive effect, it would be interesting to compare the effectiveness of hours of schooling at different points over the life cycle. One difficulty in including primary and secondary schooling hours is that in many systems there is little to no variation in hours. I also suggest that a major limitation of this paper is only focusing on CES production functions. While other work does seem to support that CES functions fits the huamn capital process well, a less restrictive functional form might allow the examination of other substitution patterns between preschool and other inputs that may be informative in understanding the human capital process. A NCES function with interactions between private and public investment is one such candidate.

Despite these limitations this paper makes a valuable contribution to the literature on the importance of preschool in two main ways. First, I estimate the production function of cognition and health with the novel feature of including preschool as a key input in the human capital accumulation process. This helps examine the role of private and public investments. It seems clear that time spent in preschool is important, primarily for cognition. It is likely to be an important omitted variable in existing papers estimating the human capital production function. Second, I examined these production functions in four different countries. The differential results reveal it is important to estimate production functions in different settings, before assuming that findings in one

place will hold in another. In this data, there were different returns to hours in Peru and Vietnam compared to India and Ethiopia. More research is needed to better understand what makes time in preschool productive in some settings but not others, (potentially a quality difference), and how to harness this to develop a more effective preschool system.

Appendices A-E

Appendix A : Descriptives Inputs

Table 2.11: Summary Statistics by Country

	Ethiopia mean/sd	India mean/sd	Peru mean/sd	Vietnam mean/sd
			Cognition	
PPVT R3	300.0	300.0	300.0	303.5
	(15.00)	(15.00)	(15.01)	(11.25)
MATHS R3	300.0	300.0	300.0	300.0
	(14.99)	(14.98)	(14.98)	(15.00)
EGRA R3	300.0	300.0	300.0	300.0
	(14.99)	(15.00)	(15.01)	(15.00)
PPVT R2	300.0	300.0	300.0	300.0
	(50.00)	(50.00)	(50.00)	(50.00)
CDA R2	300.0	300.0	300.0	300.0
	(49.97)	(49.99)	(49.99)	(49.99)
The tests were standardized by the Young Lives research team and I used these constructed measures in my estimation. This resulted in different standard deviations across rounds.				
			Health	
Z Height for age R3	-1.211	-1.449	-1.168	-1.106
	(1.066)	(1.037)	(1.063)	(1.079)
Z Weight for age R3	-1.627	-1.875	-0.341	-1.129
	(0.937)	(1.058)	(1.198)	(1.313)
Healthy R3	4.004	3.932	3.714	3.198
	(0.868)	(0.678)	(0.653)	(0.714)
Z Height for age R2	-1.453	-1.655	-1.557	-1.335
	(1.129)	(0.989)	(1.158)	(1.113)
Z Weight for age R2	-1.360	-1.866	-0.537	-1.062
	(0.927)	(0.935)	(1.027)	(1.140)
Healthy R2	1.547	1.256	1.246	1.730
	(0.661)	(0.652)	(0.583)	(0.847)
Z Height for age R1	-1.582	-1.298	-1.301	-1.116
	(1.961)	(1.478)	(1.359)	(1.335)
Z Weight for age R1	-1.435	-1.521	-0.197	-0.959
	(1.524)	(1.090)	(1.209)	(1.085)
Healthy R1	1.857	1.239	1.264	1.799
	(0.777)	(0.672)	(0.683)	(0.836)
For healthy in R1 and R2 parents were asked how healthy their child was relative to their peers, with two being more healthy, one being the same and zero being				

less healthy. For healthy in R3 it was asked about the child's health in general on a scale from one-five, ranging from very poor to very good.

			Investment	
Books R3	31.92	440.1	117.5	222.3
	(35.46)	(637.2)	(123.6)	(164.3)
Clothing R3	99.99	754.2	114.0	299.8
	(125.5)	(688.3)	(124.9)	(394.7)
Shoes R3	42.37	135.0	58.76	94.80
	(52.96)	(144.7)	(64.07)	(148.2)
Uniform R3	53.24	378.1	83.93	115.8
	(59.37)	(295.1)	(93.06)	(126.8)
Food Total R3	3.928	4.849	4.861	4.345
	(0.700)	(1.104)	(0.902)	(1.078)
Food Diversity R3	4.878	6.433	8.977	6.624
	(1.884)	(1.632)	(1.860)	(32.73)
Books R2	7.502	157.5	93.20	52.48
	(17.35)	(243.4)	(176.5)	(84.39)
Clothing R2	54.17	412.5	94.06	187.0
	(61.81)	(392.1)	(121.0)	(293.9)
Shoes R2	25.97	74.84	49.35	52.11
	(34.40)	(88.96)	(68.57)	(71.05)
Uniform R2	25.19	227.1	44.91	11.97
	(35.14)	(222.6)	(57.59)	(43.44)
Food Total R2	4.377	4.993	4.856	4.659
	(0.839)	(1.075)	(1.009)	(1.153)
Food Diversity R2	4.825	5.775	7.854	6.822
	(1.603)	(1.554)	(1.595)	(2.084)
For books, clothing, shoes and uniform we construct a measure that indicates how money was spent on each item for the study child specifically.				
Food total is the number of time the child ate in the last 24 hours (including snacks).				
Food diversity is the number of different food groups the child ate in the last 24 hours.				
			Parental Cognition	
Mum Education	2.917	3.629	7.790	6.820
	(3.967)	(4.428)	(4.529)	(3.769)
Dad Education	4.966	5.542	9.126	7.501
	(4.512)	(4.928)	(3.951)	(3.777)
Literacy Parent	0.659	0.783	1.588	1.672
	(0.875)	(0.941)	(0.712)	(0.690)
Parental education is measured in years of education. Literacy is measured with an indicator of the ease parent can read in any language, with zero being not at all, one being with difficulty and two being easily.				

		Parental Health		
Mothers Weight	51.13	46.41	58.74	48.79
	(8.132)	(9.406)	(10.39)	(7.196)
Mothers Height	158.3	151.4	149.9	152.2
	(9.546)	(6.529)	(5.915)	(5.909)
		Parental Resources		
Income R3	15025.0	77220.0	11691.5	7380.3
	(101313.5)	(180750.3)	(19781.6)	(14840.0)
Wealth Index R3	0.329	0.508	0.539	0.608
	(0.175)	(0.185)	(0.212)	(0.189)
Income R2	5741.7	39672.8	12393.7	23612.0
	(17618.9)	(55854.1)	(15736.7)	(47660.1)
Wealth Index R2	0.285	0.459	0.475	0.491
	(0.178)	(0.197)	(0.233)	(0.181)
		Prices		
Price Food R3	3.218	3.122	0.941	1.081
	(0.789)	(0.154)	(0.118)	(0.388)
Price Clothes R3	3.688	5.815	3.830	3.208
	(0.590)	(0.726)	(0.361)	(0.346)
Price Notebook R3	1.174	1.753	0.344	1.316
	(0.276)	(0.320)	(0.134)	(0.435)
Price Drug1 R3	1.701	2.463	1.765	1.309
	(0.461)	(0.543)	(0.644)	(0.818)
Price Drug2 R3	0.722	1.439	1.333	1.505
	(0.436)	(0.655)	(0.483)	(0.834)
Price Food R2	2.313	3.054	0.748	0.874
	(1.323)	(0.200)	(0.101)	(0.571)
Price Clothes R2	3.145	4.377	3.613	4.072
	(0.349)	(0.511)	(0.311)	(2.394)
Price Notebook r2	0.917	1.675	0.240	1.928
	(0.164)	(0.326)	(0.116)	(2.497)
Price Drug1 R2	0.398	1.776	1.231	2.645
	(1.35)6	(0.843)	(0.606)	(1.884)
Price Drug2 R2	0.146	1.204	1.440	1.970
	(0.920)	(0.333)	(0.430)	(1.872)
		Others		
Number Children	3.143	2.543	2.148	1.183
	(2.308)	(1.077)	(2.046)	(1.121)
Number of Older Children	2.444	0.979	1.609	0.842
	(2.251)	(1.116)	(1.951)	(1.082)
Gender	0.528	0.537	0.500	0.514

	(0.499)	(0.499)	(0.500)	(0.500)
Hours in Preschool	1.857	4.860	3.955	5.791
	(3.114)	(1.839)	(1.371)	(2.642)

Notes *Standard deviations in brackets. R1, R2, R3 refer to the first, second and third round respectively.*

Appendix B: Hours Estimation

B1. CES with control function

The following four tables are repeated from the results section in the paper. The hours variable is the one reported from the preschool questionnaire, with zeros for when the child was not attending preschool.

Table 2.12: Ethiopia

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.331 [0.25,0.45]	NA [NA,NA]	−0.006 [−0.06,0.05]
Health	0.089 [0,0.17]	0.074 [0.04,0.16]	0.555 [0.51,0.62]	1.004 [0.93,1.05]
Parental Cognition	0.016 [−0.04,0.17]	0.005 [−0.08,0.09]	−0.105 [−0.17,−0.02]	−0.015 [−0.05,0.04]
Parental Health	−0.023 [−0.05,0.05]	−0.044 [−0.1,0]	0.117 [0.08,0.25]	0.009 [−0.02,0.04]
Investment	0.89 [0.57,1.08]	0.548 [0.3,0.65]	0.514 [0.27,0.57]	−0.025 [−0.12,0.12]
Complementarity ρ	−0.322 [−0.73,0.88]	0.112 [−0.07,0.38]	−0.127 [−0.27,−0.02]	−0.295 [−0.45,0.38]
Elasticity of Substitution	0.756 [0.51,5.06]	1.126 [0.94,1.63]	0.887 [0.79,0.98]	0.772 [0.69,1.63]
Log TFP	0.009 [−0.05,0.05]	0.02 [−0.02,0.05]	0.072 [0.04,0.11]	0.004 [−0.03,0.02]
Investment Residual v	−0.828 [−1.05,−0.49]	−0.562 [−0.72,−0.34]	−0.478 [−0.53,−0.22]	−0.028 [−0.18,0.08]
Number of Children	−0.018 [−0.05,0]	−0.038 [−0.07,−0.02]	−0.082 [−0.11,−0.04]	−0.017 [−0.03,0.01]
Older Siblings	0.022 [0.01,0.06]	0.021 [0,0.04]	0.055 [0.02,0.08]	0.024 [0,0.03]
Gender	−0.001 [−0.01,0.01]	−0.001 [−0.01,0.02]	−0.012 [−0.02,0]	−0.007 [−0.01,0]
Preschool	0.028 [−0.06,0.13]	0.086 [0.04,0.17]	−0.082 [−0.11,0.02]	0.034 [−0.03,0.07]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.13: India

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.297 [0.19,0.36]	NA [NA,NA]	−0.059 [−0.09,0]
Health	0.188 [0.14,0.28]	0.223 [0.16,0.28]	0.685 [0.6,0.75]	0.85 [0.78,0.91]
Parental Cognition	0.332 [0.25,0.42]	0.018 [−0.05,0.1]	0.002 [−0.04,0.06]	0.057 [0.01,0.09]
Parental Health	0.074 [−0.01,0.2]	−0.115 [−0.24,−0.04]	0.291 [0.19,0.41]	0.032 [−0.02,0.1]
Investment	0.408 [0.19,0.54]	0.557 [0.42,0.74]	0.037 [−0.07,0.18]	0.138 [0.06,0.2]
Complementarity ρ	−0.142 [−0.37,−0.02]	−0.18 [−0.23,0.06]	−0.019 [−0.14,0.08]	0.07 [−0.03,0.16]
Elasticity of Substitution	0.876 [0.73,0.98]	0.848 [0.81,1.07]	0.981 [0.88,1.09]	1.076 [0.97,1.19]
Log TFP	−0.015 [−0.05,0.03]	−0.028 [−0.08,−0.01]	0.03 [0,0.06]	−0.002 [−0.02,0.03]
Investment Residual v	−0.229 [−0.43,−0.01]	−0.608 [−0.88,−0.45]	0.023 [−0.15,0.15]	−0.102 [−0.18,0.01]
Number of Children	0.007 [−0.01,0.03]	0.001 [−0.01,0.02]	0.001 [0,0.02]	−0.002 [−0.02,0.01]
Older Siblings	0.002 [−0.01,0.02]	−0.007 [−0.02,0.01]	−0.018 [−0.04,−0.01]	−0.004 [−0.01,0.01]
Gender	0.015 [0,0.03]	0.041 [0.02,0.05]	0 [−0.01,0.01]	0.004 [−0.01,0.01]
Preschool	−0.002 [−0.03,0.06]	0.021 [−0.05,0.07]	−0.015 [−0.06,0.01]	−0.019 [−0.05,0]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.14: Peru

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.431 [0.37,0.55]	NA [NA,NA]	−0.037 [−0.1,0]
Health	0.001 [−0.05,0.08]	0.055 [−0.04,0.11]	0.682 [0.62,0.73]	1.08 [1.01,1.13]
Parental Cognition	−0.023 [−0.13,0.19]	0.195 [0.1,0.29]	0.045 [−0.01,0.13]	0.02 [−0.03,0.04]
Parental Health	−0.138 [−0.27,0.04]	−0.104 [−0.21,−0.02]	0.182 [0.11,0.25]	−0.039 [−0.08,0.01]
Investment	1.11 [0.77,1.24]	0.394 [0.26,0.53]	0.065 [−0.09,0.19]	−0.028 [−0.09,0.12]
Complementarity ρ	−0.247 [−0.48,0.44]	−0.034 [−0.15,0.11]	0.045 [−0.3,0.2]	−0.2 [−0.27,0.2]
Elasticity of Substitution	0.802 [0.67,1.35]	0.967 [0.87,1.12]	1.047 [0.77,1.24]	0.833 [0.79,1.25]
Log TFP	−0.061 [−0.09,0]	−0.014 [−0.05,0.01]	−0.02 [−0.05,0.01]	0.015 [0.01,0.04]
Investment Residual v	−1.144 [−1.26,−0.77]	−0.358 [−0.49,−0.23]	0.009 [−0.14,0.2]	0.037 [−0.11,0.14]
Number of Children	0.037 [0,0.06]	−0.017 [−0.04,0.01]	−0.014 [−0.02,0.01]	−0.017 [−0.03,0]
Older Siblings	−0.015 [−0.03,0.02]	0.019 [0,0.05]	0 [−0.02,0.01]	0.014 [0,0.03]
Gender	0.002 [−0.01,0.02]	0.01 [0,0.02]	0.024 [0.01,0.03]	−0.009 [−0.02,0]
Preschool	0.05 [0.03,0.1]	0.029 [−0.01,0.05]	0.026 [−0.01,0.06]	0.003 [−0.02,0.03]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.15: Vietnam

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.904 [0.24,0.92]	NA [NA,NA]	−0.003 [−0.07,0.08]
Health	−0.009 [−0.06,0.07]	0.052 [−0.02,0.1]	0.587 [0.49,0.65]	0.918 [0.77,0.96]
Parental Cognition	0.18 [0.03,0.3]	0.188 [0.15,0.35]	0.099 [0.07,0.17]	0.005 [−0.04,0.04]
Parental Health	−0.016 [−0.18,0.05]	−0.05 [−0.08,0.02]	0.231 [0.19,0.31]	0 [−0.01,0.06]
Investment	0.629 [0.5,0.89]	0 [−0.11,0.37]	0.041 [−0.1,0.15]	0.029 [−0.03,0.13]
Complementarity ρ	0.077 [−0.1,0.14]	0.095 [−0.23,0.26]	−0.042 [−0.1,0.05]	0.087 [−0.16,0.36]
Elasticity of Substitution	1.084 [0.91,1.16]	1.105 [0.81,1.35]	0.96 [0.91,1.05]	1.095 [0.86,1.57]
Log TFP	−0.017 [−0.06,0.01]	0.069 [0,0.1]	0.041 [0.01,0.07]	0.01 [0,0.04]
Investment Residual v	−0.49 [−0.78,−0.2]	−0.092 [−0.79,0.07]	0.321 [0.1,0.67]	−0.208 [−0.43,−0.15]
Number of Children	0.004 [−0.01,0.03]	−0.045 [−0.07,−0.02]	−0.035 [−0.05,−0.01]	−0.003 [−0.01,0.01]
Older Siblings	−0.004 [−0.02,0.02]	0.019 [0,0.05]	−0.004 [−0.02,0.01]	0.005 [−0.01,0.01]
Gender	0.006 [−0.01,0.02]	−0.013 [−0.02,0]	0.019 [0.01,0.03]	−0.011 [−0.02,0]
Preschool	0.216 [0.16,0.25]	−0.094 [−0.11,0.03]	0.041 [0.01,0.07]	0.05 [0.01,0.08]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

B2. Investment Equation with control function

Table 2.16: Ethiopia Investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.009 [−0.05,0.06]
Health	0.01 [−0.02,0.04]	0.01 [−0.03,0.03]
Parental Cognition	0.15 [0.04,0.19]	0.14 [0.08,0.18]
Parental Health	0.07 [0.02,0.11]	0.047 [0.02,0.09]
Price Clothes	−0.015 [−0.06,0.04]	0.037 [−0.01,0.07]
Price Notebook	−0.028 [−0.08,0.02]	−0.075 [−0.12,−0.04]
Price Mebendazol	−0.01 [−0.06,0.03]	−0.029 [−0.08,0]
Price Amoxicillin	0.022 [−0.02,0.11]	−0.098 [−0.13,−0.08]
Price Food	0.064 [0.02,0.12]	−0.006 [−0.03,0.05]
Older Siblings	0.053 [−0.1,0.16]	0.024 [−0.09,0.14]
Number of Children	−0.083 [−0.17,0.08]	0.076 [−0.04,0.2]
Gender	0.073 [0.03,0.11]	−0.023 [−0.07,0.01]
Preschool	0.119 [0.06,0.19]	0.123 [0.07,0.19]
Income	0.481 [0.34,0.74]	0.245 [0.1,0.42]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.17: India Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	0.095 [0.04,0.15]
Health	0.059 [0.03,0.1]	−0.016 [−0.04,0.04]
Parental Cognition	0.008 [−0.03,0.07]	0.02 [−0.03,0.11]
Parental Health	0.016 [−0.05,0.05]	−0.004 [−0.04,0.08]
Price Clothes	−0.062 [−0.09,−0.02]	−0.002 [−0.08,0.05]
Price Notebook	−0.073 [−0.12,−0.02]	−0.098 [−0.15,−0.03]
Price Mebendazol	0.022 [−0.02,0.06]	−0.128 [−0.19,−0.05]
Price Amoxicillin	0.005 [−0.04,0.05]	0.059 [0.02,0.09]
Price Food	0.065 [0.03,0.09]	−0.019 [−0.05,0.06]
Older Siblings	0.049 [−0.02,0.1]	0.057 [0,0.12]
Number of Children	−0.115 [−0.16,−0.04]	−0.077 [−0.13,−0.03]
Gender	−0.023 [−0.05,0.02]	−0.01 [−0.04,0.03]
Preschool	0.077 [0.02,0.11]	0.045 [0.01,0.08]
Income	0.6 [0.46,0.74]	0.817 [0.53,0.99]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.18: Peru Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.018 [−0.08,0.04]
Health	−0.016 [−0.06,0.03]	0.065 [0.01,0.14]
Parental Cognition	0.108 [−0.02,0.17]	0.057 [−0.02,0.13]
Parental Health	0.121 [−0.01,0.25]	0.034 [−0.1,0.12]
Price Clothes	−0.003 [−0.04,0.04]	0.046 [0,0.08]
Price Notebook	0.034 [−0.01,0.07]	−0.033 [−0.06,0]
Price Mebendazol	−0.057 [−0.11,−0.01]	−0.033 [−0.07,0]
Price Amoxicillin	0.025 [−0.01,0.07]	0.018 [−0.02,0.05]
Price Food	0.071 [0.01,0.1]	0.126 [0.09,0.17]
Older Siblings	0.023 [−0.09,0.12]	0.032 [−0.08,0.11]
Number of Children	−0.179 [−0.27,−0.07]	−0.117 [−0.2,−0.01]
Gender	−0.002 [−0.04,0.04]	−0.016 [−0.04,0.02]
Preschool	0.001 [−0.03,0.03]	0.043 [0.01,0.07]
Income	0.625 [0.47,0.77]	0.577 [0.46,0.77]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

Table 2.19: Vietnam - investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.087 [−0.19,0.05]
Health	0.054 [0.02,0.1]	0.097 [0.03,0.13]
Parental Cognition	0.093 [0.03,0.21]	0.005 [−0.06,0.04]
Parental Health	0.042 [0.01,0.11]	0.062 [0.03,0.1]
Price Clothes	−0.192 [−0.31,−0.04]	0.009 [−0.07,0.04]
Price Notebook	0.199 [0.09,0.31]	0.14 [0.04,0.16]
Price Mebendazol	−0.003 [−0.07,0.05]	−0.023 [−0.08,0.01]
Price Amoxicillin	−0.02 [−0.07,0.09]	0.016 [0,0.04]
Price Food	0.065 [−0.02,0.12]	−0.064 [−0.09,−0.02]
Older Siblings	−0.097 [−0.16,−0.01]	−0.113 [−0.15,0]
Number of Children	0.122 [0.04,0.18]	0.004 [−0.1,0.04]
Gender	0.023 [−0.02,0.06]	0.013 [−0.03,0.04]
Preschool	−0.003 [−0.07,0.04]	0.112 [0.05,0.22]
Income	0.26 [0.1,0.3]	0.326 [0.08,0.34]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question.*

B3 .CES - no control function

Table 2.20: Ethiopia - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.395 [0.29,0.55]	NA [NA,NA]	−0.003 [−0.05,0.05]
Health	0.209 [0.11,0.23]	0.14 [0.07,0.22]	0.629 [0.56,0.66]	1.007 [0.94,1.05]
Parental Cognition	0.248 [0.17,0.33]	0.055 [0,0.11]	0.031 [−0.05,0.06]	−0.013 [−0.05,0.04]
Parental Health	0.065 [0.03,0.15]	−0.011 [−0.05,0.03]	0.162 [0.11,0.3]	0.011 [−0.01,0.04]
Investment	0.253 [0.16,0.47]	0.281 [0.13,0.36]	0.143 [0.08,0.22]	−0.038 [−0.11,0.03]
Complementarity ρ	−0.387 [−0.67,−0.09]	0.064 [−0.13,0.51]	−0.389 [−0.46,−0.14]	−0.271 [−0.54,0.48]
Elasticity of Substitution	0.721 [0.6,0.91]	1.069 [0.89,2.04]	0.72 [0.68,0.88]	0.787 [0.65,1.91]
Log TFP	0.02 [−0.03,0.06]	0.001 [−0.05,0.04]	0.09 [0.04,0.12]	0.003 [−0.03,0.02]
Investment Residual v	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	−0.003 [−0.03,0.02]	−0.013 [−0.04,0.01]	−0.071 [−0.1,−0.04]	−0.016 [−0.02,0.01]
Older Siblings	0.014 [0,0.04]	0.012 [−0.01,0.04]	0.049 [0.01,0.07]	0.023 [0,0.03]
Gender	0.019 [0,0.02]	−0.004 [−0.01,0.01]	−0.001 [−0.01,0.01]	−0.007 [−0.01,0]
Preschool	0.225 [0.12,0.28]	0.14 [0.1,0.22]	0.035 [−0.02,0.07]	0.036 [−0.02,0.07]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question. Investment residual is zero as there is no control function estimated.*

Table 2.21: India - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.368 [0.28,0.32]	NA [NA,0.04]	−0.047 [−0.08,0.1]
Health	0.217 [0.15,0.31]	0.253 [0.19,0.2]	0.682 [0.61,0.39]	0.855 [0.79,0.13]
Parental Cognition	0.375 [0.32,0.43]	0.114 [0.07,0.05]	−0.003 [−0.05,0.13]	0.073 [0.04,0.14]
Parental Health	0.111 [0.02,0.22]	−0.028 [−0.11,0.34]	0.288 [0.2,0.11]	0.047 [0,1.17]
Investment	0.272 [0.16,0.35]	0.212 [0.08,−0.08]	0.05 [−0.01,1.13]	0.08 [0.04,NA]
Complementarity ρ	−0.163 [−0.39,−0.01]	−0.317 [−0.39,0.93]	−0.013 [−0.14,NA]	0.048 [−0.06,NA]
Elasticity of Substitution	0.86 [0.72,0.99]	0.759 [0.72,NA]	0.987 [0.88,NA]	1.05 [0.94,NA]
Log TFP	−0.009 [−0.05,NA]	−0.009 [−0.08,NA]	0.029 [0,NA]	−0.003 [−0.02,NA]
Investment Residual v	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	0.007 [−0.01,NA]	0.009 [−0.01,NA]	0.001 [0,NA]	−0.001 [−0.02,NA]
Older Siblings	0.002 [−0.01,NA]	−0.006 [−0.02,NA]	−0.018 [−0.04,0.02]	−0.004 [−0.01,0.31]
Gender	0.014 [0,NA]	0.041 [0.03,NA]	0 [−0.01,0.91]	0.004 [−0.01,0.43]
Preschool	0.025 [−0.01,0.43]	0.081 [0.03,0.74]	−0.017 [−0.05,0.1]	−0.008 [−0.03,0.22]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question. Investment residual is zero as there is no control function estimated.*

Table 2.22: Peru - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.48 [0.42,0.14]	NA [NA,0.1]	−0.043 [−0.09,0.01]
Health	0.077 [0.03,0.17]	0.084 [0,0.37]	0.681 [0.63,0.25]	1.079 [1.02,0.06]
Parental Cognition	0.462 [0.33,0.55]	0.281 [0.21,0.05]	0.041 [0,0.13]	0.013 [−0.02,0.25]
Parental Health	0.127 [0,0.2]	−0.029 [−0.12,0.2]	0.18 [0.1,0.22]	−0.049 [−0.08,1.33]
Investment	0.198 [0.12,0.36]	0.129 [0.06,0.2]	0.072 [0.03,1.28]	−0.001 [−0.02,NA]
Complementarity ρ	0.049 [−0.18,0.51]	0.042 [−0.07,1.25]	0.052 [−0.17,NA]	−0.126 [−0.24,NA]
Elasticity of Substitution	1.052 [0.84,1.71]	1.044 [0.93,NA]	1.055 [0.86,NA]	0.888 [0.81,NA]
Log TFP	−0.045 [−0.11,NA]	−0.023 [−0.07,NA]	−0.021 [−0.05,NA]	0.016 [0.01,NA]
Investment Residual v	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	0.011 [−0.02,NA]	−0.023 [−0.05,NA]	−0.013 [−0.02,NA]	−0.017 [−0.03,NA]
Older Siblings	0.006 [−0.01,NA]	0.025 [0,NA]	0 [−0.02,−0.01]	0.014 [0,0.17]
Gender	0.009 [0,NA]	0.01 [0,NA]	0.024 [0.01,1.13]	−0.009 [−0.02,0.55]
Preschool	0.136 [0.09,0.6]	0.056 [0.01,0.72]	0.025 [−0.01,0.04]	0 [−0.02,0.2]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question. Investment residual is zero as there is no control function estimated.*

Table 2.23: Vietnam - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.92 [0.3,0.92]	NA [NA,NA]	0.029 [−0.03,0.1]
Health	0.032 [−0.02,0.1]	0.057 [−0.01,0.12]	0.56 [0.47,0.62]	0.932 [0.8,0.96]
Parental Cognition	0.247 [0.21,0.35]	0.189 [0.16,0.37]	0.056 [0.04,0.12]	0.008 [−0.03,0.04]
Parental Health	0.049 [−0.06,0.13]	−0.04 [−0.06,0.07]	0.189 [0.16,0.26]	0.02 [0.01,0.09]
Investment	0.424 [0.26,0.56]	−0.038 [−0.13,0.16]	0.175 [0.06,0.24]	−0.05 [−0.1,0.02]
Complementarity ρ	0.07 [−0.09,0.16]	0.162 [−0.07,0.34]	−0.021 [−0.11,0.08]	0.176 [−0.1,0.31]
Elasticity of Substitution	1.075 [0.92,1.19]	1.194 [0.93,1.52]	0.979 [0.9,1.09]	1.214 [0.92,1.46]
Log TFP	−0.03 [−0.07,−0.01]	0.07 [0,0.1]	0.045 [0.01,0.08]	0.01 [0,0.04]
Investment Residual v	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	0.017 [0,0.04]	−0.045 [−0.07,−0.02]	−0.044 [−0.05,−0.02]	−0.001 [−0.01,0.01]
Older Siblings	−0.011 [−0.02,0.01]	0.018 [0,0.04]	0.001 [−0.02,0.01]	0.002 [−0.01,0.01]
Gender	0.008 [0,0.03]	−0.013 [−0.03,0]	0.017 [0,0.03]	−0.011 [−0.02,0]
Preschool	0.248 [0.18,0.3]	−0.087 [−0.1,0.08]	0.019 [−0.01,0.05]	0.061 [0.02,0.1]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the preschool question. Investment residual is zero as there is no control function estimated.*

Appendix C: Preschool Attendance

This estimation uses a binary indicator for whether the child attends preschool or not.

C1. CES Estimation with control functions

Table 2.24: Ethiopia

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.314 [0.25,0.47]	NA [NA,NA]	0.01 [−0.03,0.06]
Health	0.072 [0,0.14]	0.087 [0.03,0.15]	0.558 [0.51,0.61]	0.996 [0.92,1.04]
Parental Cognition	0.12 [0.01,0.23]	0.041 [−0.04,0.14]	−0.075 [−0.13,0]	0.013 [−0.03,0.05]
Parental Health	−0.007 [−0.04,0.05]	−0.049 [−0.12,0]	0.164 [0.11,0.31]	−0.012 [−0.03,0.04]
Investment	0.77 [0.58,0.91]	0.544 [0.34,0.68]	0.328 [0.16,0.44]	0.026 [−0.09,0.15]
Complementarity ρ	0.308 [−0.36,0.8]	0.126 [−0.06,0.52]	−0.113 [−0.3,0.01]	−0.483 [−0.52,0.42]
Elasticity of Substitution	1.445 [0.71,4.43]	1.145 [0.94,1.84]	0.899 [0.77,1.01]	0.674 [0.66,1.74]
Log TFP	−0.055 [−0.12,−0.02]	0.014 [−0.03,0.05]	0.049 [0.02,0.08]	0.007 [−0.02,0.03]
Investment Residual v	−0.683 [−0.89,−0.49]	−0.542 [−0.7,−0.27]	−0.297 [−0.41,−0.05]	−0.08 [−0.2,0.06]
Number of Children	−0.007 [−0.04,0.02]	−0.037 [−0.07,−0.01]	−0.063 [−0.09,−0.02]	−0.016 [−0.04,0.01]
Older Siblings	0.008 [−0.01,0.04]	0.016 [−0.01,0.04]	0.037 [0,0.07]	0.017 [0,0.03]
Gender	0.019 [0,0.03]	0.007 [−0.01,0.02]	0.004 [−0.01,0.01]	−0.008 [−0.01,0]
Preschool	0.045 [0,0.12]	0.063 [0.02,0.13]	0.027 [−0.03,0.07]	−0.033 [−0.07,0.01]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.25: India

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.297 [0.21,0.39]	NA [NA,NA]	−0.043 [−0.08,0.08]
Health	0.134 [0.08,0.19]	0.221 [0.14,0.28]	0.727 [0.62,0.79]	0.869 [0.79,0.93]
Parental Cognition	0.351 [0.28,0.41]	0.023 [−0.04,0.12]	0.043 [−0.01,0.09]	0.041 [−0.01,0.08]
Parental Health	0.028 [−0.03,0.1]	−0.111 [−0.22,−0.02]	0.197 [0.16,0.37]	−0.001 [−0.09,0.05]
Investment	0.463 [0.37,0.59]	0.523 [0.28,0.67]	0.057 [−0.11,0.15]	0.176 [0.05,0.22]
Complementarity ρ	0.132 [−0.07,0.29]	−0.029 [−0.27,0.28]	−0.051 [−0.1,0.21]	0.022 [−0.09,0.18]
Elasticity of Substitution	1.152 [0.93,1.42]	0.971 [0.79,1.39]	0.952 [0.91,1.26]	1.022 [0.92,1.22]
Log TFP	−0.012 [−0.05,0.03]	−0.061 [−0.11,−0.02]	0.05 [0,0.06]	0.005 [−0.01,0.03]
Investment Residual v	−0.402 [−0.74,−0.06]	−0.618 [−0.84,−0.38]	0.162 [−0.15,0.41]	−0.161 [−0.24,−0.03]
Number of Children	−0.001 [−0.03,0.02]	0.002 [−0.01,0.02]	0.012 [−0.01,0.03]	−0.009 [−0.02,0]
Older Siblings	−0.006 [−0.02,0.02]	−0.007 [−0.03,0.01]	−0.028 [−0.04,−0.01]	0.001 [−0.01,0.01]
Gender	0.006 [−0.01,0.02]	0.041 [0.02,0.06]	−0.003 [−0.01,0.01]	0.003 [−0.01,0.01]
Preschool	0.024 [−0.06,0.05]	0.047 [−0.04,0.09]	−0.024 [−0.12,0.01]	−0.042 [−0.07,0.01]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.26: Peru

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.509 [0.4,0.82]	NA [NA,NA]	−0.047 [−0.09,−0.01]
Health	0.052 [−0.02,0.12]	0.09 [−0.04,0.15]	0.762 [0.68,0.94]	1.022 [0.95,1.07]
Parental Cognition	0.217 [0,0.31]	0.231 [0.11,0.34]	0.156 [0.07,0.22]	−0.015 [−0.06,0.02]
Parental Health	−0.201 [−0.58,0.02]	−0.179 [−0.25,0.04]	0.33 [−0.08,0.39]	0.024 [−0.08,0.06]
Investment	0.908 [0.75,1.5]	0.274 [−0.16,0.45]	−0.23 [−0.31,0.08]	0.039 [−0.01,0.15]
Complementarity ρ	−0.26 [−0.39,0.88]	0.118 [−0.08,0.28]	0.008 [−0.43,0.5]	0.527 [−0.75,0.44]
Elasticity of Substitution	0.793 [0.7,7.59]	1.134 [0.92,1.39]	1.008 [0.7,2]	2.114 [0.57,1.79]
Log TFP	−0.006 [−0.04,0.05]	−0.036 [−0.07,0.01]	−0.02 [−0.07,0]	0.033 [0,0.05]
Investment Residual v	−1.146 [−1.69,−0.85]	−0.215 [−0.42,0.35]	0.348 [−0.02,0.52]	−0.046 [−0.18,0.08]
Number of Children	−0.025 [−0.03,0]	−0.015 [−0.03,0.01]	−0.034 [−0.03,0.01]	−0.01 [−0.02,0.01]
Older Siblings	0.026 [0,0.04]	0.021 [0,0.03]	0.014 [−0.02,0.01]	0.005 [−0.01,0.01]
Gender	0.006 [−0.02,0.02]	0.009 [0,0.02]	0.033 [0.02,0.04]	−0.008 [−0.02,0]
Preschool	0.022 [−0.17,0.09]	0.076 [−0.04,0.16]	−0.017 [−0.16,0.03]	−0.023 [−0.04,0.04]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.27: Vietnam

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.829 [0.17,0.91]	NA [NA,NA]	0.051 [−0.04,0.09]
Health	0.023 [−0.05,0.08]	0.047 [0,0.09]	0.568 [0.51,0.64]	0.904 [0.77,0.95]
Parental Cognition	0.14 [0.06,0.25]	0.174 [0.15,0.41]	0.011 [−0.04,0.13]	−0.009 [−0.03,0.03]
Parental Health	−0.044 [−0.19,0.04]	−0.036 [−0.07,0.02]	0.165 [0.11,0.25]	0.007 [−0.02,0.07]
Investment	0.886 [0.65,1.02]	−0.057 [−0.14,0.45]	0.288 [0.03,0.36]	0.028 [−0.02,0.14]
Complementarity ρ	0.595 [−0.06,0.97]	0.436 [−0.03,0.33]	−0.026 [−0.11,0.04]	0.029 [−0.72,0.18]
Elasticity of Substitution	2.47 [0.89,11.27]	1.772 [0.97,1.5]	0.974 [0.9,1.05]	1.03 [0.58,1.22]
Log TFP	−0.067 [−0.1,−0.03]	0.026 [−0.01,0.07]	0.039 [0,0.07]	0.025 [0,0.06]
Investment Residual υ	−0.753 [−0.92,−0.49]	−0.125 [−0.73,0.14]	−0.05 [−0.21,0.19]	−0.213 [−0.3,−0.11]
Number of Children	0.016 [0,0.05]	−0.043 [−0.07,−0.02]	−0.037 [−0.06,−0.02]	−0.007 [−0.02,0]
Older Siblings	0 [−0.03,0.01]	0.022 [0.01,0.05]	0 [−0.01,0.01]	0.004 [0,0.01]
Gender	0.013 [0.01,0.03]	−0.011 [−0.02,0]	0.017 [0.01,0.03]	−0.012 [−0.02,0]
Preschool	−0.005 [−0.04,0.03]	0.043 [0.01,0.07]	−0.032 [−0.05,0.01]	0.019 [0,0.04]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

C2. Investment equations for control function

Table 2.28: Ethiopia - investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	0.033 [−0.04,0.07]
Health	0.024 [0,0.06]	−0.006 [−0.03,0.03]
Parental Cognition	0.052 [−0.02,0.14]	0.154 [0.11,0.21]
Parental Health	0.033 [0,0.08]	0.058 [0.02,0.11]
Price Clothes	0.004 [−0.03,0.05]	0.049 [0.01,0.09]
Price Notebook	−0.001 [−0.06,0.08]	−0.063 [−0.09,−0.02]
Price Mebendazol	0.047 [−0.01,0.08]	−0.035 [−0.08,0]
Price Amoxicillin	0.042 [0.01,0.09]	−0.117 [−0.14,−0.08]
Price Food	−0.002 [−0.06,0.04]	−0.009 [−0.06,0.04]
Older Siblings	0.14 [0,0.23]	0.047 [−0.07,0.16]
Number of Children	−0.19 [−0.28,−0.06]	0.047 [−0.08,0.18]
Gender	0.005 [−0.03,0.04]	−0.031 [−0.07,0.01]
Preschool	0.113 [0.07,0.16]	0.089 [0.03,0.13]
Income	0.441 [0.28,0.55]	0.275 [0.1,0.45]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.29: India Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	0.08 [0.04,0.15]
Health	0.018 [−0.01,0.03]	0.023 [−0.04,0.05]
Parental Cognition	0.015 [−0.01,0.04]	0.006 [−0.05,0.09]
Parental Health	−0.001 [−0.02,0.03]	−0.017 [−0.06,0.07]
Price Clothes	0.096 [0.02,0.12]	−0.014 [−0.08,0.05]
Price Notebook	0.037 [−0.04,0.07]	−0.084 [−0.15,−0.04]
Price Mebendazol	−0.056 [−0.09,0.01]	−0.093 [−0.14,−0.04]
Price Amoxicillin	0.023 [−0.01,0.05]	0.056 [0.02,0.1]
Price Food	−0.041 [−0.08,0.06]	−0.023 [−0.07,0.04]
Older Siblings	0.027 [−0.03,0.09]	0.069 [−0.01,0.12]
Number of Children	−0.015 [−0.09,0.07]	−0.089 [−0.13,−0.01]
Gender	0.012 [−0.02,0.05]	−0.01 [−0.04,0.03]
Preschool	0.022 [−0.01,0.07]	0.063 [0.02,0.11]
Income	0.178 [0.12,0.29]	0.877 [0.65,1.05]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.30: Peru Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.091 [−0.2,−0.03]
Health	−0.054 [−0.08,−0.02]	0.064 [−0.03,0.11]
Parental Cognition	−0.031 [−0.07,0.08]	0.001 [−0.15,0.09]
Parental Health	0.103 [−0.02,0.27]	−0.06 [−0.2,0.5]
Price Clothes	0.036 [0,0.06]	0.033 [−0.03,0.05]
Price Notebook	0.021 [−0.01,0.04]	−0.027 [−0.08,0.01]
Price Mebendazol	−0.053 [−0.08,−0.02]	−0.046 [−0.08,0.01]
Price Amoxicillin	0.018 [0,0.05]	0.008 [−0.03,0.03]
Price Food	−0.007 [−0.04,0.03]	0.147 [0.1,0.22]
Older Siblings	−0.165 [−0.31,−0.03]	−0.038 [−0.16,0.07]
Number of Children	0.029 [−0.07,0.13]	−0.052 [−0.18,0.04]
Gender	0.02 [−0.02,0.06]	−0.021 [−0.05,0.02]
Preschool	−0.015 [−0.05,0.02]	0.002 [−0.06,0.05]
Income	0.439 [0.34,0.56]	0.839 [0.66,1.11]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

Table 2.31: Vietnam - investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.042 [−0.13,0.03]
Health	0.053 [0.04,0.13]	0.093 [0.02,0.12]
Parental Cognition	0.166 [0.13,0.21]	0.001 [−0.06,0.06]
Parental Health	0.092 [0.02,0.12]	0.056 [0.03,0.11]
Price Clothes	−0.234 [−0.4,−0.15]	0.03 [−0.01,0.09]
Price Notebook	0.035 [−0.02,0.2]	0.167 [0.11,0.2]
Price Mebendazol	−0.016 [−0.07,0.07]	−0.028 [−0.07,0.01]
Price Amoxicillin	0.164 [0.06,0.27]	−0.007 [−0.03,0.02]
Price Food	0.07 [0.01,0.12]	−0.077 [−0.1,−0.03]
Older Siblings	−0.096 [−0.17,−0.04]	−0.104 [−0.18,−0.02]
Number of Children	0.07 [0,0.16]	−0.008 [−0.1,0.06]
Gender	0.014 [−0.01,0.05]	0.007 [−0.02,0.06]
Preschool	0.009 [−0.01,0.03]	−0.027 [−0.06,0]
Income	0.396 [0.23,0.52]	0.343 [0.17,0.43]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not.*

C3. CES - no control function

Table 2.32: Ethiopia - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.385 [0.29,0.54]	NA [NA,NA]	0.02 [−0.02,0.07]
Health	0.169 [0.07,0.22]	0.144 [0.07,0.21]	0.598 [0.53,0.64]	1.003 [0.93,1.04]
Parental Cognition	0.232 [0.15,0.32]	0.1 [0.03,0.16]	−0.023 [−0.07,0.03]	0.021 [−0.02,0.05]
Parental Health	0.046 [0.01,0.12]	−0.013 [−0.06,0.03]	0.184 [0.13,0.32]	−0.008 [−0.01,0.04]
Investment	0.402 [0.21,0.53]	0.282 [0.17,0.39]	0.172 [0.06,0.25]	−0.007 [−0.07,0.07]
Complementarity ρ	−0.069 [−0.32,0.37]	0.085 [−0.13,0.55]	−0.216 [−0.34,−0.03]	−0.435 [−0.54,0.57]
Elasticity of Substitution	0.936 [0.76,1.59]	1.093 [0.89,2.23]	0.822 [0.74,0.97]	0.697 [0.65,2.35]
Log TFP	−0.033 [−0.1,0]	−0.008 [−0.05,0.03]	0.063 [0.02,0.09]	0.005 [−0.03,0.02]
Investment Residual υ	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	−0.011 [−0.04,0.01]	−0.013 [−0.05,0.01]	−0.063 [−0.09,−0.02]	−0.013 [−0.03,0.01]
Older Siblings	0.013 [0,0.04]	0.008 [−0.01,0.04]	0.038 [0,0.07]	0.016 [0,0.03]
Gender	0.023 [0.01,0.03]	0.004 [−0.01,0.01]	0.006 [−0.01,0.01]	−0.008 [−0.02,0]
Preschool	0.151 [0.1,0.21]	0.103 [0.05,0.16]	0.069 [0,0.11]	−0.029 [−0.06,0.01]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not. Investment residual is zero as there is no control function estimated.*

Table 2.33: India - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.358 [0.27,0.31]	NA [NA,0.08]	−0.027 [−0.06,0.07]
Health	0.152 [0.09,0.21]	0.274 [0.15,0.2]	0.72 [0.63,0.37]	0.882 [0.8,0.14]
Parental Cognition	0.365 [0.3,0.43]	0.135 [0.07,0.14]	0.037 [−0.01,0.15]	0.07 [0.02,0.12]
Parental Health	0.037 [−0.03,0.11]	−0.052 [−0.11,0.29]	0.193 [0.16,0.23]	0.015 [−0.04,1.14]
Investment	0.411 [0.32,0.52]	0.185 [0.03,0.79]	0.078 [−0.07,1.3]	0.088 [0,NA]
Complementarity ρ	0.121 [−0.11,0.3]	−0.016 [−0.18,4.7]	−0.028 [−0.09,NA]	0.009 [−0.14,NA]
Elasticity of Substitution	1.137 [0.9,1.43]	0.984 [0.85,NA]	0.973 [0.92,NA]	1.009 [0.88,NA]
Log TFP	−0.017 [−0.06,NA]	−0.079 [−0.21,NA]	0.05 [0,NA]	0.002 [−0.02,NA]
Investment Residual υ	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	0.001 [−0.03,NA]	0.008 [−0.01,NA]	0.011 [−0.01,NA]	−0.007 [−0.02,NA]
Older Siblings	−0.006 [−0.02,NA]	−0.005 [−0.03,NA]	−0.028 [−0.04,0.1]	0.002 [−0.01,0.21]
Gender	0.007 [−0.01,NA]	0.041 [0.03,NA]	−0.004 [−0.01,0.94]	0.003 [−0.01,0.43]
Preschool	0.035 [−0.04,0.45]	0.1 [0,0.78]	−0.029 [−0.14,0.1]	−0.028 [−0.05,0.11]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not. Investment residual is zero as there is no control function estimated.*

Table 2.34: Peru - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.537 [0.42,0.15]	NA [NA,0.19]	−0.039 [−0.08,0.06]
Health	0.068 [−0.01,0.14]	0.094 [−0.03,0.35]	0.768 [0.68,0.33]	1.02 [0.96,0.04]
Parental Cognition	0.33 [0.22,0.45]	0.277 [0.16,0.07]	0.08 [0.06,0.16]	−0.008 [−0.03,0.57]
Parental Health	−0.011 [−0.14,0.15]	−0.137 [−0.2,0.25]	0.285 [−0.13,0.61]	0.032 [−0.06,2.35]
Investment	0.55 [0.4,0.66]	0.137 [0.05,0.31]	−0.033 [−0.13,2.59]	0.015 [−0.01,NA]
Complementarity ρ	0.132 [−0.26,0.32]	0.198 [−0.07,1.44]	0.608 [−0.52,NA]	0.598 [−0.78,NA]
Elasticity of Substitution	1.152 [0.8,1.47]	1.247 [0.94,NA]	2.55 [0.66,NA]	2.489 [0.56,NA]
Log TFP	−0.032 [−0.06,NA]	−0.048 [−0.09,NA]	−0.016 [−0.06,NA]	0.034 [0,NA]
Investment Residual υ	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	−0.023 [−0.03,NA]	−0.018 [−0.03,NA]	−0.038 [−0.03,NA]	−0.01 [−0.02,NA]
Older Siblings	0.02 [0,NA]	0.024 [0,NA]	0.014 [−0.02,0]	0.005 [−0.01,0.14]
Gender	0.014 [0,NA]	0.009 [0,NA]	0.031 [0.02,1.07]	−0.008 [−0.02,0.45]
Preschool	0.063 [−0.02,0.75]	0.093 [−0.02,0.93]	−0.101 [−0.16,0.03]	−0.021 [−0.04,0.15]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not. Investment residual is zero as there is no control function estimated.*

Table 2.35: Vietnam - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.852 [0.22,0.92]	NA [NA,NA]	0.091 [−0.02,0.12]
Health	0.107 [0.05,0.16]	0.053 [0.01,0.12]	0.574 [0.53,0.64]	0.916 [0.78,0.96]
Parental Cognition	0.42 [0.33,0.51]	0.173 [0.15,0.45]	0.028 [−0.01,0.11]	−0.009 [−0.03,0.05]
Parental Health	0.09 [−0.03,0.19]	−0.028 [−0.07,0.06]	0.174 [0.14,0.26]	0.022 [0,0.08]
Investment	0.322 [0.2,0.49]	−0.097 [−0.14,0.25]	0.252 [0.1,0.27]	−0.048 [−0.1,0.06]
Complementarity ρ	−0.044 [−0.19,0.08]	0.428 [0.02,0.35]	−0.033 [−0.1,0.05]	0.167 [−0.67,0.21]
Elasticity of Substitution	0.958 [0.84,1.09]	1.748 [1.02,1.53]	0.968 [0.91,1.05]	1.2 [0.6,1.27]
Log TFP	−0.061 [−0.1,−0.03]	0.028 [−0.01,0.07]	0.038 [0.01,0.07]	0.023 [0.01,0.07]
Investment Residual υ	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	0.037 [0.02,0.07]	−0.043 [−0.07,−0.02]	−0.036 [−0.06,−0.02]	−0.006 [−0.02,0.01]
Older Siblings	−0.014 [−0.04,−0.01]	0.021 [0,0.05]	0 [−0.02,0.01]	0.002 [0,0.01]
Gender	0.016 [0.01,0.03]	−0.012 [−0.02,0]	0.017 [0.01,0.03]	−0.013 [−0.02,0]
Preschool	0.062 [0.02,0.1]	0.047 [0.03,0.09]	−0.028 [−0.04,0.02]	0.027 [0.01,0.05]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is a binary measure of whether the child attended preschool or not. Investment residual is zero as there is no control function estimated.*

Appendix D: Hours from time use questionnaire

This estimation uses an alternative measure of hours spent at preschool derived from the time use questionnaire part of young lives.

