Human Capital Investment: An Empirical Analysis of Incentives and Returns

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Declaration of Authorship

I, Nuarpear Warn LEKFUANGFU, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This thesis focuses on three dimensions of human capital formation: investment during childhood, the role of incentives on household's investment decision and the returns to the investment. Chapter 2 examines the influence of family and school environments during different childhood periods on skill formation in adulthood. It explores a large set of childhood characteristics using a British cohort, and identifies which factors during childhood may have a legacy on cognitive and non-cognitive human capital much later in life. The data in Chapters 3 and 4 are drawn from developing countries. Chapter 3 identifies family size as a potential driver of children human capital accumulation. It then investigates if there is a trade-off between the number of younger siblings and children's outcomes as well as intra-household behavioural responses, namely household expenditure and parental labour supply. Chapter 4 considers a specific factor, life expectancy, and examines the direction in which an exogenous change in mortality risk influences parental investments and hence schooling outcomes. Finally, Chapter 5 offers a new perspective on returns to education. Using a longitudinal household surveys from Australia, the chapter estimates the direct and indirect effects of education on life satisfaction by exploring different pathways, including income, health and family life, in which more schooling can positively raise well-being.

Acknowledgements

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Contribution to chapters:

Chapter 3 and 4 are sole author papers.

Chapter 2 is coauthored with Dr.Grace Lordan.

Chapter 5 is coauthored with Professor Nattavudh Powdthavee and Professor Mark Wooden.

Chapter 1

Introduction

This thesis focuses on three dimensions of human capital formation: i) investment during childhood, ii) the role of incentives on household's investment decision, and iii) the returns to the investment.

The thesis pays particular attention to human capital investment decisions at the household level in developing countries. To do so, two chapters are contributions to our understanding of these specific characteristics in five different developing countries. To complement the findings, the other two chapters turn to much richer longitudinal datasets from western countries (Britain and Australia) in order to gain broader and longer-term perspectives on human capital formation in terms of both cognitive and non-cognitive skills.

Economic theories have long argued that parents make an optimal decision to invest in their children's human capital by weighing up the benefits and costs (Becker, 1994; Ben-Porath, 1967). Of course, this depends heavily on the technology of human capital formation, which eventually determines how skills are accumulated. A more recent literature provides an additional dimension to human capital formation. Cunha and Heckman [2007] and Cunha et al. [2010] show how the timing of investments may lead to differential returns, depending upon on the stage in the life-cycle and the type of human capital (cognitive, non-cognitive, health) under consideration. The question whether factors during childhood have a long-term legacy into adulthood forms part of an important on-going debate. While many studies find a long-term impact of interventions as well as major life-events during early ages on adult outcomes, others argue that childhood circumstances are, in fact, poor predictors of future outcomes, particularly life satisfaction (Layard et al., 2013; Frijters et al., 2014).

Chapter 2 of this thesis offers an empirical exploration of the legacy of family and schooling characteristics during childhood on cognitive and non-cognitive outcomes during adulthood. More specifically, it asks how far an empirical model can predict cognitive skills in late adulthood using childhood circumstances. It utilizes a large long-term cohort study from Britain –the National Childhood Development Study (NCDS)– and exploits the scores from cognitive ability tests taken at age 50 (in 2008). We contrast the findings with non-cognitive skills measured in the same year. To do so, the empirical models in this chapter apply the techniques proposed by Todd and Wolpin (2003,2007) to estimate skill production functions.

Chapter 2 also applies the same empirical strategies to another representative British cohort born over 30 years after– the Millennium Cohort Study– in order to draw conclusions on the predictive power of parental inputs and other family characteristics during early childhood in determining skill formation at early ages, and also to examine whether there are distinct generational differences in the skill formation technologies.

Chapter 3 focuses more precisely on the role of one specific input into human capital formation during childhood. The key objective of this chapter is use the lessons learnt about human capital development from developed country settings, particularly during the earlier ages, and broaden them to a wider cultural setting.

Chapter 3 utilises the Young Lives Dataset, a longitudinal study of young children from four developing countries (Vietnam, India, Peru and Ethiopia), to examine the effect of family size on childhood skill formation. More precisely, it looks at the effect of having additional younger siblings on the early cognitive and non-cognitive development of an older sibling from the same family. Many theoretical studies have indicated that parents may need to reduce their investment on child development when the family size becomes larger (Becker and Lewis, 1973; Becker and Tomes, 1976; Galor and Weil, 2000). However, one must also take into account parents' heterogeneous preferences for fertility before being able to draw any appropriate conclusions. In fact, households generally make a number of coordinated lifetime family decisions simultaneously, such as fertility, child investment, and labour supply (e.g. Rosenzweig and Wolpin, 1980b; Rosenzweig and Wolpin, 1980a).

Therefore, Chapter 3 employs instrument variables to examine if exogenous variation in fertility outcomes may lead to any changes in parental investment on the existing child and her human capital formation later on in life. This chapter also investigates whether there are any other adjustments the parents and the older sibling themselves undergo in response to the increase in family size, including labour supply, time allocation and household expenditure.

The main analysis in Chapter 3 exploits the exogeneity of a birth of a given gender in order to obtain a set of instrumental variables that explain fertility variation. Specifically, the instruments used are a modified version of Angrist and Evans [1998] and Angrist et al. [2010]'s sibling-sex composition. Given the strong implicit assumption of parental fertility preferences for (i) two parity, and (ii) balanced sex children, the direct application of the conventionally defined sibling sex-composition instruments may not be very suitable. Fertility stopping rules in developing country context differ from the western setting in two main ways.

First, in many countries, particularly in Africa, parents do prefer a larger number of children. Second, not all cultures prefer daughters and sons equally. The alternative instrumental variable, the disparity between the actual and the ideal number of sons (and daughters), proposed in Chapter 3 will directly account for the heterogeneous preferences for optimal fertility whilst also exploiting the exogenous variation coming from the randomness of birth of a specific gender to a family. This allows the empirical model to lead to a causal interpretation of the effect of sibship size, as a key family input, on child development over time.

While Chapter 2 and 3 deal with the input side of the production of human capital, Chapter 4 takes a step back and investigates what might incentivise parents to invest in their children in the first place. This chapter focuses specifically on how an increase in the net gains of human capital investment, via a specific channel, may alter the observed outcome of investment in terms of formal education and health. Recent studies have provided evidence that an increase in life expectancy is positively linked with a rise in education attainment, both for developed (Oster et al., 2013; Stoler and Meltzer, 2013) and developing countries (Jayachandran and Lleras-Muney, 2009; Fortson, 2011).

Chapter 4 examines the role of life expectancy on human capital accumulation in a developing country setting. More precisely, it investigates how an exogenous reduction in the landmine-induced mortality risk in Cambodia leads to higher schooling within the population. The identification strategy in Chapter 4 exploits three crucial variations in landmine-related mortality risk. The first is the spatial variation of landmine prevalence whereby the western areas of the country are more heavily affected as a result of being located along the retreating routes of Khmer Rouge during the Civil War in the 1980s. The second variation is the timing of a two-fold expansion of landmine clearance effort around the years 2005-2006, which ultimately resulted in a sharp decline in landmine casualties. Suddenly, the adjacent birth cohorts were facing a very different level of total mortality risk. The last variation is derived from a strong male-bias nature of landmine

accidents. All three variables allow the analysis in Chapter 4 to employ a difference-in-difference-in-differences specification and obtain causal interpretations of how mortality risk affects human capital development.

Chapter 5 continues to focus on the benefit side of human capital investment decisions. This chapter asks whether schooling can provide further benefits beyond financial gain, and how it is related to the overall individual subjective welfare as a whole. The chapter examines the direct and indirect effects of schooling on life satisfaction by returning to a developed country context. It estimates a structural equation model using nationally representative data for Australia (HILDA) between during the 2001-2010 period in order to obtain the direct and indirect associations between education and life satisfaction through a number of monetary and non-monetary pathways.

Following Oreopoulos and Salvanes [2011], this chapter identifies five different adult outcomes- income; employment; marriage; children; and health (physical and psychological) - as channels through which schooling may affect the overall quality of life. In order to correct for unobserved heterogeneity bias, a fixed effects (FE) model is applied on the pooled sample. However, since many of the variables show slow-moving variation within individuals, a typical FE model may end up eliminating variables of interest (Plümper and Troeger, 2007). Therefore, this chapter employs an alternative model of fixed effects vector decomposition (FEVD) outlined in (Plümper and Troeger, 2007; Boyce, 2010).

With personality traits as additional determinants of individual fixed effects in an Structural Equation Modelling (SEM) setting, the FEVD methods allows the models to estimate a FE model without the loss of information on variables that have zero or little within-person variation. This chapter applies the modified SEM analysis with a nationally representative data from Australia (HILDA) and estimates the direct association between education and life satisfaction, as well as the indirect associations through to the five adult outcomes.