D1. CES Estimation with control functions

Table 2.36: Ethiopia

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.321 [0.26,0.44]	NA [NA,NA]	−0.017 [−0.05,0.06]
Health	0.103 [0.02,0.18]	0.072 [0.03,0.15]	0.597 [0.51,0.64]	1.011 [0.93,1.07]
Parental Cognition	0.038 [−0.05,0.17]	0.026 [−0.04,0.13]	−0.104 [−0.18,−0.01]	0.009 [−0.04,0.04]
Parental Health	0.011 [−0.03,0.08]	−0.037 [−0.09,0.01]	0.144 [0.09,0.28]	−0.008 [−0.02,0.03]
Investment	0.788 [0.49,1]	0.569 [0.32,0.66]	0.344 [0.15,0.5]	−0.01 [−0.12,0.1]
Complementarity ρ	−0.526 [−0.73,0.47]	0.122 [−0.03,0.44]	−0.202 [−0.36,−0.02]	−0.518 [−0.45,0.34]
Elasticity of Substitution	0.655 [0.58,1.95]	1.139 [0.97,1.77]	0.832 [0.74,0.98]	0.659 [0.69,1.52]
Log TFP	0.038 [−0.04,0.05]	0.027 [−0.02,0.04]	0.066 [0.03,0.11]	0.002 [−0.03,0.02]
Investment Residual v	−0.64 [−0.89,−0.37]	−0.548 [−0.68,−0.34]	−0.308 [−0.47,−0.11]	−0.038 [−0.15,0.11]
Number of Children	−0.021 [−0.04,0.01]	−0.05 [−0.06,−0.02]	−0.053 [−0.09,−0.03]	−0.011 [−0.03,0.01]
Older Siblings	0.03 [0,0.05]	0.026 [0,0.04]	0.035 [0.01,0.06]	0.017 [0,0.03]
Gender	−0.002 [−0.01,0.02]	0.001 [−0.01,0.02]	−0.007 [−0.02,0.01]	−0.006 [−0.01,0]
Preschool Hours	0.06 [−0.01,0.16]	0.05 [0.02,0.11]	0.019 [−0.03,0.09]	0.016 [−0.02,0.05]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.37: India

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.282 [0.19,0.35]	NA [NA,NA]	−0.057 [−0.08,0.02]
Health	0.108 [0.06,0.2]	0.217 [0.15,0.27]	0.7 [0.61,0.77]	0.867 [0.77,0.91]
Parental Cognition	0.367 [0.29,0.43]	0.022 [−0.03,0.11]	0.009 [−0.02,0.06]	0.051 [0.01,0.08]
Parental Health	0.045 [−0.03,0.12]	−0.109 [−0.19,−0.03]	0.306 [0.21,0.4]	−0.004 [−0.03,0.08]
Investment	0.475 [0.36,0.52]	0.528 [0.38,0.7]	−0.064 [−0.1,0.03]	0.17 [0.09,0.21]
Complementarity ρ	0.091 [−0.05,0.25]	−0.166 [−0.24,0.05]	0.004 [−0.1,0.08]	0.076 [−0.03,0.13]
Elasticity of Substitution	1.1 [0.95,1.33]	0.858 [0.81,1.05]	1.004 [0.91,1.09]	1.082 [0.97,1.15]
Log TFP	−0.002 [−0.05,0.03]	−0.019 [−0.08,0]	0.027 [0.01,0.06]	−0.001 [−0.01,0.02]
Investment Residual v	−0.388 [−0.67,−0.05]	−0.62 [−0.87,−0.45]	0.14 [−0.01,0.41]	−0.127 [−0.21,−0.02]
Number of Children	−0.008 [−0.03,0.02]	0 [−0.02,0.02]	0.004 [−0.01,0.02]	−0.003 [−0.02,0.01]
Older Siblings	0 [−0.02,0.02]	−0.008 [−0.02,0.01]	−0.02 [−0.04,−0.01]	−0.004 [−0.01,0.01]
Gender	0.007 [−0.01,0.02]	0.038 [0.02,0.05]	−0.001 [−0.01,0.01]	0.005 [−0.01,0.01]
Preschool Hours	0.006 [−0.02,0.05]	0.061 [0.01,0.1]	0.049 [0.01,0.07]	−0.028 [−0.05,0.01]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.38: Peru

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.434 [0.37,0.57]	NA [NA,NA]	−0.03 [−0.08,0]
Health	−0.012 [−0.07,0.09]	0.05 [−0.03,0.11]	0.669 [0.62,0.73]	1.092 [1.02,1.14]
Parental Cognition	−0.016 [−0.12,0.14]	0.186 [0.1,0.28]	0.052 [−0.02,0.12]	0.029 [−0.04,0.05]
Parental Health	−0.147 [−0.3,0.02]	−0.1 [−0.2,0]	0.178 [0.11,0.24]	−0.035 [−0.07,0.02]
Investment	1.062 [0.75,1.17]	0.415 [0.27,0.54]	0.026 [−0.1,0.16]	−0.029 [−0.08,0.12]
Complementarity ρ	−0.213 [−0.31,0.09]	−0.07 [−0.15,0.09]	−0.106 [−0.32,0.06]	−0.051 [−0.23,0.18]
Elasticity of Substitution	0.824 [0.76,1.1]	0.935 [0.87,1.1]	0.904 [0.76,1.06]	0.952 [0.82,1.23]
Log TFP	−0.06 [−0.08,−0.01]	−0.009 [−0.06,0.01]	−0.007 [−0.03,0.01]	0.019 [0,0.04]
Investment Residual v	−1.092 [−1.16,−0.73]	−0.377 [−0.53,−0.25]	0.048 [−0.1,0.21]	0.04 [−0.1,0.11]
Number of Children	0.038 [−0.01,0.05]	−0.018 [−0.04,0.01]	−0.015 [−0.03,0]	−0.017 [−0.03,0]
Older Siblings	−0.013 [−0.03,0.02]	0.019 [0,0.05]	0.003 [−0.02,0.02]	0.014 [0,0.03]
Gender	0.003 [−0.01,0.02]	0.01 [0,0.02]	0.023 [0.01,0.03]	−0.009 [−0.02,0]
Preschool Hours	0.113 [0.08,0.18]	0.015 [−0.05,0.04]	0.075 [0.05,0.11]	−0.027 [−0.06,0]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.39: Vietnam

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.903 [0.24,0.91]	NA [NA,NA]	0.028 [−0.05,0.08]
Health	−0.003 [−0.05,0.1]	0.059 [−0.02,0.11]	0.529 [0.47,0.63]	0.896 [0.76,0.98]
Parental Cognition	0.084 [0.02,0.2]	0.17 [0.17,0.38]	0.019 [−0.08,0.12]	−0.012 [−0.03,0.04]
Parental Health	−0.048 [−0.17,0.04]	−0.039 [−0.1,0.04]	0.192 [0.12,0.25]	−0.002 [0,0.05]
Investment	0.774 [0.59,0.85]	−0.009 [−0.08,0.36]	0.245 [0.06,0.39]	0.044 [−0.03,0.12]
Complementarity ρ	0.221 [0.02,0.23]	0.154 [−0.06,0.34]	−0.051 [−0.13,0.06]	0.067 [−0.49,0.32]
Elasticity of Substitution	1.283 [1.02,1.31]	1.182 [0.94,1.53]	0.952 [0.89,1.06]	1.072 [0.68,1.46]
Log TFP	−0.067 [−0.1,−0.03]	0.076 [0,0.09]	0.043 [0.01,0.07]	0.015 [0.01,0.05]
Investment Residual v	−0.676 [−0.77,−0.39]	−0.092 [−0.65,0.07]	−0.044 [−0.23,0.14]	−0.282 [−0.46,−0.15]
Number of Children	0.017 [0,0.04]	−0.05 [−0.08,−0.02]	−0.045 [−0.06,−0.02]	−0.004 [−0.01,0]
Older Siblings	0 [−0.02,0.02]	0.022 [0.01,0.05]	0.005 [−0.02,0.01]	0.005 [−0.01,0.01]
Gender	0.01 [0,0.03]	−0.014 [−0.02,0.01]	0.016 [0.01,0.03]	−0.011 [−0.02,−0.01]
Preschool Hours	0.193 [0.17,0.25]	−0.083 [−0.12,0.04]	0.014 [−0.02,0.05]	0.046 [0.01,0.07]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

D2. Investment equations for control function

Table 2.40: Ethiopia - investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	0.008 [−0.03,0.08]
Health	0.009 [−0.03,0.06]	−0.004 [−0.04,0.01]
Parental Cognition	0.13 [0.06,0.2]	0.157 [0.11,0.21]
Parental Health	0.048 [0.01,0.12]	0.05 [0.02,0.1]
Price Clothes	0.044 [−0.01,0.1]	0.051 [0,0.08]
Price Notebook	−0.002 [−0.08,0.06]	−0.073 [−0.11,−0.04]
Price Mebendazol	0.009 [−0.05,0.04]	−0.036 [−0.08,0]
Price Amoxicillin	0.02 [−0.03,0.09]	−0.104 [−0.13,−0.07]
Price Food	0.031 [−0.03,0.11]	−0.006 [−0.06,0.04]
Older Siblings	0.116 [−0.05,0.21]	0.037 [−0.06,0.15]
Number of Children	−0.177 [−0.24,0.01]	0.059 [−0.05,0.16]
Gender	0.08 [0.03,0.12]	−0.029 [−0.08,0.01]
Preschool Hours	0.055 [−0.02,0.11]	0.071 [0.05,0.13]
Income	0.658 [0.45,0.89]	0.286 [0.09,0.46]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.41: India Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	0.098 [0.04,0.14]
Health	0.011 [−0.02,0.03]	−0.019 [−0.05,0.04]
Parental Cognition	0.023 [0,0.05]	0.01 [−0.03,0.12]
Parental Health	0.004 [−0.01,0.04]	−0.011 [−0.06,0.06]
Price Clothes	0.095 [0.06,0.13]	0.001 [−0.08,0.05]
Price Notebook	0.035 [−0.02,0.07]	−0.101 [−0.13,−0.03]
Price Mebendazol	−0.058 [−0.09,−0.02]	−0.122 [−0.17,−0.04]
Price Amoxicillin	0.018 [−0.01,0.05]	0.061 [0.03,0.09]
Price Food	−0.042 [−0.08,0]	−0.017 [−0.07,0.07]
Older Siblings	0.018 [−0.04,0.08]	0.05 [0.01,0.12]
Number of Children	−0.001 [−0.07,0.06]	−0.066 [−0.12,−0.02]
Gender	0.011 [−0.03,0.03]	−0.009 [−0.04,0.03]
Preschool Hours	0.007 [−0.02,0.04]	0.025 [−0.01,0.06]
Income	0.152 [0.08,0.2]	0.884 [0.58,1.03]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.42: Peru Investment Equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.043 [−0.09,0.01]
Health	−0.011 [−0.06,0.03]	0.067 [0.02,0.16]
Parental Cognition	0.105 [0.02,0.15]	0.051 [−0.04,0.11]
Parental Health	0.12 [−0.01,0.25]	0.012 [−0.11,0.1]
Price Clothes	−0.004 [−0.04,0.04]	0.046 [0,0.08]
Price Notebook	0.034 [−0.01,0.07]	−0.033 [−0.06,0]
Price Mebendazol	−0.056 [−0.1,0]	−0.032 [−0.06,0]
Price Amoxicillin	0.026 [−0.01,0.06]	0.018 [−0.02,0.04]
Price Food	0.072 [0,0.11]	0.125 [0.08,0.17]
Older Siblings	0.029 [−0.08,0.12]	0.034 [−0.07,0.16]
Number of Children	−0.187 [−0.27,−0.07]	−0.113 [−0.21,−0.02]
Gender	−0.002 [−0.03,0.04]	−0.014 [−0.04,0.02]
Preschool Hours	−0.003 [−0.03,0.02]	0.079 [0.05,0.12]
Income	0.628 [0.47,0.71]	0.591 [0.45,0.77]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

Table 2.43: Vietnam - investment equation

	Age 5	Age 8
Cognition	NA [NA,NA]	−0.123 [−0.23,0.01]
Health	0.062 [0.01,0.1]	0.071 [0.01,0.12]
Parental Cognition	0.132 [0.09,0.19]	−0.016 [−0.07,0.04]
Parental Health	0.093 [0.01,0.16]	0.069 [0.03,0.13]
Price Clothes	−0.219 [−0.41,−0.05]	0.015 [−0.05,0.04]
Price Notebook	0.019 [−0.08,0.23]	0.114 [0.06,0.17]
Price Mebendazol	−0.031 [−0.11,0.04]	−0.051 [−0.08,0]
Price Amoxicillin	0.165 [0.06,0.27]	0.019 [−0.01,0.04]
Price Food	0.073 [−0.03,0.12]	−0.072 [−0.1,−0.03]
Older Siblings	−0.102 [−0.19,−0.04]	−0.104 [−0.16,−0.01]
Number of Children	0.069 [−0.01,0.17]	−0.014 [−0.1,0.06]
Gender	0.013 [−0.02,0.04]	0.011 [−0.01,0.06]
Preschool Hours	0.058 [0.02,0.09]	0.139 [0.06,0.23]
Income	0.382 [0.17,0.49]	0.285 [0.15,0.4]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey.*

D3. CES - no control function

Table 2.44: Ethiopia - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.39 [0.31,0.53]	NA [NA,NA]	−0.014 [−0.04,0.05]
Health	0.186 [0.1,0.23]	0.132 [0.07,0.19]	0.636 [0.55,0.66]	1.014 [0.94,1.06]
Parental Cognition	0.253 [0.16,0.34]	0.079 [0.04,0.16]	0.001 [−0.06,0.04]	0.014 [−0.05,0.04]
Parental Health	0.072 [0.03,0.17]	−0.004 [−0.04,0.03]	0.171 [0.12,0.3]	−0.006 [−0.02,0.03]
Investment	0.301 [0.14,0.48]	0.311 [0.16,0.38]	0.117 [0.04,0.19]	−0.028 [−0.11,0.04]
Complementarity ρ	−0.434 [−0.56,−0.09]	0.061 [−0.14,0.46]	−0.324 [−0.45,−0.1]	−0.35 [−0.5,0.35]
Elasticity of Substitution	0.697 [0.64,0.91]	1.065 [0.87,1.86]	0.755 [0.69,0.91]	0.741 [0.67,1.54]
Log TFP	0.045 [−0.04,0.06]	0.004 [−0.05,0.04]	0.076 [0.03,0.11]	0.001 [−0.03,0.02]
Investment Residual v	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	−0.019 [−0.04,0.01]	−0.025 [−0.04,0]	−0.051 [−0.09,−0.02]	−0.009 [−0.03,0.01]
Older Siblings	0.031 [0.01,0.04]	0.018 [0,0.03]	0.035 [0.01,0.06]	0.016 [0,0.03]
Gender	0.013 [0.01,0.02]	−0.002 [−0.01,0.01]	0 [−0.01,0.01]	−0.006 [−0.01,0]
Preschool Hours	0.188 [0.12,0.23]	0.092 [0.07,0.15]	0.075 [0.04,0.12]	0.02 [−0.01,0.05]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey. The coefficient on investment residual is zero as there was no control function estimated.*

Table 2.45: India - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.352 [0.25,0.29]	NA [NA,0.05]	−0.043 [−0.07,0.09]
Health	0.122 [0.07,0.21]	0.237 [0.17,0.21]	0.695 [0.61,0.39]	0.871 [0.77,0.13]
Parental Cognition	0.377 [0.31,0.44]	0.128 [0.08,0.05]	0.005 [−0.03,0.04]	0.073 [0.03,0.12]
Parental Health	0.057 [−0.03,0.15]	−0.021 [−0.08,0.32]	0.302 [0.2,0.11]	0.015 [−0.02,1.14]
Investment	0.43 [0.31,0.47]	0.191 [0.07,−0.07]	−0.047 [−0.08,1.12]	0.101 [0.04,NA]
Complementarity ρ	0.075 [−0.07,0.24]	−0.274 [−0.33,0.93]	0.016 [−0.1,NA]	0.048 [−0.09,NA]
Elasticity of Substitution	1.082 [0.94,1.31]	0.785 [0.75,NA]	1.017 [0.91,NA]	1.05 [0.91,NA]
Log TFP	−0.004 [−0.05,NA]	−0.007 [−0.08,NA]	0.027 [0.01,NA]	−0.004 [−0.02,NA]
Investment Residual v	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	−0.007 [−0.03,NA]	0.01 [−0.01,NA]	0.004 [−0.01,NA]	−0.001 [−0.01,NA]
Older Siblings	0 [−0.02,NA]	−0.008 [−0.02,NA]	−0.02 [−0.04,0.04]	−0.004 [−0.01,0.21]
Gender	0.007 [−0.01,NA]	0.038 [0.02,NA]	−0.001 [−0.01,0.92]	0.004 [−0.01,0.44]
Preschool Hours	0.014 [−0.01,0.42]	0.113 [0.06,0.76]	0.046 [0.01,0.1]	−0.016 [−0.04,0.15]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey. The coefficient on investment residual is zero as there was no control function estimated.*

Table 2.46: Peru - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.48 [0.42,0.13]	NA [NA,0.08]	−0.035 [−0.08,0.01]
Health	0.071 [0.03,0.16]	0.082 [0.01,0.37]	0.664 [0.62,0.23]	1.088 [1.03,0.06]
Parental Cognition	0.444 [0.3,0.5]	0.277 [0.21,0.06]	0.03 [−0.01,0.11]	0.02 [−0.02,0.22]
Parental Health	0.092 [−0.02,0.18]	−0.023 [−0.11,0.2]	0.169 [0.1,0.09]	−0.044 [−0.07,1.28]
Investment	0.179 [0.1,0.35]	0.141 [0.06,0.19]	0.067 [0.02,1.09]	0.001 [−0.02,NA]
Complementarity ρ	0.06 [−0.13,0.14]	0.025 [−0.08,1.23]	−0.044 [−0.25,NA]	0.034 [−0.12,NA]
Elasticity of Substitution	1.064 [0.89,1.17]	1.025 [0.93,NA]	0.957 [0.8,NA]	1.035 [0.89,NA]
Log TFP	−0.055 [−0.09,NA]	−0.019 [−0.07,NA]	−0.013 [−0.04,NA]	0.022 [0.01,NA]
Investment Residual υ	0 [0,NA]	0 [0,NA]	0 [0,NA]	0 [0,NA]
Number of Children	0.011 [−0.03,NA]	−0.024 [−0.05,NA]	−0.014 [−0.03,NA]	−0.017 [−0.03,NA]
Older Siblings	0.01 [−0.01,NA]	0.026 [0,NA]	0.002 [−0.02,−0.01]	0.013 [0,0.16]
Gender	0.009 [0,NA]	0.01 [0,NA]	0.023 [0.01,1.14]	−0.009 [−0.02,0.5]
Preschool Hours	0.213 [0.18,0.63]	0.042 [−0.02,0.72]	0.071 [0.04,0.04]	−0.03 [−0.06,0.18]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey. The coefficient on investment residual is zero as there was no control function estimated.*

Table 2.47: Vietnam - no control function

	Cognition		Health	
Age	5	8	5	8
Cognition	NA [NA,NA]	0.917 [0.28,0.92]	NA [NA,NA]	0.066 [−0.03,0.11]
Health	0.074 [0.02,0.17]	0.062 [0.01,0.12]	0.534 [0.48,0.63]	0.909 [0.77,0.99]
Parental Cognition	0.287 [0.22,0.38]	0.169 [0.17,0.4]	0.032 [−0.03,0.1]	−0.013 [−0.03,0.04]
Parental Health	0.096 [−0.02,0.16]	−0.031 [−0.08,0.07]	0.201 [0.13,0.26]	0.021 [0.01,0.08]
Investment	0.278 [0.18,0.4]	−0.04 [−0.11,0.19]	0.214 [0.1,0.3]	−0.042 [−0.11,0.03]
Complementarity ρ	−0.002 [−0.09,0.1]	0.217 [−0.03,0.41]	−0.059 [−0.15,0.04]	0.114 [−0.28,0.3]
Elasticity of Substitution	0.998 [0.92,1.11]	1.278 [0.97,1.7]	0.944 [0.87,1.04]	1.128 [0.78,1.42]
Log TFP	−0.049 [−0.09,−0.02]	0.077 [0,0.09]	0.045 [0.01,0.07]	0.018 [0.01,0.05]
Investment Residual υ	0 [0,0]	0 [0,0]	0 [0,0]	0 [0,0]
Number of Children	0.037 [0.01,0.05]	−0.049 [−0.08,−0.02]	−0.043 [−0.06,−0.02]	−0.003 [−0.01,0.01]
Older Siblings	−0.018 [−0.03,0]	0.021 [0,0.04]	0.004 [−0.01,0.01]	0.002 [−0.01,0.01]
Gender	0.012 [0.01,0.03]	−0.014 [−0.02,0.01]	0.017 [0.01,0.03]	−0.012 [−0.02,0]
Preschool Hours	0.265 [0.22,0.31]	−0.077 [−0.12,0.06]	0.019 [0,0.06]	0.06 [0.02,0.08]

Notes *95% confidence intervals based on 100 bootstrap replications in square brackets. The preschool measure is the hours variable from the time use survey. The coefficient on investment residual is zero as there was no control function estimated.*

Appendix E: Measurement system loadings

Table 2.48: Measurement System Ethiopia

	Cog 8	Cog 5	Health 8	Health 5	Health 1	Invest 8	Invest 5	Parent Cog	Parent Health	Income 8	Income 5
PPVT	1	0	0	0	0	0	0	0	0	0	0
MATH	1.1353795	0	0	0	0	0	0	0	0	0	0
EGRA	0.8793223	0	0	0	0	0	0	0	0	0	0
PPVT R2	0	1	0	0	0	0	0	0	0	0	0
LANGUAGE	0	0.7021093	0	0	0	0	0	0	0	0	0
Height for age	0	0	1	0	0	0	0	0	0	0	0
Weight for age	0	0	1.0942293	0	0	0	0	0	0	0	0
Healthy	0	0	0.1740755	0	0	0	0	0	0	0	0
Height for age	0	0	0	1	0	0	0	0	0	0	0
Weight for age	0	0	0	1.0890455	0	0	0	0	0	0	0
Healthy	0	0	0	-0.08801898	0	0	0	0	0	0	0
Height for age	0	0	0	0	1	0	0	0	0	0	0
Weight for age	0	0	0	0	1.1377236	0	0	0	0	0	0
Healthy	0	0	0	0	-0.1984976	0	0	0	0	0	0
Books	0	0	0	0	0	1	0	0	0	0	0
Clothing	0	0	0	0	0	1.5987173	0	0	0	0	0
Shoes	0	0	0	0	0	1.7145685	0	0	0	0	0
Uniform	0	0	0	0	0	0.7436665	0	0	0	0	0
Food total	0	0	0	0	0	0.4557418	0	0	0	0	0
Food diversity	0	0	0	0	0	0.5812718	0	0	0	0	0
Books	0	0	0	0	0	0	1	0	0	0	0
Clothing	0	0	0	0	0	0	1.4052874	0	0	0	0
Shoes	0	0	0	0	0	0	1.4634866	0	0	0	0
Uniform	0	0	0	0	0	0	0.5733195	0	0	0	0
Food total	0	0	0	0	0	0	0.312947	0	0	0	0
Food diversity	0	0	0	0	0	0	0.6825558	0	0	0	0
Mum Education	0	0	0	0	0	0	0	1	0	0	0
Dad Education	0	0	0	0	0	0	0	0.6768316	0	0	0
Literacy	0	0	0	0	0	0	0	0.7940013	0	0	0
Mother Weight	0	0	0	0	0	0	0	0	1	0	0
Mother Height	0	0	0	0	0	0	0	0	0.2270794	0	0
Income 3	0	0	0	0	0	0	0	0	0	1	0
Wealth 3	0	0	0	0	0	0	0	0	0	1.587556	0
Income 2	0	0	0	0	0	0	0	0	0	0	1
Wealth 2	0	0	0	0	0	0	0	0	0	0	1.318667

Notes *For each latent factor the first measure's loading coefficient was normalized to one.*

Table 2.49: Measurement System India

	Cog 8	Cog 5	Health 8	Health 5	Health 1	Invest 8	Invest 5	Parent Cog	Parent Health	Income 8	Income 5
PPVT	1	0	0	0	0	0	0	0	0	0	0
MATH	1.2451524	0	0	0	0	0	0	0	0	0	0
EGRA	0.9771127	0	0	0	0	0	0	0	0	0	0
PPVT R2	0	1	0	0	0	0	0	0	0	0	0
LANGUAGE	0	0.8025405	0	0	0	0	0	0	0	0	0
Height for age	0	0	1	0	0	0	0	0	0	0	0
Weight for age	0	0	1.0984147	0	0	0	0	0	0	0	0
Healthy	0	0	0.3083763	0	0	0	0	0	0	0	0
Height for age	0	0	0	1	0	0	0	0	0	0	0
Weight for age	0	0	0	1.0122253	0	0	0	0	0	0	0
Healthy	0	0	0	0.1829518	0	0	0	0	0	0	0
Height for age	0	0	0	0	1	0	0	0	0	0	0
Weight for age	0	0	0	0	1.2322921	0	0	0	0	0	0
Healthy	0	0	0	0	0.3898903	0	0	0	0	0	0
Books	0	0	0	0	0	1	0	0	0	0	0
Clothing	0	0	0	0	0	0.8888135	0	0	0	0	0
Shoes	0	0	0	0	0	1.0364202	0	0	0	0	0
Uniform	0	0	0	0	0	0.7207172	0	0	0	0	0
Food total	0	0	0	0	0	0.3774669	0	0	0	0	0
Food diversity	0	0	0	0	0	0.5018475	0	0	0	0	0
Books	0	0	0	0	0	0	1	0	0	0	0
Clothing	0	0	0	0	0	0	1.0927354	0	0	0	0
Shoes	0	0	0	0	0	0	1.2709513	0	0	0	0
Uniform	0	0	0	0	0	0	0.5726105	0	0	0	0
Food total	0	0	0	0	0	0	0.2074873	0	0	0	0
Food diversity	0	0	0	0	0	0	0.5063354	0	0	0	0
Mum Education	0	0	0	0	0	0	0	1	0	0	0
Dad Education	0	0	0	0	0	0	0	0.8037129	0	0	0
Literacy	0	0	0	0	0	0	0	0.7334608	0	0	0
Mother Weight	0	0	0	0	0	0	0	0	1	0	0
Mother Height	0	0	0	0	0	0	0	0	0.5144492	0	0
Income 3	0	0	0	0	0	0	0	0	0	1	0
Wealth 3	0	0	0	0	0	0	0	0	0	1.520746	0
Income 2	0	0	0	0	0	0	0	0	0	0	1
Wealth 2	0	0	0	0	0	0	0	0	0	0	1.194628

Notes *For each latent factor the first measure's loading coefficient was normalized to one.*

Table 2.50: Measurement System Peru

	Cog 8	Cog 5	Health 8	Health 5	Health 1	Invest 8	Invest 5	Parent Cog	Parent Health	Income 8	Income 5
PPVT	1	0	0	0	0	0	0	0	0	0	0
MATH	0.7923761	0	0	0	0	0	0	0	0	0	0
EGRA	0.7325639	0	0	0	0	0	0	0	0	0	0
PPVT R2	0	1	0	0	0	0	0	0	0	0	0
LANGUAGE	0	0.6460957	0	0	0	0	0	0	0	0	0
Height for age	0	0	1	0	0	0	0	0	0	0	0
Weight for age	0	0	1.005712	0	0	0	0	0	0	0	0
Healthy	0	0	0.1712915	0	0	0	0	0	0	0	0
Height for age	0	0	0	1	0	0	0	0	0	0	0
Weight for age	0	0	0	1.1071356	0	0	0	0	0	0	0
Healthy	0	0	0	0.2126588	0	0	0	0	0	0	0
Height for age	0	0	0	0	1	0	0	0	0	0	0
Weight for age	0	0	0	0	0.9997136	0	0	0	0	0	0
Healthy	0	0	0	0	0.253618	0	0	0	0	0	0
Books	0	0	0	0	0	1	0	0	0	0	0
Clothing	0	0	0	0	0	0.9099076	0	0	0	0	0
Shoes	0	0	0	0	0	1.1773108	0	0	0	0	0
Uniform	0	0	0	0	0	0.5679257	0	0	0	0	0
Food total	0	0	0	0	0	0.2530294	0	0	0	0	0
Food diversity	0	0	0	0	0	0.1143394	0	0	0	0	0
Books	0	0	0	0	0	0	1	0	0	0	0
Clothing	0	0	0	0	0	0	2.9963598	0	0	0	0
Shoes	0	0	0	0	0	0	2.8447167	0	0	0	0
Uniform	0	0	0	0	0	0	1.5787567	0	0	0	0
Food total	0	0	0	0	0	0	0.4549639	0	0	0	0
Food diversity	0	0	0	0	0	0	0.6346622	0	0	0	0
Mum Education	0	0	0	0	0	0	0	1	0	0	0
Dad Education	0	0	0	0	0	0	0	0.8294131	0	0	0
Literacy	0	0	0	0	0	0	0	0.8334626	0	0	0
Mother Weight	0	0	0	0	0	0	0	0	1	0	0
Mother Height	0	0	0	0	0	0	0	0	1.123283	0	0
Income 3	0	0	0	0	0	0	0	0	0	1	0
Wealth 3	0	0	0	0	0	0	0	0	0	1.327715	0
Income 2	0	0	0	0	0	0	0	0	0	0	1
Wealth 2	0	0	0	0	0	0	0	0	0	0	1.251163

Notes *For each latent factor the first measure's loading coefficient was normalized to one.*

Table 2.51: Measurement System Vietnam

	Cog 8	Cog 5	Health 8	Health 5	Health 1	Invest 8	Invest 5	Parent Cog	Parent Health	Income 8	Income 5
PPVT	1	0	0	0	0	0	0	0	0	0	0
MATH	0.8475054	0	0	0	0	0	0	0	0	0	0
EGRA	0.8609204	0	0	0	0	0	0	0	0	0	0
PPVT R2	0	1	0	0	0	0	0	0	0	0	0
LANGUAGE	0	0.4531397	0	0	0	0	0	0	0	0	0
Height for age	0	0	1	0	0	0	0	0	0	0	0
Weight for age	0	0	1.1483595	0	0	0	0	0	0	0	0
Healthy	0	0	0.3922237	0	0	0	0	0	0	0	0
Height for age	0	0	0	1	0	0	0	0	0	0	0
Weight for age	0	0	0	1.1066332	0	0	0	0	0	0	0
Healthy	0	0	0	-0.1285197	0	0	0	0	0	0	0
Height for age	0	0	0	0	1	0	0	0	0	0	0
Weight for age	0	0	0	0	1.056952	0	0	0	0	0	0
Healthy	0	0	0	0	-0.1917078	0	0	0	0	0	0
Books	0	0	0	0	0	1	0	0	0	0	0
Clothing	0	0	0	0	0	1.9107642	0	0	0	0	0
Shoes	0	0	0	0	0	1.8730369	0	0	0	0	0
Uniform	0	0	0	0	0	1.7059994	0	0	0	0	0
Food total	0	0	0	0	0	0.7722784	0	0	0	0	0
Food diversity	0	0	0	0	0	-0.1948483	0	0	0	0	0
Books	0	0	0	0	0	0	1	0	0	0	0
Clothing	0	0	0	0	0	0	1.6139442	0	0	0	0
Shoes	0	0	0	0	0	0	1.9099347	0	0	0	0
Uniform	0	0	0	0	0	0	0.3066999	0	0	0	0
Food total	0	0	0	0	0	0	0.8089761	0	0	0	0
Food diversity	0	0	0	0	0	0	0.8923046	0	0	0	0
Mum Education	0	0	0	0	0	0	0	1	0	0	0
Dad Education	0	0	0	0	0	0	0	0.9210314	0	0	0
Literacy	0	0	0	0	0	0	0	0.6090284	0	0	0
Mother Weight	0	0	0	0	0	0	0	0	1	0	0
Mother Height	0	0	0	0	0	0	0	0	0.8639977	0	0
Income 3	0	0	0	0	0	0	0	0	0	1	0
Wealth 3	0	0	0	0	0	0	0	0	0	2.632298	0
Income 2	0	0	0	0	0	0	0	0	0	0	1
Wealth 2	0	0	0	0	0	0	0	0	0	0	1.021818

Notes *For each latent factor the first measure's loading coefficient was normalized to one.*

Events in themselves can have no developmental meaning...the environment is first filtered by the child's own characteristics. Children with different characteristics, therefore, will be affected differently by the same objective occurrence. Not only does the child screen [their] environment, [they] also influence it...The child, by [their] own nature, "conditions" [their] environment, at the same time that the social and cultural environment affects [them].

Chess, Thomas, and Birch (1965)

3

Temperament, Investment and Skill Development

An Analysis of Cognitive and Behavioural Outcomes of 3 year olds in Ireland

Abstract

Cognitive and socio-economic skills are predictive of later educational, employment and health outcomes. Despite much research into the formation of such skills there remains a substantial amount of unexplained heterogeneity in outcomes, even after accounting for early measures of skills, parental resources, investment and education levels. This paper investigates whether temperament (a key variable from psychological research) could explain some of the observed differences. Temperament is a disposition trait that dictates the way an infant responds to the world around them, characterised by their emotionality, their responsiveness and their self regulation. This paper hypothesises that temperament might influence skills in three ways. Firstly, by directly impacting skills; secondly, by affecting the type and level of investment a child receives and thirdly, by changing the productivity of any level of investment. I examine each of these by predicting skills of Irish infants at age 3. I find suggestive evidence that the more difficult the temperament, the lower the level of time investment. From these results there are few definitive conclusions about the direct or multiplicative effects of temperament on cognitive skills. Temperament does however seem to impact socio-emotional skills, with the caveat that measurement issues may result in the same construct being on both sides of the estimating equation. While temperament may not account for the unexplained differences in skill evolution, this paper shows the utility of looking beyond economics when modelling human capital development.

3.1 Introduction

Over the past few decades there has been a growing body of literature in economics that has looked at the concept of human capital (HC). According to the OECD, human capital is defined as "the knowledge, skills, competencies and other attributes embodied in individuals or groups of individuals acquired during their life and used to produce goods, services or ideas in market circumstances". It is important attribute of the macro-economy, akin to traditional physical capital (K), but considered a measure of the quality of labour. The micro-economic perspective looks at the human capital of individuals, examining how to define and measure HC, how it is related to labour market and educational outcomes, and how it develops over the lifespan.

Production functions are the methodological framework used in the human capital literature, modelling skill evolution. Each individual is endowed with a stock of skills that they develop over the life course. This stock of skills depends on parental endowments as well as environmental factors during pregnancy. Once a child is born they receive a number of different investments, private investment from their parent and public investment from the government and other institutions (e.g. schools). Human capital is a multi-component construct - consisting of cognitive skills, the typical sort of skills we think of as intelligence; non-cognitive skills - incorporating a wide array of interpersonal skills, self-control, executive functioning, grit and self esteem and although not estimated in this chapter, health skills[1]. These skills are linked to outcomes we care about such as educational attainment, labour market outcomes and financial behaviour.

A considerable amount of research has studied the interactions between skills and investment, and their dynamics over time. If we understand how skills develop, we can develop programmes that promote both the right type, magnitude and mix of public and private investment. The optimal mix will assist in maximising both individual's human capital stock and that of the overall economy. There is increased recognition of early childhood as a key period in which investment is particularly important. The first thousand days

[1]Stunting and wasting are antecedents of later developmental delays, both cognitively and physically. However, in a country like Ireland the differences in height, weight and child health were within a very small range, all of which were relatively normal. As such this work concentrated on socio-emotional and cognitive skills only.

have been defined as a sensitive period of development, a time characterised by immense potential for growth and learning. This is reflected in the brain's neurological underpinnings - a period when synapses and neurons increase in size and complexity, creating many new connections. Stimulation in this period helps to maximise developmental potential by forming more neural networks that are both strong and complex.

Within this framework, investment decisions by parents are key determinants of human capital. They make an investment decision based on their own preferences and budget constraints, and the skill endowment of the child. Typically this endowment is represented by the child's initial level of skills. One major difficulty is in measuring this initial endowment, as well identifying the correct time period. Psychologists have developed early tests of development, which are thought to capture the cognitive capacity of infants. If these measures are not available, proxies such as birth weight or head circumference can be used to try to account for different endowments that directly impact human capital development, but also affect investment decisions by parents.

Consider the following thought experiment - take two infants with the same level of initial cognitive endowment each receiving the same level of investment. Assume that they differ in some underlying measure of their disposition that makes them more or less responsive to any given amount of investment. This disposition is a continuous range from somewhat *'difficult'* (i.e. fussy, inattentive) to relative *'easiness'* (responsiveness etc.). Given the same level of inputs, they are unlikely to end up with the same level of output of human capital[2]. In this paper I propose that this difference could be explained by how they convert inputs into outputs due to a difference in disposition.

This disposition is known as temperament: an underlying manner of behaviour that is relatively stable from birth. It can be formally defined as *"individual differences in reactivity and self regulation assumed to have a constitutional basis"* (Rothbart and Derryberry (1981)). It is thought to be the precursor of later personality differences. It can be conceptualised as a three dimensional object - broadly consisting of a positive affect factor (sociability/surgency), a negative affect factor (reactivity/negative emotionality) and a control/constraint factor (persistence/effortful control). There may be different

[2]Non-cognitive and social-emotional skills are used interchangeably but refer to the same construct.

patterns of responsiveness that vary by trait, but I consider temperament as a broad measure of 'difficulty' combining information from all three attributes. I aim to incorporate this new and potentially informative construct from the child development literature into the human capital production function framework used in Economics.

The reason I think this new variable might be useful is twofold. The first hypothesis is that temperament might act as a fixed difference amongst infants that directly impacts the dynamics of development of cognitive and socio-emotional skills. For example, more difficult temperament is thought to decrease cognitive skills and non-cognitive skills, but with stronger effects on the latter. There is some evidence to suggest temperament is relatively fixed, linking it specific brain regions, or more likely different neurotransmitters Putnam, Sanson and Rothbart (2002*a*). There is reasonable evidence of a link between the serotonin transporter gene and negative emotionality, as well as potential links between dopamine and sociability (Slagt et al. (2016)). Tests of temperament stability typically indicate a moderate degree of stability over time (Bornstein et al. (2015)), for instance Bould et al. (2013) find test retest correlations of about 0.5 from each of 3-5 years, 5-6 years and 3-6 years.

The second major hypothesis is that investment by parents is likely to be less effective depending on the degree of temperamental difficulty displayed by the child. This will change the productivity of the investment, as well as likely decreasing the amount of investment any child receives. Parents may reinforce negative temperaments by investing less in their child. However this could go the other way - parents might realise that more difficult temperament may negatively impact their development and may compensate for this by investing more in the child. Both of these possibilities will be explored. Temperament may help explain the heterogeneity in the productivity of investment and in the production function of human capital skills. A meta-analysis in psychology by Slagt et al. (2016) discusses the many ways that temperament might influence child outcomes through differential sensitivity to parental inputs, focusing primarily on parenting style. I take a different approach, by looking at its interaction with measures of investment (activities and money).

To do this I use the first two rounds of data from a longitudinal cohort study from Ireland, Growing Up in Ireland. This is a nationally representative sample of all 9 months and 9 year olds in Ireland, who were subsequently tracked over

a fifteen year period. Using Irish data expands the current knowledge base on human capital, which is dominated by evidence from the UK and the USA. I focus on the younger cohort, using the first two rounds: 9 months and 3 years old. I choose these time periods as I want to focus specifically on the first thousand days, as propogated in the child development literature as the most important. This period is also right before most children begin going to any institutionalised care with an educational focus (i.e. preschool rather than a child minders). This allows me to focus specifically on parental investment in this key developmental window. I estimate the production function of two types of cognitive skills (numerical and language skills) and two types of socio-emotional skills (prosocial and antisocial behaviours). I also consider the impact of two forms types of investment by parents, a time based activity measure of investment and a proxy for the amount of monetary investment the parent expends on their child. It may be that different forms of investment will interact differently with temperament. There is also an interesting dynamic to consider the trade offs and relative efficiency of both types of investment. These considerations may contribute to informing policies aimed at assisting parents invest appropriately in their children and as a consequence increase the overall human capital levels in the population.

3.2 Literature Review

3.2.1 Skill Development and Investment Behaviour

Human capital is an important construct both for determining the aggregate productivity of an economy and for an individuals own education and employment outcomes. Human capital is considered to be a multi-faceted object, typically consisting of at least two of these three constructs: cognitive skills, socio-emotional skills and health skills. These constructs interact over time to produce an overall level of human capital. Almond and Currie (2011) review a number of studies that document the long-run implications of early interventions in the US that aimed to increase human capital. Their work shows that the benefits accrue via higher test scores, higher educational attainment, higher income and employment, higher levels of savings, reductions in crime, increased psycho-social well being and better overall physical health. There is also evidence to suggest early interventions lead to higher QALYs (quality

adjusted life years) (García et al. (2016)). Almond and Mazumder (2013) look at at how parental behaviour in the first years might accentuate initial inequality in endowments at birth and find that parents play an important role, especially in the first few years of life.

There is evidence that both socio-emotional and cognitive skills matter. The well known Jamaica study provided physically stunted children with nutrition and cognitive stimulation, which led to increase in test scores and health outcomes. There was an increase in earnings of 25% for the treated group twenty years later (Gertler et al. (2013)). Hanushek et al. (2015) report the labour market returns to cognitive skills around the world using PIAAC (Program for the International Assessment of Adult Competencies) data. Their analysis compares returns to adult skills over the life cycle in 22 different countries, focusing on prime age earnings. They find on average a one standard deviation increase in numeracy skills led to an 18% wage increase for workers, although with some variation between countries. Edin et al. (2018) discuss the rise in returns to socio-emotional skills in Sweden from 1992-2013. They find that there is a pronounced increase in wages for private sector employees and particularly at the upper end of the wage distribution. Lindqvist and Vestman (2011*b*) find strong evidence that those with lower levels of socio-emotional skills do relatively poorly in employment and earnings (higher levels of unemployment and low annual earnings). They also find that cognitive ability is a strong predictor of wages for skilled workers and those with earnings above the median.

The first thousand days of a child's life are considered to be the most productive period to intervene to ensure positive outcomes (Heckman (2012)). Not only could this prevent the onset of damaging outcomes, such as severe physical stunting, it also is a period of heightened responsiveness to inputs. Early interventions can set the child on the right path and build the appropriate levels of skills, which can be built upon over time, possibly decreasing the need for further intervention. For instance, the well known Perry Preschool Project intervened with children who were three years old and had a social rate of return of between 7-10% (Heckman et al. (2010)). In addition early investment in preventive programmes aimed at disadvantaged children is often more cost effective than later remediation (Carneiro, Cunha and Heckman (2003)). The increased returns to skills accumulated at the earliest of ages as well as their

important long-run effects has led to a plethora of research into how human capital develops, when is the best time to invest, what types of investment are the most effective and how to ensure that no child is left behind.

Findings from economics show that a wide range of fetal shocks and circumstances can have long lasting implications on the outcomes already discussed (Almond and Currie (2011)). It is suggested that this period has much larger returns to investment, and re-allocating resources from later to early can result in pareto improvements. There is also emerging evidence that the pre-birth environment can have long lasting impacts. Conti et al. (2018) show that prenatal investment (as measured by maternal smoking and excessive gestational weight gain) and environmental deprivation are correlated with measures of fetal size in the womb. They analyse the predictive power of a range of measures of fetal health (birth weight, birth length, head circumference and APGA scores[3]) on later outcomes and show that these can predict growth and cognition.

The most common approach used to understand this process is to fully specify how human capital develops in early years and see how its different dimensions (health, cognitive and socio-emotional skills) interact over time with other inputs (investment, family factors and initial endowments) to produce later outcomes (Heckman, Pinto and Savelyev (2013)). There is growing evidence that the dynamic process of skill evolution becomes more persistent with age and that the productivity of different inputs also changes over the life cycle. A complete characterisation of this process is key to identifying possible windows of opportunities when certain investments (maybe in specific dimensions) are more productive and more likely to have long-run sustainable benefits.

Economists use a production function methodology (Boardman and Murnane (1979)), which relates a set of inputs to certain outcomes. Such an approach can be done from either a static (single period) or dynamic (over time) perspective, with the advantage of the latter of being a more realistic view as to how development actually occurs. It is important to use a flexible specification of the production function that allows for different dimensions, for their interactions with different inputs in the developmental process and for these relationships to change with age (Cunha, Heckman and Schennach (2010)). Early studies used a linear production function but subsequent work has suggested that

[3]This is a method to quickly summarize the health of newborn children against infant mortality.

more complicated forms are needed. Cobb Douglas, Constant Elasticity of Substitution and Translog are functional forms that allow for more complex interactions and higher order effects of key inputs (Attanasio, Meghir and Nix (2015), Attanasio et al. (2017), Cunha and Heckman (2007)). This paper tests different functional forms rather than assuming one will fit the human capital process. It also includes a new input into the production function: temperament.

A large body of literature has emerged focusing on the determinants of the parental investment and estimating the investment equation (Cunha, Heckman and Schennach (2010)). Economists have historically been interested in how parents allocate resources to children: Gary Becker pioneered this research area pioneered in the 1960s (such as Becker (1962)). Children are born with different endowments, which are defined as genetically inherited characteristics that are predetermined prior to the accumulation of human capital. The economic theory of intra-household resource allocation suggests that parental investment could reinforce or compensate for initial endowments (Becker and Tomes (1976)). If parents are interested in maximising aggregate welfare of children, they might reinforce initial endowment allocation by investing relatively more in their better-endowed children, assuming that marginal returns to investing are higher for better-endowed children. On the other hand, equity concerns might cause parents to compensate for low initial endowments by investing more in their lesser-endowed children. This literature also looks at the optimal investment over time. When is the best time to invest, i.e. when do we get the highest return? Is there evidence for critical or sensitive periods of investment? In this paper I attempt to model what happens when a parent picks a given level of investment, as opposed to how they made this decision. I also abstract away from any dynamics or timing of investment, as will be seen in the model section there is only one period of investment.

There is some research on how best to measure investment and what are the differential effects of different types of investment. One option is to use self-reported activities between the parent and the child. Fiorini and Keane (2014) look at the impact of types of time use on skill accumulation. They found educational activities with parents had a positive effect on cognitive skills. Time allocation in different activities did not seem to matter for socio-emotional skills, which instead were predicted by parenting style. Other studies have used

measures from the HOME observation scale which measures certain aspects of the quality and quantity of emotional, social, and cognitive support available in the household. It has sub-scales on variety, responsiveness, involvement, learning and organisation. HOME incorporates both time based investment but also the materials (books, clothes, puzzles) available to the child (which depends on their monetary resources) (Doyle et al. (2013)). Other researchers have measured investment using the numbers of toys, books, puzzles and other developmental materials in the home. Monetary investment has been used by Attanasio et al. (2017), Attanasio, Meghir and Nix (2015) amongst others, as is used in the previous chapter. These authors measure investment using the amount of money spent on food, clothing, school supplies and certain medicines that goes to the subject child, as well as the number of times the child ate and the diversity of their diet.

It may be that different types of investment have different consequences for certain skills. Few studies have used both a time and money budget constraint to analyse parents' investment decisions. One notable piece of work is Del Boca, Flinn and Wiswall (2013) who use the Child Development Supplement of the Panel Study of Income Dynamics to estimate the effectiveness of time and money inputs on child skills. They incorporate money and time budget constraints and examine the effectiveness of both inputs in increasing cognitive development. They split time into active and passive time of both the mother and father, as well as looking at expenditures on the child. They find that parental time is more valuable than material inputs (books, puzzles etc.) at increasing cognitive ability. As the child ages the productivity of money inputs increases while the value of time inputs decreases. However, overall money investments seem to have limited impact on child quality.

Attanasio et al. (2017) look at the impact of a home visitation early childhood intervention in Colombia, and estimate whether the treatment impacts time and material investment. They relate these changes in different types of investment to changes in cognitive and socio-emotional skills amongst a sample of disadvantaged children. These children were one to two years old when the study started. Material investment is defined as the number of books and toys available, whereas time investment is defined as time spent with an adult in educational activities. The authors find that material investments determined socio-emotional and cognitive skills. They also find that children with better

initial skills receive more investments and mothers with higher skill levels invest more in their children, given the child's skills. They found that the intervention increases parental investments (which in turn increased skills), and that the direct effect of the intervention on skills is relatively small.

This paper examines an activity based investment measure and monetary investment using income as a proxy. While this is clearly not an accurate measure of monetary resources expended on the child (which was not available in this data), it helps us to think through the potential roles alternative inputs play. Clearly, further work should look at developing and collecting better measures of all forms of investment. I am primarily interested in the effect of temperament on different types skills and how it interacts with the available measures of investment.

3.3 Temperament

Temperament is defined as *"individual differences in reactivity and self regulation assumed to have a constitutional basis"* (Rothbart and Derryberry (1981)). The origins of the word come from the Latin *"temperamentum"* referring to the proportionate mixture of bodily humours present in the body. Originally, it took the form of the fourfold typology among Greco-Roman physicians close to 2,500 years ago. Hippocrates (460-370 BC) believed that human moods, emotions and behaviours were caused by either an excess or a lack of particular body fluids: blood, yellow bile, black bile, and phlegm. In the modern era, temperament has been a core concept in personality psychology; with personality defined by Allport (1937) as the *"dynamic organisation within the individual of these psycho-physical systems that determine [their] unique adjustment to [their] environment"*.

There are a number of different pathways through which temperament could influence outcomes (Putnam, Sanson and Rothbart (2002*b*)) and these are summarised in Figure 3.1. The first hypothesis is that temperament itself has a direct linear effect on skills. The second route is an indirect effect through other variables, such as temperament impacting the amount of investment, which in turn affects skills. Third, temperament could be a moderator, with the influence of investment varying by temperament type. Fourth, temperament and investment might interact such that the type of

investment needs to match with the type of temperament, a sort of 'goodness of fit' perspective. A fifth perspective broadens this 'goodness of fit' approach, with development as a more complicated transactional process, requiring analysis of the ongoing dynamic interaction among intrinsic child characteristics and aspects of the environment. Temperament, health status, cognitive capacities, social skills together with parent and family circumstances and the wider cultural context, are all interconnected to explain and predict development. The main hypothesis of this paper is that variation in outcomes such as psycho-social adjustment, cognitive development, and behaviour problems can be explained by temperament through three channels. That is the direct effect of temperament on skills, through an indirect effect in which children of difficult temperaments receive less investment and through a moderation channel where investment is less effective the more difficult the temperament.

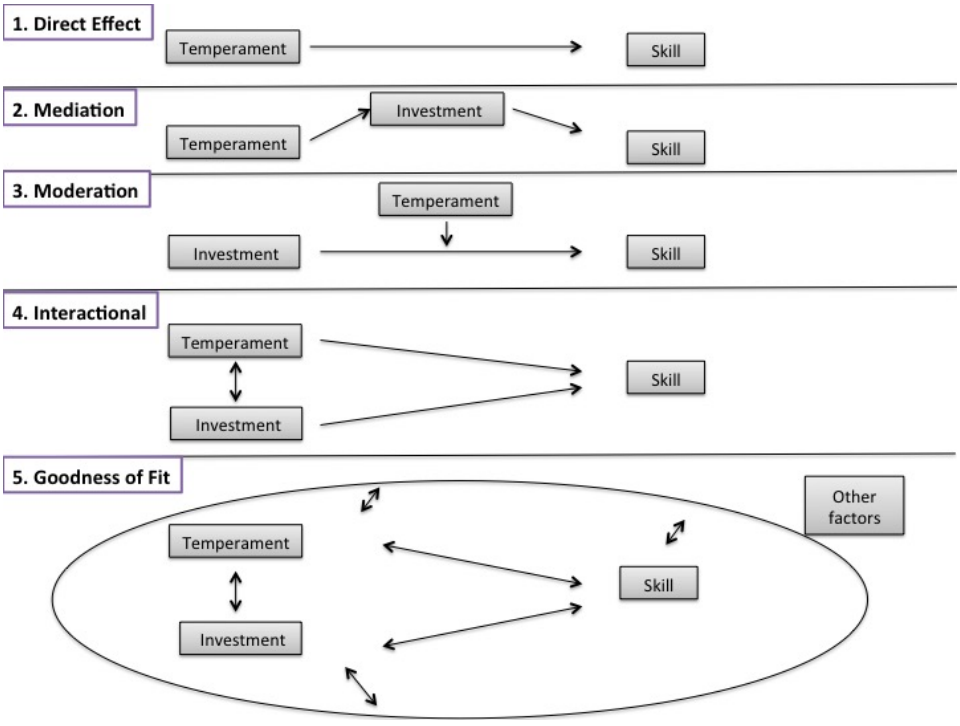


Figure 3.1: Models of Temperament

Thomas et al. (1963) conducted the first longitudinal study on temperament using the NYLS (New York Longitudinal Study), in which parents of infants aged two-six months were interviewed. The researchers identify three common temperament styles in infants: easy, difficult, and slow-to-warm-up. Buss and Plomin (1984) propose four temperamental dimensions: emotionality (the

tendency to become aroused easily and intensely), activity (preferred levels of activity and speed of action), sociability (the tendency to prefer the presence of others to being alone), and shyness (the tendency to be inhibited and awkward in new social situations). A consensus amongst trait theorists has emerged in recent years, linking the adult personality theories with the developmental perspectives on temperament. There are three broad factors that appear to consistent across both child and adult studies: a positive affect/approach factor (sociability), a negative affect factor (reactivity), and a control/constraint factor (persistence).

Many twin, family, and adoption studies investigate the genetic bases for individual differences in temperament and personality (Goldsmith (1983), Bouchard and Loehlin (2001), Saudino (2005)). Current neurological research continues to make links between temperamental variation and its neural substrates (Whittle et al. (2006)). Positive and negative affective processes have been related to systems known as Behaviour Activation and Behaviour Inhibition, respectively. These systems are related to the activity of distributed neural circuits linking cortical brain regions to limbic and brainstem regions. The limbic components are responsible for processing information that held evolutionary significance, such as the presence of reward (for approach) or threat (for fear). Theses areas then contact the brain parts that control motor reactions and the associated autonomic activity.

Other researchers moved away from examining specific brain regions and towards the role of biochemicals in predicting temperament, specifically serotonin and dopamine (Delvecchio et al. (2016)). In the quest for treatments for disorders such as affective, psychotic or impulse disorders, researchers discovered potential relationships between these biochemicals and personality (Netter (2018)). Both serotonin and dopamine are important neurotransmitters in the body, regulating many bodily functions. They both have links to sleep and memory, as well as metabolism and emotional well-being. They do however have some slightly different functions with dopamine being linked to reward systems and serotonin being a slightly more calming, regulatory chemical. However, to date the exact nature of the relationship has remained elusive with mixed results linking genotype to temperament (Slagt et al. (2016)).

There are a number of pitfalls in temperament research that need to be considered. Firstly, there is a tendency for different researchers to come up with

new labels for their temperament constructs, when in reality the content of the previous and renamed concepts are the same. This produces an apparent lack of agreement on the topic. The different questionnaires used across studies, and those for different ages within studies contribute to this apparent instability of temperament across time and samples. As outlined above, the three common constructs underpinning all temperament research are arousal, emotion and self-regulation. For example, Thomas et al. (1963) use the labels 'difficult', 'easy' and 'slow to warm up'; Buss and Plomin (1984) use 'emotionality', 'activity', 'sociability' and 'shyness'; Bates, Freeland and Lounsbury (1979) use 'fussy', 'dull', 'unadapatable' and 'unpredictable'. All of these could be said to capture the same underlying differences.

Secondly, an implicit assumption in temperament research is that, to be meaningful or important, temperament must show substantial stability over time. In the past, the estimates of temperament have shown modest stability, with correlations ranging from 0.2 to 0.4 from one period to the next. Recent developments however, have modified the conclusions about temperamental stability. When conceptual and methodological problems are controlled, higher levels of stability are found (Putnam, Sanson and Rothbart (2002*b*)). Bould et al. (2013) found that using the EAS temperament survey (Buss and Plomin (1984)) there is stability ranging from 0.52-0.64 for ages 3 to age 5, 0.59 -0.74 from 5-6 years and 0.46-0.58 for 3-6 years. They found that between differences in individuals, rather than within differences, accounted for between 69% and 82% of the variance. Bornstein et al. (2015) found that there were modest stability for temperament factors and scales. They examined two samples, the first looking at infants at 2, 5 and 13 months, the second at 6 and 12 months. They found consistent positive and negative affectivity factors at all time points in both studies. They found larger stability between the short intervals of interviews than larger ones.

Given major changes in a child's behavioural repertoire, expressions of their underlying temperament are likely to change over time. Apparent instability can arise due to measurement difficulties, either from using inappropriate measures or from difficultly for parent or observers to properly identify the underlying temperament. For instance, young infants may appear to have an irritable temperament but it could be a direct response to being hungry or in pain; as opposed to an underlying difficult disposition. Dyson et al. (2015)

examined the structural and rank order stability of temperament at age 3 and age 6 using a laboratory based measure of temperament, which overcomes some of the difficulties of using self report measures. They found the latent model at age 3 remained a good fit to age 6, with low to moderate rank stability which varied by factor.

While there is instability in temperament due to the developmental stage, the nature of assessment, the time interval between assessments and the context of the assessment, there is still likely to be some amount of real change in a child's temperament over time. There is an emerging consensus that there is immense change in many aspects of a child's development in the earliest years (Bornstein, Arterberry and Lamb (2013)). Temperament is indeed related to the underlying biological system, and given changes in such systems over infancy, temperament may also change (Saudino and Wang (2012)). For instance, there is growth in the prefrontal cortex and a shift towards using dopamine receptors that might increase the regulatory ability of children, which is a key component of the control/constraint factor of temperament (Rueda (2012)). There is also evidence that aspects of temperament such as effortful control (EC)/self regulation are influenced by external forces. Parenting behaviour can depend on effortful control displayed by their infants (Eisenberg et al. (2010)) but can also impact later displays of self regulation (Kochanska, Murray and Harlan (2000)). There is a large literature on how to promote self regulation in the first five years of life Rosanbalm and Murray (2017). There is also evidence on how parenting can impact sociability and negative affect of infants (Braungart-Rieker, Hill-Soderlund and Karrass (2010), Bates, Schermerhorn and Petersen (2012)). There is some evidence that the earliest years of life actually may display the most instability due to environmental factors but that there is increased stability from later infancy (Caspi et al. (2003)).

In order to mitigate the difficulty associated with different expressions of temperament at different ages, I used the age 3 measure of temperament, which consists of three subscales: persistence, sociability and reactivity. This scale is adaptable for later ages, which allows for valid comparisons over time of the same child that is useful for further work. The three subscales of persistence, sociability and reactivity are well established in the literature, and are used in a variety of studies from around the world, such as the Longitudinal Study of Australian Children (LSAC). This measure of temperament is used in further

rounds of GUI and maps well from the three subscales to later measures of personality trait theories (Caspi et al. (2003)). The alternative measure was the measure at nine months, a well established temperament scale for younger children. This questionnaire is different than that used at three years old and leads to divisions across four scales (dull, fussy, unpredictable and unadaptable). At this age, it may be harder for parents to correctly identify an underlying permanent temperamental disposition from more transient responses to environmental conditions. There were little differences depending on which measure was used, and as such the measure at 3 years was chosen. The biggest concern about using this measure rather than the 9 month is that it might have been influenced by past parenting behaviour.

Thirdly, parent report is the most frequent source of data on infant temperament. This leads to a problem when parent report is also used to assess parenting and outcomes. There is potential for dependence of measures, because characteristics of the parent may affect how they answer questions on key constructs. Another reporting concern is that short run behavioural problems may be confused with temperament. It is important to correctly distinguish between the two concepts (Sanson, Prior and Kyrios (1990)). In self-report studies, parents may have difficultly distinguishing between constructs, especially as the questions used to measure the different concepts have considerable overlap. So even if they are conceptually different, it may be hard to disentangle one from the other.

Temperament has not been considered previously as an important variable in human capital development. The nearest construct is the use of personality scales, such as those used in trait theory - the common OCEAN typology[4] (Goldberg (1993)). Some research has included personality measures in their definition of socio-emotional skills Heckman, Pinto and Savelyev (2013). One problem with this is how to combine things like grit, motivation, internalising and externalising problems with underlying traits to form one all encompassing measure of socio-emotional skills. Researchers argue that socio-emotional

[4]OCEAN, also known as the Big Five is one of the most commonly used trait theories from psychology. OCEAN refers to Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

abilities include things like theory of mind[5], grit[6], executive functioning[7].

Borghans et al. (2008) discuss the importance of personality psychology in economics. Economists have long included 'preference parameters' such as time preference, risk aversion, altruism and social preferences in analysis. They are considered stable, unchanging parameters, although recent research suggests this may not be the case. However, they argue that a broader set of variables should be included in economics. An individual's disposition (or temperament) is one such potential parameter. While trait theorists do admit that personality changes, there are likely to be some bounds between which changes occur. There may be neurological or genetic differences that dictate the range of manifestations of temperament.

Interaction between Temperament and Investment

As hypothesised there are three main ways in which temperament and investment could be related. Firstly, temperament may affect investment levels; a difficult temperament of the child may lead to lower investment by the parent (see Figure 3.5). Some general positive relations between parenting and temperament are to be expected: the adaptable, easy to soothe, or sociable child may elicit warm and responsive parenting, whereas the irritable, demanding, or withdrawing child may elicit parental irritation and withdrawal of contact or stimulation. Conversely, warm and responsive parenting may decrease the expression of negative emotionality in the child, and distant or inconsistent parenting may increase it. It can be hard to separate out the direction of causality. However, I assume that temperament is broadly fixed and enduring, whereas parents can adapt and change their parenting style in response. Thus I can interpret temperament as directly affecting the level of investment which in turn can impact skill development.

In psychology, the relationships between temperament and investment have been conceptualised as either additive or multiplicative. In additive models

[5]Theory of mind is the ability to attribute mental states – beliefs, intents, desires, emotions, knowledge etc – to oneself and to others and to understand that peoples mental states may differ from your own.

[6]Grit can be defined as perseverance and passion for long term goals as defined by Duckworth et al. (2007)

[7]Executive functioning are the cognitive processes that are necessary for the cognitive control of behaviour: selecting and successfully monitoring behaviours that facilitate the attainment of chosen goals.

each effect contributes individually to the outcome. In this case, investment and temperament would have separate and distinct effects on outcomes, corresponding to the coefficients on each parameter in an estimating equation. However, in comparison a multiplicative model assumes that the two variables interact to produce a multiplicative effect and this is what matters. This corresponds to the coefficient on the multiplicative term between the two variables in the estimating equation.

Additive effects have been found in psychology by several researchers. Bates (1988) followed children from infancy to 6 years. They looked at the impact of: 0-to-3 year temperament, maternal positive involvement (affection, teaching) and behaviour problems at age three. These were able to strongly predict both internalising (anxious, fearful) and externalising (acting out) behaviour problems for boys and girls at 6 years using both temperament and parental involvement separately. Similarly, Cameron (1978) in analysing NYLS data found that an index of difficult and persistent temperament at one year, along with poorer parenting at 3 years old, predicted later behaviour problems. A Canadian longitudinal study by Maziade et al. (1989) found evidence for both additive and multiplicative effects. At 12 years old, those with oppositional disorders[8] had difficult temperament and came from dysfunctional families (characterised by a lack of rule clarity, consistency, and parental consensus) measured at age seven. In contrast, almost none of the children with difficult temperaments but superior family functioning had behavioural disorders.

Research using 1500 subjects from the Australian Temperament Project (the data that is used in Chapter 4) found that the combination of infancy measures of parenting and temperament could predict externalising behaviour problems (hostile-aggressive and hyperactive-distractible) and internalising behaviour problems (anxious-fearful) when the children reached 4 to 5 years old (Sanson et al. (1991)). Temperament on its own had no direct impact on outcomes. The most difficult children had only a slightly raised incidence of problem behaviours. However, when difficult temperament occurred with poor mother-child investment, the level of risk for behavioural problems increased substantially. This combined effect of difficult temperament and a poor mother-infant relationship was the most reliable risk indicator. Likewise an easy temperament can be a resilience factor when there is a high level of psychosocial

[8]That is hostile, disobedient, and defiant behaviours directed at adults.

stress and parenting is poor (Werner and Smith (1982)). In these situations, the sociable and adaptable child may be able to elicit more care and concern from care givers. Temperament has been shown to be important in the divorce literature. Both temperament and parental styles are important in determining a child's adjustment to marital transitions. Temperament types might also be important in dictating the type of coping strategies children use (Wachs (2006), Kasen et al. (1996)).

These findings of additive and multiplicative effects for temperament suggest that it is an important variable to be included when analysing child development. There seems to be strong evidence that combinations of temperament and parenting variables affect behavioural and cognitive outcomes. This paper will consider if temperament and parental investment are important as additive and/or multiplicative factors in child development using an economic framework.

3.4 Theoretical Framework and Estimation Strategy

3.4.1 Theory

Basic Theory

Firstly, consider the simple human capital framework where human capital, denoted θ, is a multi-dimensional object, and is decomposed it into two subvectors:

$$\theta_t = (\theta_{C,t}, \theta_{N,t}) , \tag{3.1}$$

where $\theta_{C,t}$ is cognitive skills (e.g. maths and language capacities), and $\theta_{N,t}$, are socio-emotional skills (such as prosocial behaviour, externalising and internalising problems etc). In other circumstances, health is commonly used as a third component of human capital. In general different combinations of these human capital skills can affect other longer run outcomes, such as education attainment, earnings, savings behaviour. For instance, cognitive skills have been closely related to schooling completion whereas both cognitive and non-cognitive skills seem to be predictive of earnings.

Turning now to the technology of skill development (equation 3.2), the human capital vector develops over time according to a production function. This dictates how skills evolve, and how various inputs at different times may be more or less effective at increasing skills:

$$\theta_{i,t+1} = f^t(I_{i,t}, X_{i,t}, \theta_{i,t})\,. \tag{3.2}$$

Here $\theta_{i.t+1}$ is the human capital of the individual, I is investment in the child and X is a vector of covariates that may effect skills. The outcome of interest also depends on the lagged value of human capital, $\theta_{i,t}$.

The first component of this production function technology is the level of investment - I_{it}. The most typical way to model this involves a multi-period investment problem when parents make decisions about the level of investment based on their current and future consumption as well as their preferences over child quality. As with any maximisation problem, these investment decisions are subject to the relevant budget constraints. We consider two main types of investment - money μ_{it} and time τ_{it}. The investment by parents is also likely to be a function of initial levels of skills as well as fixed endowments.

The relationship between skills, past investment and past skills informs us about the dynamic relationship between investment and past skills in producing future skills. If this term is positive then we have dynamic complementarity, which is parents reinforce positive shocks with increased investment:

$$\frac{\delta^2\theta_{t+1}}{\delta\theta_t\delta It} > 0\,. \tag{3.3}$$

If instead it is negative (equation 3.4), then parents compensate for positive shocks by decreasing investment (or conversely they will increase investment in response to negative endowment or skill shocks):

$$\frac{\delta^2\theta_{t+1}}{\delta\theta_t\delta It} < 0\,. \tag{3.4}$$

We can also look at the impact of self-productivity (equation 3.5) and cross-productivity (equation 3.6) by looking at the relationship between past skills

and future skills:

$$\frac{\delta\theta_{C,t+1}}{\delta\theta_{C,t}}\,, \tag{3.5}$$

$$\frac{\delta\theta_{C,t+1}}{\delta\theta_{N,t}}\,. \tag{3.6}$$

Including Temperament

I extend this simple framework to include a new dimension, temperament. Temperament is considered a fixed characteristic of the infant, denoted as T. It enters the above model in two places. Firstly, it enters directly into the production function of skills, capturing the possible direct effect it might have on outcomes:

$$\theta_{i,t+1} = f^t(I_{i,t}, X_{i,t}, \theta_{i,t}, T_i)\,. \tag{3.7}$$

It may impact the productivity of investment, that is investment may be more or less productive at increasing skills depending on the temperament. I would assume that the higher the difficulty of the child (higher T), the less productive the same level of investment. That is that:

$$\frac{\delta\theta_{t+1}}{\delta I_t}|T = T^{+\epsilon} < \frac{\delta\theta_{t+1}}{\delta I_t}|T = T^{-\epsilon}\,. \tag{3.8}$$

Temperament is also likely to impact the amount of investment a parent makes. Parents might respond to children with difficult temperaments by compensating or reinforcing this by increasing or decreasing investment accordingly.

Including Two Types of Investment

Investment by parents is often not well defined in the literature. There is however, broad consensus that there are two main types of investment - monetary or resource investment and then time or activity based investment. Parents make decisions jointly on how much time and money to spend on their child depending on their hours and budget constraints. This paper does not explicitly model the investment choices but instead takes money and time investment as given. They do however, enter into the production function separately. I also examine their interaction to try to determine if they act as substitutions

or complements in production. This gives the production function shown in equation 3.9:

$$\theta_{i,t+1} = f^t(\mu^*_{it}, \tau^*_{it}, X_{i,t}, \theta_{i,t}, T_i)\,. \tag{3.9}$$

3.4.2 Empirical Strategy

This paper uses a longitudinal cohort study in order to examine the implied theoretical relationships between investment and skill production, focusing on a new variable, temperament, which could interact with investment and also have direct effects on outcomes. There are a number of key challenges in bringing this theory to data in order to examine the process of human capital development. Ideally, we want to estimate the production function to produce unbiased estimates of the role each input plays, as well as helping understand how parents make investment decisions. There are three main challenges i) functional form assumptions, (ii) measurement and (iii) endogeneity of inputs. This paper attempts to overcome these potential issues by estimating a number of different models, which rely on different identifying assumptions and using different constructions of the key variables. Within each functional form estimated, an increasing number of covariates were added to check the stability of the estimates to the inclusion of different controls. If the effects remain stable across models and functional forms, then the econometrician can say with reasonable confidence that these effect are likely to be indicative of a true finding.

Functional Form

First there is a clear specification issue. What is the appropriate functional form for the production function? There have been a number of different specifications typically used in the literature. These range from linear models, which impose strict assumptions about the data generating process, to more flexible alternatives that include interactions and higher order terms. A linear production function, while attractive due to its simplicity, imposes a strict separability of inputs - which implies perfect substitutability of inputs and forces complete independence between the marginal products of such inputs. This means that parents can completely compensate for a lack of time investment with increased money investment. The most commonly used alternatives are the Cobb Douglas (CD) or the Constant Elasticity of Substitution (CES). Both

functional forms impose homotheticity of inputs, implying that the relative productivity of investment and time remain constant for a given ratio of inputs. In other words, a doubling of time investment, as long as money investment was also doubled, would not affect how productive time was relative to money. The elasticity of substitution (that is, how easy it is to switch between time investment and money investment for instance) remains constant between any inputs. For Cobb Douglas this elasticity is restricted to take a value of one.

The most flexible functional form in use is the translog function. There are costs to using this functional form: namely by higher demands on the data for estimation and hypothesis testing. Translog allows the elasticity of substitution between any two factors to be different, and allows for the factors of production to be substitutes or complements. The translog model nests the CES functional form. We can test for CES using the the translog estimation. In this case, the null hypothesis is that the coefficients on higher order terms and interaction terms are zero. We can also test for Cobb Douglas given it is a special case of CES, by testing the additional assumption of elasticity of substitution is one.

The three different functional forms used in this paper are shown below: linear (equation 3.10), log log (equation 3.11) and translog (equation 3.12). For the first two functional forms we test for multiplicative effects of temperament, by including the interaction with investment in a second estimation. This is automatically included in the translog estimation.

$$Y_{it} = \beta_{0t} + \beta_{1t}\mu_{it} + \beta_{2t}\tau_{it} + \beta_{3t}T_i + \beta_{4t}Y_{it-1} + \epsilon_t \,, \tag{3.10}$$

$$lnY_{it} = ln\beta_{0t} + \beta_{1t}ln\mu_{it} + \beta_{2t}ln\tau_{it} + \beta_{3t}lnT_i + \beta_{4t}lnY_{it-1} + u_t \,, \tag{3.11}$$

$$\begin{aligned} lnY_{it} = {} & ln\beta_{0t} + \beta_{1t}ln\mu_{it} + \beta_{2t}ln\tau_{it} + \beta_{3t}lnT_i + \beta_{4t}lnY_{it-1} + ... \\ ... + {} & \frac{1}{2}\alpha_{1t}(ln\mu_{it})^2 + \frac{1}{2}\alpha_{2t}(ln\tau_{it})^2 + \frac{1}{2}\alpha_{3t}(lnT_{it})^2 + \frac{1}{2}\alpha_{4t}(lnY_{it-1})^2 ... \\ ... + {} & \gamma_{1t}(ln\mu_{it})(ln\tau_{it}) + \gamma_{2t}(ln\mu_{it})(lnT_{it}) + \gamma_{3t}(ln\mu_{it})(lnY_{it-1}) + ... \\ ... + {} & \gamma_{4t}(ln\tau_{it})(lnT_{it}) + \gamma_{5t}(ln\tau_{it})(lnY_{it-1}) + \gamma_{6t}(lnT_{it}lnY_{it-1}) + u_t \,, \end{aligned} \tag{3.12}$$

where in both equation 3.11 and 3.12, $u_t = ln\epsilon_t$.

The different functional forms imply differing degrees of complexity of the human capital production function. By estimating all of these we can begin to examine if the process is best captured by more simple forms, or if the higher order and interaction terms help to better model the process of skill accumulation.

Not withstanding the exact specification of the production function, there is a secondary concern when it comes to estimation. We need to consider the role of lagged values of the outcome but also of current and past covariates. There are three main ways to include these variables. Firstly, it may be that only contemporaneous inputs matter for the current level of output. This is known as the Current Input model (equation 3.13). Secondly, it might be that past level of output is an important lagged indicator of current levels; this is the idea that skills build on skills. The Value Added model (equation 3.14) comprises of current inputs in conjunction with this lagged value. In this scenario, the lagged outcome measure is a sufficient statistic for all inputs up to this point. There is no additional effect of lagged controls or past time and money investment on future skills except via their impact on lagged skills. If we think this assumption is false, then we can include past inputs in the estimating equation - that is a Cumulative Value Added approach (equation 3.15)). This could occur if we think there are delayed effects of past inputs, that affect current output over and beyond their effect on lagged output.

$$Y_{it} = \beta_{0t} + \beta_{1t}\mu_{it} + \beta_{2t}\tau_{it} + \beta_{3t}T_i + \delta_t X_t + \epsilon_t \,, \tag{3.13}$$

$$Y_{it} = \beta_{0t} + \beta_{1t}\mu_{it} + \beta_{2t}\tau_{it} + \beta_{3t}T_i + \beta_{4t}Y_{it-1} + \delta_t X_t + \epsilon_t \,, \tag{3.14}$$

and

$$\begin{aligned} Y_{it} = \beta_{0t} + \beta_{1t}\mu_{it} + \beta_{2t}\tau_{it} + \beta_{3t}T_i + \beta_{4t}Y_{it-1} + ... \\ ... + \delta_t X_t + \delta_{t-1}X_{t-1} + \delta_{t-2}X_{t-2} + \epsilon_t \,. \end{aligned} \tag{3.15}$$

It is hard to know, a priori, which is the best fit for skill accumulation. Both intuition and prior work suggest that the value added specification is the most appropriate. In order to circumvent this problem I estimated each model

in turn and used goodness of fit statistics to compare their performance in explaining the data. In every case the value added specification outperformed the others. I only report results from this specification (equation 3.14) for the three functional forms discussed above.

Measurement of Key Inputs

The second major issue in estimation is how to properly measure the key variables of interest. For many variables - such as temperament, cognition, social-emotional skills - the constructs are hard to define, as well as being unobservable. They are latent variables that are difficult to measure, and are likely to result in biased measures. Even variables that are observable - like income - are likely to be still measured with error. The measurement issues with survey data are well documented - such as social desirability bias, the effect of framing, and individuals not understanding the questions. Even when the survey data has been collected, there are normally multiple ways to combine it into a variable. Measurement error can introduce bias into our estimates.

There are a number of ways to deal with measurement error. One approach is to build a measurement system, where you have multiple measures of the same underlying construct. This system can be used to estimate the underlying distribution of the latent factors and the errors. By estimating the relationship between multiple observed measures and the underlying factor, one can predict the latent factor. Subsequent regressions are then adjusted for the fact that these latent factors are estimated themselves with error using common econometric adjustment techniques. However, to do this I would need at least two measures in each period of the underlying factor (and three in one period). This option was not available due to the lack of measures available in the dataset, but was used in chapter 2.

Instead, I used well established psychometric conventions of age and ability standardisation to compare across people for the core measures of cognitive and socio-emotional skills, following. I also used created multiple versions of temperament and time investment, using factor analysis and linear combinations in order to test the sensitivity of my results to different constructions.

We might also worry about the timing of inputs. In the theoretical model above, investment is considered to be the 'past' level of investment, not the

current. However, given the desire to use age three outcomes as our dependent variable limits the measures available for investment. There were no activity measures in the 9 month old survey. Instead I take the measures of investment from the age 3 years survey, which are measured concurrently to the skills. I must assume that this level of investment represents accurately the investment parents have been doing in the past. The question is asked for 'an average week' which prompts parents into thinking of the longer past, as opposed to 'in the last week'. One way to circumvent the reliance on this assumption would be to use the age 5 data as our outcome of interest. However, age 3 outcomes were focused on in this paper as it is at the end of the first thousand days - a core construct in development in economics and psychology, and allows us to consider the process without much public investment through preschools or early education facilities.

Endogeneity of Inputs

One major risk for identification is dealing with endogeneity due to unobserved shocks or missing variables. This is a particular problem for investment where unobserved shocks to cognitive or socio-emotional skills might bias the coefficients. There may also be unobserved parental preferences that might be correlated with observed current or past inputs. The latter is relevant if parents reinforce (compensate) unobserved skill shocks. This could lead to a upwards (downward) bias if parents do reinforce (compensate) for these shocks.

Typical methods for dealing with endogeneity involve finding suitable instruments that are correlated with the endogenous variable (in this case investment) but uncorrelated with the outcome of interest except for through its relationship with the endogenous variable. There are a number of potential household characteristics that are likely to directly impact investment. These are, however, likely to impact skill accumulation, and also are not randomly distributed across the population. Variables like household size would impact the amount of time a parent is able to spend with any one child and also the amount of resources a parent can spend. However, the number of siblings (embedded in household size) could impact skill accumulation through learning from siblings. There might also be unobserved characteristics that affect household size that might also affect skills. These objects amongst other demographic variables were initially thought to be reasonably informative instruments but initial

analysis revealed they violated the other necessary assumptions needed for valid instruments.

Even if I had found valid instruments for investment it would be hard to ensure that I had enough instruments for the more complex functional forms. This would restrict me to using a control function in some specifications but not all, potentially making interpretation harder. This highlights how the benefits of using more flexible and complex production functions need to be weighed up against the higher demands placed on the data, especially the requirements for establishing causality.

The approach I take is to use multiple functional forms as well as initially, using the multiple specifications in terms of lagged and included covariates. By examining if the same pattern of findings emerge then I can hopefully make some tentative suggestions of the role of lagged skills, temperament and investment. This paper is hopefully a first step in examining if temperament is a useful construct to be included in human capital production functions.

Multiple Hypothesis Testing

For all outcomes I adjust the p-values to account for the fact that I am testing multiple outcomes with multiple variables of interest. When we are testing multiple hypotheses there is some probability that we will find significance results, purely by chance due to simultaneous testing. I correct for this fact by adjusting the significance level so that the probability of observing at least one significant result due to chance remains below the desired level. This was conducted using a Romano-Wolf step down procedure. First, we come up with bootstrapped standard errors and distribution of t-statistics by conducting a bootstrap 5000 times. Then, apply the Romano-Wolf step down procedure, which adjusts the p-values associated with the individual tests to account for the effect of testing multiple outcomes. First, it calculates a t-statistic in the family of outcomes (here for the different outcomes and hypotheses), and then orders the tests in descending order of significance. The largest observed t-statistic is compared with the distribution of the maximal permuted t-statistics, from the bootstrapped procedure. If the probability of observing this test statistic is high, we fail to reject the null hypothesis that the variable of interest has no impact on any outcome in this cluster of hypotheses. On the other hand, we reject this joint null if the probability of observing this t-statistic is low. We

then proceed by excluding the most significance hypothesis, and continue until we fail to reject the null. For every null, we end up with an adjusted p-value that incorporates the probability of rejecting a null by chance due to multiple testing. I use multiple hypothesis testing in all cases except for in the translog. There are fourteen variables for multiple outcomes and using MHT wipes out any possibility of finding significant effects. The coefficients are still meaningful as they indicate whether or not we need more complex specifications to capture the dynamic process of human capital accumulation, despite not being able to properly correct for MHT.

Related to this is the question as to why MHT is used in this chapter and not others. First, it is not clear to me that MHT is useful when examining the impact of many different inputs, as is the case in chapter 4. Almost by design, it will wipe out any significant effects, which may lead to researchers overlooking economically useful, yet not statistically significant effects. Second, MHT is used here to correct for the testing of multiple outcomes that are related i.e. within the domains of socio-emotional skills and within the cognitive domains. Chapter 2 dealt with health and cognitive skills separately, representing two different domains and thus does not require MHT for multiple outcomes in the way that is required here. While potentially not necessary in this chapter, it does show that the findings are robust to MHT suggesting the effects are indeed somewhat strong, at least in the simpler functional forms.

3.5 Data

3.5.1 Dataset

The Growing Up in Ireland (GUI) longitudinal study is used in this paper[9]. GUI tracks two cohorts over fifteen years, a child cohort initially 9 years old and an infant cohort at 9 months. The first two waves of the infant cohort is used in this research, the first at 9 months and a follow up at three years old. The younger cohort sample consisted of 11,134 infants who were randomly sampled from the child benefit register[10], designed to be representative of

[9]GUI is funded by the Department of Children and Youth Affairs in Ireland and carried out by the Economic and Social Research Institute and Trinity College Dublin.

[10]All children born in Ireland are automatically added to the child benefit register and thus the sample can be considered broadly nationally representative.

the population of nine month infants in Ireland. Given the relatively small population of Ireland the sample is approximately 10% of the actual cohort population. Infants were born between 1st December 2007 and 30th June 2008, with initial data collection taking place between September 2008 and April 2009. Questionnaires were administered to the primary caregiver, the secondary caregiver and the infants (when old enough). The infants undertook a number of developmental, non cognitive and cognitive tests with a trained examiner. Weight and height of each participant is recorded in each round. The questionnaires contain detailed information on parental and background characteristics, the home environment, thoughts, feelings and behaviours of the parents and child, as well as composite measures of attachment, temperament amongst other items.

In round one there were 11,134 infants in the sample. At follow up individuals who had clearly emigrated or whose child had died were not part of the effective sample. In round two, 408 individuals were deemed not to be part of the valid sample, leaving 10,726 individuals to be contacted. The response rate was 91.7% with 9,793 individuals partaking in round two. In order to mitigate against differential drop outs, the data is re-weighted using inverse probability weighting at round two so to remain representative of the population. The re-weighting procedure is developed and recommended by the GUI team for anyone using their data. As such I take the weights as provided by the main researchers as given and apply these to my analysis. These included variables such as mothers age, parents economic status, social class, educational attainment, if the parent smoked at wave 1, breastfeeding at wave 1 and location of household at wave 1. For a full list of the variables and procedure used for reweighting please see McCroy et al. (2013).

3.5.2 Outcomes variables: Cognitive and Socio-Emotional Skills

The outcomes of interest are cognitive and non cognitive skills measured at three years of age. Cognitive skills are measured using two subtests of the British Ability Scales (BAS) - the Naming Vocabulary test (NV) which measures verbal skills, and the Picture Similarity test (PS) for non-verbal skills. Both of these skills are key components of the BAS's General Conceptual Ability Score,

which captures both general crystallised and fluid ability (Cattell (1963))[11]. Specifically, Naming Vocabulary measures a child's expressive English language capacity and the Picture Similarity component measures reasoning capacity and problem solving skills. These scales were administered by a trained practitioner. The results were first recorded as a raw score but were subsequently adjusted for both age and ability. Older children score higher on the test, simply due to an age advantage, and as such scores are adjusted in age appropriate t-scores. Scores are adjusted to take into account the difficulty of the questions they were asked. If a child is answering correctly they will move onto the harder questions; if not the practitioner will ask easier questions. This gives a valid comparison of scores across ages and questions.

Socio-emotional skills are measured using the Strengths and Difficulties Questionnaire (SDQ) (Goodman (1997)). The SDQ asks the parent of the child about a range of the child's typical behaviours and their responses are recorded as 'not true', 'somewhat true', 'certainly true'. The responses are tallied into five subscales - four negative and one positive. The four negative subscales are emotionality, hyperactivity, conduct problems and peer problems which combine to give a total difficulty score. The positive subscale measures prosocial behaviour, answering questions to do with sharing, consideration of others feelings, helpfulness, generally being liked, kind etc. The questionnaires are included in Appendix A. Summary statistics of the main outcomes variables are shown in Table 3.1.

Table 3.1: Outcomes Summary Statistics

	Non Verbal	Verbal	Negative SDQ	Positive SDQ
Mean	53.123	50.893	7.793	7.945
SD	(10.819)	(12.807)	(4.562)	(1.761)
Min	22	20	0	0
Max	80	80	32	10
N	9549	9179	9786	9786

Notes *Non Verbal and Verbal capture cognitive Abilities. SDQ is the Strengths and Difficulties Questionnaire used to capture non cognitive abilities. Higher scores on negative SDQ indicate worse outcomes, higher scores on positive SDQ indicate better outcomes.*

[11]Fluid and crystallised ability are factors of general intelligence identified Cattell (1963). Fluid intelligence is the capacity to reason and solve novel problems, independent of any knowledge from the past - essentially logical reasoning. In comparison, crystallised intelligence is the ability to use existing skills, knowledge and experience.

3.5.3 Independent variables: Investment, Income, Temperament

As mentioned in the theory section one big difficulty when bringing human capital theory to the data is measurement of the key variables. I consider a number of different possibilities for measuring investment and temperament. Across the different constructions the estimation results were qualitatively and quantitatively similar. The results reported in this paper are based on the constructions explained below[12].

Considering first the main variable of interest - temperament. As explained in Table 3.2, temperament was created using factor analysis of the temperament subindices of round two to give an overall difficulty measure[13] The temperament variable was then rescaled using an additive transformation to give all positive values, keeping the same standard deviation. The mean of the transformed temperament variable was 1.02 [0.413] with a range of [0.001, 3.31]. The higher the score, the more difficult the temperament of the child, so children with low scores are less difficult. The red line in Figure 3.2 marks those who have a temperament that is one standard deviation above the mean, with the green line indicating the same for those below the mean.

Turning now to investment. Investment is also measured at age 3 years but is taken as a measure of past investment, being asked as the 'average' amount done per week by the parent. Given it is unavailable at age 9 months, I use the measure at age 3 years as an indicator of past investment. It was created by summing together all activities and the number of days a week a parent does each activity with their child. The mean score of 34.158 (standard deviation of 8.663) indicates that on average parents do an investment activity with their child thirty four times a week. The seven activities are reading,

[12]The activity variables were combined using factor analysis to create an alternate investment score. The answers to the raw temperament questions were combined into a factor analysis, as well as creating another version that was a simple sum of the subscales.

[13]Factor analysis was also applied to temperament measure at 9 months, which gave broadly similar results. The results were robust to either measure of temperament, and given the same questionnaire is used in later rounds of work, as well as in other studies it was felt that the 3 year old measure was more appropriate. It is also less susceptible to transitory emotional states (from being hungry/tired/thirsty) of the infant, which at age 9 months may be harder to separate from the underlying disposition. Slightly older infants are better able to express themselves to fulfil these basic needs and as such an underlying disposition may be more readily observed.

Table 3.2: Variable Definitions and Construction

Variable	Question	Answer	Creation
		Time Investment	
Investment	How many days in an average week do you do X with child (7 activities).	[1 day, 2 days... 7 days]	This was summed across the seven activities to generate a total score. [0,49]
		Monetary Investment	
Equivalised Income	Reported net family income (considering all sources).	Asked which bracket fall into, and then estimate exact figure.	This figure was top and bottom censored. It also accounts for family size by considering each adult as 1 and each child as 1/3 to generate an equivalised score. Divide by 1000 for better interpretation. [5,60]
		Temperament	
Temperament	A battery of 13 questions were given about childs' mood in each round.	[Never, Not often, Usually does not, Usually does, Frequently, Almost always]	These were combined to form 3 sub indices in round 2: reactivity, sociability and persistence [0,7]. I use factor analysis to combine the three subscales into an overall difficulty score, which was rescaled to be strictly positive. [0.001, 3.3145]

Notes *The different constructions of the investment and temperament variables had correlations of 0.96 and 0.93-0.98 respectively.The subindices were created using well established best practises for the temperament measure used. I then combined these using factor analysis to order to create an underlying latent factor of temperament. This meant I did not have to impose equal weighting to each scale, allowing the underlying latent factor to be determined by the data.*

learning ABCs, learning numbers/counting, learn songs/poems/nursery rhymes, play games (jigsaws, board games, cards), paint/draw/colour/play with playdoh and playing active games. Given the seven investment categories this is approximately doing each category five days a week. There could be arguments that certain activities in this list are less or more productive than others (i.e. learning ABCs compared to active games), but given the list and the children's

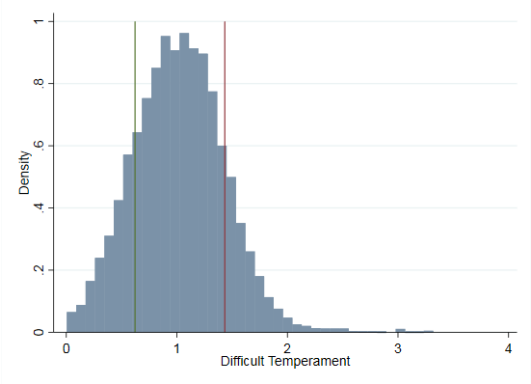


Figure 3.2: Temperament Difficult Density

age I think it reasonable to assume each category is equally productive.

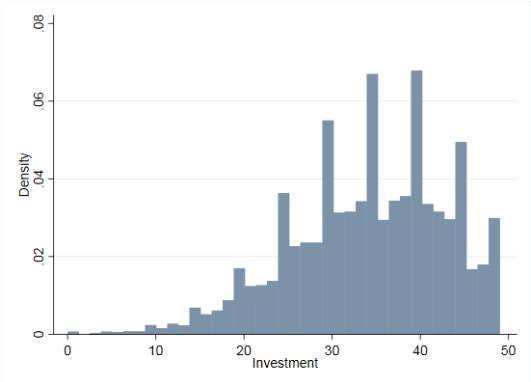


Figure 3.3: Investment Density

Figure 3.4 shows the mean and standard deviation of each component of investment. The standard deviation is roughly similar in each case. Interestingly the least conducted activity is the alphabet - potentially because parents assume their child is too young to learn the alphabet[14].

This measure of investment is considered a measure of temporal investment. The other main source of investment is the amount of money a parent spends on their child either directly or indirectly. This could include expenditure on items such as clothes, shoes, food, toys but also education and housing decisions. Unfortunately there was no such measure available. Instead, I use income as a proxy for the amount of available budget that is spent on the child. This is an imperfect measure of actual expenditure. However, assuming that the

[14]According to most developmental milestones literature the typical age of alphabet learning is around 5 years old.

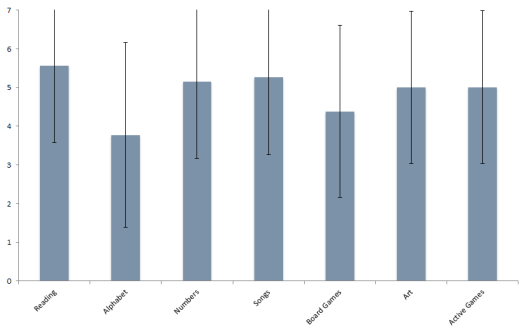


Figure 3.4: Investment Activities

amount spent on child is highly correlated with total income it might provide a first benchmark to try to quantify the effect of money versus an activity based investment measure. I use equivalised income, which adjusts for household size. It is truncated between €5,000 and €60,000[15]. In the first round there is a mean of €21,117.5, with standard deviation of 11,725.04 (the data is right skewed, with the median at €18,837.74). When the infants are three years old, the mean income has decreased to €18,246.77 with a standard deviation of 9,767.39 (with a similar right skew, the median at €15,849).

As hypothesised in the theory section temperament might impact human capital through its effect on investment, if parents change their investment levels depending on the temperament of the child. There is some evidence that this is the case. We can see differences in investment across temperament types of the child (shown in Table 3.3). Those classified as more difficult (individuals whose temperament is below one standard deviation of the mean) receive seven points less investment than those classified as least difficult (those with one standard deviation above of the mean temperament). This is equivalent of one weeks worth of one activity. This adds to the riskiness of having a difficult temperament, with a negative direct effect on skills, but also a negative indirect effect via lower parental investment. It could be that there is a third variable causing both high temperament difficulties and lower levels of investment as opposed to a causal effect from temperament to investment. Those with most difficult temperament children also have marginally lower incomes and less education.

There are some differences in investment across parents with different struc-

[15]The estimation was repeated removing the end points to check any bias that might have emerged from truncation and the findings were unchanged.

Table 3.3: Differences By Temperament Type

Temperament Difficult	Investment	Income	Education	N
		Mean/SD		Count
Least Difficult	37.046	19,052	7.598	1586
	(7.806)	(9,941.24)	(2.805)	
Middle	34.172	18,343	7.350	6745
	(8.42)	(9,806.58)	(2.863)	
Most Difficult	30.94	16,914	7.023	1450
	(9.48)	(9,272.07)	(2.921)	

Notes *Least difficult is defined as less than one standard deviation from the mean temperament. Most difficult is defined as more than one standard deviation from the mean temperament.*

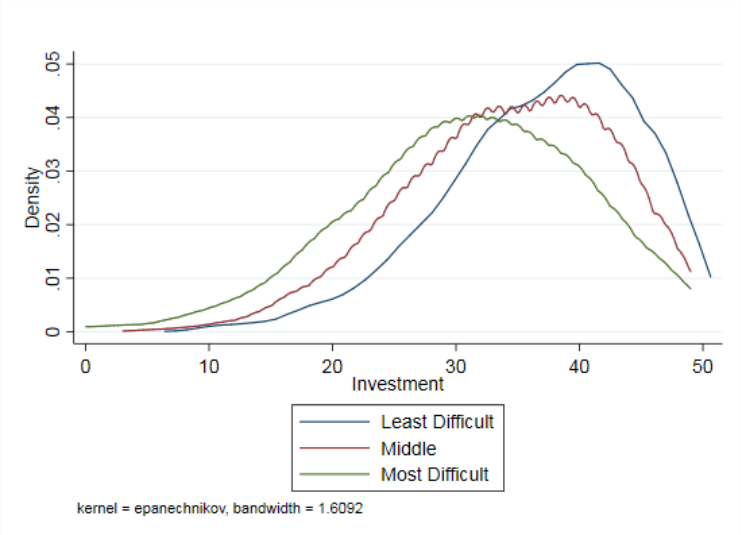


Figure 3.5: Investment by temperament type

tural characteristics (of education, social class and income decile) as shown in Figure 3.6 through 3.8. An increase of one on the investment scale is equivalent to an increase of one day in one activity[16]. There are very few individuals with no formal education. Educational categories show the largest differences across groups. For example, the difference between those with only primary school education or less, compared to those with any degree is about four points. Interestingly, time investment doesn't increase monotonically from lowest to highest income group, with very little difference across income groups, as seen by the flat investment curve. The social class variable is taken as the highest social class category of both partners in the household (or of the parent if a single parent household). Households where both caregivers are currently

[16]See Appendix A for the list of activities in each round.

economically inactive and have not held any previous employment in the past are classified as validly *'no social class'*, as they have no occupation code upon which to base their social class. Social class is defined as *'other'* when they are unemployed, or have been but do not fit into any of the preassigned categories. Again there are small differences along social class.

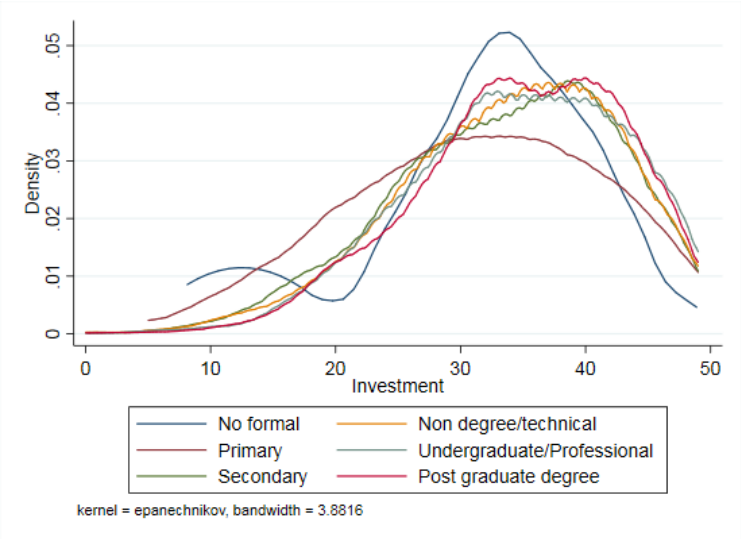


Figure 3.6: Investment by education group

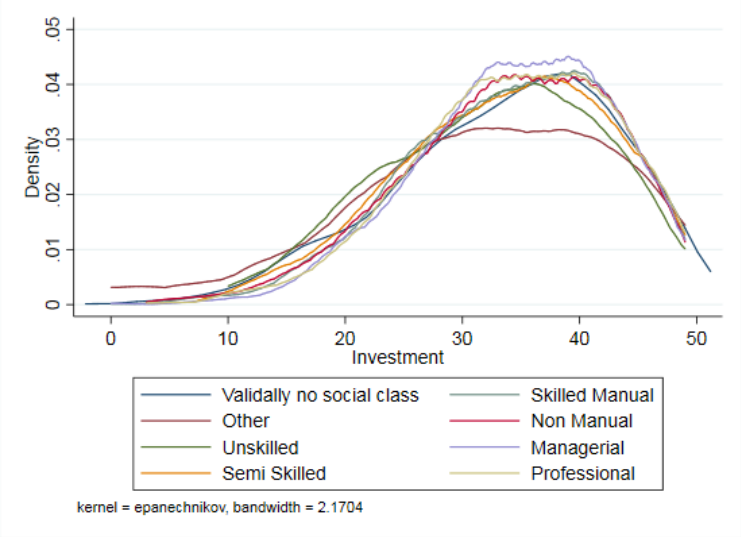


Figure 3.7: Investment by social class

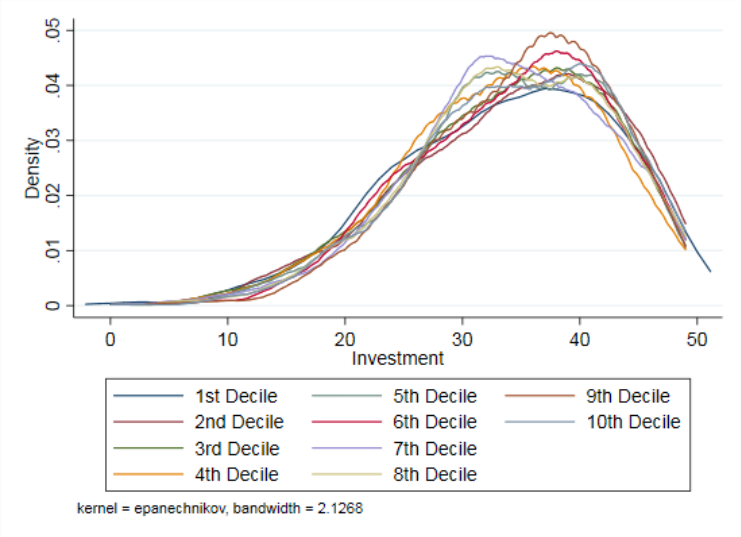


Figure 3.8: Investment by income decile

3.5.4 Controls

Table 3.4 shows a number of other variables that impact the process of human capital accumulation. One important variable is the endowment of skill the child has. Here I use the development index - which is a composite measure of overall development of the child at 9 months. This endowment may affect how the child uses investment as well as increasing skills through a building on skills channel. This variable was created using the five subscales of the Ages and Stages Questionnaire. The five developmental domains considered were communication gross motor, fine motor, problem solving and personal/social. There were 3 age ranges considered - 8, 10 and 12 months and children were tested to see if they passed the established cut off. If they did they received a score of 1. These cut offs were summed across the five domains to give a total development score between 0 (i.e. the child did not pass any cuts off in any domain for any of the test) to 15 (the child passed the 8, 10 and 12 month cut off across all five domains). In this sense it captures physical, cognitive and socio-emotional skill in one composite metric of development. While there may be benefits to separating these domains in our measure of endowment, with only one subscale for socio-emotional skills that it was appropriate to combine these into one composite measure of early age developmental potential.

There may be gender differences in skill development, or parents may invest differentially depending on the child's gender. Parental endowment of

skills is also likely to be important - here captured by the highest level of education of the parent. One other key input at this stage could be investment from an early education centre, captured using proxies for the use of formal, informal or no childcare measured at age 3 years. The quality of parenting is a contemporaneous measure from age 3 years is measured using parental stress and three measures of parenting style - consistency, warmth and hostility. I also take into account household size and employment status of the primary caregiver, both of which are likely to impact investment. These are all measured at 3 years old[17].

Table 3.4: Controls

Name	Description/How created	Value
Development Index	Composite measure of overall development of child at 9 months, based on development norms at 9, 10 and 12 months old	[0,15]
Female	Gender of child	[0,1]
Parents Highest Education	Max of primary and secondary caregivers education	[1,13]
Formal Care	Main form of care is a childcare centre	[0,1]
Informal Care	Main form of care is informal services (relative/nonrelative in home/others home)	[0,1]
No care	No use of informal/formal care	[0,1]
Parents Stress	Self report of how stressed they are	[6,30]
Parental Consistency	Parenting style - setting appropriate rules and expectations	[1,5]
Parental Warmth	Parenting style - affection and closeness	[1,6]
Parental Hostility	Parenting style - anger and frustration towards child	[1,6]
Employment status	Employed, unemployed, stay at home, student	[0,1]
Household size	Number of people in the household	[2, 7]

Some other key statistics about the sample are reported in Table 3.11 in Appendix B. 49% of the sample children were female, with an average equivalised income of about 20,000 euro. Household size averages at just over four people, with 87.8% being two parent households. In most cases the primary caregiver was employed (55.8%), with 34.7% being stay-at-home parents. Self reported stress levels are quite high. In this sample 99.66% of primary caregivers were female. At age 3, approximately 27.2% of the sample are in formal care with a childcare practitioner; 23.9% are in informal care (either via a relative or non relative in their home/others home) with the remaining 48.8% receiving no additional childcare. At 9 months, the majority (60.3%) were not attending any care, 28.7% in informal care and only 10.9% in formal childcare. Table 3.12 in Appendix B shows descriptives on key variables for those who dropped out compared to the remaining sample. Those who drop out are of slightly average lower education, lower household class and less likely to be in a couple,

[17]Where available I also included the measures of these variables from the 9 month old survey to indicate lagged covariates. However, they did not affect the results or have any impact on the outcomes of interest and as such were dropped from the final estimation.

with higher stress and higher depression of parent. The differential drop out of certain types of families could lead to biased results if a systematic group drop out. There are no difference in drop out by temperament or the initial skill level of the infant. As mentioned earlier, inverse probability weighting was applied in order to account for potential biases due to differential drop out.

3.6 Results

The following results focus on three functional forms - linear, cobb douglas and translog. For both the linear and the cobb douglas specification, I estimate two versions, one with and one without the interaction between temperament and investment. This helps to disentangle if there are direct effects (the β coefficient on temperament) and multiplicative effects, (the β term on the investment-temperament interaction term). If investment is less effective when the child has a difficult temperament then the coefficient on the interaction term should be negative. If in fact, investment is more effective the more difficult the temperament then we would expect a positive interaction term.

I am interested primarily in how the three main inputs: investment, income and temperament might differentially affect different types of cognitive and socio-emotional skills. I focus first on the results from the linear models to compare and contrast both within types of cognitive and socio-emotional skills but also across the two domains. I then go on to discuss the cobb douglas and translog specifications. I can examine if the choice of functional form changes the conclusions reached. More complex specifications might better capture the dynamic and interactive nature of human capital growth. For each skill (non-verbal, verbal, negative socio-emotional and positive socio-emotional) the first column is the log-log specification, the second includes the interaction of just temperament and investment and the third is the full translog estimation which includes higher order and interaction terms. I test for constant returns to scale by testing if the sum of the coefficients are equal to one.

In each I include the following controls that impact the process of skill accumulation: gender of the child, household size, employment status of the primary caregiver, highest education level of the parent, parental stress, parental depression at birth, the type of childcare the child attends, and parental

consistency, parental hostility and parental warmth. I also test for multiple hypothesis testing with the adjusted p-values shown in square brackets. The significance stars refer to the unadjusted p-values so I can compare what happens when simultaneous testing is accounted for.

3.6.1 Linear Models

Table 3.5 and Table 3.6 show the linear estimation for both cognitive and socio-emotional skills. Within cognitive skills I look at the development of verbal and non verbal skills - which have a correlation of about 0.4. There may be different pathways of development of maths and language skills, with different inputs being differentially productive in producing skills.

Table 3.5 shows that the most important input is the 9 month old measure of skill endowment. This suggests that early differences in skills have effects on later skill development. In contrast, there seems to be little to no effect of our measure of temperament on either skill. While the coefficients are significant and negative in three out of four cases, adjusting for MHT renders these results insignificant. There is no significant effect of the interaction term, which suggests that the productivity of parental time investment does not depend on temperament.

The coefficients on investment and income are positive and significant, as would be expected. Non-verbal and verbal outcomes are measured on the same scale and thus I can compare magnitudes of effects across the two estimations. The effect of both income and investment on verbal skills are approximately double that on non-verbal skills. This suggests that verbal skills are perhaps more malleable than non-verbal skills to both inputs by parents.The effect of the developmental index is slightly larger for verbal skills, suggesting that verbal skills are more persistent (or perhaps that the developmental index measure captures more verbal skills).

Looking now at the results from the socio-emotional skills. These can be compared both across type of socio-emotional skill but also with the cognitive skills considered in Table 3.5. In contrast to the findings there when income and investment were both important inputs, investment does not seem to matter for negative behaviours. The measure of skill endowment seems to be important for prosocial behaviour, and no impact on negative behaviour.

One counter-intuitive finding is that income has a negative effect on prosocial skills,. One potential mechanism for this could be that children from higher income households have more resources, toys, etc. and are not used to sharing with other children. However there are multiple components to this scale such as being kind to younger children, being considerate of others and getting on with others which is not necessarily accounted for by this proposed mechanism. Further research should consider the role between prosocial behaviour and income to see if this finding stands.

Table 3.5: Cognitive Skills

	Non Verbal	Non Verbal	Verbal	Verbal
Investment	0.0629***	0.0490	0.133***	0.165***
	(0.0166)	(0.0417)	(0.0198)	(0.0522)
	[0.517]	[0.595]	[0.007]	[0.008]
Income	0.0467***	0.0468***	0.161***	0.161***
	(0.0156)	(0.0156)	(0.0194)	(0.0194)
	[0.008]	[0.009]	[0.000]	[0.000]
Temp Difficult	-1.302***	-1.758	-0.786*	0.273
	(0.351)	(1.363)	(0.407)	(1.650)
	[0.379]	[0.42]	[0.947]	[0.796]
Skill Endowment	0.436***	0.436***	0.602***	0.602***
	(0.0588)	(0.0589)	(0.0657)	(0.0657)
	[0.000]	[0.000]	[0.000]	[0.000]
Temp Difficult		0.0133		-0.0308
× Investment		(0.0384)		(0.0468)
		[0.854]		[0.839]
Observations	8812	8812	8502	8502
R^2	0.061	0.061	0.101	0.101
Adjusted R^2	0.058	0.058	0.098	0.098

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender. These results are from the linear functional form.*
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Temperament plays a larger role in these estimations, having a large negative effect on both types of socio-emotional skills. There is a positive interaction term for prosocial skills, with investment being more effective the more difficult temperament is. There is potentially a role for investment in counteracting the negative direct effects of temperament. There are large positive effects of difficult temperaments on problem behaviour (increasing negative behaviours). This results are caveated by the fact that parents may be answering both the temperament and the SDQ questionnaire based on the same behaviours, and it may not be effective at separating out the constructs, in a way that would

allow me to draw definitive conclusions.