Chapter 2

Long or Short Arm of Childhood? Influence of Childhood Characteristics on Human Capital Accumulation

Abstract

This paper adopts a life course perspective to gauge the legacy that childhood factors have on adult cognitive and non-cognitive skills. We find that we can predict more of the variation in cognitive skills than non-cognitive skills at age 50. We find that schooling at age 16 and parental inputs in early childhood are the factors that leave the largest legacy on cognitive skills. An analysis of age 7 and age 16 cognitive and non-cognitive skills highlight that in early years only parental inputs matter with respect to predicting these outcomes. Conversely, at age 16 schooling matters the most with respect to predicting both cognitive and non-cognitive skills. Across the ages, childhood factors are better at explaining an externalising behaviour than other non-cognitive traits. We recognize that environments are very different for children who are growing up today. Thus we consider relatively comparable regressions at age 7 for children born in 1958 and 2000. We find that parental inputs again matter the most for predicting outcomes at this age. In this regard, the trajectory looks similar.

2.1 Introduction

For almost three decades economists have considered how the impact of childhood characteristics determine adult income, occupational status and educational outcomes [1]. There are also influential papers that highlight the ways in which childhood health significantly predicts adult labour market outcomes (e.g. Black et al., 2007; Currie, 2009;and Case and Paxson, 2011). Additionally a large literature considers how childhood factors shape health outcomes in adult life. For example, childhood socio-economic status (SES) and physical health have been shown to predict mortality (e.g. Ferrie and Rolf, 2011; Frijters et al., 2010; and Smith et al., 2009), as well as adult physical health (e.g. Blackwell et al., 2001; Luo and Waite, 2005; and Case and Paxson, 2011). It has also been highlighted that macro-level conditions in childhood (such as infant mortality rates and the business cycle) predict adult physical health and mortality (Van den Berg et al., 2009; Portrait et al., 2010; and Delaney et al., 2011). Overall the consensus is that there is a *long arm* of childhood. That is, early conditions play a role in shaping adult outcomes- at least when it comes to physical health and the labour market.

More recently, two papers have considered how childhood predicts adult life satisfaction- the typical measure of subjective wellbeing (SWB) used in the economics literature. First, Frijters et al. [2014] highlight that about 1% of the variance in average adult life satisfaction can be explained by a range of family factors for a cohort of individuals born in the UK in 1958. Second, Layard et al. [2013], taking a similar life course perspective and data from a cohort born in the UK in 1970, highlight that family SES predicts very little of adult life satisfaction. For example, their estimates suggest that family income accounts for 0.5% of the variance of life satisfaction. These studies differ from what has gone before, as rather than focusing on the significance of one specific childhood variable in an adult regression, the authors focus on the amount of variation they can explain by incorporating a large number of childhood factors in one adult regression equation. The importance of life course perspectives for the developmental origins of adult health is emphasised by Heckman [2012]. However, the literature has highlighted a legacy for family circumstances on labour market and physical health outcomes only, with the focus being on the impact of one particular variable. Nevertheless, it does seem that childhood factors are poorer predictors of future life satisfaction. This is evident from the coefficient of determination as well as the lack of significance of most childhood variables in the regression equations [2] estimated by Frijters et al. [2014] and Layard

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[1]See for example Becker and Tomes, 1986; Corcoran et al., 1992; Solon et al., 2000; Page and Solon, 2003; Galster et al., 2007; Lee and Solon, 2009; Mazumder, 2005; Case and Paxson, 2011; Datcher, 1982; Aaronson, 1998; Brooks-Gunn et al., 1993 and Solon et al., 2000

[2]We do note that the latter may be unreliable given the large number of variables that are included in the author's models and the subsequent potential for multi-collinearity.

et al. [2013]. To our knowledge, there is no study that has investigated how family and schooling conditions from different stages of childhood predict cognitive skills in late adulthood.

In this paper, we ask how far we can predict cognitive skills in late adulthood from childhood circumstances. We utilize a large long-term cohort study, the National Childhood Development Study (NCDS) and exploit the scores from cognitive ability tests taken at age 50 in 2008. We contrast the findings to non-cognitive skills, which were measured in the same year.

Our approach differs from much of the literature as it considers the link between childhood and adult outcomes by examining the simultaneous effects of a large set of mediating mechanisms rather than focusing on one variable of interest or a specific pathway. In particular, we consider a life course perspective and focus on a large number of childhood characteristics. Our focus is on how much of the variation of cognitive and non-cognitive skills can be explained by childhood characteristics. Given that non-cognitive skills are personal attributes that enable an individual to interact effectively and harmoniously with other people, it follows that poor mental health signals a lower level of soft-skills. We consider both the family and schooling environment. We argue that as a child spends different proportions of her time either at home or in school at different stages during childhood, by considering these two environments together we are better able to capture the child's early experiences.

Overall, this work finds that early childhood factors predict adult cognitive skills to a far greater extent than they can predict adult non-cognitive for the 1958 cohort. In fact, childhood schooling is a relatively insignificant determinant of the variation in non-cognitive skills for this cohort. Similarly, our childhood variables are better predictors of own earned annual income at ages 30 through 50, however they are poorer predictors of emotional health at these ages. We also find that if we consider cognitive and non-cognitive skills in childhood (ages 7, 11 and 16) contemporary family circumstances matter more for predicting cognitive skills. We also find that parental inputs are the most important childhood factor for a young child with respect to predicting any skill, however schooling is more important at age 16. In particular, schooling is highly predictive of both cognitive and soft skills at this age although the effect on soft skills is smaller. This follows through to the adult outcomes, where parental inputs and schooling are the two sets of childhood characteristics that leave an imprint on later life cognitive skills. The other childhood characteristics we consider are socio-economic status, household composition and parental health. None of the variables in these five groupings leave a notable imprint on adult soft skills.

We accept that the family and schooling environments that children are experiencing today are very different from those in which individuals born in 1958 experienced. Thus, we compare whether the influence that family and schooling had on childhood non-cognitive skills for the 1958 cohort is similar for the Millennium Cohort Study (MCS) participants who were born in the year 2000. We are careful to consider an identical measure of non-cognitive skills for both cohorts as psychologists are likely to have been doing a better job of measuring these skills over time. The idea here is that if patterns are similar in childhood, it is also likely that they follow a similar pattern in adulthood. We compare results from the MCS at age 7 to those for the NCDS at age 7 and include similar variables in our regression equations. Again, we can predict more of the variation in cognitive skills when compared to non-cognitive skills. While parental inputs were more notable in the NCDS at age 7, they still do the heaviest lifting for the MCS children at age 7 with respect to predicting skills. In this regard, the trajectory looks similar and we can expect that schooling may become more important as the MCS child progresses through their childhood years.

In what follows, the next section outlines the background and the conceptual framework. Section 2.3 details the data and empirical methodologies. Section 2.4 presents the results. It will conclude with a discussion in Section 2.5.

2.2 Background and Conceptual Framework

The literature to date has highlighted that child circumstances are good predictors of child cognitive ability (as measured by achievement and IQ tests) and physical health (e.g. Smith et al., 1997; Blau, 1999; Guo and Harris, 2000; Taylor et al., 2004; Currie and Hyson, 1999; Case et al., 2002; and Currie and Stabile, 2003). However, less is known about the *long arm* of childhood with respect to cognitive and non-cognitive skills in adulthood. In particular, we know of no study to consider how childhood factors predict cognitive skills. We believe this is owed to lack of data, rather than lack of interest, given the large number of papers that have linked childhood circumstances to later labour market and educational outcomes (e.g. Becker and Tomes, 1986; Corcoran et al., 1992; Solon et al., 2000; Page and Solon, 2003; Galster et al., 2007)[3]. Of particular interest is Case et al. [2005] who, using the same data as we do here (NCDS), highlight that children with low birth weight achieve fewer achievement examinations. Other studies on this topic using the NCDS highlight that cognitive tests administered at age 7 predict test scores at ages 11 and 16, as well as overall educational attainment and adult income (e.g. Robertson and Symons, 2003; Currie and Hyson, 1999 and Connolly

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[3]Also Lee and Solon, 2009; Mazumder, 2005; Case and Paxson, 2011; Datcher, 1982; Aaronson, 1998; Brooks-Gunn et al., 1993 and Solon et al., 2000

et al., 1992). Thus, we would expect that childhood circumstances leave a legacy on adult cognitive skills.

While there are many studies that consider the legacy of childhood on physical health (Blackwell et al., 2001; Luo and Waite, 2005; Case and Paxson, 2011 and Haas, 2008), few consider mental health. In this work, we view mental health as a non-cognitive skill [4]. This follows as such skills are personal attributes that enable an individual to interact effectively and harmoniously with others. To date, major contributions to the economics literature have highlighted that soft skills acquired in *early life* − as measured by personality − leave a legacy on physical health in later in life (Conti and Heckman, 2010; Conti et al., 2010 and Conti and Heckman, 2014). Importantly, these papers highlight that failing to condition on child personality overstates the contribution of early cognitive ability in an adult health production function. In particular, it has been highlighted that soft skills (Heckman and Kautz, 2012), and in particular personality (Conti and Hansman, 2013) predict success in adult life, where success is measured along many groups including crime, income, propensity to be employed and tobacco use.