Table 3.6: Socio-Emotional Skills

	Negative SDQ	Negative SDQ	Positive SDQ	Positive SDQ
Investment	-0.00861	0.0186	0.0146***	0.00262
	(0.00585)	(0.0148)	(0.00250)	(0.00644)
	[0.733]	[0.814]	[0.756]	[0.926]
Income	-0.0270***	-0.0272***	-0.00665***	-0.00659***
	(0.00561)	(0.00561)	(0.00234)	(0.00234)
	[0.000]	[0.000]	[0.059]	[0.067]
Temp Difficult	3.237***	4.118***	-0.760***	-1.149***
	(0.140)	(0.513)	(0.0550)	(0.224)
	[0.000]	[0.000]	[0.000]	[0.000]
Skill Endowment	-0.0240	-0.0234	0.0816***	0.0813***
	(0.0204)	(0.0204)	(0.00902)	(0.00897)
	[0.756]	[0.848]	[0.000]	[0.000]
Temp Difficult		-0.0258*		0.0114*
× Investment		(0.0142)		(0.00609)
		[0.46]		[0.458]
Observations	9006	9006	9006	9006
R^2	0.416	0.417	0.208	0.208
Adjusted R^2	0.414	0.415	0.205	0.206

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender. These results are from the linear functional form.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6.2 Non-Linear Models

Linear models may not be appropriate for accurately capturing the dynamic process of skill development. They impose perfect substitutability of inputs and forces complete independence between the marginal products of such inputs. Using both a log-linear and a translog production function allows for more complex interactions, as well as allowing for higher order effects and interactions in the latter. The first column in the following tables is the log-log specification, the second column includes the interaction of just temperament and investment and the third is the full translog estimation which includes higher order and interaction terms.

Looking at the non-linear models, broadly the same pattern emerges as in the linear models. Both investment and income have similar magnitudes of positive effects on non-verbal skills, and on verbal skills. Again, however, verbal skills are more malleable: with the coefficients on income and investment being approximately double those for nonverbal skills. These coefficients in column one and four can be interpreted as elasticities.

There is again, an important role for the lagged skill, which is positive and significant, being larger for verbal than non-verbal skills. However, in the translog estimation the sign switches to negative. It is not clear why this might be the case. For both types of cognitive skills there seems to be higher order significant effects and interactions. For ease of exposition these tables report only the coefficients that were significant for at least one of the skills. The benefits of investment increase the larger the level of investment, but there are decreasing returns to income with higher levels of income having smaller effects. There is some evidence of a substitution effect between income and investment, which suggests low income households may be able to compensate for the lack of monetary resources with time spent with the child.

The translog estimation shows the importance of looking at higher order and interactions terms in human capital accumulation. However, these results are all insignificant when MHT is applied, making it hard to draw definitive conclusions about causality. It does however suggest that complex functional forms may be needed to properly understand human capital accumulation.

Table 3.7: Cognitive Skills

	Non Verbal	Non Verbal	Non Verbal	Verbal	Verbal	Verbal
Investment	0.0325***	0.0325***	-0.175**	0.0829***	0.0848***	0.102
	(0.0112)	(0.0105)	(0.0837)	(0.0123)	(0.0121)	(0.0833)
	[0.007]	[0.007]	-	[0.000]	[0.000]	-
Income	0.0273***	0.0273***	0.183**	0.0814***	0.0814***	0.332***
	(0.00638)	(0.00638)	(0.0862)	(0.00831)	(0.00831)	(0.117)
	[0.000]	[0.000]	-	[0.877]	[0.805]	-
Temp Difficult	-0.0129**	-0.0121	-0.0486	-0.00838	0.0472	0.000774
	(0.00520)	(0.0760)	(0.0903)	(0.00571)	(0.0773)	(0.0998)
	[0.877]	[0.899]	-	[0.877]	[0.805]	-
Skill Endowment	0.0819***	0.0819***	-0.275**	0.117***	0.117***	-0.154
	(0.0119)	(0.0119)	(0.121)	(0.0137)	(0.0137)	(0.103)
	[0.000]	[0.000]	-	[0.000]	[0.000]	-
Temp Difficult		-0.000228	0.0159		-0.0155	-0.0233
× Investment		(0.0211)	(0.0208)		(0.0215)	(0.0261)
		[0.99]	-		[0.753]	-
Temperament^2			-0.0158***			-0.00890
			(0.00577)			(0.00569)
			-			-
Investment^2			0.0259***			0.00656
			(0.00809)			(0.00956)
			-			-
Income^2			-0.0314*			-0.0273
			(0.0164)			(0.0198)
			-			-
Income#Investment			-0.0203			-0.0471**
			(0.0180)			(0.0231)
			-			-
Skills#Investment			0.0756**			0.0373*
			(0.0311)			(0.0224)
			-			-
Observations	8807	8807	8807	8498	8498	8498
R^2	0.066	0.066	0.071	0.108	0.108	0.111
Adjusted R^2	0.063	0.063	0.067	0.105	0.105	0.107
CRS P value			0			.012
LR P value			0			.001

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender. These results are from the log and translog functional form.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Socio-Emotional Skills

	Negative SDQ	Negative SDQ	Negative SDQ	Positive SDQ	Positive SDQ	Positive SDQ
Investment	-0.0751***	-0.0659***	-0.295**	0.0530***	0.0432***	0.0710
	(0.0167)	(0.0203)	(0.137)	(0.0126)	(0.0121)	(0.0728)
	[0.000]	[0.001]	-	[0.001]	[0.001]	-
Income	-0.0764***	-0.0765***	-0.353*	-0.0184**	-0.0182**	-0.0578
	(0.0168)	(0.0168)	(0.198)	(0.00768)	(0.00767)	(0.101)
	[0.000]	[0.000]	-	[0.136]	[0.207]	-
Temp Difficult	0.322***	0.517***	0.285	-0.0656***	-0.289***	-0.427***
	(0.0165)	(0.157)	(0.216)	(0.00539)	(0.0857)	(0.112)
	[0.000]	[0.000]	-	[0.000]	[0.000]	-
Skill Endowment	-0.0475**	-0.0468**	-0.438**	0.124***	0.123***	0.236
	(0.0236)	(0.0236)	(0.173)	(0.0163)	(0.0161)	(0.154)
	[0.19]	[0.283]	-	[0.000]	[0.000]	-
Temp Difficult		-0.0549	0.00555		0.0622***	0.0510**
× Investment		(0.0439)	(0.0493)		(0.0237)	(0.0223)
		[0.671]	-		[0.139]	-
Temperament^2			0.113***			-0.0304***
			(0.0259)			(0.00515)
			-			-
Observations	8838	8838	8838	8984	8984	8984
R^2	0.360	0.360	0.366	0.185	0.186	0.193
Adjusted R^2	0.358	0.358	0.363	0.182	0.184	0.190
CRS P value			0			0
LR P value			0			0

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender. These results are from the log and translog functional form.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Looking now at socio-emotional skills the results are very much the same as in the linear estimation. A one percent increase in investment decrease problem behaviour by 0.07 percent, and increases positive behaviours by 0.05 percent. Again, income is increasing both types of behaviour. Skill endowment is also an important input, working in the directions we would expect.

The effects of a difficult temperament are as expected, and are much larger than any other input - suggesting it is an important input. It features significantly in three cases: directly, indirectly and in the squared coefficient. The negative effect on prosocial skills, with a positive higher order term suggests that the decrease in skills is larger at higher levels of difficult temperament, exacerbating its already negative effect. We also see that prosocial skills invest-

ment is in fact more beneficial the more difficult the temperament, as evidenced by the positive and significant interaction term. This suggests that investment can compensate for the negative effects of a difficult temperament.

For the most part, the results are pretty stable across the different specifications. The non-linear models reveal interesting patterns that are absent from a simple linear model. It is somewhat encouraging that qualitatively the results stay the same.

3.6.2.1 Subscales

There is a concern that the findings that temperament is strongly associated with both forms of socio-emotional skills could be spurious, in that I have essentially the same construct in the dependent and independent variable. This could arise due to mismeasurement, given the conceptual overlap in the self-report questionnaires.

The total difficulty measure is comprised of four subscales: peer problems, hyperactivity, conduct problems and emotionality. The estimation was repeated for the different subscales. One worry is the similarity between temperament and negative behavioural outcomes, especially as both are parental report measures. The subscales are emotional behaviour (e.g. often unhappy, downhearted or tearful), conduct problems (e.g. often fights with other children or bullies them), hyperactivity/inattention (e.g. is restless, overactive and cannot sit still for long) and peer relationship problems (e.g. is picked on or bullied by other children). The items for the emotional scale are - *"C: often complains of headaches, stomach aches, sickness; H: Many worries, often seems worried ; M : often unhappy, downhearted or tearful ; P: nervous or clingy in new situations, easily loses confidence ; X: Many fears, easily scared"*. For hyperactivity: *"B: restless, overactive, cannot stay still for long; J: constantly fidgeting or squirming ; O: easily distracted, concentration wanders; U : can stop and think before acting; Y : Sees task through to the end, good attention span"*. For peer problems : *"F: Rather solitary, tends to play alone; K: has at least one good friend; N: generally liked by other people ; S : picked on or bullied by other children; W : get on better with adults than with other children"*. Finally for conduct problems : *"E: has temper tantrums or hot tempers; G : generally obedient, usually does what adult request. L : often fights with other children, or bullies them; R: Argumentative with other adults; V : can be spiteful to others"*.

The questionnaire is shown in Appendix A.

In comparison, the temperament scale is derived from questions that focus on *"the child is pleasant in unfamiliar places, the child plays continuously for more than 10 minutes, responds to frustration intensely, smiles when unfamiliar adult, goes back to same activity after interruption, child is outgoing with adult strangers, reacts strongly (cries/screams/bodily movements), practises a new skill for 10 minutes etc*[18] *"*. There is some conceptual overlap between temperament and negative SDQ that may be difficult for parents to distinguish between, especially in behavioural based questionnaires. These self-report measures may not be good enough to separately identify these constructs. The analysis might just be capturing the correlation due to parental report as opposed to distinct causal effects and we should be careful when interpreting the coefficients.

To address this potential problem I look at the impact of temperament on each of the subcategories of the SDQ. Some of the subcategories such as peer problems, are composed of questions that are more distinct from the temperament scale. I can be more confident in the conclusions about the effects of temperament on these measures. Table 3.9 report the estimation for each scale, with the same loglog estimation as in column two of Table 3.8. The effects of temperament are similar across all subcategories, increasing problem behaviours. The largest effect is on conduct problems and emotionality, but perhaps the most useful for our purposes is the peer problem scale. A one percent increase in difficult temperament increases peer problems by 0.362 percent. This suggests that not everything is being driven by simultaneous measurement issues. Income decreases negative behaviour across all subcategories. However, now investment has a varying impact: decreasing peer problems and hyperactivity while increasing conduct problems and emotionality. It is not clear what would cause investment to have differential impacts on these items. In every instance, the interaction term is negative suggesting that investment is more effective at decreasing problem behaviours the more difficult the child is. Investment can be protective against the direct effect of negative temperament on skills.

[18]The temperament questionnaire is in Appendix A.

Table 3.9: Subscales of Negative SDQ

	Total	Peer Problems	Hyperactivity	Conduct Problems	Emotional
Investment	-0.0659***	-0.0374	-0.0919***	0.0242	0.0883***
	(0.0203)	(0.0253)	(0.0229)	(0.0231)	(0.0260)
	[0.028]	[0.607]	[0.002]	[0.673]	[0.019]
Income	-0.0765***	-0.0566**	-0.0531***	-0.0431**	-0.0463**
	(0.0168)	(0.0233)	(0.0185)	(0.0198)	(0.0215)
	[0.000]	[0.2]	[0.069]	[0.291]	[0.296]
Temp Difficult	0.517***	0.362**	0.244	0.541***	0.639***
	(0.157)	(0.165)	(0.162)	(0.162)	(0.189)
	[0.02]	[0.296]	[0.555]	[0.019]	[0.019]
Skill Endowment	-0.0468**	-0.134***	-0.0502*	0.0369	0.0165
	(0.0236)	(0.0341)	(0.0273)	(0.0306)	(0.0305)
	[0.324]	[0.002]	[0.425]	[0.673]	[0.828]
Temp Difficult	-0.0549	-0.0842*	-0.0182	-0.0995**	-0.117**
× Investment	(0.0439)	(0.0460)	(0.0453)	(0.0451)	(0.0526)
	[0.673]	[0.425]	[0.828]	[0.296]	[0.296]
Observations	8838	5174	8087	7205	5920
R^2	0.360	0.076	0.186	0.214	0.083
Adjusted R^2	0.358	0.070	0.183	0.211	0.078

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Implications of the point estimates: money or time?

The government has two main policy tools to improve child outcomes in the earliest years of life. The first is child benefit, typically providing parents with money, and the other is time off work to spend with their child, maternity and paternity leave. Under a certain set of assumptions, each option will change one of the two inputs in this model. For context in Ireland child benefit payments for the first child are €140 a month, or €1680 a year as of 2017, which is currently only one fifth of the standard deviation of income in this sample. Parents currently get maternity and paternity care, which consists of twenty six weeks paid and sixteen weeks unpaid for the mother, and two paid weeks for the father.

I assume that the child benefit is an unconditional cash transfer to the parent so that they can spend it on anything, not necessarily on the child. This reflects the measure of money investment used in this paper, income, as well as how this benefit works in Ireland. This is a loose proxy for the amount of money available to spend on the child, rather than the amount actually spent. I also assume that the increase in child benefit does not cause a change in the labour supply: the increase in income is not so large that in response parents reduce their hours (i.e. there is no income effect). The coefficient on income captures the effect of an increase in child benefit, holding all other inputs equal. Likewise I can look at the coefficient on investment as a proxy for what might happen if parents were given paid parental leave so their income is held constant but they have more time to spend doing activities with their child. This assumes that the reason parents aren't doing activities is a binding time constraint, as opposed to a lack of information.

A note of caution about using reduced form estimates in this way: for the results to be accurate I need to assume that such any increase does not lead to any other behavioural change, which is probably an unrealistic assumption. In reality, a structural model of behaviour that models the investment decisions made by parents according to their preferences and constraints would be estimated and these results could properly inform this debate. I would also need much more accurate measures of time and money investment. However, as a mini thought experiment it is useful to see the differing role money and

time could play.

Table 3.10: Summary of Findings

	Verbal Scores	Non Verbal Scores	Negative SDQ	Positive SDQ
Mean (Standard Deviation)	*50.89 (12.81)*	*53.12 (10.81)*	*7.95 (1.76)*	*7.79 (4.56)*
Range	*[20,80]*	*[22,80]*	*[0,10]*	*[0,32]*
Increase of 1SD of...				
... Income	+ 1.56 points	+0.454 points	- 0.26 points	- 0.06 points
% of the mean	3.1%	0.8 %	- 3.3%	-0.8%
... Time	+1.14 points	+0.541 points	- 0.072points	0.12 points
% of the mean	2.2%	1.0%	-0.9%	1.6%
... Temperament	-0.32 points	-0.627 points	-1.32points	-0.82 points
% of the mean	0.06%	1.2%	17.16%	10.4%
P Values of a test of				
Income=Time	0.101	0.669	0.000	0.012
Income=Income	0.000		0.269	
Time=Time	0.011		0.000	

Notes *Calculations use the coefficients from the linear model, without the interaction term, that is column 1 from tables 3.5-3.8.*

Table 3.10 looks at the findings from the linear model, not including the interaction term. This is a rough exposition of the effects of increasing various inputs, especially as the higher order and interaction terms are important. The first row shows the effect of increasing income by one standard deviation and the associated change in test scores in terms of absolute point increase, but also as a percentage of the mean on the row below. The following two rows (row three and four) show the same effect for extra time in activities. The last two rows act as a comparison for the role of temperament, although this is assumed to be something parents and children cannot change.

Looking first at the cognitive measures: the verbal and non-verbal scores. An increase of income is half a point greater than an increase in time for verbal scores, whereas they are approximately of a similar magnitude for non verbal scores. Both forms of investment are more effective for verbal than non verbal scores resulting in an extra one point for income and a half point for time. This suggests that verbal skills are potentially more malleable. This makes sense as interactions with parents are more likely to impact language skills, whereas non verbal skills are likely to be less directly influenced by the day to day interactions. A one standard deviation of income is more effective than a one standard deviation of time - but it may be much easier to increase time spent with the child by eight activities a week compared to increasing one's income by nearly €10,000. This is an important aspect to consider when evaluating

policy tools. Is it more feasible for a parent to earn an extra €9,767 (the standard deviation of income) a year or to learn how to invest/find the time to invest more in their child? Can governments be more effective at providing parents with more time or more income? For instance, interventions teaching parents how to communicate with their child at early ages have been found to be highly effective at improving later outcomes.

Looking at the non cognitive outcomes there are modest changes to both positive and negative SDQ with more time investment decreasing negative behaviours and increasing positive behaviours. The time effect is larger than the slight decrease in positive behaviour caused by increasing income. In comparison, there are larger decreases on negative skills from increasing income. An increase in income has direct effects on skill development. This could be through purchases of educational tools, play things, books as well as better nutrition, healthcare and other benefits of higher incomes.

I can compare temperament's impact to that of income and time investment on outcomes. As outlined already, income seems to be very important for verbal skills, as well as decreasing negative behaviours. Time investments have more stable effects in terms of percentage increases, with the largest effect again on verbal scores. In comparison the temperament of the child has quite small percentage change on verbal skills, but does seem to be associated with a decrease in non verbal scores of a similar magnitude to income and time. Temperament has quite large changes on the positive and negative aspects of the SDQ, caveated by the concern about simultaneous measurement.

What does this mean for policy? Both monetary payments and giving parents time to invest in their child is effective at increasing verbal skills. However, for this to hold we must assume that the money gets spent on inputs for the child and that time off results in more effective time spent with the child - both of which might not be the case. The full estimation results in the appendix show that consistent parenting is important for cognitive outcomes, and thus inconsistent parenting in combination with higher levels of time may be detrimental for outcomes. Again, this is merely a simple exposition to aid thinking about the problem and to help start the discussion on policy reforms. Hopefully future work can more robustly determine the trade off between these policy tools and these two forms of investment.

3.8 Discussion

This paper has examined the role of time investment, income and the temperament of infants in predicting cognitive and socio-emotional outcomes at age 3. In the earliest years, parents are the main provider of investment in their child's development. The government supports parents in these early years through parental leave, monetary payments (child benefit, tax subsidies, etc.), information and courses on effective parenting and free years of childcare and preschool. This paper speaks to the first two of these, by examining the role of income and time investments in the production of socio-emotional and cognitive skills. This work has also examined if temperament is a useful predictor of skills, distinct from socio-emotional skills.

The results suggest that developmental pathways differ for the various forms of cognitive (verbal and non-verbal) and non cognitive (negative and prosocial) skills. The behavioural outcomes were best captured by a linear model with an interaction term, although there was some indication that higher order terms might also matter. It was less clear cut if there was a definitive best functional form for cognitive outcomes. It seems that higher order and interaction terms warrant investigation when trying to understand human capital development.

Turning to the differential effects of different inputs, income has larger effects than does the activity based investment on every outcome except for prosocial skills. Increases in income were related to lower levels of prosocial behaviour. This is somewhat counter intuitive, warranting further investigation as to why this is the case. Both income and investment were effective at reducing negative SDQ behavioural scores. Temperament was strongly related to both measures of socio-emotional skills.

Verbal skills seem to be the most responsive to the inputs examined in this study. The point estimates implied that income and time increases resulted in at least half a point higher on verbal scores than their magnitude of effect on non-verbal scores. For both types of cognitive scores, there is suggestive evidence that investment in time and in income are substitutes in skill production and of roughly similar productivity. This implies that parents can improve skills of their children by spending time doing activities with their child. This may be more effective especially because changing income is likely to be harder to do

in the short run. I cannot however say anything about the effects of diverting current funds to the child at current income levels as I am not measuring exact monetary investment. There may also be limits to the benefits of increasing time investment, especially if there are decreasing returns to this type of investment. Both cognitive skills and non cognitive skills are strongly related to the early development measure, giving further support to the importance of the earliest years of life.

There are theoretical reasons as to why temperament might matter for the production of skills, and yet I found little direct impact of temperament on cognitive skill development. The interactions suggested that there is no differences in the productivity of investment depending on the temperament of the child. However, temperament might still matter in that children with difficult temperaments received less investment from parents. In terms of percentage increase, both negative and positive SDQ were particularly influenced by temperament. While this could be a measurement issue due to the overlap in questionnaires, it does seem that there is some real impact of temperament on both positive and negative non cognitive skills. Temperament difficulties were also associated with lower rates of investment, providing evidence that parents may be adjusting investment in response to temperament - another mechanism through which temperament can influence outcomes.

There were some differences in the amount of investment across different types of people, albeit these differences were quite small. Mean investment levels by parents were broadly similar across income decile and social class. The largest differences were across education level of the parent. There was approximately half of a standard deviation of investment between highest and lowest educational group, equivalent to four days more of one activity (or one day more of four activities). In terms of magnitudes this would result in a small difference in skills at age 3. However, it still warrants our attention given we know skills build on skills from young ages and that these gaps widen over the life cycle. Those with higher education levels are also likely to have higher incomes and be from a higher social class, and different investment behaviours will reinforce any skill advantages their children already have. Those who are already behind are likely to remain behind. One positive take away is that time investment can increase skills to the same degree as increases in income. Perhaps policies that inform parents as to the importance of and how to invest

in their children from early ages can be effective at increasing skills.

There are a number of limitations of this study, firstly the lack of identification required to interpret these results causally. I estimated the production function using a variety of different functional forms and specifications which rely on different identifying assumptions and the results broadly held across the different estimations. This suggests the findings are likely to be non-spurious but are still by no means causal. Secondly, the measures of time and money investment are both subject to criticism, and are likely to be flawed measures of the true underlying latent factors. This is a problem within early childhood development research - how does one accurately measure the different ways parents can invest in their children? How does one capture differences in the quality of such time and the differing money investment that parents can make? Hopefully, new and better methods will be developed and incorporated into data collection. Other measures such as temperament and behavioural outcomes, also need more rigorous examination. As highlighted in this paper questionnaires may not accurately distinguish between these constructs, even thought the theoretical underpinnings are distinct. Third, a structural model of investment and skill development might help with interpretation and extrapolation of results. An ideal scenario would model the utility function of the parent, the budget constraints and their beliefs, as well as the production function of the child. Structural models can derive the deep level parameters that remain constant when some aspect of the environment changes. This allows predictions about the future to be made, as well as simulating counterfactuals about what would happen in different situations. Proper simulations of policy experiments could then be conducted, that could help inform the policy debate on the optimal mix of child benefit, paternity leave, maternity leave and free childcare.

Despite these limitations, this paper has shown the importance of incorporating knowledge from other disciplines, that can be used to augment economic models and methods. Overall, this will help the understanding of the dynamics of human capital development and to think more broadly about potential omitted variables that can improve economic analysis of the accumulation of skills.

Appendix A-C

Appendix A: Questionnaires

E1. [CARD E1] Look at the card, for each statement, please indicate the answer that best describes the <child's> behaviour <u>at the present time</u>.

	Almost Never	Not Often	Variable usually does not	Variable usually does	Frequently	Almost always
A. This child is pleasant (smiles, laughs) when first arriving in unfamiliar places	☐1	☐2	☐3	☐4	☐5	☐6
B. This child plays continuously for more than 10 minutes at a time with a favourite toy	☐1	☐2	☐3	☐4	☐5	☐6
C. This child responds to frustration intensely (screams, yells)	☐1	☐2	☐3	☐4	☐5	☐6
D. This child smiles when an unfamiliar adult plays with him/her	☐1	☐2	☐3	☐4	☐5	☐6
E. This child goes back to the same activity after a brief interruption (snack, trip to toilet)	☐1	☐2	☐3	☐4	☐5	☐6
F. This child has moody "off" days when he/she is irritable all day	☐1	☐2	☐3	☐4	☐5	☐6
G. This child is outgoing with adult strangers outside the home	☐1	☐2	☐3	☐4	☐5	☐6
H. This child stays with a routine task (dressing, picking up toys) for 5 minutes or more	☐1	☐2	☐3	☐4	☐5	☐6
I. This child shows much bodily movement (stomps, writhes, swings arms) when upset or crying	☐1	☐2	☐3	☐4	☐5	☐6
J. This child is still wary of strangers after 15 minutes	☐1	☐2	☐3	☐4	☐5	☐6
K. This child stops to examine objects thoroughly (5 minutes or more)	☐1	☐2	☐3	☐4	☐5	☐6
L. This child reacts strongly (cries, screams) when unable to complete a play activity	☐1	☐2	☐3	☐4	☐5	☐6
M. This child practices a new skill (throwing, building, drawing for 10 or more minutes)	☐1	☐2	☐3	☐4	☐5	☐6

Figure 3.9: Temperament Questionnaire

F1. [CARD F1] Listed below is a set of statements which could be used to describe the Study Child's behaviour. For each item, please indicate whether it is Not True, Somewhat True or Certainly True. It would help us if you answered all items as best you can even if you are not absolutely certain. Please give answers on the basis of the Study Child's behaviour over the last six months. Use answers 1, 2 or 3 as on the card if you like.

	Not True	Somewhat True	Certainly True
A. Considerate of other people's feelings	☐1	☐2	☐3
B. Restless, overactive, cannot stay still for long	☐1	☐2	☐3
C. Often complains of headaches, stomach-aches or sickness	☐1	☐2	☐3
D. Shares readily with other children (treats, toys, pencils etc.)	☐1	☐2	☐3
E. Often has temper tantrums or hot tempers	☐1	☐2	☐3
F. Rather solitary, tends to play alone	☐1	☐2	☐3
G. Generally obedient, usually does what adults request	☐1	☐2	☐3
H. Many worries, often seems worried	☐1	☐2	☐3
I. Helpful if someone is hurt, upset or feeling ill	☐1	☐2	☐3
J. Constantly fidgeting or squirming	☐1	☐2	☐3
K. Has at least one good friend	☐1	☐2	☐3
L. Often fights with other children or bullies them	☐1	☐2	☐3
M. Often unhappy, down-hearted or tearful	☐1	☐2	☐3
N. Generally liked by other children	☐1	☐2	☐3
O. Easily distracted, concentration wanders	☐1	☐2	☐3
P. Nervous or clingy in new situations, easily loses confidence	☐1	☐2	☐3
Q. Kind to younger children	☐1	☐2	☐3
R. Often argumentative with adults	☐1	☐2	☐3
S. Picked on or bullied by other children	☐1	☐2	☐3
T. Often volunteers to help others (parents, teachers, other children)	☐1	☐2	☐3
U. Can stop and think things out before acting	☐1	☐2	☐3
V. Can be spiteful to others	☐1	☐2	☐3
W. Gets on better with adults than with other children	☐1	☐2	☐3
X. Many fears, easily scared	☐1	☐2	☐3
Y. Sees tasks through to the end, good attention span	☐1	☐2	☐3

Figure 3.10: SDQ Questionnaire

Appendix B: Summary Statistics

Summary Statistics

Table 3.11: Summary Statistics

	Round 1	Round 2
Non-Verbal Score	.	60.80
	(.)	(14.37)
Verbal Score	.	74.74
	(.)	(19.87)
Prosocial Skills	.	7.945
	(.)	(1.761)
Total Difficulties	.	7.793
	(.)	(4.562)
Development Index	12.30	.
	(2.472)	(.)
Difficult Temperament	.	8.032
	(.)	(1.884)
Investment	.	43.96
	(.)	(11.13)
Income	21463.6	18246.8
	(13529.9)	(9767.4)
Female	0.490	.
	(0.500)	(.)
Highest Education of Parent	7.268	.
	(2.897)	(.)
Household Class	5.745	5.839
	(2.115)	(2.000)
Household Size	4.063	4.325
	(1.157)	(1.118)
Employed Parent	.	0.558
	(.)	(0.497)
Student Parent	.	0.0184
	(.)	(0.134)

Unemployed Parent	.	0.0764
	(.)	(0.266)
Stay at Home Parent	.	0.347
	(.)	(0.476)
Couple	0.878	0.876
	(0.327)	(0.330)
Depression of Parent	2.456	.
	(3.635)	(.)
Warmth of Parent	.	4.743
	(.)	(0.372)
Hostility of Parent	.	1.793
	(.)	(0.491)
Consistency of Parent	.	3.990
	(.)	(0.726)
Stress of Parent	32.11	12.35
	(6.822)	(4.167)
N	11134	9793

Attritrion

Table 3.12 shows the differences across those who were in both rounds and those who were only in round 1 and subsequently dropped out (for all reasons i.e. this is not those who did not respond from the remaining effective sample). Those who dropped out were slightly less educated, with less income, less likely to be in a relationship. and highest levels of depression and stress.

Table 3.12: Summary Statistics by drop outs

	In Both Rounds	Only in Round 1	P Value Difference
Development Index	12.30 (2.458)	12.32 (2.573)	0.852
Income	21834.1 (13350.2)	18660.9 (14521.6)	0.000
Female	0.493 (0.500)	0.469 (0.499)	0.102
Highest Education of Parent	7.344 (2.868)	6.717 (3.044)	0.000
Household Class	5.839 (2.061)	5.058 (2.363)	0.000
Household Size	4.071 (1.147)	4.007 (1.232)	0.056
Couple	0.890 (0.314)	0.793 (0.405)	0.000
Depression of Parent	2.383 (3.527)	3.005 (4.314)	0.000
Stress of Parent	31.97 (6.750)	33.12 (7.247)	0.000
N	9793	1341	

Temperament by Education

Here we look at whether temperament seems to be evenly dispersed amongst the children of differently educated parents, and parents from different income quintiles (in the next section). Remembering that higher scores of temperament imply more difficult dispositions. The kernal density in Figure 3.11 groups together some of the education groups for ease of interpretation. We can see that those with no formal education and primary school only do seem to perhaps have higher levels of difficult temperaments. However as Table 3.13 shows these groups are smaller and not too much can be interpreted from the higher difficult temperaments.

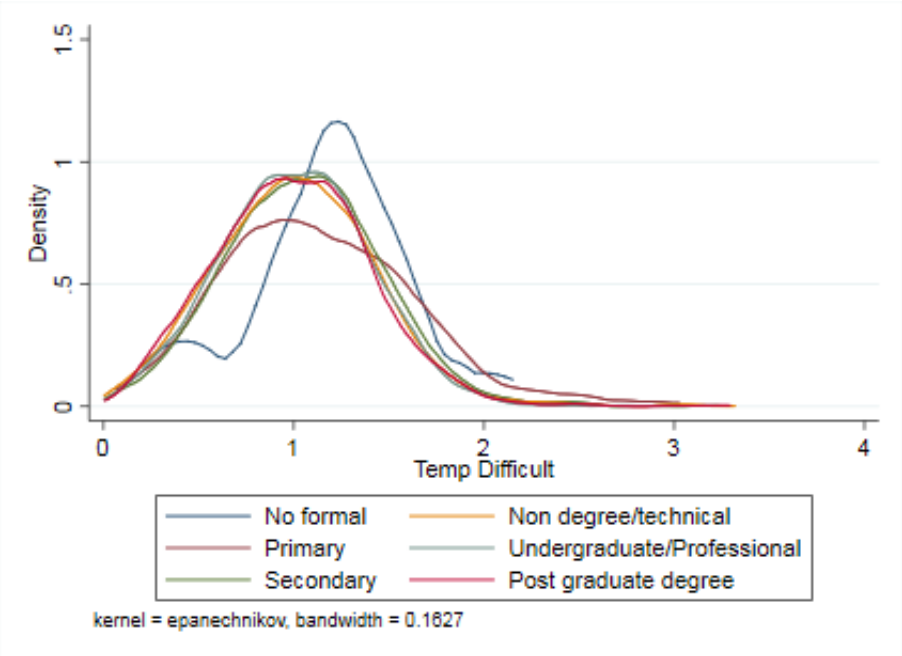


Figure 3.11: Temperament by Education

Table 3.13: Temperament by Parental Education

	Round 2	
	mean/sd	count
No formal education	1.185	15
	(0.406)	
Primary education	1.132	135
	(0.510)	
Lower secondary	1.102	628
	(0.418)	
Upper secondary	1.034	1408
	(0.411)	
Technical/vocational qualification	1.029	861
	(0.432)	
Both upper secondary and technical/vocational qual	1.039	452
	(0.417)	
Non degree third level	0.998	1899
	(0.421)	
Primary degree	1.011	1416
	(0.390)	
Professional qualification	1.006	473
	(0.406)	
Both professional qual and degree	1.015	646
	(0.399)	
Postgraduate certificate or diploma	1.003	678
	(0.409)	
Masters degree	0.989	1008
	(0.405)	
Doctorate	1.032	162
	(0.447)	
Total	1.020	9781
	(0.414)	

Temperament by Income

There is even more even dispersion of department by income quintile as can be seen in both Figure 3.12 and Table 3.14.

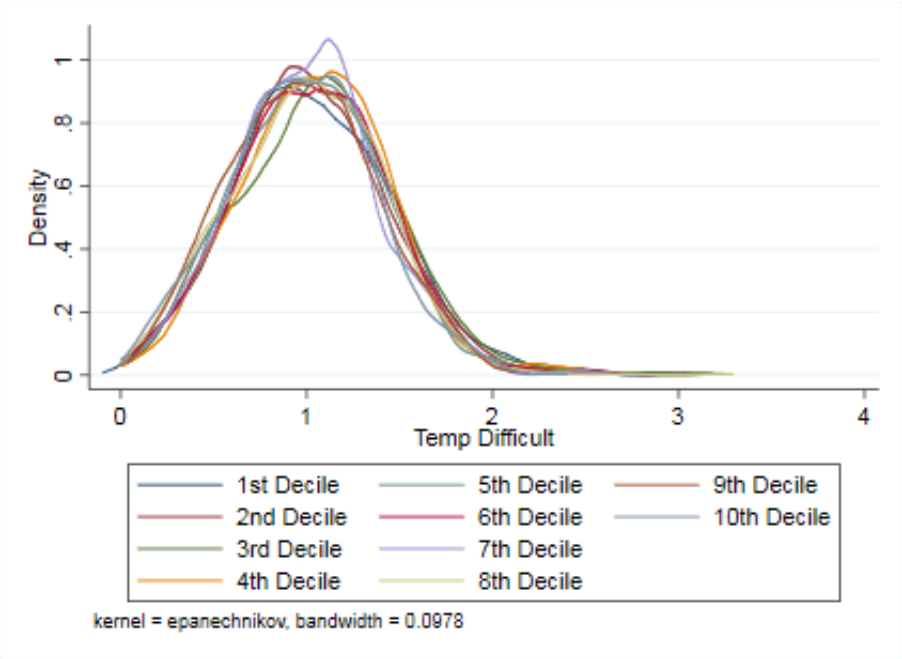


Figure 3.12: Temperament by Income

Table 3.14: Temperament by Parental Income

	Round 2	
	mean/sd	count
1	1.044	941
	(0.427)	
2	1.033	870
	(0.426)	
3	1.065	862
	(0.440)	
4	1.049	898
	(0.400)	
5	1.014	905
	(0.409)	
6	1.025	939
	(0.408)	
7	0.999	902
	(0.389)	
8	1.004	932
	(0.411)	
9	0.973	973
	(0.393)	
10	0.971	1028
	(0.393)	
Total	1.017	9250
	(0.410)	

Appendix C: Regressions

Linear Full Output

Table 3.15: Cognitive Skills

	Non Verbal	Non Verbal	Verbal	Verbal
Investment	0.0629***	0.0490	0.133***	0.165***
	(0.0166)	(0.0417)	(0.0198)	(0.0522)
Income	0.0467***	0.0468***	0.161***	0.161***
	(0.0156)	(0.0156)	(0.0194)	(0.0194)
Temp Difficult	-1.302***	-1.758	-0.786*	0.273
	(0.351)	(1.363)	(0.407)	(1.650)
Skill Endowment	0.436***	0.436***	0.602***	0.602***
	(0.0588)	(0.0589)	(0.0657)	(0.0657)
Temp Difficult		0.0133		-0.0308
× Investment		(0.0384)		(0.0468)
Female	2.093***	2.092***	3.104***	3.107***
	(0.264)	(0.264)	(0.307)	(0.307)
Highest	0	0	0	0
Education of Parent=1	(.)	(.)	(.)	(.)
Highest	-0.412	-0.399	6.533	6.505
Education of Parent=2	(4.581)	(4.582)	(5.213)	(5.212)
Highest	3.119	3.127	9.546*	9.528*
Education of Parent=3	(4.438)	(4.440)	(5.076)	(5.072)
Highest	4.084	4.091	10.55**	10.54**
Education of Parent=4	(4.416)	(4.418)	(5.060)	(5.056)
Highest	3.878	3.887	11.60**	11.57**
Education of Parent=5	(4.431)	(4.433)	(5.078)	(5.074)
Highest	4.216	4.224	11.80**	11.78**
Education of Parent=6	(4.436)	(4.437)	(5.095)	(5.091)
Highest	4.866	4.873	11.60**	11.58**
Education of Parent=7	(4.414)	(4.416)	(5.057)	(5.053)
Highest	5.385	5.395	11.75**	11.72**
Education of Parent=8	(4.420)	(4.422)	(5.067)	(5.064)

Highest	5.285	5.288	13.12***	13.11***
Education of Parent=9	(4.437)	(4.438)	(5.089)	(5.085)
Highest	5.723	5.732	12.05**	12.03**
Education of Parent=10	(4.434)	(4.436)	(5.084)	(5.080)
Highest	5.919	5.925	12.55**	12.54**
Education of Parent=11	(4.433)	(4.434)	(5.078)	(5.074)
Highest	5.645	5.651	12.11**	12.09**
Education of Parent=12	(4.427)	(4.428)	(5.076)	(5.072)
Highest	8.681*	8.688*	13.79***	13.78***
Education of Parent=13	(4.492)	(4.493)	(5.179)	(5.175)
Informal care w2	-0.101	-0.104	0.557	0.563
	(0.381)	(0.381)	(0.441)	(0.441)
Formal care w2	-0.259	-0.259	-0.468	-0.467
	(0.344)	(0.344)	(0.410)	(0.410)
Student PC R2	-0.950	-0.957	-3.192***	-3.173***
	(1.106)	(1.107)	(1.148)	(1.147)
Unemployed PC R2	-1.220**	-1.226**	0.371	0.386
	(0.555)	(0.553)	(0.662)	(0.662)
Employed PC R2	-0.230	-0.230	-0.205	-0.206
	(0.343)	(0.343)	(0.413)	(0.413)
Household Size	-0.261**	-0.261**	-0.415***	-0.415***
R2	(0.131)	(0.131)	(0.151)	(0.151)
Stress of Parent	-0.0735**	-0.0735**	-0.0478	-0.0478
R2	(0.0351)	(0.0351)	(0.0425)	(0.0425)
Consistency of	0.803***	0.803***	1.456***	1.456***
Parent R2	(0.199)	(0.199)	(0.231)	(0.231)
Warmth of Parent	0.168	0.159	-0.182	-0.162
R2	(0.387)	(0.387)	(0.432)	(0.432)
Hostility of	-0.0617	-0.0629	0.351	0.356
Parent R2	(0.305)	(0.305)	(0.358)	(0.358)
Depression of	-0.0161	-0.0157	-0.0236	-0.0245
Parent R1	(0.0378)	(0.0378)	(0.0443)	(0.0444)

Constant	38.18***	38.71***	20.40***	19.18***
	(5.086)	(5.296)	(5.762)	(6.020)
Observations	8812	8812	8502	8502
R^2	0.061	0.061	0.101	0.101
Adjusted R^2	0.058	0.058	0.098	0.098

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.16: Socio-Emotional Skills

	Negative SDQ	Negative SDQ	Positive SDQ	Positive SDQ
Investment	-0.00861	0.0186	0.0146***	0.00262
	(0.00585)	(0.0148)	(0.00250)	(0.00644)
Income	-0.0270***	-0.0272***	-0.00665***	-0.00659***
	(0.00561)	(0.00561)	(0.00234)	(0.00234)
Temp Difficult	3.237***	4.118***	-0.760***	-1.149***
	(0.140)	(0.513)	(0.0550)	(0.224)
Skill Endowment	-0.0240	-0.0234	0.0816***	0.0813***
	(0.0204)	(0.0204)	(0.00902)	(0.00897)
Temp Difficult		-0.0258*		0.0114*
× Investment		(0.0142)		(0.00609)
Female	-0.721***	-0.718***	0.390***	0.389***
	(0.0913)	(0.0913)	(0.0390)	(0.0390)
Highest	0	0	0	0
Education of Parent=1	(.)	(.)	(.)	(.)
Highest	1.451*	1.424	-0.269	-0.258
Education of Parent=2	(0.869)	(0.868)	(0.387)	(0.386)
Highest	1.354*	1.336*	-0.694**	-0.687**
Education of Parent=3	(0.716)	(0.717)	(0.346)	(0.344)
Highest	0.469	0.450	-0.855**	-0.847**
Education of Parent=4	(0.699)	(0.700)	(0.341)	(0.340)
Highest	0.270	0.247	-1.028***	-1.018***
Education of Parent=5	(0.707)	(0.708)	(0.346)	(0.344)
Highest	0.582	0.560	-0.952***	-0.942***
Education of Parent=6	(0.720)	(0.721)	(0.349)	(0.348)
Highest	0.0648	0.0461	-0.919***	-0.911***
Education of Parent=7	(0.696)	(0.697)	(0.340)	(0.339)
Highest	-0.247	-0.271	-0.903***	-0.892***
Education of Parent=8	(0.701)	(0.702)	(0.342)	(0.340)
Highest	-0.266	-0.280	-0.923***	-0.917***
Education of Parent=9	(0.714)	(0.715)	(0.348)	(0.346)

Highest	-0.348	-0.370	-1.127***	-1.117***
Education of Parent=10	(0.710)	(0.712)	(0.347)	(0.346)
Highest	-0.362	-0.380	-1.063***	-1.055***
Education of Parent=11	(0.708)	(0.709)	(0.348)	(0.346)
Highest	-0.584	-0.602	-0.884**	-0.875**
Education of Parent=12	(0.706)	(0.707)	(0.344)	(0.343)
Highest	-0.487	-0.504	-0.801**	-0.793**
Education of Parent=13	(0.767)	(0.768)	(0.366)	(0.365)
Informal care w2	-0.0899	-0.0877	0.0100	0.00910
	(0.130)	(0.130)	(0.0586)	(0.0586)
Formal care w2	-0.494***	-0.494***	0.137**	0.137**
	(0.124)	(0.124)	(0.0546)	(0.0546)
Student PC R2	-0.864**	-0.848**	-0.180	-0.187
	(0.369)	(0.370)	(0.146)	(0.146)
Unemployed PC R2	-0.159	-0.148	0.0272	0.0220
	(0.198)	(0.198)	(0.0796)	(0.0796)
Employed PC R2	-0.132	-0.131	0.0488	0.0485
	(0.122)	(0.122)	(0.0544)	(0.0544)
Household Size	-0.361***	-0.362***	-0.0159	-0.0159
R2	(0.0473)	(0.0473)	(0.0194)	(0.0194)
Stress of Parent	0.209***	0.209***	-0.0357***	-0.0356***
R2	(0.0134)	(0.0133)	(0.00557)	(0.00556)
Warmth of Parent	-0.111	-0.0950	0.600***	0.592***
R2	(0.132)	(0.131)	(0.0617)	(0.0619)
Hostility of	2.441***	2.447***	-0.490***	-0.493***
Parent R2	(0.112)	(0.112)	(0.0493)	(0.0491)
Consistency of	-0.793***	-0.792***	0.177***	0.176***
Parent R2	(0.0716)	(0.0715)	(0.0305)	(0.0304)
Depression of	0.0518***	0.0511***	0.00220	0.00251
Parent R1	(0.0158)	(0.0158)	(0.00593)	(0.00592)
Constant	4.339***	3.318***	5.722***	6.174***
	(1.155)	(1.255)	(0.535)	(0.581)

Observations	9006	9006	9006	9006
R^2	0.416	0.417	0.208	0.208
Adjusted R^2	0.414	0.415	0.205	0.206

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Non-linear Full Output

Table 3.17: Cognitive Skills

	Non Verbal	Non Verbal	Non Verbal	Verbal	Verbal	Verbal
Investment	0.0325***	0.0325***	-0.175**	0.0829***	0.0848***	0.102
	(0.0112)	(0.0105)	(0.0837)	(0.0123)	(0.0121)	(0.0833)
Income	0.0273***	0.0273***	0.183**	0.0814***	0.0814***	0.332***
	(0.00638)	(0.00638)	(0.0862)	(0.00831)	(0.00831)	(0.117)
Temp Difficult	-0.0129**	-0.0121	-0.0486	-0.00838	0.0472	0.000774
	(0.00520)	(0.0760)	(0.0903)	(0.00571)	(0.0773)	(0.0998)
Skill Endowment	0.0819***	0.0819***	-0.275**	0.117***	0.117***	-0.154
	(0.0119)	(0.0119)	(0.121)	(0.0137)	(0.0137)	(0.103)
Temp Difficult		-0.000228	0.0159		-0.0155	-0.0233
× Investment		(0.0211)	(0.0208)		(0.0215)	(0.0261)
Female	0.0452***	0.0452***	0.0443***	0.0649***	0.0649***	0.0646***
	(0.00524)	(0.00524)	(0.00524)	(0.00641)	(0.00641)	(0.00642)
Highest	0	0	0	0	0	0
Education of Parent=1	(.)	(.)	(.)	(.)	(.)	(.)
Highest	-0.0133	-0.0133	-0.0128	0.170	0.170	0.164
Education of Parent=2	(0.101)	(0.101)	(0.0999)	(0.130)	(0.130)	(0.131)
Highest	0.0638	0.0638	0.0602	0.229*	0.228*	0.221*
Education of Parent=3	(0.0969)	(0.0969)	(0.0962)	(0.127)	(0.127)	(0.128)
Highest	0.0853	0.0853	0.0815	0.242*	0.242*	0.232*
Education of Parent=4	(0.0965)	(0.0965)	(0.0958)	(0.126)	(0.126)	(0.128)
Highest	0.0790	0.0790	0.0741	0.260**	0.259**	0.249*
Education of Parent=5	(0.0968)	(0.0968)	(0.0961)	(0.127)	(0.127)	(0.128)
Highest	0.0901	0.0901	0.0877	0.265**	0.265**	0.257**
Education of Parent=6	(0.0968)	(0.0968)	(0.0961)	(0.127)	(0.127)	(0.129)
Highest	0.0987	0.0987	0.0935	0.258**	0.258**	0.247*
Education of Parent=7	(0.0965)	(0.0965)	(0.0957)	(0.126)	(0.126)	(0.128)
Highest	0.108	0.108	0.104	0.255**	0.254**	0.246*
Education of Parent=8	(0.0965)	(0.0965)	(0.0958)	(0.127)	(0.127)	(0.128)
Highest	0.107	0.107	0.104	0.287**	0.287**	0.278**
Education of Parent=9	(0.0968)	(0.0968)	(0.0961)	(0.127)	(0.127)	(0.129)
Highest	0.113	0.113	0.109	0.263**	0.263**	0.255**
Education of Parent=10	(0.0968)	(0.0968)	(0.0961)	(0.127)	(0.127)	(0.128)
Highest	0.115	0.115	0.112	0.272**	0.271**	0.263**
Education of Parent=11	(0.0968)	(0.0968)	(0.0961)	(0.127)	(0.127)	(0.128)
Highest	0.114	0.114	0.111	0.264**	0.264**	0.257**
Education of Parent=12	(0.0967)	(0.0967)	(0.0960)	(0.127)	(0.127)	(0.128)
Highest	0.167*	0.167*	0.165*	0.295**	0.295**	0.289**

Education of Parent=13	(0.0975)	(0.0975)	(0.0968)	(0.128)	(0.128)	(0.130)
Informal care w2	-0.00435	-0.00434	-0.00386	0.0132	0.0133	0.0140
	(0.00761)	(0.00761)	(0.00759)	(0.00903)	(0.00904)	(0.00902)
Formal care w2	-0.00449	-0.00449	-0.00238	-0.00487	-0.00485	-0.00349
	(0.00689)	(0.00689)	(0.00697)	(0.00850)	(0.00850)	(0.00853)
Student PC R2	-0.0152	-0.0152	-0.0154	-0.0621**	-0.0619**	-0.0619**
	(0.0230)	(0.0230)	(0.0229)	(0.0282)	(0.0282)	(0.0282)
Unemployed PC R2	-0.0224*	-0.0224*	-0.0219*	0.00995	0.0102	0.0110
	(0.0116)	(0.0116)	(0.0115)	(0.0144)	(0.0144)	(0.0143)
Employed PC R2	-0.00432	-0.00432	-0.00519	-0.00778	-0.00771	-0.00850
	(0.00691)	(0.00691)	(0.00690)	(0.00877)	(0.00877)	(0.00878)
Household Size	-0.00407	-0.00407	-0.00353	-0.00438	-0.00433	-0.00387
R2	(0.00275)	(0.00275)	(0.00274)	(0.00323)	(0.00323)	(0.00321)
Stress of Parent	-0.0188**	-0.0188**	-0.0169**	-0.0188*	-0.0189*	-0.0188*
R2	(0.00850)	(0.00850)	(0.00844)	(0.0106)	(0.0106)	(0.0106)
Consistency of	0.0643***	0.0643***	0.0614***	0.111***	0.111***	0.111***
Parent R2	(0.0145)	(0.0145)	(0.0144)	(0.0174)	(0.0174)	(0.0175)
Warmth of Parent	0.0283	0.0283	0.0192	-0.0115	-0.0103	-0.0140
R2	(0.0357)	(0.0358)	(0.0355)	(0.0405)	(0.0405)	(0.0405)
Hostility of	-0.00464	-0.00463	-0.00113	0.0191	0.0194	0.0220
Parent R2	(0.0113)	(0.0113)	(0.0113)	(0.0139)	(0.0139)	(0.0139)
Depression of	-0.000474	-0.000475	-0.000378	-0.000731	-0.000805	-0.000407
Parent R1	(0.00340)	(0.00341)	(0.00340)	(0.00427)	(0.00428)	(0.00426)
Temperament^2			-0.0158***			-0.00890
			(0.00577)			(0.00569)
Investment^2			0.0259***			0.00656
			(0.00809)			(0.00956)
Income^2			-0.0314*			-0.0273
			(0.0164)			(0.0198)
Skills^2			0.0437*			0.0741**
			(0.0235)			(0.0301)
Temperament#Income			0.00689			0.00603
			(0.00960)			(0.0110)
Temperament#Skills			-0.0211			0.0199
			(0.0258)			(0.0253)
Income#Investment			-0.0203			-0.0471**
			(0.0180)			(0.0231)
Skills#Investment			0.0756**			0.0373*
			(0.0311)			(0.0224)

Income#Skills			0.00151			-0.00394
			(0.0208)			(0.0251)
Constant	3.377***	3.377***	3.928***	2.729***	2.720***	2.646***
	(0.123)	(0.123)	(0.323)	(0.153)	(0.153)	(0.393)
Observations	8807	8807	8807	8498	8498	8498
R^2	0.066	0.066	0.071	0.108	0.108	0.111
Adjusted R^2	0.063	0.063	0.067	0.105	0.105	0.107

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.18: Socio-Emotional Skills

	Negative SDQ	Negative SDQ	Negative SDQ	Positive SDQ	Positive SDQ	Positive SDQ
Investment	-0.0751***	-0.0659***	-0.295**	0.0530***	0.0432***	0.0710
	(0.0167)	(0.0203)	(0.137)	(0.0126)	(0.0121)	(0.0728)
Income	-0.0764***	-0.0765***	-0.353*	-0.0184**	-0.0182**	-0.0578
	(0.0168)	(0.0168)	(0.198)	(0.00768)	(0.00767)	(0.101)
Temp Difficult	0.322***	0.517***	0.285	-0.0656***	-0.289***	-0.427***
	(0.0165)	(0.157)	(0.216)	(0.00539)	(0.0857)	(0.112)
Skill Endowment	-0.0475**	-0.0468**	-0.438**	0.124***	0.123***	0.236
	(0.0236)	(0.0236)	(0.173)	(0.0163)	(0.0161)	(0.154)
Temp Difficult		-0.0549	0.00555		0.0622***	0.0510**
× Investment		(0.0439)	(0.0493)		(0.0237)	(0.0223)
Female	-0.0822***	-0.0825***	-0.0832***	0.0565***	0.0567***	0.0566***
	(0.0134)	(0.0134)	(0.0134)	(0.00591)	(0.00591)	(0.00589)
Highest	0	0	0	0	0	0
Education of Parent=1	(.)	(.)	(.)	(.)	(.)	(.)
Highest	0.0846	0.0838	0.0958	-0.0653	-0.0644	-0.0707
Education of Parent=2	(0.113)	(0.113)	(0.114)	(0.0525)	(0.0513)	(0.0523)
Highest	0.0609	0.0591	0.0827	-0.101**	-0.0990**	-0.109**
Education of Parent=3	(0.0989)	(0.0985)	(0.101)	(0.0443)	(0.0431)	(0.0449)
Highest	-0.0438	-0.0453	-0.0226	-0.129***	-0.127***	-0.135***
Education of Parent=4	(0.0974)	(0.0969)	(0.0998)	(0.0438)	(0.0426)	(0.0446)
Highest	-0.0697	-0.0715	-0.0454	-0.153***	-0.151***	-0.160***
Education of Parent=5	(0.0995)	(0.0990)	(0.102)	(0.0447)	(0.0435)	(0.0456)
Highest	0.00909	0.00728	0.0245	-0.140***	-0.138***	-0.144***
Education of Parent=6	(0.100)	(0.0998)	(0.103)	(0.0450)	(0.0438)	(0.0458)
Highest	-0.103	-0.105	-0.0788	-0.136***	-0.134***	-0.143***
Education of Parent=7	(0.0975)	(0.0970)	(0.1000)	(0.0437)	(0.0425)	(0.0446)
Highest	-0.139	-0.141	-0.116	-0.133***	-0.131***	-0.141***
Education of Parent=8	(0.0980)	(0.0976)	(0.100)	(0.0440)	(0.0428)	(0.0450)
Highest	-0.115	-0.116	-0.0918	-0.132***	-0.131***	-0.141***
Education of Parent=9	(0.100)	(0.0996)	(0.102)	(0.0449)	(0.0437)	(0.0458)
Highest	-0.176*	-0.178*	-0.152	-0.167***	-0.165***	-0.175***
Education of Parent=10	(0.100)	(0.100)	(0.103)	(0.0452)	(0.0441)	(0.0460)
Highest	-0.148	-0.150	-0.127	-0.152***	-0.151***	-0.160***
Education of Parent=11	(0.0996)	(0.0992)	(0.102)	(0.0449)	(0.0438)	(0.0458)
Highest	-0.208**	-0.210**	-0.183*	-0.127***	-0.125***	-0.137***
Education of Parent=12	(0.0996)	(0.0991)	(0.102)	(0.0443)	(0.0431)	(0.0451)
Highest	-0.186*	-0.188*	-0.163	-0.119**	-0.117**	-0.126**

Education of Parent=13	(0.112)	(0.112)	(0.114)	(0.0484)	(0.0473)	(0.0492)
Informal care w2	-0.0193	-0.0190	-0.0179	-0.000266	-0.000704	-0.000714
	(0.0193)	(0.0193)	(0.0194)	(0.00878)	(0.00879)	(0.00877)
Formal care w2	-0.0718***	-0.0718***	-0.0748***	0.0185**	0.0185**	0.0195**
	(0.0177)	(0.0177)	(0.0178)	(0.00836)	(0.00834)	(0.00836)
Student PC R2	-0.107**	-0.106**	-0.108**	-0.0162	-0.0168	-0.0146
	(0.0454)	(0.0455)	(0.0450)	(0.0213)	(0.0213)	(0.0211)
Unemployed PC R2	-0.0137	-0.0129	-0.0145	0.00698	0.00597	0.00646
	(0.0270)	(0.0270)	(0.0268)	(0.0119)	(0.0119)	(0.0119)
Employed PC R2	-0.00739	-0.00716	-0.00773	0.0135	0.0132	0.0135
	(0.0177)	(0.0177)	(0.0178)	(0.00854)	(0.00853)	(0.00857)
Household Size R2	-0.0572***	-0.0570***	-0.0571***	-0.00513*	-0.00526*	-0.00458
	(0.00641)	(0.00642)	(0.00643)	(0.00289)	(0.00289)	(0.00287)
Stress of Parent R2	0.346***	0.346***	0.337***	-0.0682***	-0.0680***	-0.0645***
	(0.0228)	(0.0228)	(0.0228)	(0.00971)	(0.00972)	(0.00968)
Warmth of Parent R2	-0.105	-0.102	-0.0864	0.418***	0.415***	0.401***
	(0.0721)	(0.0721)	(0.0727)	(0.0457)	(0.0457)	(0.0452)
Hostility of Parent R2	0.624***	0.626***	0.620***	-0.138***	-0.140***	-0.137***
	(0.0284)	(0.0285)	(0.0284)	(0.0139)	(0.0138)	(0.0138)
Consistency of Parent R2	-0.348***	-0.348***	-0.336***	0.100***	0.100***	0.0968***
	(0.0327)	(0.0327)	(0.0325)	(0.0180)	(0.0180)	(0.0178)
Depression of Parent R1	0.0286***	0.0283***	0.0286***	0.00352	0.00386	0.00391
	(0.00816)	(0.00815)	(0.00808)	(0.00388)	(0.00387)	(0.00384)
Temperament^2			0.113***			-0.0304***
			(0.0259)			(0.00515)
Investment^2			-0.0207			0.0238**
			(0.0141)			(0.0108)
Income^2			0.0226			0.00152
			(0.0400)			(0.0185)
Skills^2			0.0925*			0.0163
			(0.0544)			(0.0461)
Temperament#Income			0.0224			0.00261
			(0.0267)			(0.00977)
Temperament#Skills			0.0154			0.0583**
			(0.0493)			(0.0291)
Income#Investment			0.0579			0.00776
			(0.0383)			(0.0197)
Skills#Investment			0.0563*			-0.0479**
			(0.0293)			(0.0204)

Income#Skills			0.00610			0.00375
			(0.0430)			(0.0299)
Constant	2.344***	2.306***	3.457***	1.164***	1.206***	1.075***
	(0.192)	(0.197)	(0.641)	(0.109)	(0.107)	(0.381)
Observations	8838	8838	8838	8984	8984	8984
R^2	0.360	0.360	0.366	0.185	0.186	0.193
Adjusted R^2	0.358	0.358	0.363	0.182	0.184	0.190

Notes *Standard errors in parentheses. All models include the following controls: parental consistency, warmth and hostility,parental stress, parental depression, the type of childcare, parental highest education level, household size, employment status and the child's gender.*
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Twenty-five is the new eighteen, and delayed adolescence is no longer a theory, but a reality.

Mirjana Domakonda
Psychiatrist at Colombia University

4

Risk Factors from Birth to Emerging Adulthood and their Impact on later Socio-Economic Status

A case study in Victoria, Australia

Abstract

The socio-economic position (*SES*) of an individual is one measure of success. However, the norm of using one indicator (income, education) or even multiple indicators at the same time may overlook the unstable nature of employment and other economic challenges people face. People can be employed, well educated and still be disadvantaged and in need of assistance. This paper proposes a new way to measure SES, by combining more information from multiple variables using a latent class analysis framework to designate people into *'types'*. I find that there are three main types of people in a sample of young Australians as they enter adulthood. First, there is a typical advantaged group with high levels of education, income and skilled employment. Second, a typical disadvantaged group with low levels of education and low skilled jobs. The third group is 'economically unstable' who have high levels of education and skills, but with low income and lots of employment instability. Having categorised individuals into one of these three groups, I then look at the predictors of being of a particular type. Both the type and timing of negative shocks such as unemployment spells, divorce, house and school moves are examined as possible explanations for group membership. Shocks that occur in childhood are most predictive of being typically disadvantaged, with shocks in adolescence and young adulthood being predictive of the third group. I also look at the implications of this SES typology for the next generation. I find that this third unstable group has negative effects on child outcomes.

4.1 Introduction

The last few decades have seen immense change in what is considered normal developmental milestones in early adulthood. The Australian Bureau of Statistics in 2013 released a comparison of young adults (18-34) from the 2011 Census to the same cohort from the 1976 Census (2013). There was a drop in both the percentage of people living with a partner and of being married from 65% and 64% to 42% and 29% respectively. Education levels of young people increased, the proportion of people with a bachelor degree or higher increased from 5% to 26%. The female employment rate increased, while decreasing slightly for men. This is in keeping with a general worldwide patterns of later marriage and higher rates of education. Yet simultaneously people are experiencing more instability in these transitory years. The Foundation for Young Australians (2014) estimates that on average young people take about 4.7 years to enter full time work after leaving full time education, increasing from one year in 1986. Some estimates suggest that adults will now have up to seventeen jobs in five careers over a working period of approximately five decades. This new generation is better educated, more in debt, renting for longer periods of time and often unable to get on the property ladder. They are the first generation to be financially worse off than their parents.

This drastic change in the socio-economic landscape has happened relatively quickly, and policy makers are failing to respond to the needs of the new generation of young adults, who will soon become parents in a very different economic landscape than past generations. This age group has been understudied for a number of reasons including a lack of data, as well as a shift in focus to the earliest years of development. If the government wants to ensure the best possible start for children it is important to understand the difficulties faced by their parents.

This research will document the socio-economic profiles of the current generation of individuals who are likely to start becoming parents soon. It will outline the risk profiles and examine if socio-economic shocks during their lifespan change the likelihood of being at a disadvantage in later life. I examine these questions using the Australian Temperament Project (ATP) dataset, a fifteen wave longitudinal study of 2543 individuals from Victoria, Australia that began in 1983.

The standard socio-economic measure used for adults has been one of the following: unemployment, income, education and occupation skill level. While these can be informative indicators of risk, I believe that a more multi-faceted approach can be enriching, especially given the instability of employment at this age. Additionally, people can be disadvantaged and impoverished even with a stable job.[1] There are multiple potential indicators of disadvantage and advantage, making it difficult to definitively say what the key outcome criteria should be. This paper uses latent class analysis to uncover if there are distinct groups within the sample that are differentially at risk, and that may require a different policy response. I also map out the socio-economic precursors of class membership. In doing so I focus on shocks that occur to their home environment. Social and economic shocks may add stress to the home environment, putting constraints on monetary resources, impacting parenting style and changing the amount of time a parent can spend with their child, all of which could influence outcomes.

There are a number of ways in which the socio-economic context between birth and young adulthood may matter. Firstly, the presence of socio-economic disadvantage in a formative period of the child's life (such as early childhood) may have long lasting implications (through neurological changes or the development of societal beliefs/expectations) - even if they are relatively well off in other periods of development. This is an example of the sensitive period hypothesis: that is at certain times children are particularly vulnerable to external factors, both positive and negative. I look at shocks within three distinct periods - childhood (age 0-12)[2], adolescence (13-18) and young adulthood (19-24).

A second perspective on risk suggests that socio-economic disadvantage is comprised of multiple components, and that the simultaneous occurrence of multiple risk factors is detrimental. Any one risk factor on its own might not have a negative influence but when multiple risks co-occur in one period it can

[1] Underemployment, part time and low paid work are all becoming more common in the workforce and this is a growing cause of concern.

[2] I would have liked to break this period into smaller chunks. There is a large body of evidence to suggest that both the prenatal environment and the first one thousand days are particularly important developmental windows. An optimal division of periods might look like the prenatal environment, infancy, early and middle childhood. However, given the timing of the data collection, as well as the questions asked in each round I was unable to split my data like this.

create a tipping point beyond which there are negative effects on child outcomes. Alternatively, it might not matter when the shocks occur, but instead it is the build up of the same type of shock over time. The presence of one shock might also increase the likelihood of it occurring again. Persistent disadvantage may matter more compared to one isolated shock. One shock might have short run negative effects without any lasting changes in outcomes.

By constructing shocks in different ways, and using multiple types of shocks that occur at different points in time, I can try to disentangle which of the above perspectives is most helpful in explaining outcomes. However, I do not have exogenous shocks, or any clear causal identification. This paper explores if a particular way of classifying shocks is the most informative. It also addresses the way we think about, and draw conclusions from, socio-economic risks influencing the construction of measures. Further motivation to look at the different types of socio-economic shocks (such as marital breakup compared to unemployment) is that they may pose different risks for particular socio-economic types. I examine the link between different risks and particular classes using multinomial logistical regression.

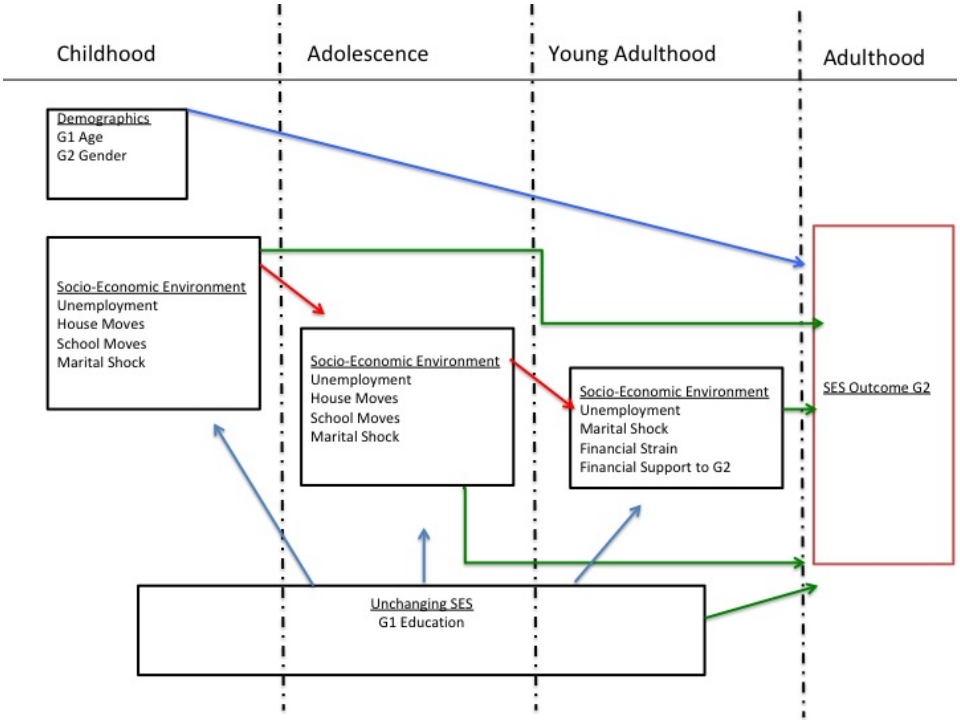


Figure 4.1: Possible Pathways of Risk

I find that there are three main classifications of socio-economic profiles, roughly dividing the sample into thirds. The first is a typically advantaged group with high income, high skills and high education. The second is a typically structurally disadvantaged group with low levels of education and skills. They do however, have relatively stable employment. The third group, which is often overlooked, has high levels of education and skilled jobs, but has the lowest income in addition to changing and losing their job at the highest frequencies. Shocks in childhood are informative in predicting the likelihood of being in the disadvantaged group, whereas shocks that occur in adolescence and young adulthood seem to impact being in an economically unstable group. Structural features such as parental education are predictive of being in the structurally disadvantaged group.

An additional goal of this paper is to examine if different groups pose differential risks for the next generation. The ATP offers a unique opportunity to link the first two generations to a new generation. To date around 1100 infants have been born to participants from the main study, known as the generation three (G3). I examine if socio-economic classification is associated with parental behaviours that are known to lead to negative developmental outcomes (known as ACEs (adverse childhood experiences)). I also look at the SES classifications' impact on early measures of development: the problem subscale of the Brief Infant Toddlerhood Socio-Emotional Assessment (BITSEA). This subscale has been linked to negative development outcomes in elementary school and is one of the most commonly used screening tools for problem behaviour in infancy and toddlerhood. [3] I find that being in an unstable SES grouping at age 28 results in negative behavioural outcomes for your child, even after controlling for other risk factors such as parenting behaviour, parenting style, past behaviours and income.

[3]There were no measures of cognition at infancy, and given the rolling nature of children's births, the later age samples were too small. In a higher income country like Australia, there is unlikely to be much stunting and wasting, with the other available health measures being purely self reported 'how healthy is your child' measures. The BITSEA was the most concrete available option for looking at a measure of human capital of the infants, but future work should look at a wider array of components of human capital, amongst other outcomes. The collection of G3 data is ongoing and will continue to recruit new children as they are born as well as tracking the existing children into older ages.

4.2 Literature Review

4.2.1 Different ways to think about risk over the life cycle

I focus on outcomes at age 28 as by this age most emerging adults live independently, are in long-term relationships, and have clear career paths ahead of them. It is a time of relative stability that likely captures accurately their future life course (Wood et al. (2018)). In Australia 2015, the average age of first time mothers was 28.9 years(2017*b*). Thus, 28 represents the beginning of the period in which people are becoming parents. It also lies just outside the current understanding of adolescence/young adulthood from psychology.

Contemporary definitions of adolescence suggest an inclusive and extended time period of 10-24 years (Sawyer et al. (2012)), which captures the classical period of adolescence (approximately 13-19 years) as well as emerging adulthood (20-24 years). This extended period of adolescence represents a crucial transition period between childhood and adulthood. This developmental transition involves significant biological, psychological and social changes, which give rise to adult-like functioning. In our evolutionary history, adolescence was distinguished by puberty, with adulthood characterised by copulation. This led to the general understanding of adolescence as the literally *'teen'*-age period, loosely 13-19 years. However, nowadays cultural changes have resulted in an extension of the period between puberty (which is beginning earlier in most modern societies), and marriage/child birth. Second, neurological evidence has shown that the brain is extremely plastic and undergoes drastic growth in the period between 13 and 24 (Arnett (2000)). This new understanding of development underpins the decision to treat age 28 as the key point at which to examine the economic position of the sample, marking the onset of adulthood.

Childhood and adolescence risk have long been suggested to pose threats to development. Within the psychological literature, the main stressors are psychosocial variables such as parenting styles, mental health risks and substance abuse. The seminal epidemiological study on early risk exposures is the San Diego Adverse Childhood Experiences study, conducted by Felitti et al. (1998). Here they retrospectively asked individuals about their early exposure to one

of seven risk categories - focusing primarily on abuse (psychological, physical and sexual), and household dysfunction (substance abuse, mental wellness, mistreatment of mother and criminal behaviour). They found that a cumulative risk approach, in which individuals were given a score of one through seven, depending on their exposure to risks in childhood, and this was correlated with negative health and social outcomes. Individuals who had experienced four or more categories of childhood risk exposure, compared to those who had experienced none, had on average a *"4- to 12-fold increased health risks for alcoholism, drug abuse, depression, and suicide attempt; a 2-to 4-fold increase in smoking, poor self-rated health, 50 sexual intercourse partners, and sexually transmitted disease; and a 1.4- to 1.6-fold increase in physical inactivity and severe obesity"*. The seven categories of adverse childhood experiences were strongly interrelated and people with multiple categories of childhood exposure were likely to have multiple health risk factors later in life.

However, it remains unclear if a multi-risk approach, a cumulative risk approach or a persistent risk approach matters the most for development. Are certain types of risk more likely to lead to particularly bad outcomes? Is it more damaging if a risk factor is present in a highly susceptible time period[4]? Are there tipping points for negative outcomes if enough risks occur simultaneously, or is it the build up of risks that persist over time that is the most damaging?

The cumulative risk (CR) approach typically creates a dichotomy for each risk factor (0 = no risk, 1 = risk) and then sums across the different risk types. This simplifies the creation of risk scores, but has many limitations. Firstly, it ignores the intensity of the risk exposure; secondly, it involves arbitrary decisions on the cut off between risk and no risk, and thirdly, it involves an additive risk approach precluding interactions between risks. Proponents of

[4]That is the critical/sensitive period hypothesis. This phrase was first used in the context of language acquisition - when the the ability to acquire language was strongly linked to age. Early thinkers believed there was a developmental window in which individuals must learn language, and that if appropriate learning didn't occur in this period an individual would never fully grasp full fluency in any language. There is limited evidence for this *'critical'* approach which is quite deterministic (Snow and Hoefnagel-Höhle (1978)). Instead, researchers propose a sensitive period hypothesis which suggests there are increased periods of responsiveness to either positive or negative stimuli. The concept has gone beyond the linguistic community, with studies focusing on other aspects of child development (Murray and Cooper (1997), Hertzman and Wiens (1996)).

the cumulative risk approach believe using alternative measures of risks is not possible due to low statistical power, higher order interaction terms, low robustness and collinearity among risk factors. There is a trade off between a cumulative risk approach and a more detailed multiple risk approach. Evans, Li and Whipple (2013) review the current literature using CR as a measure of multiple risk. They suggest that relative to other measures (factor analysis, summary scores, structural equation models) that the CR approach is valid and useful, but care should be given to address some of the aforementioned drawbacks.

There is another perspective that risk should not be examined as a singular event that only exerts a negative effect at that time point. Researchers point to the importance of the persistence of risk factors over time (McLoyd (1998)). Not only does experiencing a negative risk at one point increase the likelihood of experiencing a subsequent risk factor, but this persistence has been associated with the most damaging effects for child outcomes. Persistent poverty is one of the most detrimental risks for a wide range of outcomes. For instance, it has been shown that interventions of moving neighbourhoods are more successful at earlier ages, whereas at later ages there are little benefits and in fact can have negative consequences due to disruption effects. The argument here is that the duration of exposure to a better environment during childhood is a key determinant of an individuals' long-term outcomes (Chetty, Hendren and Katz (2016)).

Within psychology and epidemiology there has been a move away from examining the totality of the life cycle, and instead with more attention paid to early indicators of risk. There are a number of reasons for this shift. Firstly, there is a lack of good longitudinal studies of risk, with a lot of existing studies fraught with missing data, measurement error and attrition. Secondly, the growth of RCTs and interventions has been primarily focused amongst younger children, and short run consequences. Thirdly, there is a growing body of evidence to suggest that negative trajectories emerge from as early as in the antenatal environment. It seems that exposure to risks in pregnancy and the first year of life can cause wide gaps to emerge and these trajectories can become firmly established. A lot of research argues that the most effective and cost-efficient time to intervene is during the earliest years (Walker et al. (2011), Leffel and Suskind (2013)).

The idea of a sensitive period of development and the importance of the earliest years is common in economics. There is growing attention on the earliest antecedents of differences in child outcomes, with a similar consensus to that of the psychological and epidemiological literature, that investing earlier is the most beneficial (Doyle et al. (2009)). Cost-benefit calculations suggests that returns on investment in the earliest years are much higher than when interventions occur at later ages (Heckman (2006)). This had lead to a worldwide push for increased investment in early education. Policy makers have reflected this shift in their own thinking, seen for instance in the Obama administration's report (2015) as well as recent reports from the UK (Betram and Pascal (2011)). Heckman's model of dynamic complementarity and self-productivity within the human capital development is the foundation of how economists view skill development. Both the fact that skills in period t build on skills developed in period *t-1* (self-productivity) and that investments in period t can be more beneficial given a higher level of capability in period *t-1* (dynamic complementarity) suggests further reason to focus on earlier time periods (Heckman (2007)).

4.2.2 (Some) Different types of risks

There is a large body of literature looking at the effect of parental job loss on outcomes. These studies focus on the proximal effects of job loss, primarily on education and academic outcomes. In part this is due to identification limitations, but also because longer run effects are much harder to disentangle. Stevens and Schaller (2011) found that short-run unemployment spells increased the probability of grade retention by 0.8 percentage points. They found that this effect was strongest for those with lower educated parents. Uncovering a causal effect of job loss on outcomes can be difficult, requiring an exogenous shift causing job loss. Even then, it is hard to know through what channel job loss is impacting outcomes.

Studies have attempted to circumvent the identification problem using inventive methods to exploit natural variation in the environment, for instance by examining the effects of factory closures on child outcomes. The identifying argument is that the firm closure is unrelated to parental characteristics and is likely to be randomly assigned, once controlling for level of income. Oreopoulos, Page and Stevens (2008) followed father-child pairs in Canada. Those whose

fathers experienced an employment shock had annual earnings of 9% lower than similar children with parents who did not experience an employment shock. A similar identification strategy was conducted using Norwegian data by Rege, Telle and Votruba (2011), where they found fathers exposure to plant closures led to a substantial decline in children's GPA. In contrast, maternal exposure to plant closures led to an increase in school performance, which they suggest is due to increased time spent with the child.

There are a number of channels through which parental job loss could impact outcomes in the long and short run. It could decrease the quality of parenting, particularly if parents are stressed, leading to negative outcomes. On the other hand, it could increase parenting time with and attention for the child if parents are now at home more and can invest more in their child. Job loss could add financial pressure and parents may have to reduce monetary investment in their child. It could have knock on effects on the relationship between the parents, which may increase fighting or increase the likelihood of experiencing a marital break up, which again could impact child outcomes.

This brings the discussion onto the other major disruptive shock - divorce or separation[5]. There are again many potential effects of having divorced/separated parents. There could be a reduction in economic resources following a break up, changes in parental time and in parenting practices, an increase in parenting stress and a child's own emotional response (Bernardi and Radl (2014)). Numerous studies have found a strong negative association between divorce and a wide range of child outcomes. However, uncovering a causal effect is again difficult - as there is no clear counterfactual. Divorce could be predicated by family stress or parental disputes - and it is this stress that is causing the negative association. The divorce event itself may in fact have positive effects in ameliorating the environment (Amato (2010)). Using a large sample of Indonesian households, Gertler, Levine and Ames (2004) found that the loss of a parent had large negative effects on children's school enrolment. They used three years of data, in which over 3000 children had lost a parent within the year prior to the study. They use community fixed effects to account

[5]In this analysis I also include spousal death in the risk variable. While the effect of a parents death may be a different, the numbers of deaths were extremely low in the sample. Both events cause a change in household composition from two parent to a one parent household. It was decided to combine these into one measure, although arguments could be made against this decision.

for the endogeneity problem that families who are more likely to experience loss of a parent might already be disadvantaged, as well as matching households to create a control group. A child whose parents had recently died was two times more likely to drop out of school than those with living parents, with the effects being largest at the transition between primary and junior secondary and then again from junior secondary to senior secondary.

As with unemployment, researchers have tried to uncover the exogenous effect of divorce by using creative identification strategies. Frimmel, Halla and Winter-Ebmer (2016) use an instrumental variable approach, by using the number of female workers in a firm which has been shown to be related to the likelihood of marital separation in the future. They find negative and persistent effects on children, with boys more likely to have lower levels of education, worse labour market outcomes and more likely to die early. Girls had lower education, were more likely to have a child, and had no differences in employment. A recent review of divorce across fourteen countries by Bernardi and Radl (2014) found parental divorce was negatively associated with children's tertiary education level: children of separated parents were seven percentage points less likely to achieve a university degree compared to those children from intact families. Amato and Anthony (2014) found associations between divorce and parental death on a wide range of behavioural outcomes in two datasets, the Early Childhood Longitudinal Study, Kindergarten Cohort (age 5 through 10) and the National Educational Longitudinal Study (age 12 thorough 18) in the US. They found small yet significant effect sizes using fixed effects models. There was a wide range of outcomes examined, with some children's outcomes improving, others declining and others showing no change.

There is a large body of work looking at how house and school moves can affect child outcomes. The basic hypothesis is that these transitions cause instability in the environment; and that this can lead to negative outcomes. Rumbold et al. (2012) found that children who moved house two or more times before age 2 had an increased scores on internalising problems at age 9. They found no effects for those who moved at later ages, no effects of the lifetime number of moves or from differences in upward vs downward mobility. They were no effects on cognitive skills. Coley and Kull (2016) show that mobility during middle childhood and early adolescence was negatively associated with cognitive skills but that these effects were only present in the very short

run. There were long-run negative effects on the psychosocial functioning. A study in Norway found that children with more residential moves were more likely to drop out of high school, have lower income and to experience early parenthood (Tonnessen, Telle and Syse (2016)). The relationship between early education attainment and both school moves and household moves have been examined in Wales using 121,422 children by Hutchings et al. (2013). They found that frequent school moves and house moves had a negative effect on school achievement, with larger effects found for moves between ages 4 - 6. The largest effects were found with frequent school moves (two or more) by age 6 on achievement in language, maths and science. The authors posit that one of the major drawbacks of their study, which is also relevant to this work, is that they do not know why they move. The move itself may not be the causal mechanism but instead a variable that is causing both the school/house move and the negative outcome.

An additional point to note is that the quality of the neighbourhoods and of the schools have been linked to better development outcomes. Chetty, Hendren and Katz (2016) analysed the moving-to-opportunity programme in which families were randomly selected to move from high poverty to lower poverty neighbourhoods in the mid 1990s. In this case, a house move generated positive effects on the long term earnings for children, as well increasing the likelihood of living in a good neighbourhood themselves. They found the positive effects were concentrated amongst those who were young (under 13) when the move occurred. House moves can have differential effects depending on when they occur but also due to the quality of the move. There are likely to be other potential environmental influences that can impact parents and children but I restricted the analysis to the those discussed in this review.

4.2.3 Measures of socio-economic position (SEs)

Typically, most studies focus on a wide range of social, economic and psychological outcomes. There are many different indicators of economic security and *wellness* at different points in the life cycle, and a particular indicator may be of specific interest to researchers. Typically, theoretical or empirical considerations underlie the decision to focus on a particular outcome. Economists in particular might be interested in the differential effects on certain types of outcomes - education attainment may respond in a different way than income for instance.

There is merit in examining the differential effects on particular outcomes, and in focusing on one particular outcome that is most relevant. However, I felt that a more composite measure may give a better overall picture of the general socio-economic position that may not be captured in a singular measure.

This research looks at socio-economic standing at age 28. I restrict the outcomes to economic variables rather than measures of psychosocial functioning. Education, income, occupation and employment are of primary interest for economists - but also predict a wide range of important health and social outcomes. Policy makers increasingly care about enhancing the well-being of their citizens and one key way to do this is to ensure a high quality of life via sufficient income and education to ensure individuals can meet their basic needs.

Galobardes et al. (2006*a*) conducted a comprehensive review of socio-economic measures typically used by health and epidemiology. They discuss the disadvantages and advantages of each indicator, which will not be repeated here[6]. They suggest the appropriate indicators of socio-economic position will vary depending on the individual's life stage. For instance, in childhood, they focus on indicators of parental education, occupation, income and living conditions, whereas in young adulthood they focus on educational attainment. Active professional life can be characterised by measures such as asset transfers, household conditions, income, employment, wealth, deprivation, partners socio-economic standing, various measures of occupation and income.

A latent class analysis (LCA) is used across a number of fields and is the approach used in this paper. It is related to K-means, and other forms of cluster analysis. The key advantage of LCA is that it takes into account the multi-dimensional nature of SES but reduces this complexity into particular classes with distinct profiles. Fairley et al. (2014) used a latent class analysis to define subgroups of women with similar SEP profiles using nineteen different measures, across 11,326 British women. In their analysis they had five distinct groups which varied in level of employment and economic deprivation. They define the groups as (i) least socio-economically deprived and most educated, (ii) employed and not materially deprived, (iii) employed and no access to money, (iv) benefits

[6]Interested parties should refer to papers by Galobardes et al. (2006*a*) and Galobardes et al. (2006*b*) as they offer a comprehensive outlook on different constructions of socio-economic positions.

and not materially deprived, and (v) most economically deprived. If they had just used employment as the indicator of SES they would overlook these distinct subclasses and important variation within them. Dahly and Gilthorpe (2011) suggest a three class structure in their sample of 987 males and 819 females in the CEBU Longitudinal Health and Nutrition Survey, from the Philippines. LCA has also been used in studies looking at obesity (Øvrum (2011)) and reading achievement (Hansen and Munk (2012)). It is rarely used in economics but could be a useful way to gain a deeper understanding of the complexity of the socio-economic profiles. It is a well established modelling technique that allows the extraction of meaningful patterns from high dimensional intricate data. The major disadvantage of LCA is its replicability, there is no guarantee that another population would be characterised by the same class types; or if the exact class structure will hold over time. However, it reveals interesting sub-patterns that would be overlooked by looking at separate indicators.

Socio-economic position is often examined as social class by sociologists. Historically, social class has been considered a measure of ones position in society. Up until the 1980s, this was very much an occupation based typology with 'professionals' at the top and manual workers at the bottom. People's standing in society was considered skill based. The most commonly used measure within the social sciences is perhaps the EGP - Erikson-Goldthorpe-Portocarero - whose typically form consists of seven classes according to an individuals employment position (Connelly, Gayle and Lambert (2016)). This typology divides people based on an individuals' employment position, differentiating between employees and employers and amongst employees in routine, semi routine or technical employment and those in a broader service relationship with their employer such as professionals and managers. This typology is commonly used in America, Europe, and of relevance to this work, Australasia (Marks (1999)) This schema includes class groupings of managers and professionals, routine white collar workers, self-employed and small business people, and three divisions of manual workers based on levels of skill and supervision (Erikson, Goldthorpe and Portocarero (1982)). However, simply using an occupation based classification of social class has come under much criticism of late.

The latest research tries to encompass a wider view of what class is, taking into account not only measures of economics but also measures of cultural and social well being. Savage et al. (2013) used a latent class analysis approach

to divide a nationally representative sample of British individuals into new social groupings, which they believed more accurately captured society today. They looked at measures of the cultural capital of individuals through the activities people took part in, measures of their social ties (the number of people in different occupations as well as the mean skill score of such occupations), in addition to their assets and income. The latent class model revealed a 7 class structure: elite, established middle class, technical middle class, new affluent workers, traditional working class, emergent service workers, precariat[7] (lowest on all aspects, poor economic capital). They believed that inclusion of cultural and social capital was important for accurately capturing social class today.

This work was replicated in Australia by Sheppard and Biddle (2017) who found a six class typology fit their data best. They coined these: the precariat, ageing workers, new workers, established middle class, emerging affluent and established affluent class. They found 50% of individuals belong to the two middle classes (new workers and established middle), with approximately one quarter in the affluent group. The others state that class should encompass other measures beyond income and occupation skills, given the importance of cultural and social influences on individuals position in society.

These new methods of defining socio-economic class/position are not without criticism. Mills (2014) believing it to be a 'theory free dredging exercise' that was not useful, meaningful or valid. Dorling (2014) takes a more reasoned approach discussing both occupation based measures of class and the need to include other variables. Certainly, sociologists have been thinking about socio-economic position for quite some time, especially given the rise of the NEET group (not in employment, education or training) in Western economies. There is no consensus yet as to what variables should be included in modern measures of class, but certainly there is recognition of a need to adapt previous measures of SEP to an ever-changing society.

[7]The precariat is used by soicologists and economists to refer a social class formed by people suffering from precarity a condition of existence without predictability or security, affecting material or psychological welfare.

4.2.4 Impacts of shocks on outcomes in economics

Economists have attempted to examine how shocks, investments and abilities interact and develop over the lifespan. The outcome of interest has often been some measure of *human capital*, which can be extended to include measures of cognitive skills, social skills and health outcomes. Where possible, economics link in administrative data on longer term outcomes such as educational attainment, crime rates, income and health outcomes. These are normally treated as separate entities, each being an outcome with its own production function. The economic framework focuses on utility functions of the parents, the production function of the skill and the corresponding budget constraints, while attempting to model parental investment and the channels through which a shock could affect an outcome. While this is a valuable line of inquiry to better understand processes and decision making of parents (for an example paper in this area see Yi et al. (2015)), its falls beyond the scope of this study. There is no data available on investments by parents, nor a suitable instrument and thus have no way to examine the mechanisms through which the proposed shocks could affect development.

Almond, Currie and Duque (2017) have examined the current state of the research looking at the earliest years of children's lives since their seminal Almond and Currie (2010) review. They show how various shocks that have been examined by the economics literature - including nutritional shocks, prenatal maternal stress, infectious diseases, pollution, weather and climate change, natural disasters and the effects of alcohol and substance use in pregnancy. There is also a substantial amount of studies looking at how parental investment impacts child development, and how these investments respond to shocks. Shocks can lead to a change in investment - such as a conditional cash transfer causing higher monetary investment (Gertler (2004)) or the introduction of parental leave policies leading to an increase in time investment (Tanaka (2005)). There is some evidence though that parents may respond counter-cyclically to adverse shocks, increasing investment in response to an external negative factor (Ferreira and Schady (2009)), especially in higher income countries. This relies on parents being able to invest in spite of shocks. Other research has suggested that certain shocks are particularly damaging at certain time points - for instance, Coelli (2011) found that parental job loss at ages 16-18 led to substantial falls in income and reduced education attainment for

the next generation. This suggests that financial constraints at key turning points may impact education attainment. Credit constraints is an important factor for education attainment in the modern economy (Belley and Lochner (2007)).

Almond, Currie and Duque (2017) discuss that often studies examine the effects of a shock that occurs in the earliest years of a child life with outcomes measured at some point in the distant future. There is little attention paid to what happens in the interim periods. Economists are interested in adult productivity and earnings, but there is often no consideration of what is happening in the household in the interim period (typically the adolescent years). The conventional belief is that early age interventions are the most cost effective, but there is also a lack of studies of interventions targeting later ages and examining the longer run benefits of such policies.

There is some evidence of fade out - early age gains in test scores often disappear a few years after any positive intervention. Occasionally, there are long run gains to school attainment and non cognitive skills (Garces, Thomas and Currie (2002)). It is difficult to find data to track individuals over time in a meaningful way. For instance, the dataset used by this research can measure some self reported shocks[8], factors that are likely to add to stress and uncertainty to the household, and yet there is no measure of the mechanisms through which this could affect the child. There are no parental investment measures here and I therefore rely on the assumption that increased negative shocks leads to less investment by the parent[9]. Likewise, there is very little data on child outcomes through the life course to estimate skill formation using a dynamic model.

There is a large literature on the effects of specific shocks to parental income on child outcomes. Research has suggested it is useful to divide the life course into multiple stages (Cunha and Heckman (2007), Cunha, Heckman and Schennach (2010)). There has been a growing number of papers attempting to document how the timing of income matters (Carneiro, Salvanes and Tominey (2016)). In addition, persistent exposure to government aid has been shown to

[8]The shocks identified in the past subsection: marital break up, job loss, financial strain, school moves and home moves.

[9]Investments can be pro- or counter-cyclical in response to shocks to the home environment, thereby serving as reinforcers or protectors against shocks.

benefit outcomes, whereas shorter exposure has little effect (Akee et al. (2010)). Carneiro et al. (2015) look at how the timing of parental income matters for intergenerational mobility using a unique dataset from Norway. They divide the life span into three key periods - early (0-5), middle (6-11) and late (12-17) childhood. They find that the timing of income matters more for their outcomes (primarily, education attainment), than the level of permanent income in the household. They find a U-shaped curve in terms of the effects of income on improving outcomes. Amongst richer families schooling tends to increase when income is shifted from early to late childhood. They also show that when income in early childhood rises but falls in middle childhood, individuals' education levels increase initially but then decrease. This suggests that schooling is maximised when income is equalised across periods, conditional on the level of permanent income. This supports the proposition that we shouldn't invest all resources in early childhood, despite the higher returns at this time that are documented elsewhere (Doyle et al. (2009)). This evidence is looking specifically at the effect of income, but it could be much broader than simply an income change, such as the direct result of other shocks (such as parental wellness, unemployment or something else).

In practice it is very hard to identify shocks that are unanticipated and uncorrelated with other factors that affect human capital investments and outcomes. Establishing universal evidence on the impact of a shock is difficult. There is evidence for both compensatory and reinforcing investment behaviour, and the effectiveness and nature of these behaviours can be heterogeneous across individuals and contexts. Often studies just look at the short-run effects, as making predictions about what happens in the long run can be tricky. Drawing inferences about the longer-term impacts based on negative impacts in the short term can be misleading. In some cases, short-term effects will understate the longer-term consequences (such as when health problems emerge only after a long lag); in other contexts, the longer-term consequences will be modest relative to those in the short-term. This is discussed in depth by Frankenberg and Thomas (2017).

4.2.5 Pathways to the next generation

The *foetal origins* hypothesis is commonplace in epidemiology and points to the importance of the in utero environment as an important predictor

of many later adult diseases (Lucas, Fewtrell and Cole (1999)). The link between maternal behaviour while pregnant and child birth weight, later diseases and developmental delay has been at the forefront of research. There are many potential links between parental antenatal mental health, parental substance use and other risky behaviours and negative child outcomes, even after controlling for interim factors such as post-natal depression and parenting style. Economic studies have adopted this hypothesis and examine the consequences of interventions in pregnancy aimed to increase positive maternal behaviours on outcomes (Almond and Currie (2011)). While this paper is not intervention based, it is hoped to extend the research by examining the link between the socio-economic standing of a parent at age 28 and the likelihood of engaging in behaviours that are detrimental for child outcomes, while controlling for the past parental mental illness and substance use. It is hypothesised that those who are more disadvantaged and who experience more instability prior to becoming parents are more likely to engage in behaviours that are detrimental for their child and lead to worse outcomes. One potential intervention period may actually occur prior to pregnancy, helping young adults navigate the economic landscape before they embark on parenthood.

One avenue through which the child could be impacted in utero is through parental stress. Persson and Rossin-Slater (2018) found that in utero exposure to maternal stress from family ruptures affected later mental health outcomes for that child. Prenatal exposure to the death of a maternal relative increased the take up of ADHD medications during childhood (age 10) by 25% and anti-anxiety/depression medications in adulthood (age 35) of 13% and 8% respectfully. They were able to identify these effects by exploiting the timing of death of a relative such that some experienced the shock in utero whereas others experienced it soon after birth. They find negative effects of stress on birthweight and preterm births, as well on hospitalisation throughout childhood. They find no evidence of changes in maternal behaviour or in income, and suggest it is primarily via cortisol exposure. This suggests that there are large welfare gains from minimising fetal stress caused by family ruptures and from other stressors such as unemployment. Given the likelihood of experiencing certain stressors are higher amongst the poor, this is one channel that may exacerbate the intergenerational persistence of poverty. Black, Devereux and Salvanes (2014) examined the effect of the death of a grandparent during

pregnancy on children's outcomes, using a sibling fixed effect model. They found negative effects on birth outcomes, especially for those whose grandparent died suddenly (as indicated by the type of death). They did not find any long run effects. Black et al. (2013) found that exposure to low dose radiation, particularly during the middle period of pregnancy led to a decline in IQ scores, education attainment and earnings. This effect seemed to persist across a second generation, with the children of people who were affected in utero, having lower cognitive scores.

A second transmission mechanism is via parental substance use (alcohol, drugs and smoking) both during pregnancy and in the first few years of development, which can have adverse effects on later development (Azuma and Chasnoff (1993), Hofhuis, De Jongste and Merkus (2003), Arria et al. (2006)). Clinical and animal trials have suggested there may be fundamental neurological changes from exposure to drugs. However, large cohort studies that control for concurrent environmental influences (such as poverty, low parental investment) can render prenatal influences non-significant (Jones (2006)).

Of particular concern for outcomes is smoking behaviour. A review by Mund et al. (2013) found that smoking in pregnancy is the most important avoidable cause of adverse pregnancy outcomes. It represents the first major risk to the unborn - being linked to low birth weights, genetic and cellular alterations, as well as increasing the likelihood of certain diseases, neurology and psychological behaviour - even after controlling for other risk factors (Wehby et al. (2011)). While smokers can be persuaded and helped not to smoke during pregnancy (about 45% of women who smoke will stop), about 80% continue to smoke a year postpartum. This second-hand smoke exposure may be as damaging as the child inhales smoke, and also toxins can be transmitted between mother and child via breastmilk. A Norwegian study by Háberg et al. (2007) found independent effects of pre and post pregnancy smoking, with independent negative effects on children's respiratory systems when exposed to smoking. They found the highest risk of negative outcomes was due to maternal smoking during pregnancy but later exposure also mattered for lung functioning and wheezing. Rückinger et al. (2010) found impacts on behavioural outcomes: children not exposed to tobacco smoke compared to children exposed both pre- and post-natally to tobacco smoke had twice the estimated risk of being classified as abnormal according to the total difficulties score of the SDQ at

10 years of age. Children who were only exposed prenatally had a 90% higher relative risk whereas children who were only postnatally exposed had a 30% higher relative risk.

There is also a strong negative association between both antenatal and postpartum depression and subsequent developmental outcomes of the child (Murray and Cooper (1997), Muzik and Borovska (2010), Goodman et al. (2011), Field (2011)). There are many possible causal pathways between mental illness and development. For instance, exposure to toxins in the womb if the parent is taking medication, or due to increased cortisol/hormonal changes due to mental illness could alter the physiological development of the fetus. At birth, the presence of toxins could continue to impact physiological development, but it is more likely to impact parental ability to engage with their infant. This is a period of rapid brain growth - by age 3 the brain is 90% of its adult size and is constantly adding circuitry - almost 700-1000 synapses per second (Shonkoff and Fisher (2013)). If parental interaction with their child is impaired due to mental illness, brain growth may be stunted as well as having adverse effects on attachment bond between parent and child.

While the exact causal mechanism between stress, both prenatal and postnatal substance use, and mental illness have not been definitively uncovered, I believe there is sufficient evidence that these factors are risk indicators for subsequent negative child outcomes. In the final section of the analysis I examine if there is a link between these *'risky predictors'* of adverse outcomes and the socio-economic position of the parent, independent of prior substance use and mental wellness.

Early measures of development can indicate both current difficulties but are also predictive of a wide range of later problem behaviour. One such scale that is available in this data is the BITSEA (Brief Infant Toddlerhood Social Emotional Assessment); a shortened version of the ITSEA (consisting of 42 items as opposed to 169). It has been shown to have good psychometric properties (Briggs-Gowan et al. (2004)), and is a useful screening tool for problem behaviours (de Wolff et al. (2013)). It has two major subscales: problem behaviours and competency behaviours. The BITSEA is most often used as a diagnostic tool with a standard cut-off point for at risk infants.

BITSEA scores have been linked elementary school outcomes at age 6 (Briggs-Gowan and Carter (2008)). Of-concern BITSEA problem scores measured at age 12-36 months predicted parent-reported clinical levels of problems and for psychiatric disorders. This was supported by teacher-reported measures. Low competence scores predicted later teacher-reported sub-clinical/clinical problems and parent-reported disorders.

This is by no means an exhaustive review of the available evidence on how pre and post natal environmental factors can impact a wide range of measures of child development. This topic encompasses a wide range of disciplines: genetics, neuroscience, other medical subdisciplines, sociology, psychology, epidemiology, and more recently economics - and it is difficult to comprehensively cover the different influences, mechanisms and outcomes in this review.

4.3 Methodology

4.3.1 Latent Class Analysis

Latent class analysis (**LCA** hereafter) is a technique used to predict an underlying unobserved variable from observed patterns of data. It allows researchers to group observations into categories, each one of which contains individuals who are similar to each other and distinctly different from individuals in other categories. It is a form of cluster based segmentation, somewhat akin to K-means cluster analysis that is used frequently in machine learning and is perhaps more familiar to economists. I decided against using a K-means based analysis due to a number of theoretical and methodological advantages of LCA.

With a high dimensional dataset, cluster analysis can be used to reduce the dimensionality into meaningful groupings. LCA has its foundations in statistical theory and modelling. When allocating observations to clusters it is necessarily the case that there will be some uncertainty: an observation can be equally close to two clusters. This is taken into account by the LCA algorithm. It also considers the size of the clusters, which is a important feature in making allocation decisions, which no other typical cluster based method incorporates. Probability theory states that if an individual is equally likely to be in two clusters, and one cluster is larger than the other the respondent is more likely to be in this cluster (due to Bayes' theorem). LCA is the only method that

complies with this principle. Methodologically it allows for a wide range of data types to be feed into the algorithm, it allows for missing data and it classifies individuals to a cluster, even if they are missing some data, based on the responses that are available. K-means uses a missing completely at random assumption which is more restrictive than the missing at random assumptions used in LCA. The biggest disadvantage of LCA compared to K-means is that it is relatively slower, which in some applications can be extremely important. However, here the sample is relatively small ($n = 1055$) and computation time is not an issue.

There are two main components to LCA. The latent class probabilities describes the distribution of classes of the latent variable within which the observed measures are (locally) independent of one another. This typically consists of the number of classes and the relative sizes of the classes within the sample. The econometrician may apriori have some belief about the number of classes: informed by theory, other research or looking at the correlations within the data itself. It is important to test a number of different class sizes, starting with class k=1 and increasing the number of classes until the model is either no longer able to be estimated, or the diagnostic tests clearly indicate a best fit. The other part of the model are the conditional probabilities. These represent the probability of an individual in a given class of the latent variable being at a particular level of the observed variable.

More formally, let $\boldsymbol{Y_i} = (Y_{i1}, Y_{i2}, ...Y_{iM})$ be a vector of M survey items for the ith individual where Y_{im} takes possible values 1, 2, ... r_m. The statistical dependence between items are due to an unobserved class grouping. When the class structure is introduced, within class variables are independent (McCutcheon (1987)). The population consists of mutually exclusive and exhaustive groups and the distribution of items varies across classes. Let $l_i = 1, 2, ...L$ be the class membership of the ith individual and let $I(y{=}k)$ be the indicator function that takes value 1 if $y{=}k$ and 0 otherwise.

If one could observe class membership, l_i, the joint probability that the ith individual belongs to class l and provides responses $\boldsymbol{y_i} = (y_{i1}, ..., y_{iM})$ would be:

$$Pr(\boldsymbol{Y}_i = \boldsymbol{y}_i, l_i = l) = \gamma_l \Pi_{m=1}^{M} \Pi_{k=1}^{r_m} \rho_{mk|l}^{I(y_{im}=k)}, \tag{4.1}$$

where $\gamma_l = Pr(l_i = l)$ denotes the marginal rate of lth-class membership in

the population and $\rho_{mk|l} = Pr(Y_{im} = k|l_i = l)$ represents the probability of response k to the mth item given class membership in l. The ρ parameter is known as the *'item response probability'*. Therefore the marginal probability of item responses without regard for the unseen class membership is:

$$Pr(\boldsymbol{Y}_i = \boldsymbol{y}_i) = \sum_{l=1}^{L} \gamma_l \Pi_{m=1}^{M} \Pi_{k=1}^{r_m} \rho_{mk|l}^{I(y_{im}=k)} . \tag{4.2}$$

Here I assume local independence - that is the items $Y_{i1}, Y_{i2}, ...Y_{iM}$ are unrelated within each class. Thus we can draw conclusions about the unseen class variable.

In practise we estimate the latent class model to get estimates of γ_l and ρ_{mkl} using maximum likelihood estimation. The log-likelihood function is:

$$lnL = \sum_{I=1}^{n} ln \sum_{l=1}^{L} \gamma_l \Pi_{m=1}^{M} \Pi_{k=1}^{r_m} \rho_{mk|l}^{I(y_{im}=k)} , \tag{4.3}$$

which is maximised using the expectation maximisation algorithm and Newton-Raphson algorithm. This is repeated to ensure that a global, not a local maximum is found. There can be multiple solutions when estimating LCA models using maximum likelihood techniques, as it can converge around a local maximum. Best practice includes using multiple iterations of the algorithm, different starting values in the estimation and ensuring that the largest log-likelihood is replicated in at least two final stage solutions. Further details about the specific details of the estimation techniques are detailed in Appendix A on LCA results, with the details of the poLCA package in R explained[10].

4.3.2 Multiple Imputation

One of the major problems with longitudinal studies is missing data. The amount of missing data can be high due to two major factors: sample attrition over time and non-response within a survey period. The implications of missing data depend on associations between variables of interest and the probability that some or all of the relevant data are missing (Rubin (1976)). There are

[10]This estimation was also replicated using MPlus. MPlus is a software program that is perceived to be the gold standard for LCA in epidemiology and psychology. There were no significant differences between either method and thus this research reports the estimates from R, which is more commonly used in economics.

typically three types of missing data: missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). The precise definitions of each can vary, but here I think about missing in terms of the mechanism that created this missing data. If *'missing-ness'* is completely unrelated to observed or unobserved factors then data are said to MCAR and the results will be unbiased. However this assumption is unlikely to hold. Sometimes there can be an association between the variables and the probability of the data being missing, but this can be explained by observed values of the other variables (after conditioning on the other variables there is no association). In this case, data can be MAR conditional on observables.

In economics the analysis is often restricted to those with complete data. This creates a selection problem in that certain types of people may be more likely to drop out of a longitudinal study. Also certain types of questions may be more likely to be left blank, especially if they correspond to a sensitive topic. In longitudinal studies, people may miss a round of data, or miss some items but still complete the majority of the questions. If these individuals are thrown out then a potentially rich source of information is lost. Certain types of person may then be ignored if the reason items are missing are intrinsically linked to some underlying characteristic.

A second method which can be used is inverse probability weighting, in which the sample is re-weighted to make it representative of the population at large after each wave. One must assume that conditional on observables, missing-ness is ignorable. Then a weighed least square estimation procedure is used. However, selection of the correct weights can be difficult, and using the wrong weights can cause inconsistencies.

If neither of these options are used, there is a third method: multiple imputation. Often researchers fill in for missing variables by imputing the mean, or by carrying forward the past value of a variable or using a future value. None of these strategies are valid, and involve many subjective decisions by the researcher. The use of multiple imputation allows for uncertainty in predicting missing values by inserting appropriate variability into multiply imputed variables of which one can never know their true value. This is commonly used in epidemiology and psychology, but rarely in economics. For multiple imputation to be valid, MAR must hold.