Less is known about how childhood factors predict adult soft skills. Specific to mental health, we note Gibb et al. [2012] who consider data from a 30-year longitudinal study in New Zealand to examine the link between childhood SES and adult outcomes. Overall, they find that childhood income significantly predicts long-term educational achievement and economic circumstances. However, they do not find a relationship between income and adult mental health attainment. Elsewhere, Elovainio et al. [2012], using the Young Finns study data, consider the symptoms of depression among adolescents and young adults. In particular, their empirical work finds that the link between childhood SES and depressive symptoms fades over time. That is, there is adaptation. Hatch et al. [2007] consider if childhood cognitive ability predicts mid-life mental health using the British 1946 birth cohort. Their results show that childhood cognitive ability predicts anxiety and depression in women but not men. Thus, the evidence for a legacy on soft-skills or mental health is non-existent or muted.

This work differs from other studies on the basis that rather than focusing solely on the legacy of family circumstances; we also consider the legacy of schooling. We view this addition as important for a more comprehensive understanding of the childhood legacy. Given that a child spends the majority of their time either at home or in school, by

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[4]In many works in economics, the term "non-cognitive" is often used as a contrast of cognitive ability. In Borghans et al.(2008) and many other studies, personality traits are the main focus for non-cognitive ability. As defined in their studies, personality inventories capture patterns of thought, feelings and behaviour. In this analysis, non-cognitive is defined more broadly, and thus encompass not only personality traits (Big-Five) but also include psycho-emotional measures. These measures, in particular a measure of positive well-being as well as malaise also strongly influence how each individual think, feel and act.

considering these factors together we are better able to capture the child's early experiences. Moreover, studies have found that many aspects of schooling do matter. It is well-documented that smaller class size leads to better cognitive performance (e.g. Angrist and Lavy, 1999; Krueger, 1999). Recent papers show that disruptive peer groups have adverse effect on individual achievement (e.g. Carrell and Hoekstra, 2010; Neidell and Waldfogel, 2010). Classroom sorting by ability is also found to have significant impacts on student performance (e.g. Epple et al., 2002). Moreover, teacher quality in the classroom, for example teaching training or years of experience, is crucial for student achievement (e.g. Rockoff, 2004; Rothstein, 2010; Harris and Sass, 2011). Nevertheless, many studies find that the impact of schooling during childhood on educational performance seems to fade out over the life course (e.g. Rothstein, 2010; Carrell and West, 2010; Chetty et al., 2011). We note that while significant progress has been made on how schooling may affect cognitive performance, less is known about how school environment affects behavioural outcomes or soft skills in general (e.g. Finn et al., 1989; Finn et al., 2003 and Chetty et al., 2011).

Overall, the pathways in which childhood family and schooling conditions can potentially predict cognitive and non-cognitive skills are similar. First, these conditions may influence cognitive and non-cognitive skills directly with childhood events that occur during important developmental periods serving to permanently alter the trajectory of cognitive and non-cognitive skills over the life-course. Second, these conditions may influence these outcomes cumulatively with the exposure to certain family or schooling characteristics accumulating over the life-course. Third, childhood environment may predict adult and non-cognitive skills indirectly, if these factors serve to alter other pathways that in turn are related to these skills. For example, childhood factors may set in motion cascading events, like lifestyle behaviours (such as drinking alcohol or illegal drug taking), that have a more temporally proximate effect on cognitive and non-cognitive skills.

2.3 Data and Methodology

The NCDS is a continuing study that follows the lives of 17,000 people living in Great Britain who were born in the week of March 3, 1958. The survey also added about 700 children who were born in the same week and immigrated to Great Britain before their sixteenth birthday. Sweeps were carried out in in 1965 (age 7), 1969 (age 11), 1974 (age 16), 1981 (age 23), 1991 (age 33), 1999-2000 (age 41-42), 2004-2005 (age 46-47) and in 2008 (age 50).

In this work we consider the relationship between schooling and family characteristics (as measured in childhood) and adult cognitive and non-cognitive abilities. Specifically, we are interested in how family and schooling variables measured at ages 0, 7, 11 and 16 predict cognitive and non-cognitive skills at age 50, and which of them matter more. Age 50 is chosen as it the most recent wave of the NCDS, as well as the only wave where cohort members responded to four cognitive ability tests. First, *Word List Recall* is a test of verbal fluency and recall where participants are required to learn a list of 10 common words. This test measures the efficacy of long-term memory. Second, *Delayed Word List Recall* tests the participant's delayed memory where he is asked to recall as many words as they can from an original list presented (Brown and Dodgeon, 2010). Third, the *Animal Naming Test* measures phonemic and semantic verbal fluency. Forth, *Letter Cancellation* is a test of attention, mental speed and visual scanning within one minute. From this, a score for speed of cognitive processing is calculated (see Appendix 2.8 for details).

To construct one measure of adult cognitive skills, we follow the psychometric literature (Gorsuch, 1983; Thompson, 2004) and recent work in child development (Cunha et al., 2010; Heckman et al., 2013) and use exploratory factor analysis to reduce the dimensionality of the outcomes of interest. We take the approach of identifying underlying latent factors rather than directly calculating simple averages because it avoids imposing arbitrary weightings. It is most likely that different items may not contribute equally to the variance of one particular trait. Aggregation by average indices also does not correct for measurement error, which are particularly problematic in psychological instruments. In contrast, latent factor variables account for this problem (Cunha et al., 2010; Heckman et al., 2013)[5].

To extract an underlying latent factor which is a statistical proxy for cognitive ability at age 50, we first determine the number of factors to retain based on a scree plot from an orthogonal exploratory analysis and the eigenvalue of each individual factor [6]. Using oblique rotation, we allow for correlations among latent skill factors. At this stage, we omit variables that are weakly loaded onto a factor or cross-loaded on multiple factor. In essence, the final list of measures is retained if they are strongly related to one and only one factor. Finally, we re-run the exploratory factor analysis and rotate this result, allowing the resulting factors to be correlated. Confirmatory factor analysis (CFA) is then performed to check whether our constructed factors are correctly characterised and to produce an interpretable system (Gorsuch, 1983; Thompson, 2004). In the case of

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[5]We note however that all our results are robust to utilizing outcomes that are derived from the simple mean of our variables of interest.

[6]Please refer to Figure 2.3 in Appendix 2.6 for more details.

cognitive skills at age 50, we start with using the total score from our four original proxies in the NCDS. Having followed these steps, we extract one cognitive factor variable[7].

We follow a similar procedure for our measures of non-cognitive skills at age 50. We begin by creating a list of questionnaire items relating to socio-emotional status derived from three instruments in the NCDS: (i) the *Short Form-36* (SF-36), (ii) the *Warwick-Edinburgh Mental Well-Being Scale* (WEMWBS) and (iii) the *Rutter Malaise Inventory Score*. The SF-36 is a 36-item questionnaire that measures quality of life. Here, we focus on 2 sub-scales. The *Role Emotional* (RE) component is a three-item scale that evaluates the extent, to which emotional factors interfere with work or other activities and the *Emotional Health* (EH) consists of a 5-item scale that evaluates feelings principally of anxiety and depression over the past year (Ware Jr and Sherbourne, 1992). The WEMWBS is a 14-item scale of positive mental wellbeing, including SWB and psychological functioning. For example, the respondent is asked to rate the frequency of her feeling optimistic about the future in the past 2 weeks (Stewart-Brown and Jan-mohamed, 2008). The Malaise Inventory measures levels of psychological distress, or depression (Rutter et al., 1970). At age 50, the information is available only 9 out of 24 original items[8].

We begin with all of the individual questions (35 items altogether)[9]. By following the procedure outlined previously, we extract two latent factor variables, which are easily labelled as *positivity* and *malaise*. Altogether, we present the distribution of standardised cognitive and non-cognitive skills (of age 50, 16, 11 and 7) in our NCDS sample in Figure 2.1 and 2.2. Particularly for psychological or socio-emotional measures, the application of factor analysis is shown to help account for measurement errors (Cunha et al. [2010]) and thus allow us to increase the precision of the findings .

We focus mainly on the following equation:

$$Skill_{i,50} = \sum_{a=1}^{16} \sum_{k=1}^{K} \beta_{ka} X_{i,ka} + \gamma B_{i,0} + \varepsilon_{i,50} \tag{2.1}$$

where $Skill_{i,50}$ is one of the three factor variables, which represent the cognitive skills, positivity and malaise for NCDS child i at age 50. $B_{i,0}$ is a vector of the baseline variables at age 0 that are included in all of our specifications. In particular, these capture child circumstances at birth and specifically include gender, birth weight, fixed

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[7]See Appendix 2.6 Table 2.1 for details.

[8]Please refer to Table 2.2 in Appendix 2.6 for details.

[9]It is possible for us to use the individual items here as they are not binary variables as in the case of the cognitive scores. While exploratory factor analysis is suited to continuous and ordered variables, it is not suited to a system of binary variables only. Hence, we focus on the aggregate scores rather than individual question items for the cognitive analysis.

effects capturing region of birth, mother's age, father's age, an indicator as to whether the child is the first child, gestation in weeks of the pregnancy, a fixed effect to denote whether English is the mother tongue, maternal education and paternal education.

Our goal is then to determine the childhood variables that matter the most with respect to predicting adult skills. Thus, we focus on a large number of schooling and family characteristics. These are described in Table 2.1. In particular, the first four columns depict the sweeps of the NCDS (age 0, age 7, age 11 and age 16) with an x indicating that a particular variable was available and included in the analysis. The next column assigns each variable to a group. The final column in Table 2.1 provides a description of each variable. We consider five groups of childhood variables: socio-economic status (SES); household composition (HH); parental inputs (INPUT); parental health (HTH); and schooling (SCH). More specifically, SES comprises of variables that capture the economic conditions of the child [10]; parental direct inputs capture explicit parental investment; household composition captures the structure of the family; parental health captures the physical health and healthful behaviours of the child's parents; and schooling captures the schooling environment[11] .

To examine the contribution of each group at a particular age, $X_{i,ka}$, on later skills, is not as straightforward as sequentially adding each dimension of variables one age block at a time, starting from birth up until age 16 and examining the R-squared. While, such an approach would take into account the complementarity nature of cognitive and non-cognitive skills in a dynamic setting (Cunha et al., 2010), it would not allow for the fact that the R-squared measures the fraction of the total variation explained independently by the group being added, in addition to the common variation of the groups yet to be added. Thus, we utilize a straightforward method proposed by Berlinski and Carneiro [2012] and calculate bounds of the magnitude of marginal contribution from each separate group. To net out a positive effect coming from the mere addition of more variables, we report our findings in terms of adjusted R-squared. We do this at an aggregate level (across the four sweeps during childhood periods) and at a sweep level.

To obtain the lower bound of the marginal contribution of a particular group, we first estimate the complete model following Todd and Wolpin's (2003, 2007) cumulative specification on the skill production function. In this case, we estimate Equation 1 and include

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[10]We acknowledge that many of the SES may not be highly time-variant across different ages of the children. In Appendix 2.6, we investigate how father's occupational status, as our main proxy for SES, may switch over 3 ages. And we find that overtime, approximately 50 % of the fathers switch their occupational status by the time the child reached 16 years old. (see Table 2.8)

[11]To deal with missing data values and sample attrition, we make the assumption that data are missing at random. This is reasonable given it has been shown that attrition is not systematically associated with SES (Case and Paxson [2010]). Therefore, we impute missing values of our explanatory variables by the variable's mean. We create a dummy for each variable that takes the value of 1 if the data is missing and zero otherwise, and add this to our analysis. Refer to Table 2.9

all of the variables across all groups documented in Table 1. Therefore, the complete model takes into account all groups throughout the entire childhood (0-16 years). We then obtain the adjusted R-squared for the complete model ($AdjR^2_{complete}$). Next, we omit one group of variables at a time. So for a variable group ka, the associated lower bound contribution to the variance of the outcome is given by the difference of adjusted R-squared between the complete model minus that emanating from a model excluding group ka ($AdjR^2_{complete \backslash ka}$). Formally, this is:

$$Lower_{ka} = AdjR^2_{complete} - AdjR^2_{complete \backslash ka} \qquad (2.2)$$

Conversely, the upper bound contribution to the variance of the outcome is equal to the difference between the adjusted R-squared emanating from a model that includes age 0 baseline characteristics only ($AdjR^2_{ka}$) and group ka minus a model that includes age 0 characteristics only ($AdjR^2_{basic}$) [12]. That is:

$$Upper_{ka} = AdjR^2_{ka} - AdjR^2_{basic} \qquad (2.3)$$

Thus, we can summarise how important any group of variables is at any childhood age by focusing on the lower bound ($Lower_{ka}$) and upper ($Upper_{ka}$) of the marginal adjusted R squared[13][14]. Note that the comparative magnitude of $Upper_{ka}$ and $Lower_{ka}$ in fact depends on the correlation between the variable group ka to all other covariates[15]

We take advantage of the longitudinal nature of the cohort data in two ways. First, we combine the variables under the same group across childhood period (sweep 0-3 of the NCDS) and explore the broad impact of each five themed group on the skill outcomes. Thus for the complete model, we estimate:

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[12]We choose baseline characteristics on two criteria: (i) the variable is determined by the time of birth and that (ii) it is most likely to be time-invariant throughout. Therefore, we decide to categorise parental education as a baseline variable, even if by itself, it can explain a considerably high variation of children's skills.

[13]We note that adding this number of variables to a regression can result in symptoms of multicollinearity. However this will not affect our adjusted R-squared. Individuals interested in obtaining the tables of our coefficients can contact the authors.

[14]To deal with missing data values and sample attrition, we make the assumption that data are missing at random. This is reasonable given it has been shown elsewhere that attrition is not systematically associated with SES (Case and Paxson, 2010). Therefore, we impute missing values of our explanatory variables by the variable's mean. We create a dummy for each variable that takes the value of 1 if the data is missing and zero otherwise.

[15]According to Berlinski and Carneiro [2012], with multivariate measures, we only know for certain that $AdjR^2_{complete} > AdjR^2_{complete \backslash ka} > AdjR^2_{ka} > AdjR^2_{basic}$. Therefore, we can tell that $AdjR^2_{ka} - AdjR^2_{basic} > 0$ and $AdjR^2_{complete} - AdjR^2_{complete \backslash ka} > 0$. However, given the relationship, we simply cannot predict if $AdjR^2_{ka} - AdjR^2_{basic}$ is larger or smaller than $AdjR^2_{complete} - AdjR^2_{complete \backslash ka}$.

$$Skill_{i,50} = \gamma B_{i,0} + \sum_{k=1}^{5} \beta I_{i,k0-16} + \varepsilon_{i,50} \qquad (2.4)$$

where $I_{i,k0-16}$ represents group of variables, k, namely SES, HH, INPUT, HTH and SCH. Second, we also run the models where each group is defined for each sweep (so separate groups at age, a, (0, 7, 11 and 16)). Thus for the complete model with age dynamic, we estimate:

$$Skill_{i,50} = \gamma B_{i,0} + \sum_{a=0}^{16} \sum_{k=1}^{5} \beta_{ka} I_{i,ka} + \varepsilon_{i,50} \qquad (2.5)$$

2.4 Empirical Results

2.4.1 Adult outcomes

The main results are illustrated in Figure 2.3. The first three columns highlight the contribution that childhood SES (combined from age 0, 7, 11 and 16 sweeps) has on cognitive skills, positivity and malaise respectively. Looking at the upper bound scores, it is clear that childhood SES can explain more of the variation in an adult's cognitive skills than their non-cognitive skills. The figure also suggests that SES may be better at explaining malaise than positivity. However, if we turn to the precise estimates in Table 2.2, which decomposes the results by the age of the input, the contribution of SES overall is negligible. For example, for cognitive skills the upper bound never suggests an adjusted R squared that exceeds 1% and the lower bound is zero. For both positivity and malaise the upper bound never exceeds 0.5%. Thus, SES can explain very little of the variation in adult cognitive and non-cognitive skills.

Similarly, Figure 2.2 illustrates that across all skills, the contribution of childhood household composition to the variance of the cognitive and non-cognitive outcomes at age 50 is negligible. This is further highlighted by the results in Table 2.2 which highlights that the separate contribution from HH at every age is virtually 0%. The same conclusion can be drawn for parental health.

The remaining two groups are parental inputs and schooling. These groups do seem to be able to explain more of the variation in adult cognitive ability. For example, the aggregate contribution of parental inputs is 0.03 (upper bound) and 0.008 (lower bound). Thus, we can explain at most about 3% of the variation in adult cognitive ability. Considering Table 2.2, parental inputs at each childhood age explain independently similar amounts of variation in cognitive ability at age 50 (1.3% upper bound and 0.3%

lower bound). In comparison, the explanatory power of schooling characteristics is low during the early childhood, but grows stronger at age 16. For example, age 7 schooling can explain less than 0.5% of the variation in cognitive outcomes, but at age 16 we can explain between 2% and 4% of this outcome.

Considering adult non-cognitive skills, from Table 2.2 the legacy of our age specific groups on our non-cognitive skills measures is small (at best the adjusted R-squared is still less than 0.5%). The finding is similar for the schooling variables. For ages 7 and 11 it seems the explanatory power of these variables is small (less than 0.5%). Schooling at age 16 can explain between 0.5% and 1% of malaise, but less than 0.5% of the variation in positivity.

Bringing all the groups together across all ages we can explain approximately 10% of the variation in cognitive skill at age 50. With the same set of variables, we can explain about 4.5% of the variation in malaise and 1% of the variation in positivity. Thus, overall, childhood leaves a greater legacy on cognitive skills. This legacy is mainly left by differences in schooling at age 16, followed by differences in parental inputs during childhood. The former is intuitive as this is the year that students take exams which will decide whether they (i) attend university and (ii) what they will study. Thus, it may be through variation in occupation type through which schooling at this age perseveres a legacy on cognitive skills. That is, it is likely that certain occupation types are more likely to keep an adult cognitively sharp. For non-cognitive skills, we can explain more of malaise which is a negative soft skill (and akin to mental health) when compared to positivity (a positive soft skill somewhat akin to life satisfaction).