When there are associations between variables of interest and probability of data being missing that persist after conditioning on observed data then the data is said to be missing not at random. Whether the data is MNAR, or MAR depends critically on the observed data that is fed into the analysis: the more informative they are about the missing-ness mechanism the more plausible the MAR assumption becomes.

Using multiple imputation, the missing entries of incomplete datasets are filled in d times. This creates multiple versions of the same dataset which are then analysed as a complete dataset. The estimates are pooled, with adjustments made for the standard errors using standard procedures.

The general idea is as follows. Let $\mathbf{W}_{mis}$ denote the matrix of missing data and $\mathbf{W}_{obs}$ is the matrix of observations. One assumes that MAR holds, and used to estimate the $E(\boldsymbol{\theta}|\mathbf{W}_{obs})$, the posterior mean of $\boldsymbol{\theta}$ given the observed observations. Here $\boldsymbol{\theta}$ is the matrix containing all the parameter(/s) of interest. By iterated expectations we have:

$$E(\boldsymbol{\theta}|\mathbf{W}_{obs}) = E[E(\boldsymbol{\theta}|\mathbf{W}_{obs}, \mathbf{W}_{mis})|\mathbf{W}_{obs}] \tag{4.4}$$

If $\hat{\boldsymbol{\theta}}_d = E(\boldsymbol{\theta}|\mathbf{W}_{obs}, \mathbf{W}_{mis}^{(d)})$ for imputed data set d, then approximate $E(\boldsymbol{\theta}|\mathbf{W}_{obs})$ as:

$$\overline{\boldsymbol{\theta}} = D^{-1} \sum_{d=1}^{D} \hat{\boldsymbol{\theta}}_d \,, \tag{4.5}$$

where D is the number of imputations. Furthermore, the sampling variance is obtaining by estimating $Var(\theta|\mathbf{W}_{obs})$ using:

$$Var(\theta|\mathbf{W}_{obs}) = E[Var(\boldsymbol{\theta}|\mathbf{W}_{obs}, \mathbf{W}_{mis})|\mathbf{W}_{obs}] + Var[E(\boldsymbol{\theta}|\mathbf{W}_{obs}, \mathbf{W}_{mis})|\mathbf{W}_{obs}] \,, \tag{4.6}$$

which suggests:

$$\begin{aligned} \widehat{Var}(\theta|\mathbf{W}_{obs}) &= D^{-1} \sum_{d=1}^{D} \hat{\mathbf{V}}_d + (D-1)^{-1} \sum_{d=1}^{D} (\hat{\boldsymbol{\theta}}_d - \overline{\boldsymbol{\theta}})(\hat{\boldsymbol{\theta}}_{\boldsymbol{d}} - \overline{\boldsymbol{\theta}})' \\ &\equiv \bar{\boldsymbol{V}} + \boldsymbol{B} \end{aligned} \tag{4.7}$$

where $\bar{\boldsymbol{V}}$ is the average of the variance estimates across imputed samples and $\mathbf{B}$ is the between-imputation variance.

It is important to always compare the summary statistics and results from the multiple imputation to the complete case analysis. If the MAR assumption is not valid, then using multiple imputation methods will produce inconsistent results. In this scenario the complete case results will be consistent and should be used despite the limitations imposed by the smaller sample and the potential for selection bias. In the ideal situation there will be little difference between the two[11].

4.3.3 Multinomial Logistic Regression

When the outcome of interest is categorical I cannot use normal linear regression techniques. Instead multinomial logistic regression can be used, an extension of the normal binary logit model, when the unordered response has more than two outcomes. Let y denote a random variable taking on the values *(0,1,...J)*, where J is a positive integer and let $\boldsymbol{x}$ is a set of conditioning variables. In the case y denotes class grouping, and $\boldsymbol{x}$ is the set of household economic shocks and demographics.

I am interested in how changes in the elements of $\boldsymbol{x}$ affect the response probabilities, *P(y = j |x)*, for all *j*. Since the probabilities must sum to unitary, *P(y = 0| x)* is determined once I know the probabilities for *j = 1,...J*.

Let $\boldsymbol{x}$ be a 1 x K vector with first element unity. The MNL model has the following response probabilities:

$$P(y = j|\boldsymbol{x}) = exp((\boldsymbol{x\beta_j})/\Big[1 + \sum_{h=1}^{J} exp(\boldsymbol{x\beta_h})\Big], \qquad j = 1, ...J \qquad (4.8)$$

where $\boldsymbol{\beta_j}$ is a *Kx1* vector for *j=1, ... , J*. As the response probabilities sum to unity we derive the following:

[11] As will be seen later the use of multiple imputation here brings the sample from 726 (complete case i.e. no missings of any of the independent variables) to 1055. If I were wiling to impute the outcomes, then I could have also imputed the full set of data for every single observation (n=2543). However this may have created inaccurate estimates as I would be relying on increasingly small amounts of data from much earlier rounds to impute a number of outcomes at wave 15. I did not think this approach was valid and thus restricted the sample to those who took part in wave 15. Biases from attrition will still be present but this strategy reduces the problem of missing data within waves or if someone missed waves of collection in their history, but who are still essentially part of the study.

$$P_X(y=0|\boldsymbol{x}) = 1/\Big[1+\sum_{h=1}^{J} exp(\boldsymbol{x}\boldsymbol{\beta_h})\Big]\,. \tag{4.9}$$

When J=1, this is equivalent to the binary logit model. The partial effects of the model are complicated. For continuous x_k we have:

$$\frac{\partial P(y=j|\boldsymbol{x})}{\partial x_k} = P(y=j|\boldsymbol{x})\Big\{\beta_{jk} - \Big[\sum_{h=1}^{J}\beta_{hk}exp(\boldsymbol{x}\boldsymbol{\beta_h})\Big]/g(\boldsymbol{x},\boldsymbol{\beta}\Big\}\,, \tag{4.10}$$

where β_{hk} is the kth element of β_h and $g(\boldsymbol{x},\boldsymbol{\beta}) = 1+\sum_{h=1}^{J} exp(\boldsymbol{x}\boldsymbol{\beta_h})$. The direction of effects are not determined entirely by $\boldsymbol{\beta}_{jk}$. A change in $\mathbf{x}$ may lead to an increase in the probability of being in j compared to j^*. However when $\mathbf{x}$ changes there is a corresponding change in the likelihood of being in another $j^{'}$. If the likelihood of being in this other $j^{'}$ increases by enough then the overall effect of a change in $\mathbf{x}$ can lead to an actual decrease in probability of being in j even though there is a positive coefficient in the main results. Thus interpretation of MNL output must be carefully examined. This paper uses margins to display results, which takes into account these different effects to give the overall effect.

Estimation of the MNL model is carried out by maximum likelihood. For each i the conditional log likelihood is written as:

$$l_i(\boldsymbol{\beta}) = \sum_{j=0}^{J} 1[y_i=j].log[p_j(\boldsymbol{x_i},\boldsymbol{\beta})]\,, \tag{4.11}$$

where the indicator function selects the appropriate response probability for each observation. $\boldsymbol{\beta}$ is estimated by maximising $\sum_{i=1}^{N} l_i(\boldsymbol{\beta})$. This log-likelihood function is globally concave and can be maximised with confidence in the consistency and asymptotic normality of the function.

One property of MNL is known as *Independence of Irrelevant Alternatives* which is often violated in choice problems with options that similar[12]. IIA

[12]The alternate model is multinomial probit (MNP) that does not impose IIA. MNP assumes the error terms are normally distributed, as well as allowing for correlations between the terms. However, allowing for more flexibility in the error terms comes at the cost of requiring more constraints on the error variance-covariance structure for identification. The estimation was repeated using a probit model. There was very little difference in the results, with the coefficients from the probit model being slightly smaller in magnitude, but with the

states that discrimination between j alternatives reduces to a series of pairwise comparisons that are unaffected by characteristics of any alternatives other than the pair under consideration. In many choice problems, this will not hold: when deciding between two options the elements of a third option do impact the decision. In these situations the estimates from a MNL will be inconsistent. In this estimation, I am examining the likelihood of being of a member of a particular group type. IIA implies that the likelihood of being of type one vs type two only depends on the individuals' characteristics and preferences, and not on characteristics of type three. Similarly, this must hold for the likelihood of being type two vs type three and again, for type three vs type one. This is also not a typical choice problem in that individuals are making decisions over the variables that feed into the analysis that designates people into group assignment. I used model based tests of IIA, as well as estimating a MNP and both supported the use of MNL[13].

4.3.4 Empirical Model

I estimate a simple multinomial logit model to investigate the likelihood of being one of three types of economic position at age 28. As outlined earlier I pick age 28 as the period of examination for two reasons. This is the last round of the main survey and thus is a natural end point for analysis. However, beyond this empirical consideration, this age is after the instability of emerging adulthood which lasts up till about age 25. The early twenties are characterised by many changes in education, occupation and income.

Each individual i ends up being in a particular *type* which depends on their current life circumstances and past decisions. The group you end up in *g= (1, 2, 3)* is a consequence of parental structural features (such as education, parental age), child features (gender) and environmental exposure at different time points to negative economic shocks. The shocks included are maternal and paternal unemployment, marital break up (divorce, separation or parental death), school

same direction and significance.

[13]One of the major difficulties of MNL in applied work is that it is not clear how to test IIA. There are some theoretical guidelines on how to test it but these turn out to be computationally demanding and hard to apply to empirical settings. Model based tests typically estimate a more general model, that does not impose IIA and then test constraints that lead to IIA. However these tests are often underpowered to detect any differences and thus could fail to distinguish if IIA holds or not.

moves, house moves and financial difficulties. I can also include controls of children's personality, parenting style and parenting mental health/substance use[14].

I consider each of these shocks that occur in three separate time periods. I have fourteen waves of data prior to the outcome, but the demands on estimating the effects per wave were too strong. There is also a significant degree of correlation from wave to wave. The variable creation section details how I created the measure of risk for each of the three time periods: childhood, adolescence and emerging adulthood. I use the MNL framework with three groups and with a vector of predictors and controls consisting of economic shocks, parents education, parents age and child gender.

I do not have any experimentally imposed variation in the shocks. For unbiased estimates of the effects I use a conditional independence assumption, which states that the shocks are exogenous to the outcome and that there are no missing variables that impact both the outcome and the likelihood of experiencing the shock. On the first point, I can be confident that there is no feedback from the outcome to the predictors as the outcome occurs 4 years after any independent variable used. Outcomes measures come from the child, whereas the shocks are all measures of the parent and home environment. On the second point, I control for a large number of variables that are likely to predict both outcome and shocks, such as education and job type of the parent, as well as their mental health, their parenting style and personality. The results were robust to different inclusions of variables.

Given the MNL specification the probability of being in class g:

$$Prob_g = \frac{exp(V_g)}{\sum_{g=1}^{g} exp(V_g)} \,. \tag{4.12}$$

There are three categories of g, whose intercepts and coefficients are allowed to vary by category. For ease of exposition I drop the i subscript. The most disaggregated specification has separate risk types for each time period and is

[14]There were no effects of the latter group of covariates on the overall model's estimates and as such I use the more parsimonious model. These variables posed problems for the multiple imputation step. These sorts of variables are significantly under-reported and are difficult to predict from other observables - which is the procedure underlying multiple imputation.

shown below:

$$\begin{aligned} V_g =& \mu_g + \mu_{gm} E^m + \mu_{gf} E^f + \mu_{gc} \boldsymbol{C} \\ &+ \sum_{t=1}^{t=3} \beta_{gt} U_t + \sum_{t=1}^{t=3} \alpha_{gt} M_t + \sum_{t=1}^{t=2} \gamma_{gt} S_t + \sum_{t=1}^{t=2} \delta gt H_t + \sum_{t=2}^{t=3} \rho_{gt} F_t \,. \end{aligned} \tag{4.13}$$

Here E^j for $j = m, f$ is the highest education of the mother and father, $\mathbf{C}$ is a vector of controls, U is unemployment shocks, M is loss of parent due to separation, divorce or death, S is school moves , H is house moves, and F is financial strain. The time periods are denoted *t=1*, childhood, *t=2*, adolescence and *t=3*, young adulthood.

If instead I assume that the more shocks experienced at any one time point is what causes the most harm then I conceptualise risk as the sum of risks in any time period. This is known as cumulative risk. Common pitfalls to using this approach include that it is additive, preventing any analysis of synergies or interactions between key risks, that it has no information on risk factor intensity, and that it treats each risk factor equally. However, it has been shown to outperform the use of singular risk factors in multiple studies (see Evans, Li and Whipple (2013)), especially given recent evidence that the cumulative nature of stress can be especially detrimental for outcomes. This is shown in equation 4.14.

$$\begin{aligned} V_g =& \mu_g + \mu_{gm} E^m + \mu_{gf} E^f + \mu_{gc} \boldsymbol{C} \\ &+ \sum_{t=1}^{t=3} \kappa_{gt} R_t \,, \end{aligned} \tag{4.14}$$

where $R_t = (U_t + M_t + S_t + H_t + F_t)$ for each individual i at t =*1, 2, 3* as before.

The third way to conceptualise risk is to assume that when the shock occurs is not important but instead it is the accumulation of specific types of negative events over time. This perspective suggests that the type of risk does indeed matter, but the timing doesn't and it is repeated exposure to the risk that is harmful. This can allow us to see if certain risks are most harmful, which may lead to practical policy implications. This is shown in equation 4.15.

$$
\begin{aligned}
V_g =& \mu_g + \mu_{gm} E^m + \mu_{gf} E^f + \mu_{gc} \boldsymbol{C} \\
&+ \beta_g \sum_{t=1}^{t=3} U_t + \alpha_g \sum_{t=1}^{t=3} M_t + \gamma_g \sum_{t=1}^{t=2} S_t + \delta_g \sum_{t=1}^{t=2} H_t + \rho_g \sum_{t=2}^{t=3} F_t \,.
\end{aligned} \tag{4.15}
$$

I estimate separately each of the above using MNL. I use a stepwise procedure in which I begin by only including one time period, then pairs of periods before using all three. This procedure allows the examination of the stability of estimates to the inclusion of other periods of risk. The results showed remarkable stability across models, and thus I report the model with all time periods included. This allows me to answer the primary questions of this paper: is there a most informative way to conceptualise risk and what are the associations between both the time periods and the types of risk and later socio-economic position.

4.4 Data

4.4.1 Overview

The Australian Temperament Project is a longitudinal study that began in 1983 with the recruitment of 2543 infants (born to 2443 families) aged between 4 and 8 months and their parents. This sample was recruited from infant welfare centres across the state of Victoria, Australia. Centres were selected to reflect the urban-rural population balance and provided a sample representative of the population of Victoria at that time. Over the next 27 years there were fifteen waves of data collected from the primary caregiver (which in nearly all cases was the mother). The exact age of the child and in what year is shown in Table 4.1 There were eight waves of data collection from the child themselves beginning in 1994 when they were 11-12 years old. The questionnaires covered a wide range of topics: demographics, psychological, social, economical and environmental factors. There was a large degree of sample attrition over time, due to families moving outside of Victoria, failing to contact some families and family non participation. This attrition can create a biased sample, especially if a certain group of people are more likely to drop out. The sample in this analysis is not representative of the population in Victoria, neither that of 1983 nor of the present day. The project is ongoing with the next generation of individuals.

These consist of the newborns of the ATP participants. Naturally this occurs at different time points, there are some families with children who are 6 years old as part of the third generation of the study, with other participants are only pregnant now. There are also many participants with multiple children taking part in the third generation. It is hoped to capture as many of this generation as possible, and to follow them at the following periods: pregnancy, 8 weeks, 1 year, 4 years, 6 years and subsequently into the future.

Table 4.1: Survey Design

	Early Childhood				Middle Childhood					Adolescence			Young Adulthood		
	Wave 1-4				Wave 5-9					Wave 10-12			Wave 13-15		
Wave	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Year	1983	1984	1985	1986	1988	1989	1992	1994	1995	1996	1998	2000	2002	2006	2010
Age	4-8mnth	1-2	2-3	3-4	5-6	7-8	9-10	11-12	12-13	13-14	15-16	17-8	19-20	23-24	27-28

4.4.2 Sample

The sample consists of any individual who completed the age 28 (wave fifteen) survey. I excluded those whose parents took part in wave fifteen, but whose child didn't. As I am primarily interested in the life outcomes of the child at this age I need those who had outcome data at this time point. I can compare the full sample at baseline, to the baseline characteristics of those not in wave fifteen and to those in wave fifteen. In Table 4.2 below I compare mothers and fathers ages, and education levels. The sample sizes here differ across variable type due to missing variables. Those who are in wave fifteen come from on average better educated families, from higher levels of occupation types and sightly older parents compared to those who are not in the final wave.

From now on, unless otherwise noted I focus on this sample of individuals - those who were still participating at wave fifteen. This resulted in the final sample of 1055 participants, of which 726 had complete variables that I need for the LCA analysis. These 726 observations are the complete case sample, and 1055 is the full sample which consists of the complete case plus those with multiple imputed variables.

Table 4.2: Baseline covariates

	Full Sample		Not in Wave 15		In Wave 15		p-value
	mean/sd	count	mean/sd	count	mean/sd	count	
Mothers Age	27.89	2440	27.55	1420	28.36	1020	0.00
	(4.534)		(4.709)		(4.236)		
Fathers Age	30.48	2393	30.30	1379	30.71	1014	0.0523
	(5.157)		(5.324)		(4.914)		
Fathers Education	1.984	2447	1.797	1397	2.232	1050	0.00
	(1.020)		(0.914)		(1.097)		
Mothers Education	1.742	2488	1.538	1435	2.019	1053	0.00
	(1.030)		(0.882)		(1.146)		

Notes *Mothers and fathers education levels are measured using a 4 part scale, with 1 indicating not above high school, 2 having some further education, 3 having tertiary education and 4 having postgraduate education.*

4.5 Variable Creation and Descriptives

4.5.1 Outcome - Socio-Economic Standing

There were a number of hypothesised variables that could be used as a measure of economic standing at age 28[15]. These included measures of income, financial strain, work experiences, education, employment etc. As stated previously, the standard economic *'risk'* factor at age 28 has been unemployment. While, this is definitely one valuable indicator of risk I believe that a more multifaceted approach is necessary, especially given the somewhat natural instability of employment at this age. In this sample, only eighteen people were unemployed at age 28.[16] There are large numbers of people who are only just finishing school, still in training or are simply unsure of the best career path for them at this age.Simply by looking at if someone is working glosses over a lot of variability in socio-economic status. In fact, there are very few people who

[15]The full explanations of each variable are explained in Appendix A

[16]This is also symptomatic of the sample being relatively well off in comparison to the general population. One group that is of particular interest to policy makers is NEET - not in employment, education or training - but this group is just not observed in the data. The youth unemployment rate in Victoria as of 2018 was 11.4% (unemployment amongst 15-24 year olds). However despite this relatively advantaged sample, there is still a lot of variation in economic difficulty faced by the participants.

are only studying or only working, with many people engaging in multiple activities. Measures such as self reported financial difficulty (inability to meet rent/mortgage payments, to pay bills, to pay for food etc), number of jobs, experiences of being made redundant, purposefully quitting and seeking work for long periods; and receiving a lot of government or parental financial support contribute to the overall socio-economic status of adults. These are in addition with more standard measures such as unemployed status, occupation type, education level and weekly income.

These outcomes are not independent and analysing them as such might oversimplify a more complex picture. For instance, being unemployed means you are likely to have lower income, receive parental and government support and experience higher levels of financial difficulties. Likewise getting a high level of education implies you are more likely to work in a highly skilled occupation, with higher incomes and may be less likely to suffer negative work experiences. However, a rudimentary examination of this data has revealed that it is hard to definitively say what is the normal trajectory up to age 28. Some of the well established facts like higher education levels resulting in lower levels of job seeking turn out not to be commonplace; which isn't surprising when one thinks of the economic landscape today. If you are highly educated, you may have more job opportunities, and be more likely to look around for a better job. Or likewise, you may not want to settle for a job that is below your skill level and may spend more time looking for jobs, despite being highly employable. One interesting pattern is that the lowest (just high school) and highest education group (postgraduate) report less the lowest amount of time job searching, whereas those with bachelor degrees and further training experience a lot of job search.

Table 4.3: Class Sizes in Sample

Class	N	Percentage
1	414	39.24
2	345	32.7
3	296	28.06
Total	1055	100

The latent class analysis suggested that there were three distinct classes within the sample[17]. Table 4.4 shows how each of the measures of socio-economic standing at age 28 corresponds with each of the different classes. A score of one indicates that this class (1, 2, 3) has the highest average score on that indicator, whereas a score of three indicates that this class has the lowest average score for that same indicator. For the advantages high average scores imply positive outcomes, i.e. higher income, higher skilled jobs, higher educational level, higher scores on national examinations (enter score) and more promotions. Thus class 1 has the highest level of all five of these, as indicated in table with the number 1. However, for these variables class 2 is worse off (as indicated by a score of 3) for some variables, but not all. The reverse ordering holds for the disadvantages, where higher scores imply worse outcomes, i.e. class 3 does the worst in every single measure that is considered a disadvantage, having the highest level of unemployment, financial difficulties, etc. In Appendix A, I also report the full summary statistics table, both of the complete case and of the multiply imputed outcomes.

Class 1 have the highest occupation scores, enter scores[18], education level and income. This represents a group of individuals who are socio-economically advantaged in society. They are the most likely to have been promoted and least likely to have been fired, have quit their jobs, or been made redundant. They have the lowest level of financial difficulty and are not very likely to have financial support either from government or their parent.

In comparison, class 2 represents a structurally disadvantaged group of individuals, having the lowest occupation skill scores, education levels, and enter scores. What is interesting is this group has on average higher incomes than class 3 (despite having lower education/occupation skills scores). They receive government allowances, as well as having some level of income support from their parents. They report the lowest number of jobs since finishing education (despite having finished education the earliest), as well as low levels of seeking work, being fired/made redundant, quitting intentionally and being

[17]I also conducted the latent class analysis with an expanded set of variables including mental health, substance use and familial structure relations (married, divorced, have a child, living at home). The classes remained virtually unchanged, suggesting that the economic grouping is not being organised by psycho-social variables.

[18]An enter score is the end of secondary school grade that students used to enter college. It was replaced in 2010 by the Australian Tertiary Admission Rank.

Table 4.4: Socio Economic Profile of the Classes

	Class 1	Class 2	Class 3
		Advantages	
Enter Score	1	3	2
Occupation Score	1	3	2
Education	1	3	2
Income	1	2	3
Promotions (WKEX1)	1	2	3
		Disadvantages	
Unemployed	3	2	1
Financial Difficulty	3	2	1
Income Support from parent	3	2	1
Other Financial Support from parent	3	2	1
Government Allowances	3	2	1
Number of jobs	2	3	1
Intentionally leave job (WKEX2)	2	3	1
Fired/Dismissed (WKEX3)	2	3	1
Made redundant/contract ended (WKEX4)	3	2	1
Seeking work for over a month(WKEX5)	2	3	1

Notes *An enter score is the grade on the test Australians used to do at the end of secondary school. An occupation score is a score designed to give an indication of the skill level of a job. For the variables listed under advantages 1 indicates highest score and is thus is the best off, with 3 being the lowest. For the variables under disadvantages, 1 indicates the highest score and thus the worst off, with 3 indicating a low score which on this scale indicates an absence of a disadvantage*

promoted. This class exemplifies the classic definition of lower socio-economic status, and yet these individuals who despite their low education, enter scores and occupation types are not struggling financially and do not have much job instability.

The third class is characterised by the highest levels of job insecurity and lowest income. They have a lot of employment problems - with the highest rates of intentionally leaving their job, being fired, seeking work for over a month and being made redundant. They are financially dependent on their parents, the most likely to be living at home, the least likely to be married, with high rates of financial difficulty. This class has the second highest average education, enter scores, and occupation scores. And yet they earn the least income. This classification is perhaps the most risky, being disadvantaged in a way that is different than class 2.

In summary, class 1 are the most advantaged and socio-economically well off, class 2 are *'classically'* socio-economic disadvantaged but seem financially stable whereas class 3 have a mix of the two - experiencing job insecurity, dependent on their parents and struggling financially - despite being better educated and of higher occupations than class 2. Another way to think of these groupings would be along an ability-hard working spectrum. Class 1 are likely to be hard working and high ability (as characterised by their high incomes and high education), class 2 are hard working with lower ability (lower skills occupation, lower education and yet mid level income) whereas class 3 occupy the space characterised by both ability levels and then not hard working. On average they have higher education and skills than class 2 and yet this does not translate into higher incomes or stable employment.

The main disadvantage of latent class analysis is also a core aspect of its methodology. It takes the structure and patterns of this particular sample and predicts the number and type of distinct classes underlying this sample. So while this might be valid for this sample, I cannot infer anything about a different population. It would be interesting to expand this to other settings to see if the same divisions emerge.

4.5.2 Inputs - socio-economic History

I hypothesise that the history of socio-economic stresses would be predictive of later socio-economic position, making it more likely to be in class 2 or class 3 with the more periods of exposure to any one risk or through exposure to multiple risks in any one period. I list below the main variables considered in the analysis[19]. Where possible a score by time period - childhood, adolescence and adulthood - was created. Ideally I would like to have broken this down into more periods, especially within the childhood period. However for most of the key variables, such as parental unemployment, the questions were only initially asked in wave five and as such I cannot look at shocks in early versus late childhood with the data available.

- **G1 Parent Ed** Ordinal [1,4] Max of mother and father education. This indicates the highest education achieved by wave 15, divided into four

[19]in another specification I included the history of parental substance use, and mental health problems but these caused no changes to the main findings. These measures can be problematic, as they are often under-reported in surveys as well as intentionally left blank.

levels: 1 (not above high school), 2 (some further education), 3 (tertiary education i.e. bachelors) and 4 (postgraduate).

- **Mother Ed** Ordinal [1,4] Max of mother education.
- **Father Ed** Ordinal [1,4] Max of father education.
- **Epoch: Mother Unemployed** Ordinal [0,2]. This variable indicates if G1 mother experiences unemployment in 0 periods, 1 period or 2 periods or more during the epoch.
- **Epoch: Father Unemployed** Ordinal [0,2]. This variable indicates if G1 father experiences unemployment in 0 periods, 1 period or 2 periods or more during the epoch.
- **Epoch: Parent Unemployed A** Ordinal [0,2]. This variable indicates if either parent G1 experiences unemployment in 0 periods, 1 period or 2 periods or more during the epoch.
- **Adult Financial Strain** [0,2] This variable indicates if G1 experienced financial strain in no waves (0), 1 wave (1) or 2 or more waves (2) in adulthood.
- **Adol Financial Strain** Binary [0,1] This variable indicates if G1 experienced financial strain in adolescence (only reported in wave 12).
- **Epoch: Marital Status Negative** Ordinal [0,2] This variable indicates the number of waves G1 had a marital status of widowed, divorced, separated with 0 being no waves, 1 being 1 wave and 2 being 2 or more waves[20].
- **Epoch: Times Moved School** Discrete [0, 2]. Indicates the number of times child moved school in this epoch. - 0 - no times, 1 - 1 time, 2 - 2 or more times
- **Epoch: Times Moved House** Ordinal [0,2]. Indicates the number of

[20]I considered using a measure that included if individuals were a single parent. The inclusion of this indicator resulted in a variable that had a correlation of 0.94 with the original. In the first wave when this is recorded (wave 4) there are less than 1% of the final sample used who are single. I decided instead to focus on a measure that captured change from current state and then how long they stayed in that state.

times child moved house - in no waves (0), 1 wave (1) or 2 or more waves (2) in adulthood.

- **Epoch: Own house Attend Private School** Binary [0,1] Indicates if parents owned their house or not.
- **G1: X age** Discrete Continuous [16,57].
- **G2: Female** Binary [0,1] Sex of G2 (1 is female).

Table 4.5: Division of Time Periods

Waves	Ages	Period
1-9	1-12	Childhood
10-12	13-18	Adolescence
13-14	19-24	Young Adulthood
15	28	Adulthood (outcome)

The descriptive statistics of the independent variables by group are shown in Table 4.6. The comparison of the multiple imputation version and complete case version are found in Appendix B. In the multiple imputation version there are slight increases in the mean score across all groups in the risk factors. However, the means and standard deviations remain in the same proportions to each other across the groups and broadly similar enough to suggest the imputation worked well, allowing the sample size to increase without much loss of accuracy.

Table 4.6: Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd	P Value
Child: G1 Mother unemployed	0.177	0.288	0.238	0.029
	(0.462)	(0.593)	(0.530)	
Child: G1 Father unemployed	0.213	0.263	0.268	0.405
	(0.504)	(0.586)	(0.572)	
Adolescence: G1 Mother unemployed	0.103	0.201	0.179	0.008
	(0.368)	(0.521)	(0.460)	
Adolescence: G1 Father unemployed	0.183	0.221	0.245	0.304
	(0.473)	(0.514)	(0.541)	
Adult: G1 Mother unemployed	0.107	0.149	0.190	0.047
	(0.345)	(0.420)	(0.464)	
Adult: G1 Father unemployed	0.128	0.165	0.186	0.265
	(0.365)	(0.443)	(0.451)	
Child: Negative Marital	0.171	0.309	0.276	0.007
	(0.523)	(0.687)	(0.654)	
Child: School Moves	1.282	1.279	1.262	0.927
	(0.609)	(0.633)	(0.669)	
Child: House Moves	1.178	1.183	1.252	0.487
	(0.844)	(0.865)	(0.839)	
Adolescence: Negative Marital	0.220	0.320	0.402	0.002
	(0.592)	(0.690)	(0.757)	
Adolescence: School Moves	0.336	0.368	0.440	0.106
	(0.575)	(0.583)	(0.641)	
Adolescence: House Moves	0.349	0.446	0.453	0.080
	(0.617)	(0.668)	(0.709)	
Adolescence: Financial Strain	0.428	0.566	0.651	0.000
	(0.596)	(0.656)	(0.701)	
Adult: Negative Marital	0.308	0.436	0.529	0.001
	(0.670)	(0.775)	(0.837)	
Adult Financial Strain	0.425	0.584	0.646	0.001
	(0.681)	(0.798)	(0.784)	
Max G1 Fathers Education	2.455	1.843	2.373	0.000
	(1.152)	(0.881)	(1.125)	
Max G1 Mothers Education	2.216	1.652	2.174	0.000
	(1.194)	(0.955)	(1.180)	
N	414	345	296	

Notes *For all risks they had a score of 0 (shock did not occur in any wave), 1 (the shock occurred in only one wave) and 2 (the shock occurred in one wave or more). Parental education was on a scale of 1-4, from no more than high school, some further education, tertiary education and postgraduate education.*

I also define risk in two other ways. The main analysis looks at each type of risk in each time period. However as stated earlier, it may be that it is the cumulative effect of multiple risk factors in any period that matters. For each time period I created a cumulative risk score which was the sum of the risks in that period. The number of risks considered in each period varied (due to data limitations) and as such I can't compare across periods as to when the most risks occurred.

Table 4.7: Cross Section Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd	P Value
Total Childhood Risk	3.022	3.324	3.296	0.044
	(1.583)	(1.881)	(1.731)	
Total Adolescent Risk	1.621	2.125	2.371	0.000
	(1.547)	(1.819)	(1.917)	
Total Young Adult Risk	0.969	1.336	1.553	0.000
	(1.238)	(1.555)	(1.643)	
N	414	345	296	

Notes *The score for each period is created by summing the scores of each individual risk factor in that period*

Then I created a persistent shock variable, which looks at the effects of each type of shock separately but summed over the life span. As each risk did not occur in every period I cannot compare the magnitudes meaningfully across risk type.

Table 4.8: Time Series Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd	P Value
Total Mother Unemployment	0.387	0.639	0.607	0.001
	(0.820)	(1.138)	(1.005)	
Total Father Unemployment	0.525	0.651	0.699	0.103
	(0.969)	(1.118)	(1.121)	
Total Negative Marital Risk	0.700	1.065	1.208	0.00
	(1.508)	(1.817)	(1.941)	
Total School Moves Risk	1.617	1.646	1.702	0.476
	(0.797)	(0.822)	(0.859)	
Total Financial Difficult Risk	0.853	1.151	1.297	0.000
	(1.086)	(1.231)	(1.286)	
Total House Moves Risk	1.528	1.63	1.705	0.147
	(1.098)	(1.193)	(1.189)	
N	414	345	296	

Notes *The score for each type of risk is created by summing the scores of the three periods (if available) for that type of risk.*

4.6 Results

The results reported below are the marginal effects from the multinomial logistic regression using the data from the multiple imputation. The relative risk coefficients, as well as both marginal and relative risk coefficients from the complete case data are reported in Appendix C and Appendix D respectively. I began with just including shocks from one period (childhood, adolescence or adulthood). In the next estimation I then include two periods (childhood and adolescence, adolescence and adulthood) before considering a model with the full history of socio-economic shocks. The results are very similar across models regardless of which periods are included. The marginal effects below correspond to the model including all periods. These margins necessarily sum to zero: showing the overall change in probability of being in each class when one of the inputs changes. It is worth reiterating the three classes: class 1: advantaged, class 2: classic disadvantage and class 3: unstable disadvantage.

4.6.1 Main Analysis

Different shocks at different time points are associated with particular socio-economic profiles. Table 4.9 shows the marginal effects. Events that happen in childhood are associated with an increase in the likelihood of being in class 2. Maternal unemployment increases the likelihood of being in class 2 by 5.91%, while decreasing the likelihood of being in class 1 by roughly the same amount. Periods of marital break up in this period are associated with a 7.2% increase in likelihood of being in class 2. In comparison, events that occur during adolescence and adulthood are more associated with being part of the unstable disadvantaged class. Parental financial strain in young adulthood is associated with increased risk of 5.09%, experiencing numerous school moves increases the likelihood by 4.33%, While not significant, negative maternal experiences are associated with an increased likelihood of being in class 3. Structural factors such as parental education levels are particularly predictive of being in class 2 - the class that is also the lowest educated class at age 28. Education levels are somewhat persistent across generations, even with an overall increase in education levels from one generation to the next.

The following figures display the same information as Table 4.9 but are helpful is seeing the patterns discussed. They show the change in the probability

Table 4.9: Average Marginal Effects

	Class 1	Class 2	Class 3
Child: G1 Mother unemployed	-0.0444	0.0591*	-0.0147
	(0.0333)	(0.0320)	(0.0311)
Child: G1 Father unemployed	0.0171	-0.0183	0.00119
	(0.0350)	(0.0301)	(0.0304)
Adolescence: G1 Mother unemployed	-0.0577	0.0496	0.00813
	(0.0418)	(0.0349)	(0.0350)
Adolescence: G1 Father unemployed	0.00234	-0.00846	0.00612
	(0.0369)	(0.0327)	(0.0328)
Adult: G1 Mother unemployed	-0.00929	-0.0371	0.0464
	(0.0455)	(0.0426)	(0.0382)
Adult: G1 Father unemployed	-0.0281	0.00324	0.0249
	(0.0467)	(0.0423)	(0.0388)
Child: Negative Marital	-0.0397	0.0724**	-0.0327
	(0.0345)	(0.0299)	(0.0291)
Child: School Moves	0.00854	0.0121	-0.0207
	(0.0295)	(0.0274)	(0.0266)
Child: House Moves	0.0110	-0.0252	0.0142
	(0.0205)	(0.0195)	(0.0189)
Adolescence: Negative Marital	-0.00103	-0.0408	0.0419
	(0.0404)	(0.0380)	(0.0336)
Adolescence: School Moves	-0.0180	-0.0253	0.0433*
	(0.0275)	(0.0274)	(0.0262)
Adolescence: House Moves	-0.0333	0.0251	0.00821
	(0.0249)	(0.0238)	(0.0229)
Adolescence: Financial Strain	-0.0472	-0.00399	0.0512*
	(0.0301)	(0.0270)	(0.0263)
Adult: Negative Marital	-0.0382	0.0189	0.0193
	(0.0308)	(0.0312)	(0.0275)
Adult: Financial Strain	-0.0224	0.0000370	0.0223
	(0.0265)	(0.0239)	(0.0236)
Max G1 Fathers Education	0.0423***	-0.0747***	0.0324**
	(0.0152)	(0.0147)	(0.0142)
Max G1 Mothers Education	0.0349**	-0.0615***	0.0266**
	(0.0144)	(0.0144)	(0.0134)
N	1055	1055	1055

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of being in class 1, 2 or 3 depending on the type of shock for childhood (Figure 4.2), adolescence (Figure 4.3) and young adulthood (Figure 4.4) separately. A triangle indicates when the change was significant. For each shock the darkest square is class 1, the mid colour class 2 and the lightest class 3 (also ordered

from left to right).

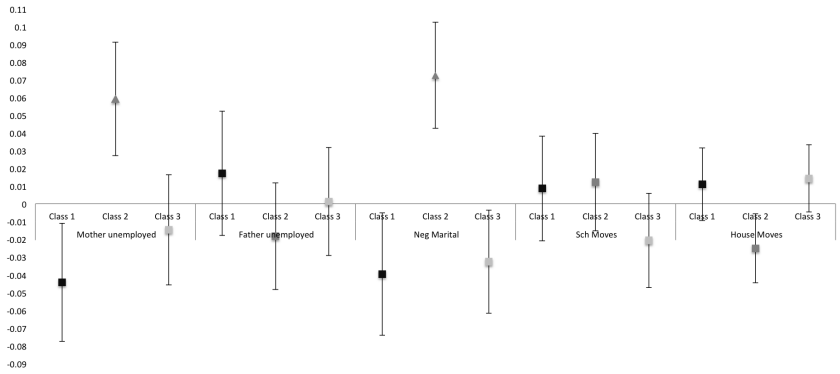


Figure 4.2: Change in Probability of Being in Class 'X' - childhood shock

Notes *This chart shows the margins point estimates and their associated 95% confidence interval. Triangles indicate when a coefficient is significant, otherwise the point estimate is a square. Black is class 1, grey is class 2 and light grey is class 3.*

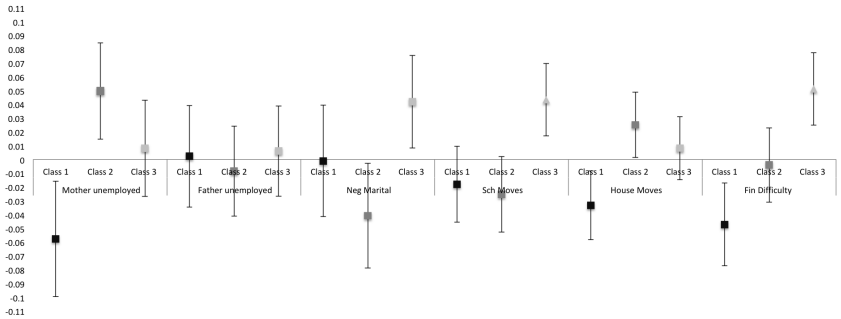


Figure 4.3: Change in Probability of Being in Class 'X' - adolescence shock

Notes *This chart shows the margins point estimates and their associated 95% confidence interval. Triangles indicate when a coefficient is significant, otherwise the point estimate is a square. Black is class 1, grey is class 2 and light grey is class 3.*

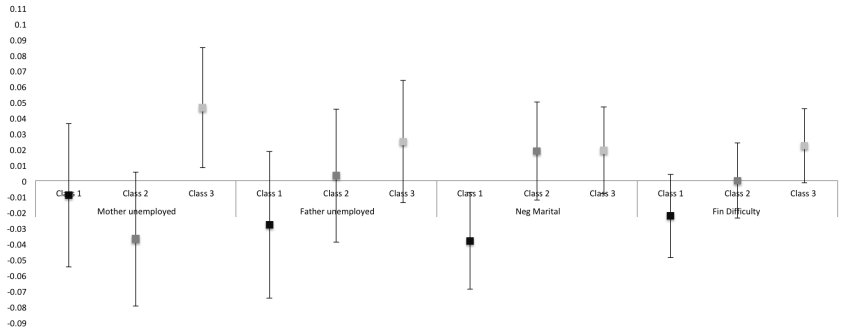


Figure 4.4: Change in Probability of Being in Class 'X' - young adult shock

Notes *This chart shows the margins point estimates and their associated 95% confidence interval. Triangles indicate when a coefficient is significant, otherwise the point estimate is a square. Black is Class 1, grey is Class 2 and light grey is Class 3.*

It is difficult to draw causal conclusions about these results. However they do suggest that there are differential risk indicators in the history of an individuals life, both in terms of risk type and in riskiness of certain periods. I conducted specification tests for IIA using a variety of methods, the Hausman-McFadden test, a second version of the Hausman test and the Small-Hsaio test. In each case they failed to reject the IIA assumption lending more credibility to the models. The results were also robust to the inclusion of alternative confounders.

4.6.2 Cumulative Risk

The cumulative risk scores were created by summing the different risk factors in each epoch to create a overall risk score for that epoch. This suggests a somewhat different picture than the disaggregated approach. Table 4.10 shows that young adulthood risks and adolescent risks increase the likelihood of being in class 3 as opposed to class 1. There is no effect of childhood risk, which contradicts the findings from the previous section. It could be that the risks cancel each other out in this period. We can still see the persistence of parental education on outcomes, with structural familial factors mattering for class 2 as before.

Table 4.10: Average Marginal Effects

	Outcome 1	Outcome 2	Outcome 3
Total Childhood Risk	-0.00164	0.00999	-0.00835
	(0.0102)	(0.00964)	(0.00902)
Total Adolescent Risk	-0.0299**	0.00377	0.0262***
	(0.0119)	(0.0107)	(0.00945)
Total Young Adult Risk	-0.0283**	0.000700	0.0276**
	(0.0135)	(0.0120)	(0.0116)
Max G1 Fathers Education	0.0431***	-0.0749***	0.0318**
	(0.0150)	(0.0146)	(0.0140)
Max G1 Mothers Education	0.0335**	-0.0588***	0.0252*
	(0.0143)	(0.0143)	(0.0132)
N	1055	1055	1055

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing number of risks per period.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

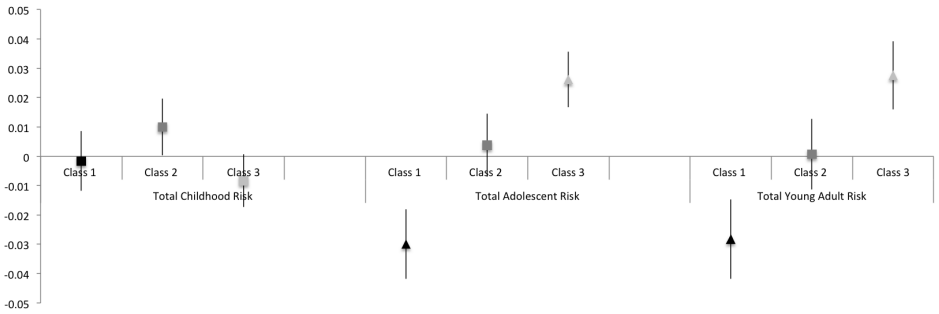


Figure 4.5: Change in Probability of Being in Class "X" - across time

Notes *This chart shows the margins point estimates and their associated 95% confidence interval. Triangles indicate when a coefficient is significant, otherwise the point estimate is a square. Black is Class 1, grey is Class 2 and light grey is Class 3.*

4.6.3 Persistent Risk

The persistent risk specification shown in Table 4.11 confirm the previous suggestions that different types of risk factors are associated with differences in later life. Financial risks and negative marital status increase the probability of being in class 3 and maternal unemployment is related to class 2. There are no differences due to house moves or paternal unemployment. In the case of house moves and school moves there is no way to know if the move is positive or negative and this can vary by person and by move. In some cases, moving to a better neighbourhood may override any negative instability caused by the move and there is no way to break down these changes into positive and negative ones in the available data. It seems that maternal unemployment, marital breakdown and negative marital statuses have the highest impacts, in addition to structural features such as parental education This is suggestive of intergenerational disadvantage.

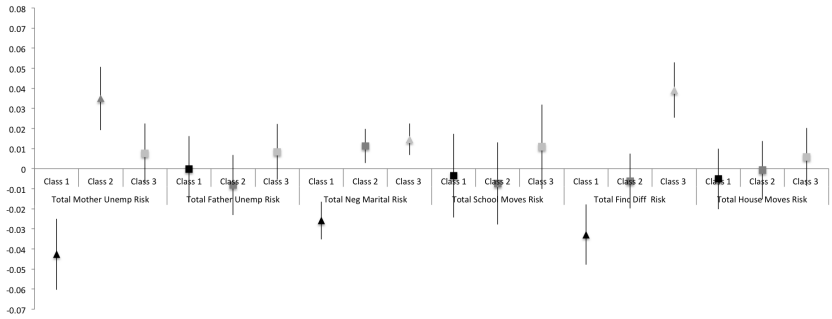


Figure 4.6: Change in Probability of Being in Class "X" - over time

Notes *This chart shows the margins point estimates and their associated 95% confidence interval. Triangles indicate when a coefficient is significant, otherwise the point estimate is a square. Black is Class 1, grey is Class 2 and light grey is Class 3.*

Table 4.11: Average Marginal Effects

	Outcome 1	Outcome 2	Outcome 3
Total Mother Unemployment Risk	-0.0426**	0.0350**	0.00762
	(0.0177)	(0.0158)	(0.0148)
Total Father Unemployment Risk	-0.000198	-0.00818	0.00838
	(0.0165)	(0.0149)	(0.0138)
Total Negative Marital Risk	-0.0258***	0.0113	0.0146*
	(0.00940)	(0.00847)	(0.00788)
Total School Moves Risk	-0.00347	-0.00738	0.0109
	(0.0209)	(0.0204)	(0.0210)
Total Financial Difficulty Risk	-0.0329**	-0.00618	0.0391***
	(0.0150)	(0.0136)	(0.0138)
Total House Moves Risk	-0.00507	-0.000753	0.00582
	(0.0151)	(0.0145)	(0.0144)
Max G1 Fathers Education	0.0439***	-0.0748***	0.0309**
	(0.0151)	(0.0147)	(0.0142)
Max G1 Mothers Education	0.0326**	-0.0590***	0.0264**
	(0.0143)	(0.0144)	(0.0133)
N	1055	1055	1055

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing across period per risk.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6.4 Association with Other Risk Factors

The LCA used what could be considered economic variables to create our outcome. However there are other domains of risk that are damaging to a persons' overall well being. These have negative effects not only on the individual themselves, but also have negative spillovers on society and potentially onto the next generation. Table 4.12 describes how mental health, substance use and living arrangements varied across socio-economic classifications. I report summary statistics using the non imputed data. The proportion of missings collectively across all variables was under 5%, with the maximum of missing for any one variable was 10%.

Table 4.12: Social Risks at age 28 by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd	P value
Number of Days 5 + drinks	2.303	2.859	2.846	0.020
	(2.959)	(4.483)	(4.217)	
Number of Days Marijuana	0.526	0.844	2.014	0.000
	(2.790)	(3.547)	(5.767)	
Number of Days Smoking	2.440	7.115	8.155	0.000
	(7.306)	(12.03)	(12.58)	
G2: Anxiety	0.142	0.188	0.289	0.000
	(0.350)	(0.391)	(0.454)	
G2: Depression	0.196	0.236	0.418	0.000
	(0.398)	(0.425)	(0.494)	

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Asides from the number of days with 5 or more drinks where the amount of time is similar across classes (class 2 and 3 reporting half of a day more than class 1), there are big differences across classes in all other variables. Class 3 have the highest number of days smoking, drinking 5 or more drinks and using marijuana. Smoking and drinking is elevated in class 2 as well, but marijuana use is less common than it is in class 3. There are also higher levels of anxiety and depression reported by class 3. This class seems to be particularly vulnerable to psychologically damaging behaviours and mental illness. It is impossible to know if aspects of their socio-economic profile make them more likely to engage in certain behaviours, if these behaviours influence their socio-economic profile, or if there is some other underlying unmeasured variable linking both. One piece of evidence suggesting that these variables are not driving the class classification is that when they are included in the LCA the same class assignment occurs for nearly every observation.

There are also differences in the life circumstances across classes as can be seen in Table 4.13. Class 2 have highest rates of marriage and are the most likely to have a child. Class 3 are the least likely to be married, most likely to live at home and the least likely to have a child. Class 1 are independent, unlikely to live at home and have higher rates of marriage than class 3.

Table 4.13: Life Circumstances at age 28 by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd	P Value
G2: Living at home	0.104	0.128	0.189	0.000
	(0.306)	(0.335)	(0.392)	
G2: Married	0.421	0.472	0.242	0.000
	(0.494)	(0.500)	(0.429)	
G2: Divorced	0.0150	0.0217	0.00722	0.718
	(0.122)	(0.146)	(0.0848)	
G2: Has a child	0.114	0.296	0.166	0.000
	(0.318)	(0.457)	(0.372)	

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

4.7 Pathways to the next generation

This section examines how the socio-economic classification at age 28 impacts parenting behaviours and the outcomes of the next generation. Anyone who took part in the main ATP G1G2 study was eligible to take part in G3. This resulted in a cohort of individuals who are in the G3 but who are not part of the sample analysed, given I restricted the sample to individuals who completed the final wave of the main study.

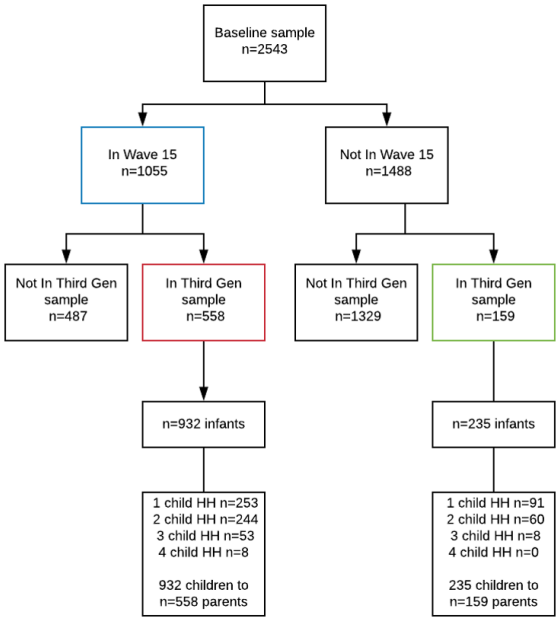


Figure 4.7: Mapping of adults and children from baseline to G3

Thus the cohort of participants in G3 are those who took part in wave fifteen (and as such are classified into one of the three groups). This results in a total of 558 G2 individuals - which is approximately half of those from wave 15 (and is shown in Figure 4.7). There are 497 individuals who are part of the final wave who either have not had a child yet or have chosen not to participate in the third generation study. There are 159 individuals who didn't take part in wave 15, but who when contacted choose to participate in the G3. However given we do not have a class grouping for them they are excluded from this piece. However, the sample of actual G3 participants is is larger than 558 individuals due to multiple G3 children per G2 participant. This provides within parent variation in G3 outcomes. As can be seen in Figure 4.7 most people had either one or two children, but there was still 61 families with three or more children. The sample is either n=558 G2's or n=932 G3's.

Table 4.14: Descriptive Statistics - LCA

	Class 1	Class 2	Class 3
Total G3	452	312	168
Household Size G3	G2 Parent	G2 Parent	G2 Parent
1 child	92	88	73
2 child	128	82	34
3 child	28	16	9
4 child	5	3	0
Total G2 now in G3	253	189	116
Total G2 in W15	414	345	296
% G2 Participation in G3	61.11%	54.78%	39.19%
Numbers of G3 per HH			
Mean	1.78	1.65	1.448
SD	0.714	0.703	0.637
N	253	189	116

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. G2 refers to the sample child as analysed throughout, and G3 refers to their offspring.*

Table 4.14 shows the breakdown of who is participating in G3 and the numbers of kids by LCA class. Class 1 are the most likely to participate in the generation three study and class 3 are the least likely (61.11% vs. 39.19%). While it is tempting to conclude that class 3 are the least likely to have had a child in the follow up: this would be incorrect. Again I do not know whether individuals are not participating because they haven't had a child or if they have had a child but chosen to not participate. Selection into G3 comes from these two sources. It was not possible to get the data breakdown for the number

of people contacted who have had children but who did not want to participate. The number of children per household also decreases across the classes with class 1 having on average 1.78 children compared to class 3's 1.448 kids per household.

From now on when describing the variables, I do this for each G3. Each G2 has a different pregnancy and first year of life with each child - and thus when the variable is used to describe an aspect of the G3 and/or their relationship with the G2 the relevant n is 932. The main measure of parental behaviour examined was ACEs, that is adverse childhood experiences, measured both during pregnancy and at age 1[21]. The ACEs were created from the variables shown in Table 4.15 and are created for each child (i.e. two children of the same parent will have two different ACE scores, although likely to have higher correlations than the ACE score between two children of different parents). The ACE score constructed at wave 15 (age 28) will however be the same for both children born to the same parent.