A possible critic of our work is that between the ages of 16 and 50 is a black box. Unfortunately, the NCDS do not gather information on cognitive skills for any other adult sweep. However, measures of soft skills are consistently gathered. In particular, the malaise index previously described is gathered at ages 23, 33, 42, 46 and 50. In addition, individual income is gathered at age 33, 42, 46 and 50. This outcome is highly correlated with cognitive ability. Thus, we reconsider our models with these alternative outcomes. While these are not reported for brevity [16], a few things are noteworthy. First, our models can always explain more of individual income than personal malaise. Specifically for malaise, we can explain 12%, 6%, 5%, 4.5% and 1% at ages 23, 33, 42, 46 and 50. In contrast, we can always explain more than 20% of the variation in personal income with the complete list of our childhood variables. For income, parental inputs are predictive, with the imprint fading with age. By age 50, the bounds are between 0.5% and 1.4%. Schooling can explain up to 2% of the variation in income at any one age.

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[16]Please refer to Appendix 2.7.

For malaise, schooling is the only variable that leaves a notable legacy. For example, the bounds are between 1.4% and 3% at age 23. At age 50, the lower bound is 1%.

2.4.2 Cognitive and non-cognitive skills in childhood

The results so far suggest that family and schooling variables leave more of a legacy on adult cognitive skills when compared to non-cognitive skills, albeit the contribution of particular variable group is usually small. This conclusion is supported by an additional analysis of individual income and malaise. We now consider whether the same childhood variables are good predictors of cognitive and non-cognitive skills contemporaneously. Thus, we consider additional outcomes, which pertain to cognitive and non-cognitive skills measured at ages 7, 11 and 16[17].

For age 7, we have nine proxies that capture knowledge in different subject areas. Firstly, the *Southgate Reading Test* is a measure of reading ability particularly suited to identifying poor readers. Second, arithmetic ability is measured using the 10-item *Problem Arithmetic Test* (Pringle et al., 1966). We next utilize a measure of perceptual and motor ability derived from the *Copying Design Test* and *Drawing-a-Man Test*. The last set of proxies is derived from the teacher's assessment of the child's performance in five categories: numeracy, oral ability, reading ability, awareness of the world around him and creativity. We utilize exploratory factor analysis to bring these nine proxies together to form one latent variable that captures underlying cognitive ability at age 7[18]. We can easily extract one factor whose loadings are greater than 0.7 on every variable, except those that capture perceptual and motor abilities (¿0.4)[19].

Similarly at age 11, we consider a number of proxies for cognitive ability. These are as close as possible to our measures included at age 7. The first is a reading comprehension test, which has 35 items to be answered over twenty minutes. Second, the mathematics test has forty items. Third, the general ability test consists of forty verbal and forty non-verbal items, which were tested and recorded individually by teachers with the purpose to measure mental ability. Finally, there is a *Copying Design Test* which aims to measure perceptual and motor ability. The remaining variables are again variables that capture the teacher's assessment of the child's performance in a number of areas. These are numeracy, oral ability, reading ability and awareness of the world around him. The cognitive factor extracted for age 11 is similar to that at age 7, so far as all our proxies load positively, with the only load that is ¡0.7 attributed to the Copying design Test (0.4).

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[17]A detailed description of the variables that are utilised to measure these skills can be found in the Appendix 2.8.

[18]See Table 2.10 in Appendix 2.6 for details.

[19]The CFA procedure confirms that the derived factor is well-defined (see Appendix 2.6 Table 2.14.)

Again at age 16, we take a similar approach. The full list of cognitive measurements available at age 16 comprises 8 proxies: a mathematics test; a reading comprehension test; and a teacher-assessed score on six individual subjects. Specifically, the mathematics test is a 27-item multiple choice ability assessment, which contains numerical and geometric questions. In the reading comprehension test, the child was required to choose from a selection of five words, which appropriately complete sentences. The child answered 35 questions in total with scores lying between 0 and 35. For each subject assessment, the class teacher scores the child's ability on mathematics, English, modern languages, science, social studies and practical tasks [20]. As before, we perform the exploratory factor analysis on the standardised scores from these proxies and are able to extract one factor variable as our measure of cognitive ability at age 16[21].

To measure non-cognitive skills, we utilise the Rutter Behaviour scale that was administered at ages 7, 11 and 16[22]. Across all three sweeps, the Rutter Behaviour Scale was answered by the child's parent (usually the mother). Starting from the full list of questionnaire items, we decide to select only those individual items of the Rutter Scale in the NCDS that are analogous to behaviour measures available in the Millennium Cohort Survey (MCS). This is mainly because we will later compare our empirical findings from the birth cohorts in the NCDS to the results from the MCS cohort born forty years later. Therefore, to account for possible changes in the signal-noise ratio of some psychological measures over time, we construct equivalent measures of non-cognitive outcomes for these two generations[23]. Using exploratory factor analysis, we can identify two factors for the three sweeps that can easily be labelled '*externalising*' and '*anxious*' at age 7 and age 11. At age 16, we identify an additional factor that can easily be labelled '*hyperactivity*'.

Age 7 results: At age 7, we have three main measures of skills: cognitive, externalising behaviour (soft) and anxious (soft). We follow the same approach by looking at the bounds of the marginal contribution of a particular group of childhood characteristics at each preceding age. Figure 2.4 illustrates our main findings for the age 7 outcomes.

For cognitive ability at age 7, comparing across all five groups, parental inputs leave the greatest legacy. Overall, childhood parental inputs raise the model's adjusted R-squared by at least 0.085 (lower bound). Thus at a minimum, we are able to explain about 9% of the variance in cognitive skills. At this age, school characteristics do not

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[20]Teacher's rating ranges from (1) little ability, (2) below average, (3) CSE grades 2-4 (4) O-Level and (5) A-level ability equivalent.

[21]See Appendix 2.6 Table 2.10 and 2.13

[22]The specific questions included from this instrument changed slightly in each individual sweep. We document the details in the Appendix 2.6 Table 2.16

[23] Further details can be found in Table2.12 in Appendix 2.6.

play a strong role in explaining cognitive ability. This is likely because children still spend more time in the family environment at this age . This could also explain why the bounds are greater for household composition [0.004, 0.039] when compared to schooling [0.01, 0.016] (see Table 2.3). From Table 2.3, overall SES; parental health; and schooling variables do contribute to explaining cognitive skills at age 7 but the absolute magnitude is low. Noticeably, parental inputs at age 7 are the most important, explaining at least 8% of variation in cognitive skills (at most 13%). Clearly, this is the input that does the heavy lifting at this age, however altogether age 0 and age 7 childhood variables can explain close to 30% of the variation in contemporaneous cognitive skills.

For non-cognitive abilities (Table 2.3), we can explain less of the variation as compared to cognitive skills. For example, Table 2.3 suggests that we can explain between 2.5% and 3.2% of the variance in externalising behaviour at age 7 with parental inputs. In contrast, we can at most 1% of the variance of anxiety at this age. On the one hand, the other childhood groups do not account for much of the variance in these skills (always less than 1%). Overall, our cumulative model at age 7 can explain about 9% of the variation in externalising behaviour, as compared to 5% of the variation in anxiety.

Age 11 results: Figure 2.5 illustrates our overall results at age 11 and highlights that parental inputs remain the strongest predictor of cognitive ability. Here we consider the individual contributions of age 7 and 11 inputs. Specifically, from Table 2.4, parental inputs at age 11 can explain between 5% and 13% of the variation in cognitive ability. The legacy from age 7 parental inputs is independently between 2% and 9%. While schooling at age 7 leaves only a small legacy on age 11 cognitive skills (at best 1% of the variation is explained by these variables), schooling at age 11 can explain somewhere between 3% and 7% of the variation. Parental health at ages 7 and 11 explain less than 1% of the variation in cognitive skills. For household composition, the bounds are similar for ages 7 and 11. That is, between 0% and 3% of the variation is explained. SES at age 7 leaves a similar legacy on age 11 cognitive skills. SES at age 11 is more important, explaining at least 3% of the variation in cognitive skills (at most 7%).

For externalising behaviour, most of the age 7 variables leave no real imprint on these skills, explaining at best 0.7% of its variation. The exception here is parental inputs whose lower bound is 0.5% and upper bound is 1.8%. At age 11, parental inputs again explain the most variation in current externalising behaviour (between 0.8% and 2%). The remaining groups can never explain more than 1% of the variation in externalising behaviour). Overall, the cumulative model can explain about 9% of the variation in externalising behaviour.

The variables we consider at age 0, 7 and 11 can explain little of the variation in anxiety, assessed at age 11. For instance, parental health, parental inputs and schooling at age 11 explain the most variation in this outcome, 0.05% each. In addition, the cumulative model can explain only about 3% of the variation in anxiety.

Age 16 results: Considering cognitive ability at age 16, two inputs stand out: parental inputs and schooling. Figure 2.6 captures the aggregate contribution of the collection of childhood characteristics from ages 7, 11 and 16. More precisely, from Table 2.5, schooling at age 16 is a very important predictor of cognitive outcomes at the same age. Specifically, we can explain between 12% and 27% of the variation in this outcome. Conversely, schooling at age 11 can explain between 0.5% and 6% of the variation. At age 7, this figure is less than 1%. The contribution of parental inputs at age 16 to cognitive ability is also significant. That is, we can explain between 2.6% and 14% of the variation in this outcome. For parental inputs at age 11 these bounds are between 1% and 10%. At age 7, the same figures are 0.5% and 8.7%. The remaining variable groups, SES, household composition and parental health, all have a lower bound of 0%. The upper bound does not exceed 4%. Together, these variables can explain, at the upper bound, more than half of the variation in cognitive skills (56%).

For non-cognitive skills at age 16, the absolute magnitude of the contribution from all the variable groups is much lower than for cognitive skills at the same age. For externalising behaviour, it seems that schooling matters the most, explaining between 1% and 3.5% of the variation in this variable. The legacy of schooling from age 7 and 11 is negligible— less than 1% on the upper bound. Parental inputs at age 16 can explain between 0.6% and 1.8% of the variation in externalising behaviour. There is a positive legacy from earlier parental inputs. For example, the bounds for age 7 parental inputs are between 0.03% and 2.4%. The same figures for parental inputs at age 11 are 0.01% and 1.7%. Parental health at age 16 can explain a small proportion of the variation in externalising skills— between 0.5% and 2%. For ages 7 and 11, the contribution of parental health is close to 0%. Household composition and SES at age 16 have identical bounds— between −0.1% and 2.7%. At age 11 and age 7, the bounds are again similar (0% to 2% and about 0% to 1.7% respectively). Overall, together the groups can account for 11% of the variation in externalising behaviour.

For hyperactivity, schooling at age 16 again has the most predictive power. Here, it can explain between 0.6% and 1.5% of the variation. Schooling at ages 7 and 11, does not leave a strong legacy (upper bound does not exceed 0.5%). In fact, for no other variable group does the upper bound exceed 1%, and the lower bound is always less than 0.3%. For anxiety at age 16, schooling at age 16 can explain between less than

1% of the variation and no other variable group has greater predictive power. For both hyperactivity and anxiety at age 16, we can explain about 5% of the variation with our cumulative model.

2.4.3 Millennium Cohort Study and Today's Relevance

The NCDS cohort were born in 1958, so a pertinent question is whether family and schooling variables predict cognitive and non-cognitive skills to the same extent for children who are young today. To investigate this we consider the Millennium Cohort Study (MCS), which is a similar initiative to the NCDS that began following the lives of around 19,000 children born in the UK in 2000-2001. In particular, the available data relates to surveys conducted at age ¡1, 3, 5 and 7. We focus on the outcomes when the MCS were 7 years old so as to make direct comparison to our previous findings using the NCDS cohort from the same age. Thus, we focus here on variables available at age 0 and age 7. Our idea is that if the predictive power of childhood family and schooling circumstances is similar for the MCS when compared to the NCDS children at age 7, it is suggestive that the trajectory of the legacy may be similar into adulthood.

In particular, we create similar aggregate measures of non-cognitive and cognitive abilities at age 7 using exploratory factor analysis. For the cognitive factor variable, we utilise three psychometric instruments. Specifically, these instruments are the *British Ability Scales* (*Pattern Construction* and *Word Reading*); and *Progress in Mathematics* (PiM). The *Pattern Construction Test* is a test of non-verbal reasoning and spatial visualisation in which children construct patterns using flat squares or solid cubes. *Word Reading* assesses a child's English reading ability. The PiM assesses a child's mathematical skills by asking her to complete a series of calculations. Finally, we also include a 5-point-scale assessment of proficiency by the child's teacher in reading, writing, speaking, science, numeracy, information and communications technology (ICT) and creative art. Using exploratory factor analysis we can extract one underlying latent factor that captures cognitive ability[24].

Given that psychologists have likely become better at measuring soft skills over time, we utilize parental responses to the *Strengths and Difficulties Questionnaires* (SDQ) to measure these skills. The SDQ is a 25-item questionnaire that was completed independently by the child's parent. It normally is divided in five sub scales, which are emotional symptoms, conduct problems, hyperactivity, peer problems and pro-social behaviour. In order to construct a comparable measure of soft skills to the NCDS, we select the items that are analogous to what we utilised in the NCDS [25]. So the measure is the same

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[24]See Appendix 2.6 Table 2.17 for details.
[25]See Appendix 2.6 Table 2.16 for details.

for both cohorts. Utilising exploratory factor analysis we again obtain two latent factor variables at age 7 that can easily be labelled as *externalising behaviour* and *anxiety*.

To create the groups of childhood variables, we focus on childhood characteristics that are analogous to the variables chosen for our NCDS analysis. These are described in Table 2.6 where the first two columns depicts the sweeps of the MCS (age 0, and age 7) with an x indicating a particular variable was available and included in the analysis. We create the familiar five groupings: socio-economic status (SES), household composition (HH), parental inputs (INPUT), parental health (HTH) and schooling (SCH).

MCS results: Table 2.7 documents the MCS results for age 7. Consistent with the NCDS results parental inputs are the most important determinant for cognitive skills at age 7. In particular, we can explain between 3% and 4% of these skills with these variables. However, these bounds are significantly lower than the bounds found in the NCDS analysis (8% to 13% approximately). Schooling at age 7 can explain between 1% and 1.6% of the variation in cognitive skills for the NCDS cohort. This compares to 0% for the MCS. SES at age 7 implies a slightly stronger contribution to cognitive skills when compared to the NCDS (1% to 4.6% versus 0.2% to 3.3% for the MCS and NCDS respectively. However, SES at age 0 may be more important for the MCS cohort. That is, we can explain between 0.2% to 3.6% of the variation in cognitive skills with these variables in the MCS, as compared to between 0 and 1.7% for the NCDS. Household composition and parental inputs at age 0 give similar small contributions to cognitive skills at age 7 for both cohorts. Overall, the cumulative model for the MCS can explain about 22% of the variation in cognitive skills versus 29% for the NCDS cohort. The model reveals that similar variables matter across both cohorts, albeit their contributions have slight differences across cohorts. In particular, the MCS has no particular variable that does the *heavy lifting*, whereas for the NCDS parental inputs were the forerunner at explaining cognitive outcomes.

For externalising behaviour, the lower bounds of all variable groups do not exceed 1%. Notably, parental inputs at age 7 now matter less than in the NCDS. That is, they can explain between 0.5% to 2% of the variation in externalising behaviour. Characteristics at age 0 seem to matter more for the MCS child. For instance, parental SES can explain between 0.1% and 2.8% of the variation in externalising behaviour for this cohort, versus about 0% for the NCDS. However, these differences are small, with the most notable difference being that parental inputs have less predictive power for the MCS children with respect to predicting externalising behaviour. Moving to parental health, at age 0 the upper bound is 2.7% for the MCS versus 0.7% for the NCDS. Parental health at age 7 can explain a maximum of 3.5% of the variation for the MCS cohort as compared to

0.3% for the NCDS children. Overall, the cumulative model for the MCS can explain about 15% of the variation in externalising behaviour versus 9% for the NCDS cohort.

Looking at anxiety at age 7, family characteristics from age 0 in the MCS predict more of the variance in this soft skill. For example, parental health can explain up to 2.4% of the variation in anxiety in comparison to 0.2% for the NCDS. The same figures are 2.8% and 0.2% for SES respectively. For both the MCS and the NCDS the imprint of parental inputs and household composition at age 0 and age 7 is negligible. SES at age 7 also matters more for the MCS cohort, predicting between 0.6% and 4% of the variation in anxiety. The same figures for the NCDS are 0.1% and 0.3%. Parental health also matters more for NCDS children, with bounds of 0.8% and 3.4% as compared to an imprint for the NCDS cohort that is virtually zero. For both cohorts schooling at age 7 does not predict anxiety. The upper bound for parental inputs is 0.7% in the MCS versus 11% in the NCDS. Overall, the cumulative model can explain about 10% of the variation in anxiety versus 5% for the NCDS cohort.

Given the focus on the transmission of mental health through generations in the literature (Rutter, 2006; Powdthavee and Vignoles, 2008; Akbulut and Kugler, Akbulut and Kugler and Johnson et al., 2011), we were also interested to see if maternal mental health played a significant role in predicting outcomes at age 7. At age 7, mothers and fathers responded separately to the self-assessed six-item *Kessler Psychological Distress Scale* [26]. Specifically, both parents were asked how often in the past 30 days the respondent had felt (i) so depressed that nothing could cheer you up; (ii) hopeless; (iii) restless or fidgety; (iv) that everything you did was an effort; (v) worthless; and (vi) nervous. For each question, respondents score four points ranking from (0) 'none of the time' to (4) 'all of the time'. The questions form a 24-point scale and the following cut-offs were used: 0-3 'No or low distress', 4-12 'medium', and 13 or over 'high'. In the model, we use both the mother's scale and the father's scale to gain insight on their aggregated explanatory power. For brevity, these results are not shown [27], however while parental mental health is not very predictive of cognitive ability (bounds are between 0.1% and 1%), the imprint on contemporaneous soft skills is more evident. Specifically, for externalising behaviour the bounds are between 2.7% and 6%. The same figures are 5% and 9% for anxiety. Given that we do not have a measure of parental mental health, we will not digress further.

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[26]In the MCS, the term *father* is used loosely. It is referred to the child's natural father when he is present in the household. Otherwise, any questions directed to the father are responded by mother's partner. In this analysis, we employ mean imputation to missing variables, and this also is applicable to Kessler Scale when the *father* is completely absent.