There are other variables that impact child development in addition to the developmental outcomes themselves that could differ in important ways across the classes. Table 4.16 summarises some of these variables - maternal age, birthweight, the constructed ACEs and the scales of the BITSEA. There is very little difference across the classes in birthweight or parental age. Contrary to expectations there are also very little differences in the ACEs measure during pregnancy across the classes. It seems that conditional on taking part people behave similarly in pregnancy. This might be a selection issue or perhaps

[21]The ACEs were created by loosely following the methodology of the San Diego Adversity Study (Felitti et al. (1998)). This was outlined earlier in the literature review but I repeat it here. In the San Diego study individuals were given an exposure risk score of [0,7] based on answers to questions on three forms of abuse - psychological, physical and sexual ; and four measures of household dysfunction - substance use, mental wellness, mother treated violently, and criminal behaviour. These were associated with a increased risk in later adult health risk behaviours and diseases. Persons who had experienced four or more categories of childhood exposure, compared to those who had experienced none, had 4-to 12-fold increased health risks for alcoholism, drug abuse, depression, and suicide attempt; a 2-to 4-fold increase in smoking, poor self-rated health, 50 sexual intercourse partners, and sexually transmitted disease; and a 1.4-to 1.6-fold increase in physical inactivity and severe obesity. The number of categories of adverse childhood exposures showed a graduated relationship to the presence of adult diseases including heart disease, cancer, chronic lung disease, skeletal fractures, and liver disease. The seven categories of adverse childhood experiences were strongly interrelated and persons with multiple categories of childhood exposure were likely to have multiple health risk factors later in life.

Table 4.15: ACEs

Variable	Description
	Pregnancy
Alcohol Use	=1 if drank during pregnancy at all
Smoking Use	=1 if smoked during pregnancy at all
Marijuana Use	=1 if use marijuna during pregnancy at all
Other drug use	=1 if use drugs during pregnancy at all
Mental Health	=1 if had anxiety/depression
Total ACE0	Sum of risks [0,5]
	Age 1
Alcohol Use	=1 if drank every day/ 3-4 days a Iek in the past month
Smoking Use	=1 if smoke at all in past month
Marijuana Use	=1 if did marijuana at all in past month
Other drugs	=1 if did other drugs
Mental Health	=1 if had depression/anxiety
Total ACE1	Sum of risks [0,5]

social desirability effects in which participants know what sort of behaviours to report. However if this was the case you would expect it to persist beyond just pregnancy and into the age 1 behavioural measure, especially given the first year of life is probably as important as pregnancy in parents eyes. At age 1, parents from both class 2 and 3 are engaging in more risky behaviours with both a higher mean score and higher variance. The score across all classes increases from pregnancy to age 1.

The next set of variables are outcomes related to the child directly, the BITSEA problem and competency scale which measures negative and positive behaviours. There are differences across the classes in the problem score of the BITSEA with 25.8% of children born to G3 being at risk compared to just 9% of the other two categories. Despite similar mean scores 17.9% of class 2 children are particularly at risk to be in the clinical cut off of competency subscale, with lower rates of at risk children from class 1 and class 3. This is due to the higher variance of competency scores amongst class 2 children. Ideally we would have liked to have used measures of cognition and other measures of socio-emotional skills, similar to those used in the other two chapters. However, to maximise the sample size available I used the age 1 cohort, whose only outcome variable of the child was the BITSEA scale. The older children are completing a wider array of cognitive and socio-emotional tests, but given the different timings of birth there are much fewer children of older ages. I also decided against using health as an indicator of human capital here, given the little differences found in birth weight and because stunting and wasting are of little significance to

Table 4.16: Descriptive Statistics - LCA

	Class 1	Class 2	Class 3	
	Age			P Value
Mean	31.14	30.28	31.078	0.000
SD	(2.211)	(2.347)	(2.435)	
N	442	310	166	
	Birthweight (kg's)			
Mean	3.419	3.40	3.41	0.838
SD	(0.659)	(0.629)	(0.718)	
N	259	196	106	
	ACE0			
Mean	0.214	0.205	0.220	0.0269
SD	(0.481)	(0.509)	(0.494)	
N	452	312	168	
	ACE1			
Mean	0.312	0.443	0.444	0.000
SD	(0.665)	(0.764)	(0.789)	
N	414	298	151	
	BITSEA-Problem			
Mean	6.226	6.374	8.958	0.00
SD	(3.688)	(3.912)	(4.683)	
N	267	202	112	
	BITSEA-Problem Cut Off			
Mean	0.097	0.099	0.258	0.000
SD	(0.297)	(0.299)	(0.440)	
N	267	202	112	
	BITSEA-Competence			
Mean	16.260	16.319	16.546	0.954
SD	(2.769)	(3.912)	(2.716)	
N	266	201	112	
	BITSEA-Competence Cut Off			
Mean	0.139	0.179	0.116	0.451
SD	(0.346)	(0.384)	(0.321)	
N	266	201	112	

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. ACEs are the number of adverse childhood experiences during pregnancy (ACE0) and at age 1 years old (ACE1). BITSEA is the Brief Infant-toddler Social and Emotional Assessment used to diagnose problematic behaviour in young infants. The cut off point is a binary variable for those whose scores mean they are in the clinical range of risk.*

children in a higher income country such as Australia.

The distribution of risks by type are shown below in Figure 4.8 and Figure 4.9 at age 0 and at age 1. These show that there are only a few people with multiple risk factors. In the subsequent analysis I use a binary outcome variable of either having a risk factor or not. The drawback of this approach is that we cannot tell whether magnitude of the risks matters for future negative outcomes.

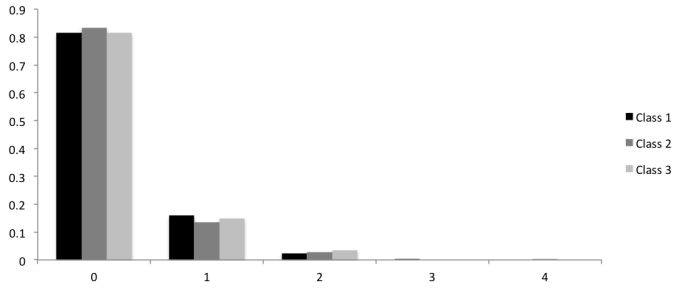


Figure 4.8: Distribution of ACE at pregnancy

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Black is Class 1, grey is Class 2 and light grey is Class 3.*

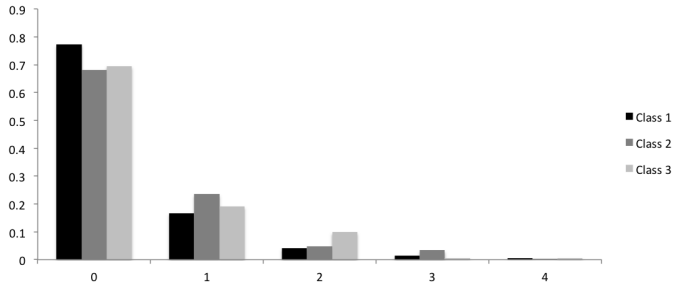


Figure 4.9: Distribution of ACE at year 1

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Black is Class 1, grey is Class 2 and light grey is Class 3.*

In what follows I attempt to predict the likelihood of experiencing adverse childhood exposures at age 0 and age 1 based on what group you belong to. At age 0, I also add in a control for substance use and mental illness at wave 15. While these variables were correlated with particular latent classes, they were not used to define the classes. This allows me to include class as a valid predictor. At age 1, I add in ACEs during pregnancy as an additional control.

Table 4.17: ACE's

	ACE 0	ACE 0	ACE 1	ACE 1	ACE 1
Class type=2	0.876	0.790	1.593**	1.595**	1.503**
	(0.179)	(0.166)	(0.321)	(0.320)	(0.301)
Class type=3	0.991	0.892	1.491*	1.490*	1.380
	(0.227)	(0.206)	(0.353)	(0.352)	(0.339)
ACE W15		3.601***			2.359***
		(0.939)			(0.550)
ACE0				1.316	1.148
				(0.270)	(0.245)
N	932	921	863	862	853

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Odds ratios are reported. Standard errors in parentheses. The standard errors are clustered at the G2 parent level. Class 1 is the omitted class. All outcomes and lagged ACEs are binary. * p<0.10, ** p<0.05, *** p<0.01*

Table 4.17 shows that engaging in risky behaviour during pregnancy is not related to the latent class, but it is highly dependent on behaviours at wave 15. If you smoke, drink, do drugs and have mental problems prior to becoming a parent you are likely to continue with these behaviours while pregnant. This suggests that economic grouping does not independently affect behaviour in pregnancy. Pregnancy is a time when parents regardless of economic grouping, are equally aware of the risks of certain behaviours and the likelihood of engaging in negative behaviours is more dependent on past habits. What is most informative is the prediction of age 1 risky behaviour by the parent. Now being in a more disadvantaged economic standing (class 2 or class 3), is associated with a higher likelihood of the parent engaging in a risk factor during the first year. This finding is robust to the inclusion of past measures of risky behaviours. It seems that being in group 2 relative to group 1 is the most risky, raising the likelihood of experiencing at least one adverse childhood exposure by 1.5 times. There is also an elevated risk of being in

group 3 relative to group 1. Economic classification is having an effect on the likelihood of engaging in risk factors for development that is independent of past psycho-social behaviours.

Table 4.18: BITSEA Problem Behaviour Cut Off

	A	B	C	D	E
Class type=2	1.019	1.079	1.023	0.976	0.973
	(0.352)	(0.367)	(0.364)	(0.355)	(0.359)
Class type=3	3.239***	3.248***	3.010***	2.575***	2.766***
	(1.031)	(1.034)	(0.981)	(0.885)	(0.964)
G3 Gender		0.978	0.974	0.985	0.975
		(0.238)	(0.240)	(0.256)	(0.262)
G3 birth order		0.723*	0.734*	0.767	0.746
		(0.125)	(0.127)	(0.140)	(0.145)
ACE1			1.434	1.203	1.210
			(0.401)	(0.340)	(0.347)
ACE W15			1.333	1.459	1.619
			(0.439)	(0.493)	(0.567)
Warm Parent				1.272	1.193
				(0.405)	(0.394)
Hostile Parent				2.336***	2.451***
				(0.576)	(0.605)
Anxious Parent				0.546***	0.524***
				(0.113)	(0.109)
Log Current weekly income					0.845
					(0.168)
N	581	581	576	576	549

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Odds ratios are reported. Standard errors in parentheses. The standard errors are clustered at the G2 parent level. Class 1 is the omitted class. All outcomes and lagged ACEs are binary. The sample size is smaller due to missing values of the BITSEA for some children. * p<0.10, ** p<0.05, *** p<0.01*

The other main outcome of interest about is a measure of child development. The SES classification might impact child development outcomes directly or indirectly via behaviours and parenting. The outcome is the clinical cut off of the problem subscale of the BITSEA, measured at age 1. The reasons for using this measure of development are mentioned above. Table 4.18 shows that being having a parent in class 3 relative to class 1 results in three times the likelihood of having a score on the problem sub scale of the BITSEA that is in the clinical cut off level. This suggests that there is some link from parent to child, most likely due to the investment behaviour of this group - that is causing increased

risk of negative development outcomes. Unfortunately I cannot examine the possible causal mechanisms: time spent with the child, monetary resources available etc. However the finding that group classification increases likelihood of being in the clinical cut off on this scale, even after controlling for parenting style. It seems the socio-economic position is having an effect on problem behaviours independent of the best available measure of quality of parenting. It would be interesting to examine if this finding holds as the children get older, and if other domains of human capital are impacted by class grouping.

4.8 Discussion

This paper has made three main contributions. Firstly, it proposes a new way to think about socio-economic position, by using a machine learning technique (LCA) to reduce the dimensionality of the data and reveals a richer understanding of the various socio-economic profiles of people in emerging adulthood today. Thinking about socio-economic position more broadly is an important step forward especially in an economy where people may be employed with higher levels of education than ever before, but still could be considered disadvantaged in other ways. The third class uncovered in this data are a distinct group, one that makes sense but that is not often talked about, potentially akin to the precariat class found in other research (Sheppard and Biddle (2017), Savage et al. (2013)). This group is characterised by high levels of education but with unstable employment. The other two groups uncovered were a classically advantaged (class 1) and a classically disadvantaged group (class 2), characterised by high educated people in high income high skilled jobs and low educated people in low skilled jobs, but with relatively stable employment.

Secondly, this chapter associates different types of risk factors to each of these distinct profiles. The rich multi-wave data structure provides a rich set of variables, that allows me to distinguish the time period and the type of shocks that occur. The full history from birth through to emerging adulthood is used in this chapter. I also show that multiple imputation can be used as a useful method for dealing with missing data that is not often used in economics. It could be a way to increase sample sizes in cases where otherwise researchers are restricted to only those individuals with complete data. It is an improvement

on just imputing the mean of the sample or the mean plus random noise and could be used more in research (van Ginkel et al. (2019)).

I found that different types of shocks at different time periods were important in predicting the likelihood of being in a particular class. In general, being in class 2 was associated with structural features such as low levels of parental education - which highlights the intergenerational persistence of low education. It is also associated with childhood shocks, particularly periods of negative marital status and maternal unemployment. In comparison, shocks that occur in adolescence and young adulthood increase the probability of being in class 3, in particular financial difficulty and negative marital risk. This helps us understand the potential risks of certain shocks. However, this work is not causal and more research is needed to properly uncover causal linkages between past shocks and current socio-economic position.

Third, I examined if there were consequences of these socio-economic classifications on a third generation. This is a somewhat unique feature of this data that allows for three generations worth of respondents to be analysed. The new generation of children born to the original ATP child is continuing to be followed, allowing for further research on later outcomes. This could be particularly interesting to map out if the same socio-economic classification holds when this group are emerging adults, and how persistent socio-economic profiles are. There are likely to be selection biases in this sample, in that some people might decide not to have a child whereas others may have had a child but no longer want to participate. However, conditional on both having a child and participating I documented differences in parenting behaviours and child outcomes due to the socio-economic classification, even after controlling for parenting style and other relevant variables. The most salient was a large increase in the likelihood of being classified as above the clinical cut off for problem behaviour if your parent was in the unstable employment class (class 3). Future work will be able to examine these trajectories for all components of human capital mentioned in this thesis, cognitive, socio-emotional and health outcomes, with further data collection.

I began this thesis by suggesting that both the changing economy and changing development milestones created a new landscape for individuals to navigate, and that policy makers should do more to help individuals as they

enter adulthood. The third group uncovered in this thesis is a key example of a group that has been largely disregarded by policy. This group is characterised primarily by job instability, and seem to be having trouble both finding and keeping jobs that match their education levels. Policy makers could focus on improving short-run job search programmes for individuals entering the labour force, but who are struggling to find appropriate employment. Some of this group might benefit from a skills focused third level training or apprenticeship, especially if this matching problem is due to a lack of demand for certain types of degrees (compounded by the increase in people doing degrees that do not map onto a specified career path). This group is also characterised by a number of co-occurring problems such as substance misuse and mental illness, which are also common in second class. More preventative and curative support on both a grassroots and national level is needed to reduce the prevalence of such problems in society. We also saw how maternal unemployment, marital break up and family financial stress seemed to increase the likelihood of people being in group 2 or group 3. Perhaps more government support, both in terms of financial aid and free counselling might help mitigate against the negative consequences of these risks, or prevent them from occurring in the first place. These are but a few suggestions of policy proposals that could help both the individual themselves, but also the new generation of children being born. As this chapter has tried to convey socio-economic position is a complex, broad construct and as such policies aimed at improving overall well-being will most likely have to be equally multifaceted.

Appendix A : Economics Measures - Latent Class Analysis

Measures of Socio-Economic Position

- **G2: Education** Ordinal [1,4] This indicates highest education achieved by wave 15 - 1 (not above high school), 2 (some further education), 3 (tertiary education, bachelors degree) and 4 (postgraduate education).
- **G2: Occupation** Ordinal [0,100] This is the ANU-4 (developed by Australian National University) score with higher scores indicating a more highly 'skilled' job - medical professionals get a score of 100 with general labourers getting a score of 0. This can be loosely used to divide the sample into blue collar and white collar jobs.
- **G2: Self reported weekly income** [1,15] This corresponds to income bands.
- **G2: Enter Score** [0,99] The enter score is the test that people use at the end of high school to get into university. It is a state wide ranking system that places people according to their percentile rank.
- **G2: Unemployed now** [0,1] Is currently unemployed.
- **G2: Number of Jobs** [0,10] Number of jobs they have had since leaving school.
- **G2: Financial Difficulty Score** [0,8] Number of self reported financial difficulties. The sum of: went without meals, couldn't pay bills, couldn't make mortgage/rent, pawned/sold something, unable to heat home, financial help from family/friends, help from welfare community, increased credit card/bank debts.
- **G2: Work experiences : promoted** [0,4]. This is asked in the context of the how many times in last 4 years, with 0 being no times, 1 being once, 2 being 2 times, 3 being 3 or 4 times, and 4 being 5 or more times.
- **G2: Work experiences : intentionally left job** [0,4] This is asked in the context of how many times in the last 4 years, with 0 being no times, 1 being once, 2 being 2 times, 3 being 3 or 4 times, and 4 being 5

or more times.

- **G2: Work experiences : was fired/dismissed** [0,4] This is asked in the context of the last 4 years with 0 being no times, 1 being once, 2 being 2 times, 3 being 3 or 4 times, and 4 being 5 or more times.
- **G2: Work experiences : contract ended/made redundant** [0,4] This is asked in the context of the last 4 years with 0 being no times, 1 being once, 2 being 2 times, 3 being 3 or 4 times, and 4 being 5 or more times.
- **G2: Work experiences : seeking work for over a month** [0,4] This is asked in the context of the last 4 years with 0 being no times, 1 being once, 2 being 2 times, 3 being 3 or 4 times, and 4 being 5 or more times.
- **Income from Parent** [0,1] G2 receives income support from parent.
- **Other Support from Parent** [0,5] The number of non direct income supports that G2 receives. This is a sum of the following : help with bills, a loan or gift of money, paid education course fees and give substantial material support.

Latent Class Analysis using R

Latent Class Analysis looks for a latent grouping structure that is unobserved to the econometrician, but that can be revealed through the probability of responses to certain indicator variables. It is a probabilistic mechanism to look at class structures, categorising individuals based on their responses into the most likely "type". This classification occurs via the analysis of the structure of the relationship between the observed variables. It used is an alternative to factor analysis, which is creates a variable score for something that is unobserved, and instead focuses on a person centric approach.

I conducted the analysis in R using the poLCA package. I repeated the analysis in MPlus, the statistical programme used for LCA in epidemiology and psychology. This analysis supported the same latent class structure. The repetition of the LCA in another program was important for a number of reasons. First, it provides further assurance that the class structure does exist.

The estimation procedure in R and MPLUS are slightly different but the fact that the same results was obtained when using either is promising sign for its robustness. Second, the poLCA package has more flexible diagnostic tests than MPlus so the use of both allows the testing a number of different aspects of the structure. Third, I can derive the conditional probabilities are reported which are useful for discriminating what is actually going on in the different types.

In this package variables must all be of integer value and positive non zero. Variables were recoded so that these requirements were met. In reality all this meant was recoding a [0,1] ([No, Yes]) variable to [1,2], and a similar plus one procedure for other ordinal variables. For all variables used there was a clear ordering and non ordinal variables such as enter score and occupational score were discretised into quartiles, with increasing magnitude implying higher enter scores and higher occupational scores. Using the full range of integer scores was not possible, in that the model would not converge with that many discrete choices.

I set the maximum number of iterations to 3000, this is the number of iterations through which the estimation algorithm will cycle. The number of times the model will be repeated was set to 10. This meant the entire estimation procedure of 3000 iterations was repeated 10 times. This means the algorithm is likely to find the global - rather than local maximum - of the log likelihood function. In all of the models typically the global was found in 2 to 3 repetitions. First, repeated from earlier in this chapter are the goodness of fit statistics of the latent class analysis.

Table 4.19: Goodness of Fit tests - R

Model (N Class)	Log-likelihood	Resid. df	AIC	BIC	aBIC	cAIC	Entropy
1	-13897.30	989.00	28254.05	28044.43	28320.05	6859.06	-
2	-13411.55	922.00	27748.95	27326.52	27881.95	6404.45	0.712
3	-13063.40	855.00	27519.07	26883.83	27719.07	6147.83	0.784
4	-12922.41	788.00	27703.49	26855.45	27970.49	6016.32	0.784
5	-12802.66	721.00	27930.39	26869.56	28264.39	5848.93	0.819

Notes *AIC, BIC, aBIC and cAIC are various information criteria estimators about the relatively quality of the underlying statistical model. They each adopt a various method for defining 'quality', with no agreed upon definitive best test. The entropy statistic assesses the extent to which the groups identified in a latent class analysis are different from one another, with high values suggesting it is a good model fit.*

As we can see from Table 4.19 the log likelihood decreases as the number of groups increases, as does the residual degrees of freedom. This is built into the

structure of the LCA and as such are not used to determine the best model. Ideally we would have agreement on the other measures of goodness of fit, whereas there is slight disagreement depending on what measure you were to use here. AIC and aBIC both suggest that three classes fit the data best. One useful statistic shown here is the entropy statistic quantifies the uncertainty in a random variable or model via the probability density of probability mass function of that random variable. In LCA it can be interpreted as an estimate of how distinct the identified clusters are from one another. In other words, it assesses the extent to which the groups identified in a latent class analysis are different from one another. Values of entropy approaching one suggest that the model is good fit, with zero being approached when the model is being overfit (i.e. k=n where k is number of classes and n is number of observations). While a five class structure is suggested here the entropy statistic is very close between models with between three and five classes, all of which generate a high entropy statistic of around 80%.

I chose the three class structure based on this goodness of fit table. However, an argument could be made that the four class structure might have been equally valid, with an equal entropy statistic and a lower BIC score. While most statisticians place more weight on the adjusted BIC, it is still worth exploring what a four class structure looks like given the subjective decision by the researcher to use a three, not four class structure. The four class structure kept a structurally well off group, similar to that in the three class structure, with high education, income and skills. It had a likewise, unstable economic group characterised by the lowest income, highest financial difficulties, most number of job changes. The main difference was a split amongst the the structurally disadvantaged group which divided into two, seemingly on a high and low skills basis. While this distinction might have interesting policy implications, it felt that the three group distinction not only fit the data better based on available statistics it was felt representative of the economic divisions in the economy. A three class structure comes at a cost of potentially overlooking meaningful differences amongst people, but has the advantage of simpler interpretations in the first instance.

The following tables (4.20-4.36) show the probability of answering X, given the class type[22], and is given by PR(X). For occupation and enter score I

[22]Remember Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged

divided the cohort into quartiles, with increasing scores indicating higher skilled occupations and higher scores on the end of school exams. For binary variables, 1 is equivalent to answering NO, and 2 is answering YES. These tables can help us figure out what the characteristics of each class are.

Table 4.20: Occupation

	Pr(1)	Pr(2)	Pr(3)	Pr(4)
Class 1:	0	0.084	0.285	0.631
Class 2:	0.090	0.744	0.133	0.033
Class 3:	0.057	0.426	0.310	0.207

Table 4.21: Education

	Pr(1)	Pr(2)	Pr(3)	Pr(4)
Class 1:	0.026	0.064	0.767	0.143
Class 2:	0.454	0.505	0.041	0
Class 3:	0.211	0.307	0.439	0.042

Table 4.22: Enter Score

	Pr(1)	Pr(2)	Pr(3)	Pr(4)
Class 1:	0.021	0.003	0.285	0.692
Class 2:	0.046	0.283	0.552	0.119
Class 3:	0.033	0.123	0.367	0.477

Table 4.23: Unemployed

	Pr(1)	Pr(2)
Class 1:	0.999	0.001
Class 2:	0.978	0.022
Class 3:	0.966	0.034

Table 4.24: Government Allowance

	Pr(1)	Pr(2)
Class 1:	0.968	0.032
Class 2:	0.816	0.184
Class 3:	0.811	0.189

Table 4.25: Income Support Parent

	Pr(1)	Pr(2)
Class 1:	0.989	0.011
Class 2:	0.975	0.025
Class 3:	0.839	0.161

Table 4.26: Other Financial Support - Parent

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)
Class 1:	0.594	0.296	0.092	0.015	0	0.004
Class 2:	0.574	0.281	0.096	0.049	0	0
Class 3:	0.252	0.367	0.168	0.152	0.061	0

Table 4.27: Number Jobs

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)	Pr(9)	Pr(10)	Pr(11)
Class 1:	0	0.376	0.409	0.172	0.038	0	0	0	0.002	0.002	0
Class 2:	0.035	0.511	0.330	0.101	0.009	0.006	0.008	0	0	0	0
Class 3:	0	0.035	0.220	0.366	0.189	0.121	0.022	0.017	0.020	0.007	0.003

Table 4.28: Income

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)	Pr(9)	Pr(10)	Pr(11)	Pr(12)	Pr(13)	Pr(14)	Pr(15)
Class 1:	0.002	0	0.005	0	0.001	0.004	0.008	0.028	0.047	0.096	0.263	0.318	0.128	0.043	0.056
Class 2:	0	0.003	0.0002	0.012	0.013	0.026	0.018	0.070	0.120	0.165	0.237	0.244	0.060	0.014	0.018
Class 3:	0.014	0.006	0.019	0.023	0.056	0.065	0.093	0.101	0.101	0.138	0.214	0.122	0.030	0	0.019

group and Class 3 are the more insecure group.

Table 4.29: Financial Difficulty

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
Class 1:	0.775	0.168	0.040	0.007	0.007	0	0.002	0
Class 2:	0.624	0.161	0.131	0.056	0.020	0.006	0	0.003
Class 3:	0.340	0.227	0.192	0.114	0.085	0.023	0.017	0.003

Table 4.30: WorkEx 1

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1:	0.256	0.321	0.269	0.150	0.003
Class 2:	0.469	0.272	0.172	0.079	0.008
Class 3:	0.529	0.248	0.152	0.068	0.004

Table 4.31: WorkEx 2

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1:	0.525	0.363	0.095	0.014	0.002
Class 2:	0.635	0.303	0.057	0	0.005
Class 3:	0.160	0.377	0.320	0.125	0.017

Table 4.32: WorkEx 3

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1:	0.948	0.052	0	0	0
Class 2:	0.958	0.033	0.006	0	0.003
Class 3:	0.641	0.289	0.056	0.013	0

Table 4.33: WorkEx 4

	Pr(1)	Pr(2)	Pr(3)
Class 1:	0.998	0.002	0
Class 2:	0.996	0.004	0
Class 3:	0.838	0.152	0.010

Table 4.34: WorkEx 5

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1:	0.916	0.066	0.012	0.001	0.005
Class 2:	0.973	0.016	0	0	0.011
Class 3:	0.423	0.372	0.119	0.034	0.051

Summary Statistics

Table 4.35: Summary Statistics of Varibles used to create Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Occupation Score Quartile	3.486	2.065	2.602
	(0.689)	(0.533)	(0.851)
G2: Education	3.044	1.564	2.325
	(0.530)	(0.547)	(0.847)
Enter Score Quartile	3.652	2.705	3.295
	(0.599)	(0.708)	(0.803)
G2: Number of Jobs	1.905	1.596	3.497
	(0.948)	(0.903)	(1.481)
G2: Weekly Income	11.51	10.47	9.017
	(1.814)	(2.026)	(2.786)
G2: Financial Difficulty Score	0.307	0.722	1.578
	(0.692)	(1.135)	(1.545)
G2: Receives Government support	0.0315	0.186	0.190
	(0.175)	(0.390)	(0.393)
G2:Income from parent	0.0105	0.0221	0.170
	(0.102)	(0.147)	(0.377)
G2: Other support from parent	0.560	0.605	1.433
	(0.792)	(0.841)	(1.191)
Promoted	1.319	0.892	0.753
	(1.021)	(1.018)	(0.962)
Intentionally left job	0.594	0.453	1.502
	(0.727)	(0.657)	(0.964)
Dismissed/Fired	0.0519	0.0518	0.466
	(0.222)	(0.313)	(0.671)
Contract ended/made redundant	0.00247	0.00304	0.182
	(0.0497)	(0.0551)	(0.413)
Sought work for more than 1 month	0.106	0.0517	0.976
	(0.423)	(0.399)	(1.078)
N	414	345	296

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Appendix B : Inputs

Proportion missing - by class

Table 4.36: Missing Variables by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Child: Mother Unemployment	0.106	0.113	0.111
	(0.309)	(0.317)	(0.315)
Child: Father Unemployment	0.106	0.107	0.108
	(0.309)	(0.310)	(0.311)
Adolescent: Mother Unemployment	0.0821	0.0783	0.0777
	(0.275)	(0.269)	(0.268)
Adolescent: Father Unemployment	0.0821	0.0783	0.0777
	(0.275)	(0.269)	(0.268)
Adult: Mother Unemployment	0.138	0.194	0.142
	(0.345)	(0.396)	(0.350)
Adult: Father Unemployment	0.140	0.203	0.142
	(0.348)	(0.403)	(0.350)
Child: Marital Shock	0.0290	0.0348	0.0338
	(0.168)	(0.183)	(0.181)
Child: School Moves	0.116	0.104	0.111
	(0.321)	(0.306)	(0.315)
Child: House Moves	0.111	0.107	0.108
	(0.315)	(0.310)	(0.311)
Adolescent: Marital Shock	0.0821	0.0783	0.0777
	(0.275)	(0.269)	(0.268)
Adolescent: School Moves	0.116	0.104	0.111
	(0.321)	(0.306)	(0.315)
Adolescent:House Moves	0.111	0.107	0.108
	(0.315)	(0.310)	(0.311)
Adolescent: Financial Strain	0.181	0.212	0.159
	(0.386)	(0.409)	(0.366)
Adult: Marital Shock	0.138	0.194	0.142
	(0.345)	(0.396)	(0.350)
Adult: Financial Strain	0.145	0.194	0.149
	(0.352)	(0.396)	(0.356)
Father Education	0.00483	0.00580	0.00338
	(0.0694)	(0.0760)	(0.0581)
Mother Education	0.00242	0	0.00338
	(0.0491)	(0)	(0.0581)

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Summary Statistics - by epoch and type

The summary statistics of the non multiply imputed and multiply imputed shocks are shown in Table 4.37 and 4.38. There are very little differences between the two sets of summary statistics, except for in perhaps the imputation of divorce/separations periods. Remember each variable is coded as the number of waves in this time (childhood, adolescence and young adulthood) that they experience this type of shock, from no periods (0) , one period (1) or two or more periods (2). Looking first at maternal and paternal unemployment across all periods. There are higher levels of all types of unemployment across basically all periods (father unemployment in childhood) in class 2 and 3 than class 1. It varies by type and by epoch as to if class 2 or 3 is higher. The levels of unemployment are still not that high overall with the largest being 0.231 of a period on average for fathers of class 3 in childhood.

The average number of periods in which participants are experiencing periods of one parent households (classified as negative marital relations which can be due to divorce, separation, death) increases from childhood through to young adulthood but still the average is quite low (no more than 0.429). This could be from the fact that single parents may not re-couple easily so once you have split up you are more likely to be single in future periods. The group experienced the most strain in childhood is class 2, whereas in adolescence and young adulthood it is again class 3.

For the other shocks of interest - school and house moves - we see that on average kids move school and house about 1.2 times during their childhood. This decreases to about 0.4 in adolescence for both types of move. Financial strain is measured only in adolescence and young adulthood, with again the highest levels experienced by the parents of class 3. The structural characteristics that we felt were important are mothers and fathers education level. This measure is 1 through 4, 1 being high school or less, 2 being some further education, 3 being a bachelors degree and 4 postgraduate degree. The parents of class 2 are much lower educated by about 0.6 less than class 1 and class 3 for fathers education and by about 0.5 less for mothers education. Class 3 have the highest levels of maternal education, with class 1 having the highest father (although these are all very similar). Average education levels aren't that high across the board.

The multiply imputed results make sense. Typically these should adjust for missing variables in the way we would expect. For instance parents who are undergoing a stressful time might be less likely to have taken part in one wave, or to have missed out a question. This will lead to upward adjustment of variables like negative marital status and unemployment.

Raw Data (non multiply imputed)

Table 4.37: Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Child: G1 Mother unemployment	0.165	0.291	0.222
	(0.440)	(0.608)	(0.509)
Child: G1 Father unemployment	0.203	0.184	0.231
	(0.502)	(0.500)	(0.549)
Adolescence: G1 Mother unemployment	0.110	0.188	0.170
	(0.392)	(0.503)	(0.466)
Adolescence: G1 Father unemployment	0.182	0.211	0.208
	(0.475)	(0.516)	(0.501)
Adult: G1 Mother unemployment	0.103	0.157	0.175
	(0.337)	(0.432)	(0.459)
Adult: G1 Father unemployment	0.0997	0.148	0.160
	(0.311)	(0.414)	(0.416)
Child: Negative Marital	0.162	0.327	0.208
	(0.523)	(0.707)	(0.571)
Child: School Moves	1.213	1.135	1.151
	(0.612)	(0.678)	(0.686)
Child: House Moves	1.117	1.085	1.160
	(0.855)	(0.899)	(0.856)
Adolescence: Neg Marital	0.210	0.265	0.335
	(0.582)	(0.627)	(0.706)
Adolescence: School Moves	0.344	0.363	0.434
	(0.604)	(0.583)	(0.646)
Adolescence: House Moves	0.385	0.475	0.472
	(0.672)	(0.696)	(0.738)
Adolescence: Financial Strain	0.399	0.507	0.613
	(0.587)	(0.643)	(0.710)
Adult: Negative Marital	0.268	0.381	0.429
	(0.619)	(0.725)	(0.766)
Adult: Financial Strain	0.316	0.444	0.528
	(0.578)	(0.738)	(0.731)
Fathers Education	2.519	1.987	2.425
	(1.178)	(0.927)	(1.152)
Mothers Education	2.285	1.771	2.311
	(1.188)	(1.003)	(1.183)
N	291	223	212

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Multiple Imputation

Table 4.38: Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Child: G1 Mother unemployment	0.177	0.288	0.238
	(0.462)	(0.593)	(0.530)
Child: G1 Father unemployment	0.213	0.263	0.268
	(0.504)	(0.586)	(0.572)
Adolescence: G1 Mother unemployment	0.103	0.201	0.179
	(0.368)	(0.521)	(0.460)
Adolescence: G1 Father unemployment	0.183	0.221	0.245
	(0.473)	(0.514)	(0.541)
Adult: G1 Mother unemployment	0.107	0.149	0.190
	(0.345)	(0.420)	(0.464)
Adult: G1 Father unemployment	0.128	0.165	0.186
	(0.365)	(0.443)	(0.451)
Child: Negative Marital	0.171	0.309	0.276
	(0.523)	(0.687)	(0.654)
Child: School Moves	1.282	1.279	1.262
	(0.609)	(0.633)	(0.669)
Child: House Moves	1.178	1.183	1.252
	(0.844)	(0.865)	(0.839)
Adolescence Negative Marital	0.220	0.320	0.402
	(0.592)	(0.690)	(0.757)
Adolescence: School Moves	0.336	0.368	0.440
	(0.575)	(0.583)	(0.641)
Adolescence: House Moves	0.349	0.446	0.453
	(0.617)	(0.668)	(0.709)
Adolescence: Financial Strain	0.428	0.566	0.651
	(0.596)	(0.656)	(0.701)
Adult: Negative Marital	0.308	0.436	0.529
	(0.670)	(0.775)	(0.837)
Adult: Financial Strain	0.425	0.584	0.646
	(0.681)	(0.798)	(0.784)
Fathers Education	2.455	1.843	2.373
	(1.152)	(0.881)	(1.125)
Mothers Education	2.216	1.652	2.174
	(1.194)	(0.955)	(1.180)
N	414	345	296

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Cumulative shocks per epoch

The cumulative shocks measure the sum of shocks per period. In childhood there were five shocks resulting in a maximum of ten, in adolescence there were seven shocks so a maximum of fourteen, and young adulthood there are four risks resulting in a maximum of eight. Thus I cannot make any statements about the relative riskiness of any one period in terms of numbers of shocks individuals experience. We can however compare across classes within period. In childhood class 2 experience slightly more shocks on average with a slightly higher variance, but overall similar levels. In comparison the difference from class 1 up to the highest (class 3 now) is much larger in adolescence and young adult.

Raw Data (non multiply imputed)

Table 4.39: Cross Section Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Total Childhood Risk	2.859	3.022	2.972
	(1.607)	(1.967)	(1.706)
Total Adolescent Risk	1.629	2.009	2.231
	(1.657)	(1.753)	(1.905)
Total Adult Risk	0.787	1.130	1.292
	(1.115)	(1.532)	(1.554)
N	291	223	212

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Multiple Imputation

Table 4.40: Cross Section Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Total Childhood Risk	3.022	3.324	3.296
	(1.583)	(1.881)	(1.731)
Total Adolescent Risk	1.621	2.125	2.371
	(1.547)	(1.819)	(1.917)
Total Adult Risk	0.969	1.336	1.553
	(1.238)	(1.555)	(1.643)
N	414	345	296

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Persistent shocks over time

The time series risk sums the number of periods experiencing a shock across the entire life span. Again, the total possible score varies depending on the particular risk. Financial difficulties were only available in adolescence and young adulthood, school and house moves only in childhood and adolescence. In every category bar school moves, class 1 has the lowest risk - and as outlined earlier school moves could be a positive influence. The average number of periods of risk is broadly similar for marital risk, house moves. Financial difficulty and father unemployment are higher for class 3, with mother unemployment higher for class 2.

Raw Data (non multiply imputed)

Table 4.41: Time Series Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Total Mother Unemployment Risk	0.378	0.637	0.566
	(0.840)	(1.169)	(0.998)
Total Father Unemployment Risk	0.485	0.543	0.599
	(0.937)	(1.012)	(1.064)
Total Negative Marital Risk	0.639	0.973	0.972
	(1.463)	(1.727)	(1.779)
Total School Moves Risk	1.557	1.498	1.585
	(0.774)	(0.788)	(0.891)
Total Financial Difficulty Risk	0.715	0.951	1.142
	(0.999)	(1.175)	(1.243)
Total House Moves Risk	1.502	1.561	1.632
	(1.161)	(1.293)	(1.264)
N	291	223	212

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Multiple Imputation

Table 4.42: Time Series Risk Inputs by Latent Class

	Class 1 mean/sd	Class 2 mean/sd	Class 3 mean/sd
Total Mother Unemployment Risk	0.387	0.639	0.607
	(0.820)	(1.138)	(1.005)
Total Father Unemployment Risk	0.525	0.651	0.699
	(0.969)	(1.118)	(1.121)
Total Negative Marital Risk	0.700	1.065	1.208
	(1.508)	(1.817)	(1.941)
Total School Moves Risk	1.617	1.646	1.702
	(0.797)	(0.822)	(0.859)
Total Financial Difficulty Risk	0.853	1.151	1.297
Total House Moves Risk	1.528	1.63	1.705
	(1.098)	(1.193)	(1.189)
N	414	345	296

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group.*

Appendix C : Multiple Imputation Regression Output - Relative Risk Coefficients

These tables show the full set of regressions using the multiple imputation data. All columns include structural characteristics of parental education, parents age and gender of the child. Column A includes childhood shocks, column B is just adolescence shocks, column C is just young adulthood shocks, column D has childhood and adolescence, column E has adolescence and young adulthood, and column F is all three periods. This is the specification in the main part of the chapter.

Main Analysis

Table 4.43: Relative Risk Coefficients Full Model

	A	B	C	D	E	F
2						
Child: G1 Mother	1.586***			1.405*		1.391*
unemployed	(0.263)			(0.254)		(0.252)
Child: G1 Father	0.949			0.902		0.895
unemployed	(0.153)			(0.159)		(0.160)
Child: Neg	1.462***			1.420**		1.439**
Marital	(0.194)			(0.252)		(0.260)
Child: Sch	1.053			1.024		1.020
Moves	(0.161)			(0.160)		(0.160)
Child: House	0.903			0.894		0.888
Moves	(0.0967)			(0.0978)		(0.0982)
Adol: G1 Mother		1.567**		1.368	1.575**	1.395
unemployed		(0.299)		(0.282)	(0.312)	(0.297)
Adol: G1 Father		0.951		0.994	0.913	0.964
unemployed		(0.163)		(0.183)	(0.164)	(0.185)
Adol: Neg		1.208		0.990	1.077	0.868
Marital		(0.154)		(0.166)	(0.196)	(0.193)
Adol: Sch		0.942		0.965	0.939	0.961
Moves		(0.142)		(0.146)	(0.141)	(0.146)
Adol: House		1.204		1.197	1.197	1.197
Moves		(0.156)		(0.161)	(0.156)	(0.162)
Adol: Financial		1.170		1.159	1.126	1.122
Strain		(0.163)		(0.164)	(0.178)	(0.178)
Adult: G1 Mother			1.050		0.930	0.900
unemployed			(0.250)		(0.228)	(0.224)
Adult: G1 Father			1.163		1.133	1.092
unemployed			(0.270)		(0.276)	(0.273)
Adult: Neg			1.252*		1.173	1.187
Marital			(0.148)		(0.201)	(0.208)
Adult: Financial			1.125		1.065	1.063
Strain			(0.136)		(0.147)	(0.148)
Max G1 Fathers	0.684***	0.680***	0.680***	0.686***	0.679***	0.684***
Education	(0.0574)	(0.0570)	(0.0564)	(0.0582)	(0.0572)	(0.0584)
Max G1 Mothers	0.732***	0.743***	0.748***	0.733***	0.742***	0.732***
Education	(0.0591)	(0.0595)	(0.0599)	(0.0596)	(0.0599)	(0.0599)
G1: Fathers Age	1.021	1.019	1.021	1.023	1.020	1.023
	(0.0248)	(0.0249)	(0.0248)	(0.0252)	(0.0252)	(0.0255)
G1: Mothers Age	0.926***	0.938**	0.933**	0.929**	0.938**	0.930**
	(0.0265)	(0.0268)	(0.0265)	(0.0269)	(0.0271)	(0.0272)
G2: Female	0.854	0.867	0.880	0.855	0.871	0.857
	(0.134)	(0.135)	(0.137)	(0.134)	(0.137)	(0.136)

3						
Child: G1 Mother	1.271			1.106		1.070
unemployed	(0.203)			(0.195)		(0.192)
Child: G1 Father	1.137			0.987		0.958
unemployed	(0.184)			(0.179)		(0.177)
Child: Neg	1.319**			0.993		0.989
Marital	(0.178)			(0.177)		(0.177)
Child: Sch	0.884			0.912		0.906
Moves	(0.134)			(0.142)		(0.142)
Child: House	1.078			1.032		1.022
Moves	(0.112)			(0.112)		(0.112)
Adol: G1 Mother		1.309		1.258	1.235	1.206
unemployed		(0.260)		(0.267)	(0.255)	(0.262)
Adol: G1 Father		1.060		1.064	1.001	1.016
unemployed		(0.179)		(0.198)	(0.180)	(0.199)
Adol: Neg		1.339**		1.342*	1.165	1.169
Marital		(0.164)		(0.213)	(0.201)	(0.236)
Adol: Sch		1.252		1.233	1.251	1.232
Moves		(0.179)		(0.181)	(0.181)	(0.183)
Adol: House		1.141		1.143	1.119	1.129
Moves		(0.147)		(0.151)	(0.146)	(0.150)
Adol: Financial		1.533***		1.530***	1.370**	1.373**
Strain		(0.224)		(0.225)	(0.219)	(0.218)
Adult: G1 Mother			1.320		1.214	1.216
unemployed			(0.289)		(0.275)	(0.279)
Adult: G1 Father			1.232		1.185	1.184
unemployed			(0.274)		(0.277)	(0.280)
Adult: Neg			1.363***		1.189	1.192
Marital			(0.152)		(0.187)	(0.188)
Adult: Financial			1.300**		1.154	1.154
Strain			(0.163)		(0.161)	(0.163)
Max G1 Fathers	0.970	1.000	0.976	1.001	1.003	1.003
Education	(0.0778)	(0.0817)	(0.0788)	(0.0824)	(0.0826)	(0.0831)
Max G1 Mothers	1.003	0.993	1.014	0.994	1.001	1.002
Education	(0.0748)	(0.0750)	(0.0767)	(0.0756)	(0.0764)	(0.0769)
G1: Fathers Age	1.012	1.013	1.019	1.014	1.018	1.019
	(0.0245)	(0.0249)	(0.0249)	(0.0252)	(0.0253)	(0.0256)
G1: Mothers Age	0.967	0.975	0.963	0.975	0.971	0.971
	(0.0275)	(0.0280)	(0.0277)	(0.0283)	(0.0282)	(0.0285)
G2: Female	1.127	1.173	1.184	1.167	1.189	1.187
	(0.178)	(0.187)	(0.188)	(0.188)	(0.191)	(0.193)
Observations	1055	1055	1055	1055	1055	1055
Childhood	Yes	No	No	Yes	No	Yes
Adolescence	No	Yes	No	Yes	Yes	Yes
Adult	No	No	Yes	No	Yes	Yes

Notes *Column A includes childhood shocks, column B is just adolescence shocks, column C is just young adulthood shocks, column D has childhood and adolescence, column E has adolescence and young adulthood, and column F is all three periods. Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Class 1 is omitted class. Specification is multinominal logit, and coefficients are relative risk ratios. Standard errors in parentheses. Inputs have been multiply imputed when missing. Cumulative risks were created by summing the individual risks in that period to create a total score per period.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Cumulative risk

Table 4.44: Class Prediction - cross section risk

	A	B	C	D	E	F
2						
Total Childhood Risk	1.093*			1.048		1.039
	(0.0522)			(0.0567)		(0.0566)
Total Adolescent Risk		1.151***		1.131**	1.112*	1.099
		(0.0568)		(0.0627)	(0.0664)	(0.0696)
Total Adult Risk			1.160***		1.090	1.083
			(0.0663)		(0.0757)	(0.0757)
Max G1 Fathers Education	0.675***	0.688***	0.681***	0.687***	0.689***	0.688***
	(0.0557)	(0.0570)	(0.0563)	(0.0571)	(0.0572)	(0.0572)
Max G1 Mothers Education	0.747***	0.744***	0.753***	0.744***	0.747***	0.747***
	(0.0592)	(0.0593)	(0.0598)	(0.0592)	(0.0597)	(0.0597)
G1: Fathers Age	1.021	1.021	1.023	1.020	1.022	1.021
	(0.0244)	(0.0246)	(0.0247)	(0.0246)	(0.0247)	(0.0247)
G1: Mothers Age	0.935**	0.939**	0.932**	0.940**	0.937**	0.938**
	(0.0262)	(0.0265)	(0.0262)	(0.0265)	(0.0266)	(0.0266)
G2: Female	0.860	0.878	0.881	0.870	0.880	0.874
	(0.133)	(0.136)	(0.136)	(0.135)	(0.136)	(0.136)
3						
Total Childhood Risk	1.090*			0.994		0.974
	(0.0514)			(0.0518)		(0.0515)
Total Adolescent Risk		1.275***		1.278***	1.184***	1.194***
		(0.0615)		(0.0675)	(0.0674)	(0.0707)
Total Adult Risk			1.317***		1.190**	1.195**
			(0.0772)		(0.0830)	(0.0845)
Max G1 Fathers Education	0.954	0.993	0.978	0.993	0.998	0.998
	(0.0754)	(0.0801)	(0.0788)	(0.0801)	(0.0810)	(0.0810)
Max G1 Mothers Education	1.002	0.990	1.013	0.990	1.000	1.001
	(0.0741)	(0.0744)	(0.0760)	(0.0744)	(0.0755)	(0.0756)
G1: Fathers Age	1.015	1.013	1.019	1.014	1.016	1.017
	(0.0242)	(0.0245)	(0.0248)	(0.0245)	(0.0247)	(0.0248)
G1: Mothers Age	0.967	0.976	0.963	0.976	0.972	0.971
	(0.0273)	(0.0278)	(0.0275)	(0.0279)	(0.0279)	(0.0280)
G2: Female	1.136	1.175	1.190	1.176	1.188	1.196
	(0.178)	(0.186)	(0.188)	(0.187)	(0.189)	(0.191)
Observations	1055	1055	1055	1055	1055	1055
Childhood	Yes	No	No	Yes	No	Yes
Adolescence	No	Yes	No	Yes	Yes	Yes
Adult	No	No	Yes	No	Yes	Yes

Notes *Column A includes childhood shocks, column B is just adolescence shocks, column C is just young adulthood shocks, column D has childhood and adolescence, column E has adolescence and young adulthood, and column F is all three periods. Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Class 1 is omitted class. Specification is multinominal logit, and coefficients are relative risk ratios. Standard errors in parentheses. Inputs have been multiply imputed when missing.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Persistent risk

Table 4.45: Class Prediction - time section risk

	(1) F
2	
Total Mother Unemp Risk	1.268**
	(0.119)
Total Father Unemp Risk	0.973
	(0.0845)
Total Neg Marital Risk	1.116**
	(0.0557)
Total School Moves Risk	0.984
	(0.109)
Total Finc Diff Risk	1.071
	(0.0831)
Total House Moves Risk	1.011
	(0.0811)
Max G1 Fathers Education	0.685***
	(0.0575)
Max G1 Mothers Education	0.746***
	(0.0599)
G1: Fathers Age	1.022
	(0.0251)
G1: Mothers Age	0.931**
	(0.0268)
G2: Female	0.856
	(0.134)
3	
Total Mother Unemp Risk	1.155
	(0.104)
Total Father Unemp Risk	1.031
	(0.0858)
Total Neg Marital Risk	1.131**
	(0.0544)
Total School Moves Risk	1.050
	(0.123)
Total Finc Diff Risk	1.260***
	(0.103)
Total House Moves Risk	1.035
	(0.0846)
Max G1 Fathers Ed	0.992
	(0.0813)
Max G1 Mothers Ed	1.006
	(0.0761)
G1: Fathers Age	1.017
	(0.0252)
G1: Mothers Age	0.969
	(0.0281)
G2: Female	1.151
	(0.184)
Observations	1055

Notes *Column F is all three periods. Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Class 1 is omitted class. Specification is multinominal logit, and coefficients are relative risk ratios. Standard errors in parentheses. Inputs have been multiply imputed when missing. The risk score was created by summing the number of risks across all periods that risk occured.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D : Complete Case Regression Output - Relative Risk and Marginal Effects

The following tables are the results (marginal effects) using the same procedure and covariates as in the main body of the chapter and in appendix C but now with the sample restricted to those with who had complete data on the relevant inputs. The results between the multiple imputed and complete case are very similar, especially for the more aggregated cumulative and persistent risks approach. In the most broken down approach in the complete case, we now see significant effects of father unemployment in childhood increasing the likelihood of being in class 2. Negative marital shocks in this period also impact being in class 2. Negative marital breakdown in adolescence increase likelihood of being in class 3. Again while these are not found in the larger sample with multiply imputed cases, they still fit the general story of the results that childhood seems to matter for class 2 and later periods for class 3.

Complete case

Table 4.46: Average Marginal Effects

	Outcome 1	Outcome 2	Outcome 3
Child: G1 Mother unemployed	-0.0607	0.0808**	-0.0202
	(0.0393)	(0.0328)	(0.0359)
Child: G1 Father unemployed	0.0451	-0.0627*	0.0176
	(0.0374)	(0.0347)	(0.0339)
Adolescence: G1 Mother unemployed	-0.0324	0.0204	0.0120
	(0.0475)	(0.0404)	(0.0417)
Adolescence: G1 Father unemployed	0.0246	0.00382	-0.0284
	(0.0411)	(0.0364)	(0.0375)
Adult: G1 Mother unemployed	0.00190	-0.0246	0.0227
	(0.0527)	(0.0453)	(0.0452)
Adult: G1 Father unemployed	-0.0793	0.0407	0.0386
	(0.0541)	(0.0463)	(0.0464)
Child: Negative Marital	-0.0578	0.140***	-0.0821**
	(0.0408)	(0.0352)	(0.0370)
Child: School Moves	0.0409	-0.0254	-0.0156
	(0.0308)	(0.0281)	(0.0283)
Child: House Moves	0.0143	-0.0265	0.0122
	(0.0231)	(0.0212)	(0.0215)
Adolescence: Negative Marital	0.0509	-0.121***	0.0700*
	(0.0470)	(0.0445)	(0.0409)
Adolescence: Sch Moves	-0.00737	-0.0303	0.0377
	(0.0309)	(0.0284)	(0.0279)
Adolescence: House Moves	-0.0199	0.0190	0.000879
	(0.0275)	(0.0248)	(0.0253)
Adolescence: Financial Strain	-0.0462	-0.0152	0.0614**
	(0.0322)	(0.0295)	(0.0286)
Adult: Negative Marital	-0.0593	0.0527	0.00657
	(0.0370)	(0.0331)	(0.0325)
Adult: Financial Strain	-0.0347	-0.000729	0.0354
	(0.0322)	(0.0291)	(0.0281)
Fathers Education Level	0.0337*	-0.0459***	0.0122
	(0.0178)	(0.0166)	(0.0168)
Mothers Education Level	0.0246	-0.0633***	0.0387**
	(0.0172)	(0.0163)	(0.0159)
N	726	726	726

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Cumulative risk

Table 4.47: Average Marginal Effects

	Outcome 1	Outcome 2	Outcome 3
Total Childhood Risk	0.00756	0.00654	-0.0141
	(0.0110)	(0.0102)	(0.0102)
Total Adolescent Risk	-0.0175	-0.00448	0.0220**
	(0.0125)	(0.0114)	(0.0112)
Total Young Adult Risk	-0.0423***	0.0127	0.0296**
	(0.0158)	(0.0138)	(0.0135)
Fathers Education Level	0.0374**	-0.0521***	0.0147
	(0.0176)	(0.0168)	(0.0166)
Mothers Education Level	0.0223	-0.0612***	0.0389**
	(0.0171)	(0.0165)	(0.0157)
N	726	726	726

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing number of risks per period.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Persistent risk

Table 4.48: Average Marginal Effects

	Outcome 1	Outcome 2	Outcome 3
Total Mother Unemployment Risk	-0.0401**	0.0367**	0.00343
	(0.0202)	(0.0167)	(0.0172)
Total Father Unemployment Risk	0.0109	-0.0154	0.00445
	(0.0194)	(0.0177)	(0.0172)
Total Negative Marital Risk	-0.0209*	0.0158	0.00508
	(0.0118)	(0.0102)	(0.0102)
Total School Moves Risk	0.0154	-0.0240	0.00861
	(0.0242)	(0.0225)	(0.0224)
Total Financial Difficulty Risk	-0.0423**	-0.00780	0.0501***
	(0.0177)	(0.0160)	(0.0153)
Total House Moves Risk	0.000316	-0.00151	0.00119
	(0.0165)	(0.0152)	(0.0154)
Fathers Education Level	0.0379**	-0.0506***	0.0127
	(0.0176)	(0.0168)	(0.0167)
Mothers Education Level	0.0220	-0.0614***	0.0395**
	(0.0171)	(0.0165)	(0.0159)
N	726	726	726

Notes *Class 1 is the typical advantaged group, Class 2 is the typical disadvantaged group and Class 3 is the more insecure group. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing across period per risk.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E : Comparison of LCA to typical measures of SES

This paper proposes a different way to think about socio-economic class. This was motivated by a number of reasons, namely due to the changing economy and the desire for a holistic measure of socio-economic status. One useful exercise is to compare the results from the estimation using LCA class as an outcome compared to one of the more traditional measures such as income or education. This can help us to think through when this new measure might be most useful, but also what are the disadvantages compared to using a more standard outcome measure. There may be some circumstances in which the broken down SES categories make more sense, depending on the research/policy question. One problem of using outcomes like education and income is the simultaneity of these outcomes for instance your education level is going to partly determine your income.

I compare the results for the three types of risk in the complete case analysis to the same specification but instead using either income or education as an outcome. These were chosen because they are two of the most commonly used indicators of socio-economic well being. I cannot use unemployment as a comparison due to the tiny proportion of individuals who were unemployed at wave fifteen (as discussed earlier). To try and make the results comparable to the LCA I split education and income into three groups. There were a number of possible ways to split the data which potentially could affect the results. For education there was an intuitive split into those with high school or less education, for those who went on to further education that wasn't university, and then those who went on to university for either bachelor, masters or doctorate level. This roughly corresponds with the three LCAs we have where class 1 would be the top education, class 2 would be the lowest and class 3 the middle. Although there is still a range of education levels within each class as can be seen in Table 4.21[23]. This roughly divides the sample into thirds.

For income there was not a clear delineation into thirds. The weekly income had fifteen discrete bins and ranged from no income up to $2200 or above. The size of the bins vary from $50 increments for the second and third bin,

[23]In Table 4.21 education is increasing from 1 to 4, whereas in the analysis that follows education is decreasing from 1 to 3 to make it comparable to the classes.

then seven $100 bins from $100-$799, the eleventh bin is 800-999, the twelth and thirteenth are of $499, the fourteenth from $2000-2199 with the last bin anything above this. The majority of people had income between $700 and $1499. To try to distribute the numbers evenly but also to capture the natural divisions in earnings, I created three groups. The first had income over $1000 a week, the second had income between $700 and $1000 with the third group having income less than $700.

Table 4.49 shows the numbers of people in each class and what group they would be in for education and income. As can be seen across the main diagonal there is a lot of overlap in the classifications. The off diagonals shows that differences do emerge between the simple uni-dimensional classification and the LCA classification.

Table 4.49: Crosstab across group and education and income

	Education			Income		
LCA	1	2	3	1	2	3
1	380	22	9	221	145	42
2	9	175	158	111	133	87
3	143	92	60	48	104	142

Notes *LCA Class 1 is the typical advantaged group, LCA Class 2 is the typical disadvantaged group and LCA Class 3 is the more insecure group.*

The results from using education and income for the three classifications of risk are shown below, with education results in table 4.50-4.52 and income in tables 4.53-4.55. These can be compared to the complete case margins in Appendix D for latent class, tables 4.46-4.48. In the disaggregated estimation, the results for education are somewhat similar to those of the latent class. There are however some differences, in that school moves now seem to increase likelihood of being in the lowest level of education (equivalent broadly to being in class 2). It is not as clear cut that events in childhood increase likelihood of being in lowest education group and events in adolescence seem to be related to being in class 3 - which was the finding of the latent class approach. For income there was very little significance of anything bar potentially young adult negative marital, something that was significant for education too but not for the latent class.

When comparing the results from the cross section there are again slightly

different significant findings, for income young adult risk increases the likelihood of being in the lowest income group - which is consistent with the latent class ; whereas for education only adolescent risk seems to matter increasing likelihood of having lowest levels of education. This is a bit different than latent class analysis, when it increased likelihood of being in class 3 - which had higher average education than class 2. Education levels matter for persistence of education, more so than income. Again for income there is basically no effect of the time aggregated risk factors. There does seem to be effects on education, with negative marital status increasing likelihood of being in the middle education group (which is still quite low) and financial difficulties increasing likelihood of being in the very low education group. Again these are different than the conclusions from the persistent risk.

Table 4.50: Average Marginal Effects Education

	Education 1	Education 2	Education 3
Child: G1 Mother unemployed	-0.0158	0.0270	-0.0112
	(0.0379)	(0.0339)	(0.0308)
Child: G1 Father unemployed	-0.00251	-0.0438	0.0463*
	(0.0382)	(0.0365)	(0.0256)
Adolescence: G1 Mother unemployed	-0.0293	0.0105	0.0187
	(0.0455)	(0.0404)	(0.0342)
Adolescence: G1 Father unemployed	0.0220	-0.00333	-0.0186
	(0.0408)	(0.0380)	(0.0296)
Adult: G1 Mother unemployed	-0.0124	0.00591	0.00649
	(0.0512)	(0.0467)	(0.0362)
Adult: G1 Father unemployed	-0.0194	0.0701	-0.0507
	(0.0518)	(0.0461)	(0.0411)
Child: Negative Marital	-0.0886**	0.0995***	-0.0109
	(0.0393)	(0.0342)	(0.0303)
Child: School Moves	0.0219	0.0229	-0.0448*
	(0.0309)	(0.0283)	(0.0238)
Child: House Moves	0.0156	-0.0232	0.00767
	(0.0232)	(0.0214)	(0.0185)
Adolescence: Negative Marital	0.0251	0.0187	-0.0438
	(0.0467)	(0.0432)	(0.0361)
Adolescence: School Moves	-0.0268	0.0164	0.0104
	(0.0307)	(0.0281)	(0.0233)
Adolescence: House Moves	-0.00783	-0.0402	0.0480**
	(0.0274)	(0.0258)	(0.0204)
Adolescence: Financial Strain	-0.0335	-0.000652	0.0342
	(0.0320)	(0.0298)	(0.0242)
Adult: Negative Marital	-0.0124	-0.0467	0.0591**
	(0.0368)	(0.0357)	(0.0264)
Adult: Financial Strain	-0.0187	-0.00905	0.0277
	(0.0316)	(0.0296)	(0.0234)
Fathers Education Level	0.0501***	-0.0158	-0.0343**
	(0.0177)	(0.0169)	(0.0147)
Mothers Education Level	0.0603***	-0.0176	-0.0427***
	(0.0171)	(0.0165)	(0.0148)
N	720	720	720

Notes *Education 1 is the highest education group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.51: Average Marginal Effects Education

	Education 1	Education 2	Education 3
Total Childhood Risk	-0.00144	0.00818	-0.00674
	(0.0110)	(0.0102)	(0.00871)
Total Adolescent Risk	-0.0196	-0.00103	0.0206**
	(0.0124)	(0.0116)	(0.00931)
Total Young Adult Risk	-0.0186	0.000876	0.0178
	(0.0154)	(0.0143)	(0.0112)
Fathers Education Level	0.0566***	-0.0246	-0.0320**
	(0.0175)	(0.0168)	(0.0147)
Mothers Education Level	0.0595***	-0.0112	-0.0482***
	(0.0170)	(0.0164)	(0.0149)
N	720	720	720

Notes *Education 1 is the highest education group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing number of risks per period.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.52: Average Marginal Effects Education

	Education 1	Education 2	Education 3
Total Mother Unemp Risk	-0.0200	0.0201	-0.0000963
	(0.0189)	(0.0169)	(0.0142)
Total Father Unemp Risk	0.00288	-0.00533	0.00244
	(0.0193)	(0.0179)	(0.0140)
Total Negative Marital Risk	-0.0239**	0.0185*	0.00547
	(0.0113)	(0.0101)	(0.00862)
Total School Moves Risk	-0.00903	0.0247	-0.0157
	(0.0242)	(0.0223)	(0.0191)
Total Financial Difficulty Risk	-0.0248	-0.00927	0.0341***
	(0.0173)	(0.0162)	(0.0126)
Total House Moves Risk	0.00692	-0.0286*	0.0217*
	(0.0165)	(0.0154)	(0.0128)
Fathers Education Level	0.0564***	-0.0211	-0.0353**
	(0.0175)	(0.0168)	(0.0148)
Mothers Education Level	0.0603***	-0.0139	-0.0464***
	(0.0170)	(0.0164)	(0.0149)
N	720	720	720

Notes *Education 1 is the highest education group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing across periods per risk.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.53: Average Marginal Effects Income

	Income 1	Income 2	Income 3
Child: G1 Mother unemployed	0.0407	-0.0201	-0.0206
	(0.0374)	(0.0390)	(0.0347)
Child: G1 Father unemployed	-0.0168	0.00919	0.00760
	(0.0383)	(0.0380)	(0.0325)
Adolescence:G1 Mother unemployed	-0.0448	0.0308	0.0139
	(0.0453)	(0.0463)	(0.0405)
Adolescence: G1 Father unemployed	-0.0169	-0.0102	0.0270
	(0.0413)	(0.0416)	(0.0345)
Adult: G1 Mother unemployed	0.0355	-0.0953*	0.0598
	(0.0503)	(0.0538)	(0.0420)
Adult: G1 Father unemployed	0.0492	-0.0781	0.0289
	(0.0506)	(0.0558)	(0.0452)
Child: Negative Marital	0.00972	0.0468	-0.0566
	(0.0396)	(0.0382)	(0.0355)
Child: School Moves	-0.0249	0.0452	-0.0202
	(0.0313)	(0.0316)	(0.0278)
Child: House Moves	-0.0160	-0.00263	0.0186
	(0.0232)	(0.0237)	(0.0211)
Adolescence: Negative Marital	0.0281	-0.00246	-0.0257
	(0.0469)	(0.0458)	(0.0398)
Adolescence: Sch Moves	-0.0106	-0.0191	0.0297
	(0.0312)	(0.0320)	(0.0273)
Adolescence: House Moves	0.0272	-0.0245	-0.00276
	(0.0272)	(0.0282)	(0.0248)
Adolescence: Financial Strain	-0.0215	0.0186	0.00286
	(0.0322)	(0.0326)	(0.0287)
Adult: Negative Marital	-0.0830**	0.0108	0.0723**
	(0.0388)	(0.0370)	(0.0300)
Adult: Financial Strain	-0.000497	-0.000148	0.000645
	(0.0319)	(0.0322)	(0.0280)
Fathers Education Level	0.0132	-0.0335*	0.0203
	(0.0182)	(0.0185)	(0.0165)
Mothers Education Level	0.00717	0.00371	-0.0109
	(0.0175)	(0.0179)	(0.0161)
N	708	708	708

Notes *Income 1 is the highest income group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.54: Average Marginal Effects Income

	Income 1	Income 2	Income 3
Total Childhood Risk	-0.00768	0.0157	-0.00807
	(0.0111)	(0.0111)	(0.00990)
Total Adolescent Risk	-0.00346	-0.00275	0.00621
	(0.0124)	(0.0127)	(0.0111)
Total Young Adult Risk	-0.0115	-0.0169	0.0284**
	(0.0153)	(0.0156)	(0.0130)
Fathers Education Level	0.00954	-0.0322*	0.0227
	(0.0180)	(0.0183)	(0.0163)
Mothers Education Level	0.00623	0.00713	-0.0134
	(0.0173)	(0.0177)	(0.0159)
N	708	708	708

Notes *Income 1 is the highest income group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing number of risks per period.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.55: Average Marginal Effects Income

	Income 1	Income 2	Income 3
Total Mother Unemployment Risk	0.0134	-0.0193	0.00592
	(0.0188)	(0.0195)	(0.0164)
Total Father Unemployment Risk	-0.00216	-0.0174	0.0195
	(0.0193)	(0.0197)	(0.0162)
Total Negative Marital Risk	-0.0189	0.0148	0.00410
	(0.0119)	(0.0113)	(0.00999)
Total School Moves Risk	-0.0186	0.0174	0.00117
	(0.0246)	(0.0247)	(0.0218)
Total Financial Difficulty Risk	-0.0134	0.00168	0.0117
	(0.0175)	(0.0177)	(0.0153)
Total House Moves Risk	0.00299	-0.00929	0.00630
	(0.0167)	(0.0169)	(0.0150)
Fathers Education Level	0.00875	-0.0306*	0.0219
	(0.0181)	(0.0184)	(0.0165)
Mothers Education Level	0.00867	0.00485	-0.0135
	(0.0174)	(0.0178)	(0.0160)
N	708	708	708

Notes *Income 1 is the highest income group, with 2 and 3 being lower levels. Coefficients are the marginal probability increase of being in each group due to a one unit increase in the shock variables. Standard errors in parentheses. Risk scores were calculated by summing across periods per risk.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5

Conclusion

This thesis studies how human capital develops in the earliest years of a child's life, as well as examining how shocks over the the child's lifespan impact later socio-economic status. While lacking clear identification it provides thought-provoking evidence of some interesting patterns that informs the literature on human capital and the impact of risk factors on SES.

Chapter 2 looked at the impact of preschool on cognitive and health outcomes in four LMICs: Ethiopia, India, Peru and Vietnam. There was little evidence for any impact on cognitive and health outcomes at age 5 and 8 in India, but for every other country there seemed to be positive impacts of additional hours of schooling. This occurred through an increase in concurrent cognitive skills, with some evidence on a preschool readiness channel in Ethiopia. There were no effects of preschool on health outcomes. Future work should focus on developing the links between preschool quality and child outcomes, as well as attempting to account for the endogeneity of the preschool decision.

Chapter 3 introduced and explored the use of a psychosocial variable: tem-

perament and its potential role in the production function of cognitive and socio-emotional skills. It argues that temperament, an early measure of personality, is fundamentally different than constructs like grit, motivation or behavioural-based measures of socio-emotional skills and should be included as an important input in production function estimation. There is suggestive evidence that parents invest less in their child the more difficult the temperament, which results in lower skills. There were few definitive conclusions about temperament's impact on cognitive skills, with some suggestive evidence that it is related to non-verbal skills. There were connections between temperament and measures of socio-emotional skills. However, the current methods used to measure these variables make it difficult to evaluate the role of temperament in predicting skills. Nevertheless, the chapter highlights the importance of continued work on measurement of key variables as well as closer work with psychologists and child development specialists when thinking about the process of skill accumulation.

Chapter 4 examined the effect different types of shocks that occur at different points in the lifespan (childhood, adolescence and emerging adulthood) have on SES outcomes at adulthood. It proposes a new method to categorise individuals into SES classes and correlates these types with different risk factors. It showed that there are benefits to thinking about risk in different ways: both type- and time- specific shocks, cumulative shocks in each period and the persistent build up of shocks over time. This can help us to think more broadly about risk factors. It also linked this classification with outcomes of the next generation, exploiting the rich multigenerational nature of the data available. Further work may be able to answers questions about intergenerational mobility, as well as using latent class analysis in other datasets to see if a similar classification emerges.

Taken together, my thesis has examined the process of human capital development, focusing on preschool and temperament as potential important inputs in skill accumulation. It also linked a variety of risk factors to later socio-economic status and highlighted how this can influence skills of the next generation.

Bibliography

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

Aizer, Anna, and Flavio Cunha. 2012. "The production of human capital: Endowments, investments and fertility." National Bureau of Economic Research.

Akee, Randall KQ, William E Copeland, Gordon Keeler, Adrian Angold, and E Jane Costello. 2010. "Parents' incomes and children's outcomes: a quasi-experiment using transfer payments from casino profits." *American Economic Journal: Applied Economics*, 2(1): 86–115.

Allport, G.W. 1937. *Personality: a Psychological Interpretation.* Oxford, England:Holt.

Almond, Douglas, and Bhashkar Mazumder. 2013. "Fetal origins and parental responses." *Annu. Rev. Econ.*, 5(1): 37–56.

Almond, Douglas, and Janet Currie. 2010. "Human Capital Development Before Age Five." National Bureau of Economic Research Working Paper 15827.

Almond, Douglas, and Janet Currie. 2011. "Killing Me Softly: The Fetal Origins Hypothesis." *Journal of Economic Perspectives*, 25(3): 153–72.

Almond, Douglas, Janet Currie, and Valentina Duque. 2017. "Childhood circumstances and adult outcomes: Act II." National Bureau of Economic Research.

Amato, Paul R. 2010. "Research on divorce: Continuing trends and new developments." *Journal of marriage and family*, 72(3): 650–666.

Amato, Paul R, and Christopher J Anthony. 2014. "Estimating the effects of parental divorce and death with fixed effects models." *Journal of Marriage and Family*, 76(2): 370–386.

Ames, Patricia, Vanessa Rojas, and Tamia Portugal. 2009. *Starting school: who is prepared? Young Lives' research on children's transition to first grade in Peru.* Young Lives.

Apps, Patricia, Silvia Mendolia, and Ian Walker. 2013. "The impact of pre-school on adolescents' outcomes: Evidence from a recent English cohort." *Economics of education review*, 37: 183–199.

Arcidiacono, Peter, and John Bailey Jones. 2003. "Finite mixture distributions, sequential likelihood and the EM algorithm." *Econometrica*, 71(3): 933–946.

Arnett, Jeffrey Jensen. 2000. "Emerging adulthood: A theory of development from the late teens through the twenties." *American psychologist*, 55(5): 469.

Arria, Amelia M, Chris Derauf, Linda L LaGasse, Penny Grant, Rizwan Shah, Lynne Smith, William Haning, Marilyn Huestis, Arthur Strauss, Sheri Della Grotta, et al. 2006. "Methamphetamine and other substance use during pregnancy: preliminary estimates from the Infant Development, Environment, and Lifestyle (IDEAL) study." *Maternal and child health journal*, 10(3): 293.

Attanasio, Orazio, Costas Meghir, and Emily Nix. 2015. "Human capital development and parental investment in india." National Bureau of Economic Research.

Attanasio, Orazio, Costas Meghir, Emily Nix, and Francesca Salvati. 2017. "Human capital growth and poverty: Evidence from Ethiopia and Peru." *Review of economic dynamics*, 25: 234–259.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina. 2015. "Estimating the production function

for human capital: Results from a randomized control trial in Colombia." National Bureau of Economic Research.

Australia's mothers and babies - 2015 in brief: Australian Institute of Health and Welfare. 2017*b*. "Australia's mothers and babies - 2015 in brief: Australian Institute of Health and Welfare." Australian Institute of Health and Welfare.

Azuma, Scott D, and Ira J Chasnoff. 1993. "Outcome of children prenatally exposed to cocaine and other drugs: a path analysis of three-year data." *Pediatrics*, 92(3): 396–402.

Barnett, W Steven. 2011. "Effectiveness of early educational intervention." *Science*, 333(6045): 975–978.

Bates, J.E. Bayles, K. 1988. "Attachment and the development of Behavior Problems." In *Clinical implications of attachment.* , ed. J. Belsky T. Nezworski, 253–299. Hillsdale, NJ:Lawrence Erlbaum.

Bates, John E, Alice C Schermerhorn, and Isaac T Petersen. 2012. "Temperament and parenting in developmental perspective." *Handbook of temperament*, 425–441.

Bates, John E, Claire A Bennett Freeland, and Mary L Lounsbury. 1979. "Measurement of infant difficultness." *Child development*, 794–803.

Becker, Gary S. 1962. "Investment in human capital: A theoretical analysis." *Journal of political economy*, 70(5, Part 2): 9–49.

Becker, Gary S. 2009. *Human capital: A theoretical and empirical analysis, with special reference to education.* University of Chicago press.

Becker, G. S, and N. Tomes. 1976. "Child endowments and the quantity and quality of children." *Journal of political Economy*, 84(4, Part 2): S143–S162.

Behrman, Jere R, John Hoddinott, John A Maluccio, Erica Soler-Hampejsek, Emily L Behrman, Reynaldo Martorell, Manuel Ramírez-Zea, and Aryeh D Stein. 2014. "What determines adult cognitive skills? Influences of pre-school, school, and post-school experiences in Guatemala." *Latin American economic review*, 23(1): 4.

Belley, Philippe, and Lance Lochner. 2007. "The changing role of family income and ability in determining educational achievement." *Journal of Human capital*, 1(1): 37–89.

Berlinski, Samuel, Sebastian Galiani, and Marco Manacorda. 2008. "Giving children a better start: Preschool attendance and school-age profiles." *Journal of public Economics*, 92(5-6): 1416–1440.

Berlinski, Samuel, Sebastian Galiani, and Paul Gertler. 2009. "The effect of pre-primary education on primary school performance." *Journal of Public Economics*, 93(1-2): 219–234.

Bernardi, Fabrizio, and Jonas Radl. 2014. "The long-term consequences of parental divorce for children?s educational attainment." *Demographic research*, 30: 1653–1680.

Betram, Tony, and Christine Pascal. 2011. "The OECD Thematic Review of Early Childhood Education and Care : Background Report for the United Kingdom."

Black, Sandra E, Aline Bütikofer, Paul J Devereux, and Kjell G Salvanes. 2013. "This is only a test - the long-run impacts of prenatal exposure to radioactive fallout." National Bureau of Economic Research.

Black, Sandra, Paul J Devereux, and Kjell Salvanes. 2014. "Does grief transfer across generations? In-utero deaths and child outcomes." National Bureau of Economic Research.

Boardman, Anthony E, and Richard J Murnane. 1979. "Using panel data to improve estimates of the determinants of educational achievement." *Sociology of education*, 113–121.

Borghans, Lex, Angela Lee Duckworth, James J Heckman, and Bas Ter Weel. 2008. "The economics and psychology of personality traits." *Journal of human Resources*, 43(4): 972–1059.

Bornstein, Marc H, Martha E Arterberry, and Michael E Lamb. 2013. *Development in infancy: A contemporary introduction.* Psychology Press.

Bornstein, M. H., D. L. Putnick, M. A. Gartstein, C.S Hahn, N. Auestad, and D. L. O'Connor. 2015. "Infant Temperament: Stability

by Age, Gender, Birth Order, Term Status, and SES." *Child Development*, 86(3): 844–863.

Bouchard, T. J, and J. C Loehlin. 2001. "Genes, evolution, and personality." *Behavior genetics*, 31(3): 243–273.

Bouguen, Adrien, Deon Filmer, Karen Macours, and Sophie Naudeau. 2018. "Preschool and Parental Response in a Second Best World Evidence from a School Construction Experiment." *Journal of Human Resources*, 53(2): 474–512.

Bould, Helen, Carol Johnson, Jonathan Sterne, and Ricardo. Araya. 2013. "The emotionality activity sociability temperament survey: factor analysis and temporal stability in a longitudinal cohort." *Personality and Individual Differences*, 54: 628–633.

Braungart-Rieker, Julia M, Ashley L Hill-Soderlund, and Jan Karrass. 2010. "Fear and anger reactivity trajectories from 4 to 16 months: The roles of temperament, regulation, and maternal sensitivity." *Developmental psychology*, 46(4): 791.

Briggs-Gowan, Margaret J, Alice S Carter, Julia R Irwin, Karen Wachtel, and Domenic V Cicchetti. 2004. "The Brief Infant-Toddler Social and Emotional Assessment: screening for social-emotional problems and delays in competence." *Journal of pediatric psychology*, 29(2): 143–155.

Briggs-Gowan, Margaret J, and Alice S Carter. 2008. "Social-emotional screening status in early childhood predicts elementary school outcomes." *Pediatrics*, 121(5): 957–962.

Buss, A.H., and R. Plomin. 1984. *Temperament: Early Developing Personality Traits.* Hillsdale, NJ:Erlbaum.

Cameron, J. R. 1978. "Parental treatment, children's temperament, and the risk of childhood behavioral problems: 2. Initial temperament, parental attitudes, and the incidence and form of behavioral problems." *American Journal of Orthopsychiatry*, 48(1): 140.

Camilli, Gregory, Sadako Vargas, Sharon Ryan, and W Steven Barnett. 2010. "Meta-analysis of the effects of early education interventions on cognitive and social development." *Teachers college record*, 112(3): 579–620.

Carneiro, Pedro, Flavio Cunha, and James J Heckman. 2003. "Interpreting the evidence of family influence on child development." *The economics of early childhood development: lessons for economic Policy.*

Carneiro, Pedro Manuel, Italo Lopez Garcia, Kjell G Salvanes, and Emma Tominey. 2015. "Intergenerational mobility and the timing of parental income."

Carneiro, Pedro Manuel, Kjell G Salvanes, and Emma Tominey. 2016. "Family Income Shocks and Adolescent Human Capital."

Caspi, Avshalom, HonaLee Harrington, Barry Milne, James W Amell, Reremoana F Theodore, and Terrie E Moffitt. 2003. "Children's behavioral styles at age 3 are linked to their adult personality traits at age 26." *Journal of personality*, 71(4): 495–514.

Cattell, Raymond B. 1963. "Theory of fluid and crystallized intelligence: A critical experiment." *Journal of educational psychology*, 54(1): 1.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment." *American Economic Review*, 106(4): 855–902.

Coelli, Michael B. 2011. "Parental job loss and the education enrollment of youth." *Labour Economics*, 18(1): 25–35.

Coley, Rebekah Levine, and Melissa Kull. 2016. "Cumulative, Timing-Specific, and Interactive Models of Residential Mobility and Children's Cognitive and Psychosocial Skills." *Child development*, 87(4): 1204–1220.

Connelly, Roxanne, Vernon Gayle, and Paul S Lambert. 2016. "A Review of occupation-based social classifications for social survey research." *Methodological Innovations*, 9: 2059799116638003.

Conti, Gabriella, Mark A Hanson, Hazel Inskip, Sarah Crozier, Cyrus Cooper, and Keith Godfrey. 2018. "Beyond birth weight: The origins of human capital." IFS Working Papers.

Cueto, Santiago, Alejandra Miranda, Juan León, and M Vásquez. 2016. "Education trajectories: From early childhood to early adulthood in Peru."

Cunha, Flavio, and James Heckman. 2007. "The technology of skill formation." *American Economic Review*, 97(2): 31–47.

Cunha, Flavio, and James J Heckman. 2008. "Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation." *Journal of human resources*, 43(4): 738–782.

Cunha, Flavio, James J Heckman, and Susanne M Schennach. 2010. "Estimating the technology of cognitive and noncognitive skill formation." *Econometrica*, 78(3): 883–931.

Currie, Janet. 2001. "Early childhood education programs." *Journal of Economic perspectives*, 15(2): 213–238.

Dahly, D, and M Gilthorpe. 2011. "P1-16 A latent class analysis of socioeconomic status and obesity in young adults from Cebu, Philippines." *Journal of Epidemiology & Community Health*, 65(Suppl 1): A71–A71.

Del Boca, Daniela, Christopher Flinn, and Matthew Wiswall. 2013. "Household choices and child development." *Review of Economic Studies*, 81(1): 137–185.

Delvecchio, Giuseppe, M Bellani, Alfredo Carlo Altamura, and Paolo Brambilla. 2016. "The association between the serotonin and dopamine neurotransmitters and personality traits." *Epidemiology and psychiatric sciences*, 25(2): 109–112.

Dempster, Arthur P, Nan M Laird, and Donald B Rubin. 1977. "Maximum likelihood from incomplete data via the EM algorithm." *Journal of the Royal Statistical Society: Series B (Methodological)*, 39(1): 1–22.

Dercon, Stefan, and Alan Sánchez. 2013. "Height in mid childhood and psychosocial competencies in late childhood: Evidence from four developing countries." *Economics & Human Biology*, 11(4): 426–432.

de Wolff, Marianne S, Meinou HC Theunissen, Anton GC Vogels, and Sijmen A Reijneveld. 2013. "Three questionnaires to detect psychosocial problems in toddlers: a comparison of the BITSEA, ASQ: SE, and KIPPPI." *Academic pediatrics*, 13(6): 587–592.

Dorling, Danny. 2014. "Thinking about class." *Sociology*, 48(3): 452–462.

Doyle, Orla, Colm Harmon, James J Heckman, Caitriona Logue, and Seong Moon. 2013. "Measuring investment in human capital formation: An experimental analysis of early life outcomes." National Bureau of Economic Research.

Doyle, Orla, Colm P Harmon, James J Heckman, and Richard E Tremblay. 2009. "Investing in early human development: timing and economic efficiency." *Economics & Human Biology*, 7(1): 1–6.

Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly. 2007. "Grit: perseverance and passion for long-term goals." *Journal of personality and social psychology*, 92(6): 1087.

Duncan, Greg J, and Katherine Magnuson. 2013. "Investing in preschool programs." *Journal of Economic Perspectives*, 27(2): 109–32.

Dyson, Margaret W, Thomas M Olino, C Emily Durbin, H Hill Goldsmith, Sara J Bufferd, Anna R Miller, and Daniel N Klein. 2015. "The structural and rank-order stability of temperament in young children based on a laboratory-observational measure." *Psychological assessment*, 27(4): 1388.

Edin, Per-Anders, Peter Fredriksson, Martin Nybom, and Bjorn Ockert. 2018. "The rising return to non-cognitive skill."

Education in Vietnam, development history, challenges and solutions. 2005*b*. "Education in Vietnam, development history, challenges and solutions."

EDUCATION LAW. No. 38/2005/QH11 of June 14, 2005. 2005*a*. "EDUCATION LAW. No. 38/2005/QH11 of June 14, 2005." Vietnamese Government.

Eisenberg, Nancy, Maša Vidmar, Tracy L Spinrad, Natalie D Eggum, Alison Edwards, Bridget Gaertner, and Anne Kupfer. 2010. "Mothers' teaching strategies and children's effortful control: A longitudinal study." *Developmental psychology*, 46(5): 1294.

English Homeownership 2017-2018. 2019*b*. "English Homeownership 2017-2018." English Housing Survey.

Erikson, Robert, John H Goldthorpe, and Lucienne Portocarero. 1982. "Social fluidity in industrial nations: England, France and Sweden." *The British Journal of Sociology*, 33(1): 1–34.

Evans, Gary W, Dongping Li, and Sara Sepanski Whipple. 2013. "Cumulative risk and child development." *Psychological Bulletin*, 139(6): 1342.

Fairley, Lesley, Baltica Cabieses, Neil Small, Emily S Petherick, Debbie A Lawlor, Kate E Pickett, and John Wright. 2014. "Using latent class analysis to develop a model of the relationship between socioeconomic position and ethnicity: cross-sectional analyses from a multi-ethnic birth cohort study." *BMC public health*, 14(1): 835.

Felitti, Vincent J, Robert F Anda, Dale Nordenberg, David F Williamson, Alison M Spitz, Valerie Edwards, Mary P Koss, and James S Marks. 1998. "Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The Adverse Childhood Experiences (ACE) Study." *American journal of preventive medicine*, 14(4): 245–258.

Ferreira, Francisco HG, and Norbert Schady. 2009. "Aggregate economic shocks, child schooling, and child health." *The World Bank Research Observer*, 24(2): 147–181.

Fessler, Pirmin, and Alyssa Schneebaum. 2019. "The educational and labor market returns to preschool attendance in Austria." *Applied Economics*, 1–20.

Field, Tiffany. 2011. "Prenatal depression effects on early development: a review." *Infant behavior and development*, 34(1): 1–14.

Fiorini, Mario, and Michael P. Keane. 2014. "How the Allocation of Children's Time Affects Cognitive and Noncognitive Development." *Journal of Labor Economics*, 32(4): 787–836.

Frankenberg, Elizabeth, and Duncan Thomas. 2017. "Human Capital and Shocks: Evidence on Education, Health, and Nutrition." In *The Economics of Poverty Traps*. University of Chicago Press.

Frimmel, Wolfgang, Martin Halla, and Rudolf Winter-Ebmer. 2016. "How does parental divorce affect children's long-term outcomes?"

Galobardes, Bruna, Mary Shaw, Debbie A Lawlor, John W Lynch, and George Davey Smith. 2006*a*. "Indicators of socioeconomic position (part 1)." *Journal of Epidemiology & Community Health*, 60(1): 7–12.

Galobardes, Bruna, Mary Shaw, Debbie A Lawlor, John W Lynch, and George Davey Smith. 2006*b*. "Indicators of socioeconomic position (part 2)." *Journal of Epidemiology & Community Health*, 60(2): 95–101.

Garces, Eliana, Duncan Thomas, and Janet Currie. 2002. "Longer-term effects of Head Start." *American economic review*, 92(4): 999–1012.

García, Jorge Luis, James J Heckman, Duncan Ermini Leaf, and María José Prados. 2016. "The life-cycle benefits of an influential early childhood program." National Bureau of Economic Research.

García, Jorge Luis, James J Heckman, Duncan Ermini Leaf, and María José Prados. 2016. "The Life-cycle Benefits of an Influential Early Childhood Program." National Bureau of Economic Research Working Paper 22993.

Gertler, Paul. 2004. "Do conditional cash transfers improve child health? Evidence from PROGRESA's control randomized experiment." *American economic review*, 94(2): 336–341.

Gertler, Paul, David I Levine, and Minnie Ames. 2004. "Schooling and parental death." *Review of Economics and Statistics*, 86(1): 211–225.

Gertler, Paul, James Heckman, Rodrigo Pinto, Arianna Zanolini, Christel Vermeerch, Susan Walker, Susan Chang-Lopez, and Sally

Grantham-McGregor. 2013. *Labor market returns to early childhood stimulation: A 20-year followup to an experimental intervention in Jamaica.* The World Bank.

Goldberg, Lewis R. 1993. "The structure of phenotypic personality traits." *American psychologist*, 48(1): 26.

Goldsmith, H. H. 1983. "Genetic Influences on Personality from Infancy to Adulthood." *Child Development*, 54(2): 331–355.

Goodman, Robert. 1997. "The Strengths and Difficulties Questionnaire: a research note." *Journal of child psychology and psychiatry*, 38(5): 581–586.

Goodman, Sherryl H, Matthew H Rouse, Arin M Connell, Michelle Robbins Broth, Christine M Hall, and Devin Heyward. 2011. "Maternal depression and child psychopathology: A meta-analytic review." *Clinical child and family psychology review*, 14(1): 1–27.

Grantham-McGregor, Sally, Yin Bun Cheung, Santiago Cueto, Paul Glewwe, Linda Richter, Barbara Strupp, International Child Development Steering Group, et al. 2007. "Developmental potential in the first 5 years for children in developing countries." *The lancet*, 369(9555): 60–70.

Háberg, Siri E., Hein Stigum, Wenche Nystad, and Per Nafstad. 2007. "Effects of Pre- and Postnatal Exposure to Parental Smoking on Early Childhood Respiratory Health." *American Journal of Epidemiology*, 166(6): 679–686.

Hagos, Belay, and John Hoddinott. 2018. "Early learning in Ethiopia : equitable access and learning Early Learning Partnership Ethiopia System Diagnostic Report."

Hansen, K, and I Munk. 2012. "Exploring the measurement profiles of socioeconomic background indicators and their differences in reading achievement: A two-level latent class analysis." *IERI Monograph Series: Issues and Methodologies in Large-Scale Assessments*, 5: 49–77.

Hanushek, Eric A, Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2013. "Returns to Skills around the World: Evidence from PIAAC." National Bureau of Economic Research Working Paper 19762.

Hanushek, Eric A, Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2015. "Returns to skills around the world: Evidence from PIAAC." *European Economic Review*, 73: 103–130.

Heckman, James J. 2000. "Policies to foster human capital." *Research in economics*, 54(1): 3–56.

Heckman, James J. 2006. "Skill formation and the economics of investing in disadvantaged children." *Science*, 312(5782): 1900–1902.

Heckman, James J. 2007. "The economics, technology, and neuroscience of human capability formation." *Proceedings of the national Academy of Sciences*, 104(33): 13250–13255.

Heckman, James J. 2012. "Invest in early childhood development: Reduce deficits, strengthen the economy." *The Heckman Equation*, 7: 1–2.

Heckman, James J, Seong Hyeok Moon, Rodrigo Pinto, Peter A Savelyev, and Adam Yavitz. 2010. "The rate of return to the HighScope Perry Preschool Program." *Journal of public Economics*, 94(1-2): 114–128.

Heckman, James, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the mechanisms through which an influential early childhood program boosted adult outcomes." *American Economic Review*, 103(6): 2052–86.

Helmers, Christian, and Manasa Patnam. 2011. "The formation and evolution of childhood skill acquisition: Evidence from India." *Journal of Development Economics*, 95(2): 252–266.

Hertzman, Clyde, and Michele Wiens. 1996. "Child development and long-term outcomes: a population health perspective and summary of successful interventions." *Social science & medicine*, 43(7): 1083–1095.

Hofhuis, Ward, JC De Jongste, and PJFM Merkus. 2003. "Adverse health effects of prenatal and postnatal tobacco smoke exposure on children." *Archives of disease in childhood*, 88(12): 1086–1090.

Home People, population and community Births, deaths and marriages Live births Birth characteristics in England and Wales. 2017*a*. "Home People, population and community Births, deaths and marriages Live births Birth characteristics in England and Wales."

Hoot, James L, Judit Szente, and Belete Mebratu. 2004. "Early education in Ethiopia: Progress and prospects." *Early Childhood Education Journal*, 32(1): 3–8.

How Young People are Faring in the Transition from School to Work. 2014. "How Young People are Faring in the Transition from School to Work." Foundation for Young Australians.

Hutchings, Hayley A, Annette Evans, Peter Barnes, Joanne Demmler, Martin Heaven, Melanie A Hyatt, Michelle James-Ellison, Ronan A Lyons, Alison Maddocks, Shantini Paranjothy, et al. 2013. "Do children who move home and school frequently have poorer educational outcomes in their early years at school? An anonymised cohort study." *PloS one*, 8(8): e70601.

Jones, Hendree E. 2006. "Drug addiction during pregnancy: Advances in maternal treatment and understanding child outcomes." *Current Directions in Psychological Science*, 15(3): 126–130.

Kasen, Stephanie, Patricia Cohen, Judith S. Brook, and Claudia Hartmark. 1996. "A multiple-risk interaction model: Effects of temperament and divorce on psychiatric disorders in children." *Journal of Abnormal Child Psychology*, 24(2): 121–150.

Kaul, Venita, and Shipra Sharma. 2017. "Early childhood policies in India: a historical analysis." *The Sage handbook of early childhood policy*, 32.

Kochanska, Grazyna, Kathleen T Murray, and Elena T Harlan. 2000. "Effortful control in early childhood: continuity and change, antecedents, and implications for social development." *Developmental psychology*, 36(2): 220.

Kolb, Bryan. 2009. "Brain and behavioural plasticity in the developing brain: Neuroscience and public policy." *Paediatrics & child health*, 14(10): 651–652.

Lan, Pham, Nicola Jones, Thi Thuy, and Minna Lyytikainen. 2007. "Education For All in Vietnam: high enrolment, but problems of quality remain."

Leffel, Kristin, and Dana Suskind. 2013. "Parent-directed approaches to enrich the early language environments of children living in poverty." Vol. 34, 267–278.

Lindqvist, Erik, and Roine Vestman. 2011*a*. "The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment." *American Economic Journal: Applied Economics*, 3(1): 101–28.

Lindqvist, Erik, and Roine Vestman. 2011*b*. "The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment." *American Economic Journal: Applied Economics*, 3(1): 101–28.

Lucas, A, MS Fewtrell, and TJ Cole. 1999. "Fetal origins of adult disease: the hypothesis revisited." *BMJ: British Medical Journal*, 319(7204): 245.

Marks, Gary N. 1999. "The Measurement of Socioeconomic Status and Social Class in the LSAY Project Technical Paper No. 14."

Marriages in England and Wales. 2016. "Marriages in England and Wales." Office National Statistics.

Martinez, Sebastian, Sophie Naudeau, and Vitor Pereira. 2012. "The promise of preschool in Africa: A randomized impact evaluation of early childhood development in rural Mozambique."

Maziade, M., R. Cote, H. Bernier, P. Boutin, and J Thivierge. 1989. "Significance of extreme temperament in infancy for clinical status in preschool years. I: Value of extreme temperament at 4-8 months for predicting diagnosis at 4.7 years." *The British Journal of Psychiatry*, 154(4): 535–543.

McCroy, Cathal, James Williams, Aisling Murray, Amanda Quail, and Maeve Thornton. 2013. "Design, instrumentation and procedures for the infant cohort at wave two (3 years)." Growing Up In Ireland - National Longitudinal Study of Children.

McCutcheon, Allan L. 1987. *Latent class analysis*. Sage.

McLoyd, Vonnie C. 1998. "Socioeconomic disadvantage and child development." *American psychologist*, 53(2): 185.

Mills, Colin. 2014. "The great British class fiasco: A comment on Savage et al." *Sociology*, 48(3): 437–444.

Mund, Mathias, Frank Louwen, Doris Klingelhoefer, and Alexander Gerber. 2013. "Smoking and pregnancy?a review on the first major environmental risk factor of the unborn." *International journal of environmental research and public health*, 10(12): 6485–6499.

Murray, Lynne, and Peter J Cooper. 1997. "Postpartum depression and child development." *Psychological medicine*, 27(2): 253–260.

Muzik, Maria, and Stefana Borovska. 2010. "Perinatal depression: implications for child mental health." *Mental Health in Family Medicine*, 7(4): 239.

Netter, Petra. 2018. "Benefits and limitations of drug studies in temperament research: biochemical responses as indicators of temperament." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373(1744): 20170165.

Nores, Milagros, and W Steven Barnett. 2010. "Benefits of early childhood interventions across the world:(Under) Investing in the very young." *Economics of education review*, 29(2): 271–282.

Number of jobs, labour market experience and earnings growth: results from a national longitudinal study. 2019*a*. "Number of jobs, labour market experience and earnings growth: results from a national longitudinal study." U.S. Bureau of Labour Statistics.

Oreopoulos, Philip, Marianne Page, and Ann Huff Stevens. 2008. "The intergenerational effects of worker displacement." *Journal of Labor Economics*, 26(3): 455–483.

Øvrum, Arnstein. 2011. "Socioeconomic status and lifestyle choices: evidence from latent class analysis." *Health economics*, 20(8): 971–984.

Persson, Petra, and Maya Rossin-Slater. 2018. "Family ruptures, stress, and the mental health of the next generation." *American Economic Review*, 108(4-5): 1214–1252.

Phillips, Deborah A, and Jack P Shonkoff. 2000. *From neurons to neighborhoods: The science of early childhood development.* National Academies Press.

Putnam, Samuel P, Ann V Sanson, and Mary K Rothbart. 2002*a*. "Child temperament and parenting." *Handbook of parenting*, 1: 255–277.

Putnam, S. P., A. V. Sanson, and M. K. Rothbart. 2002*b*. "Child temperament and parenting." In *Handbook of Parenting. Children and Parenting.* Vol. 1 of *Carnegie Rochester Conference Series on Public Policy*, , ed. M. H. Bornstein, M. H. Bornstein. Mahwah, NJ:Erlbaum.

Rege, Mari, Kjetil Telle, and Mark Votruba. 2011. "Parental job loss and children's school performance." *The Review of Economic Studies*, 78(4): 1462–1489.

Rosanbalm, KD, and DW Murray. 2017. "Promoting Self-Regulation in the First Five Years: A Practice Brief. OPRE Brief 2017-79." *Administration for Children & Families*.

Rothbart, M.K, and D. Derryberry. 1981. "Development of Individual Differences in Temperament." In *Advances in Developmental Psychology.* Vol. 1 of *Carnegie Rochester Conference Series on Public Policy*, , ed. M.E. Lamb and A. Brown, 37–86. Hillsdale, NJ:Erlbaum.

Rubin, Donald B. 1976. "Inference and missing data." *Biometrika*, 63(3): 581–592.

Rückinger, Simon, Peter Rzehak, Chih-Mei Chen, Stefanie Sausenthaler, Sibylle Koletzko, Carl-Peter Bauer, Ute Hoffmann, Ursula Kramer, Dietrich Berdel, Andrea Von Berg, et al. 2010. "Prenatal and postnatal tobacco exposure and behavioral problems in 10-year-old children: results from the GINI-plus prospective birth cohort study." *Environmental health perspectives*, 118(1): 150.

Rueda, M Rosario. 2012. "Effortful control." *Handbook of temperament*, 145–167.

Rumbold, Alice R, Lynne C Giles, Melissa J Whitrow, Emily J Steele, Christopher E Davies, Michael J Davies, and Vivienne M Moore. 2012. "The effects of house moves during early childhood on child mental health at age 9 years." *BMC Public Health*, 12(1): 583.

Sánchez, Alan. 2017. "The structural relationship between early nutrition, cognitive skills and non-cognitive skills in four developing countries." *Economics & Human Biology*, 27: 33–54.

Sanson, A, F Oberklaid, R Pedlow, and M Prior. 1991. "Risk Indicators: Assessment of Infancy Predictors of Pre-School Behavioural Maladjustment." *Journal of Child Psychology and Psychiatry*, 32(4): 609–626.

Sanson, Ann, Margot Prior, and Michael. Kyrios. 1990. "Contamination of measures in temperament research." *Merill-Palmer Quarterly*, 36: 179–192.

Santín, Daniel, and Gabriela Sicilia. 2018. "Does preschool education attendance matter? Evidence from a natural experiment in Spain." *Applied Economics*, 50(47): 5050–5063.

Saudino, Kimberly J, and Manjie Wang. 2012. "Quantitative and molecular genetic studies of temperament." *Handbook of temperament*, 315–346.

Saudino, K. J. 2005. "Behavioral Genetics and Child Temperament." *Journal of Developmental and Behavioral Pediatrics*, 26(3): 214–223.

Savage, Mike, Fiona Devine, Niall Cunningham, Mark Taylor, Yaojun Li, Johs Hjellbrekke, Brigitte Le Roux, Sam Friedman, and Andrew Miles. 2013. "A new model of social class? Findings from the BBC's Great British Class Survey experiment." *Sociology*, 47(2): 219–250.

Sawyer, Susan M, Rima A Afifi, Linda H Bearinger, Sarah-Jayne Blakemore, Bruce Dick, Alex C Ezeh, and George C Patton. 2012. "Adolescence: a foundation for future health." *The Lancet*, 379(9826): 1630–1640.

Sheppard, Jill, and Nicholas Biddle. 2017. "Class, capital, and identity in Australian society." *Australian Journal of Political Science*, 52(4): 500–516.

Shonkoff, Jack P, and Philip A Fisher. 2013. "Rethinking evidence-based practice and two-generation programs to create the future of early childhood policy." *Development and psychopathology*, 25(4pt2): 1635–1653.

Slagt, Meike, Judith Semon Dubas, Maja Deković, and Marcel AG van Aken. 2016. "Differences in sensitivity to parenting depending on child temperament: A meta-analysis." *Psychological Bulletin*, 142(10): 1068.

Snow, Catherine E, and Marian Hoefnagel-Höhle. 1978. "The critical period for language acquisition: Evidence from second language learning." *Child development*, 1114–1128.

Stevens, Ann Huff, and Jessamyn Schaller. 2011. "Short-run effects of parental job loss on children's academic achievement." *Economics of Education Review*, 30(2): 289–299.

Tanaka, Sakiko. 2005. "Parental leave and child health across OECD countries." *The Economic Journal*, 115(501).

The Economics of Early Childhood Investments, The Obama White House. 2015. "The Economics of Early Childhood Investments, The Obama White House." The Obama White House.

Thomas, A., S. Chess, H. Birch, G. Hertzig, and S. Korn. 1963. *Behavioural Individuality in Early Childhood.* New York:New York University Press.

Tonnessen, Marianne, Kjetil Telle, and Astri Syse. 2016. "Childhood residential mobility and long-term outcomes." *Acta Sociologica*, 59(2): 113–129.

UNICEF. 2017. "The India Early Childhood Education Impact Study." UNICEF.

van Ginkel, Joost R, Marielle Linting, Ralph CA Rippe, and Anja van der Voort. 2019. "Rebutting Existing Misconceptions About Multiple Imputation as a Method for Handling Missing Data." *Journal of personality assessment*, 1–12.

Wachs, TD. 2006. "Contributions of temperament to buffering and sensitization processes in children's development." *Annuals Academic Science*, 1094: 28–39.

Walker, Susan P, Susan M Chang, Christine A Powell, and Sally M Grantham-McGregor. 2005. "Effects of early childhood psychosocial stimulation and nutritional supplementation on cognition and education in growth-stunted Jamaican children: prospective cohort study." *The lancet*, 366(9499): 1804–1807.

Walker, Susan P, Theodore D Wachs, Sally Grantham-McGregor, Maureen M Black, Charles A Nelson, Sandra L Huffman, Helen Baker-Henningham, Susan M Chang, Jena D Hamadani, Betsy

Lozoff, et al. 2011. "Inequality in early childhood: risk and protective factors for early child development." *The Lancet*, 378(9799): 1325–1338.

Wehby, George L, Kaitlin Prater, Ann Marie McCarthy, Eduardo E Castilla, and Jeffrey C Murray. 2011. "The impact of maternal smoking during pregnancy on early child neurodevelopment." *Journal of human capital*, 5(2): 207–254.

Werner, E. E., and R.S. Smith. 1982. *Vulnerable but invincible: A longitudinal study of resilient children and youth.* New York:McGraw Hill.

Whittle, S, N. B. Allen, D.I. Lubman, and M Yücel. 2006. "The neurobiological basis of temperament: towards a better understanding of psychopathology." *Neuroscience & Biobehavioral Reviews*, 30(4): 511–525.

Woldehanna, Tassew. 2011. "The effects of early childhood education attendance on cognitive cevelopment: evidence from urban Ethiopia." *Ethiopian Journal of Economics*, 20(1).

Woldehanna, Tassew. 2016. "Inequality, preschool education and cognitive development in Ethiopia: Implication for public investment in pre-primary education." *International Journal of Behavioral Development*, 40(6): 509–516.

Woldehanna, Tassew, and Liyousew Gebremedhin. 2012. *The effects of pre-school attendance on the cognitive development of urban children aged 5 and 8 years.* Young Lives.

Woldehanna, Tassew, Jere R Behrman, and Mesele W Araya. 2017. "The effect of early childhood stunting on children's cognitive achievements: Evidence from young lives Ethiopia." *Ethiopian Journal of Health Development*, 31(2): 75–84.

Wood, David, Tara Crapnell, Lynette Lau, Ashley Bennett, Debra Lotstein, Maria Ferris, and Alice Kuo. 2018. "Emerging adulthood as a critical stage in the life course." In *Handbook of life course health development.* 123–143. Springer, Cham.

Yi, Junjian, James J Heckman, Junsen Zhang, and Gabriella Conti. 2015. "Early Health Shocks, Intra-household Resource Allocation and Child Outcomes." *The Economic Journal*, 125(588).

Young Adults: Then and Now. 2013. "Young Adults: Then and Now." Australian Bureau of Statistics.

Zhang, Shiying. 2017. "Effects of attending preschool on adolescents' outcomes: evidence from China." *Applied Economics*, 49(27): 2618–2629.