[27]Please refer to Table 2.22 in Appendix 2.7

2.5   Discussion and Conclusion

This paper adopts a life course perspective in order to gauge the legacy that childhood factors have on adult cognitive and non-cognitive skills. To achieve this we utilize the NCDS. This work differs from other studies as rather than focusing solely on the legacy of family circumstances; we also consider the legacy of schooling. We view this addition as important given that a child spends the majority of their time either at home or in school, so by considering these factors together we are better able to capture the child's early experiences. Our main outcome measures are proxies of cognitive and non-cognitive skills measured at age 50. To our knowledge no study in economics considers the long run legacy of childhood factors on non-cognitive skills. In our work, our proxy of non-cognitive skills is based on a number of instruments used to measure mental health attainment.

Overall, we find that we can predict more of the variation in cognitive skills when compared to non-cognitive skills. We draw a similar conclusion when we consider soft skills across other sweeps in the NCDS. For cognitive skills, the most important variable groups are early parental inputs and schooling at age 16. On the other hand, the legacy of early parental inputs explains a smaller variation of non-cognitive skills at age 50.

We also consider how our childhood variables can predict cognitive and soft skills during childhood. Again, given our set of childhood characteristics, we can predict significantly more of the variation in cognitive skills as compared to soft skills, as defined by behavioural scores. We also find that parental inputs are the most important childhood factor for a young child. However, schooling is more important at age 16. In particular, schooling is highly predictive of both cognitive and soft skills at this age, albeit the imprint on soft skills is smaller.

Overall, the analysis of the NCDS 1958 cohort suggests that childhood circumstances account more of the variation of cognitive skills , in comparision to non-cognitive skill attainment. This is consistent with work by Frijters et al. [2014] and Layard et al. [2013], to the extent that life satisfaction may be viewed as a manifestation of soft skills. In addition, it is consistent with evidence, which suggests that non-cognitive traits, like personality traits do not stabilize until age fifty onwards, while cognitive skills (like IQ) stabilize in childhood (Schuerger and Witt, 1989; Hopkins and Bracht, 1975). Overall, our findings suggest that non-cognitive skills are more malleable in later life. This is consistent with previous findings in development psychology (see Borghans et al., 2008 for a recent review of the literature).

We recognize that children born in 1958 were born into an environment that is very different to children who are growing up today. Thus we also consider the influence of

family and childhood factors on cognitive and non-cognitive skills in childhood. Specifically, we consider comparable regressions at age 7 for the NCDS and MCS cohorts. This analysis again reveals that childhood factors predict more of the variation in contemporaneous cognitive skills in comparison to non-cognitive skills. However, while parental inputs were more notable in the NCDS at age 7, they still do the heaviest lifting for the MCS children at age 7. In this regard, the trajectory looks similar and we can expect that schooling will become more important as the MCS child progresses through childhood. We also note that parental health is more important in determining soft skills in childhood for the MCS cohort. A subsequent analysis reveals that paternal mental health is also highly correlated with soft skills at age 7.

Nevertheless, our analysis rely heavily on the assumption of the linear relationship between childhood variables and key adult outcomes. We are also cautious with making any causal inference from the findings, provided the strong assumption on the structure of error terms (inclusively omitted variable bias, measurement errors and attrition) [28] Therefore, our work simply highlight the amount of the total variation in the relevant outcome that can be explained by the variables we observe. Thus, future research could seek some way to establish causality in this relationship.

We are aware that a selected variable can encompass more characteristics than what it is directly represented, therefore may exaggerate the marginal size of the R-squared. Particularly, the available measures we used as parental inputs from the NCDS is far from perfect. The advance of the current literature on childhood development on home environment have indicated many other inputs, which are absent in the survey, are much better at capturing skill development. More importantly, our analysis do not capture heterogeneous parental beliefs or expectation, which are found to be important. Under this consideration, a single variable chosen in the analysis, for example parental discussion, may encompass a broader variation of confounding parenting styles and their beliefs, rather than the precise act of discussion. Therefore we encourage our readers, when interpreting our results, to think of our choice of variables in their aggregate, thematic term, rather than a single sole factor.

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[28]The problem of omitted variables is a key issue that made us decide to use the methodology of adding and omitting variables, and therefore presenting our results in bounds instead of precise magnitude in the first place.

Figures

FIGURE 2.1: Distribution of average cognitive at different ages
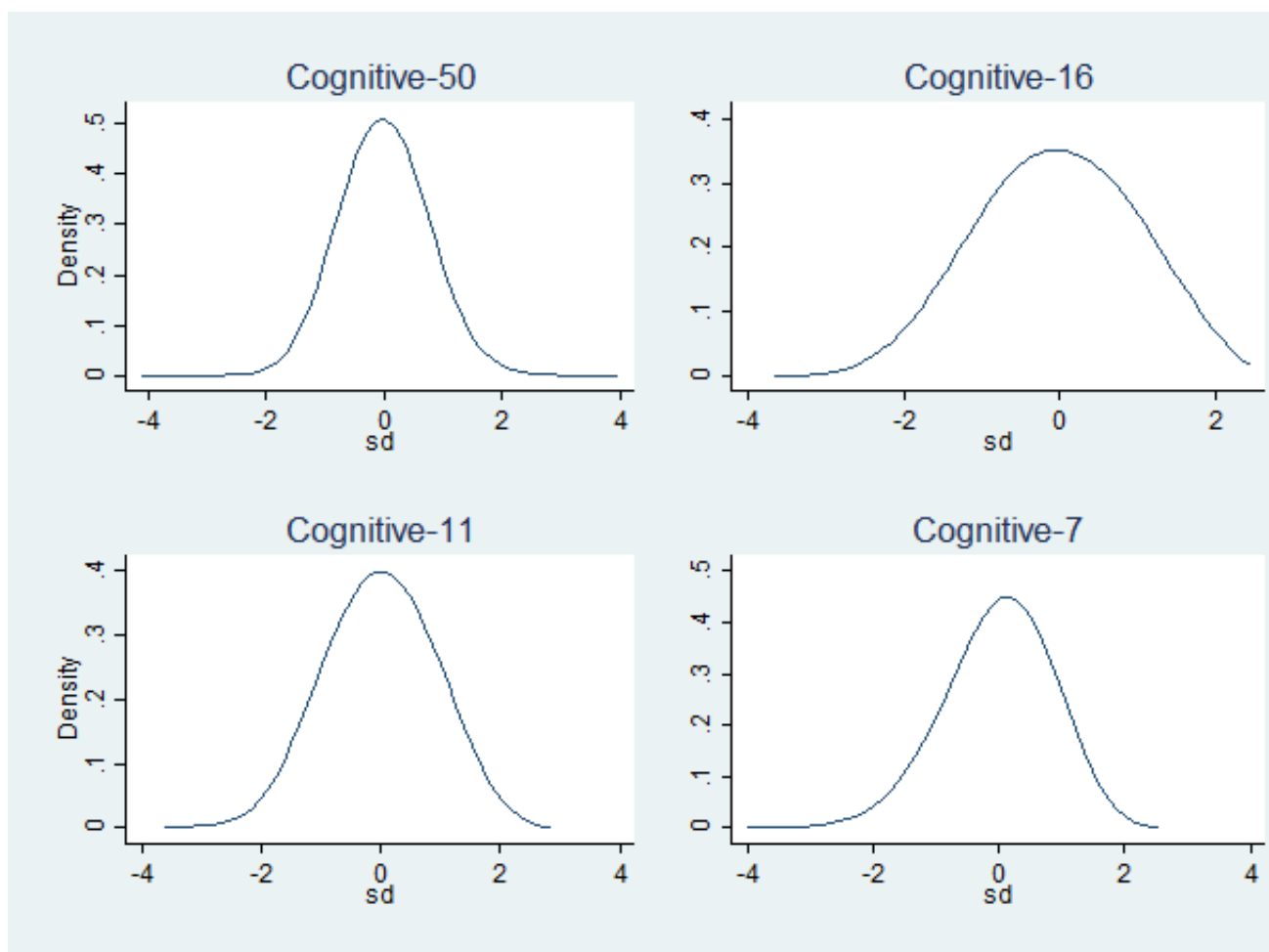
FIGURE 2.2: Distribution of average non-cognitive at different ages
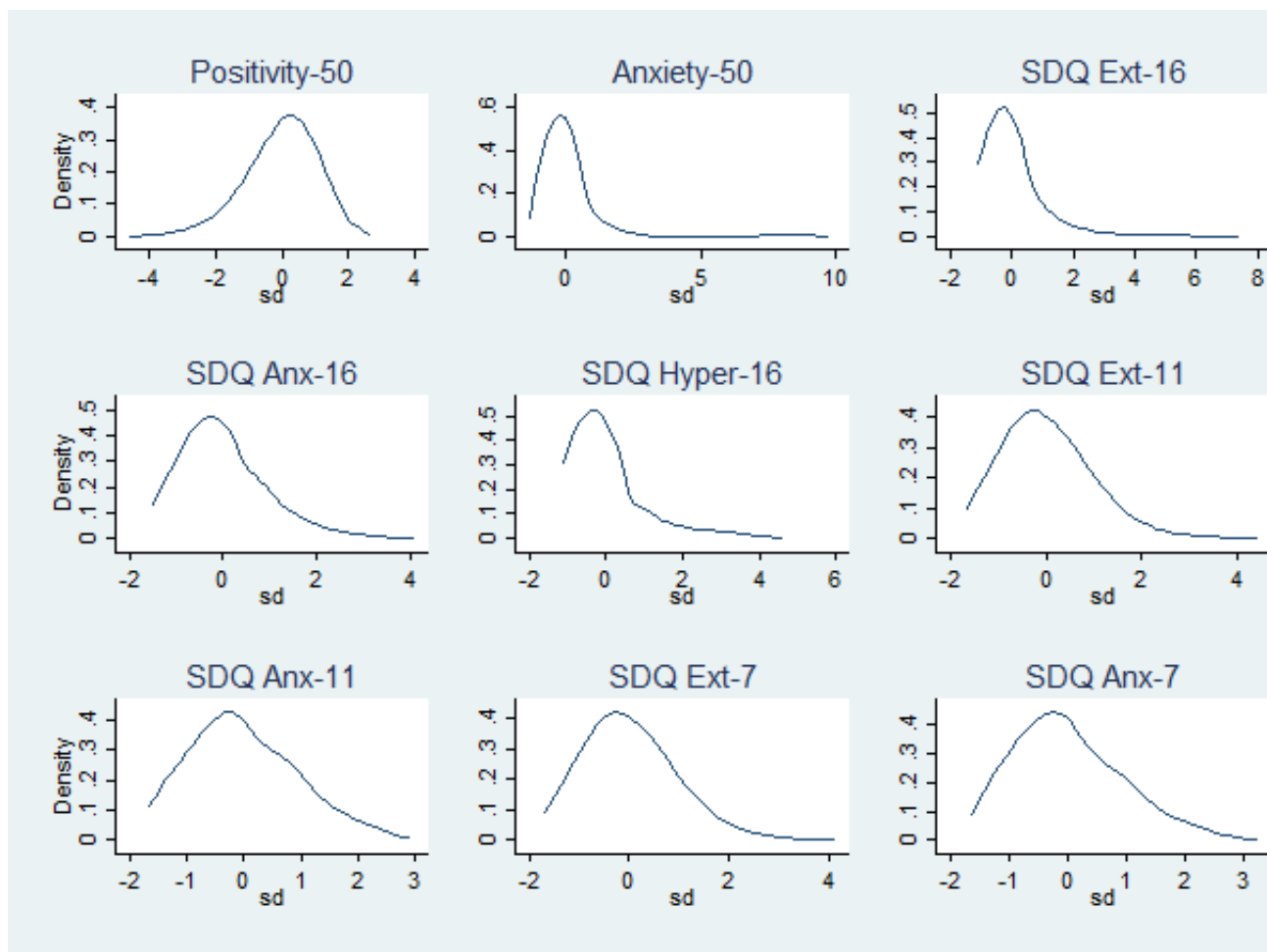
FIGURE 2.3: Outcomes at age 50
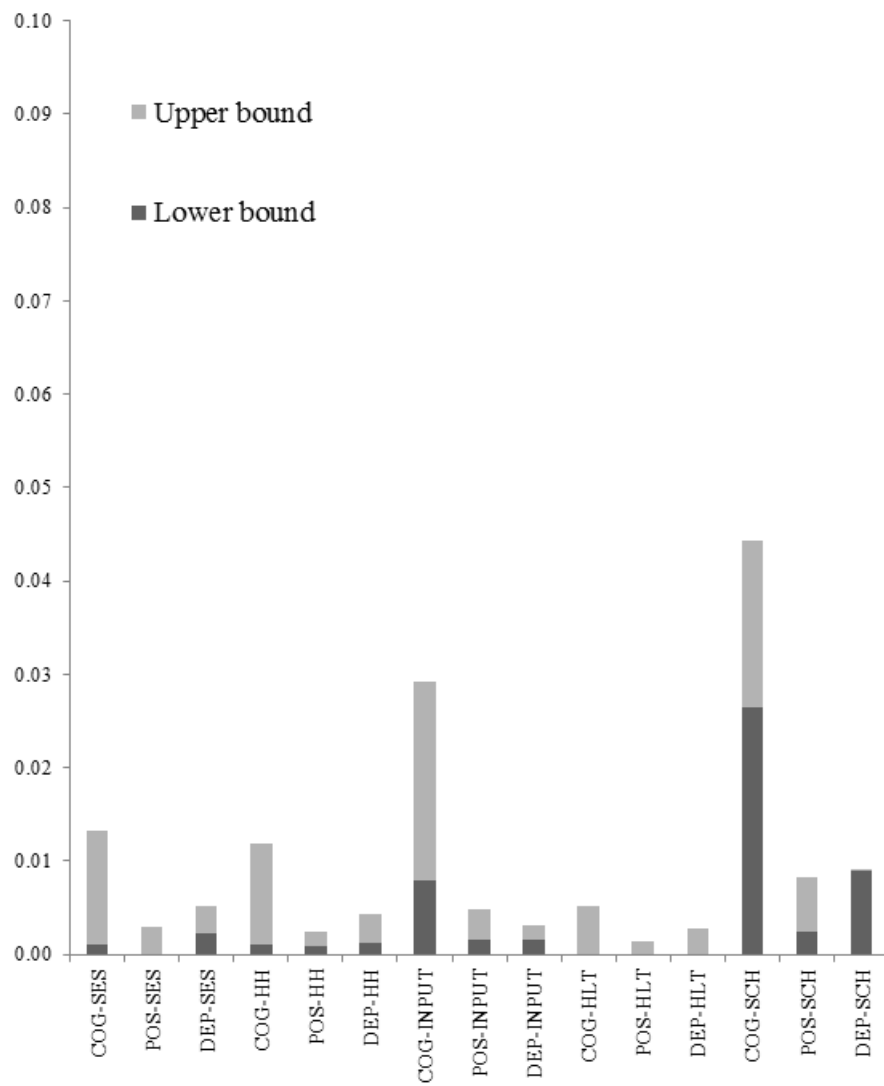
FIGURE 2.4: Marginal contribution of childhood characteristics on adj-R^2 of outcomes at age 7
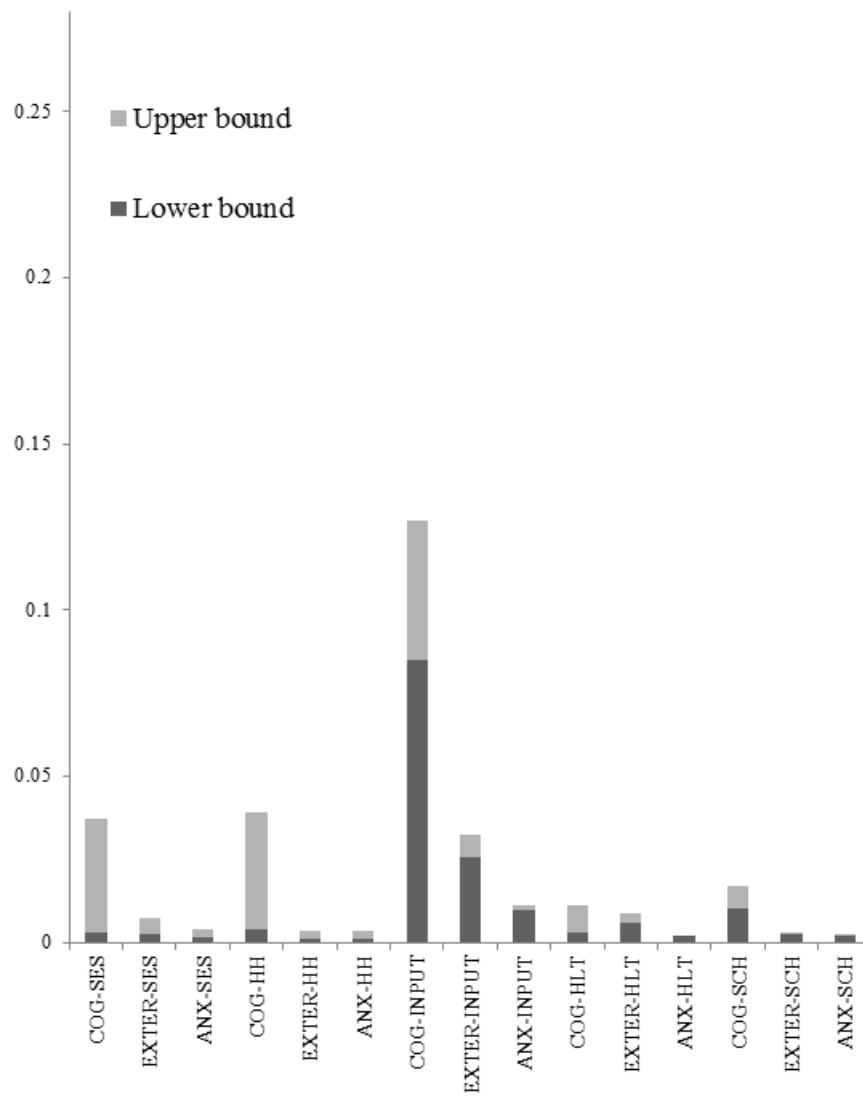
FIGURE 2.5: Marginal contribution of childhood characteristics on adj-R^2 of outcomes at age 11
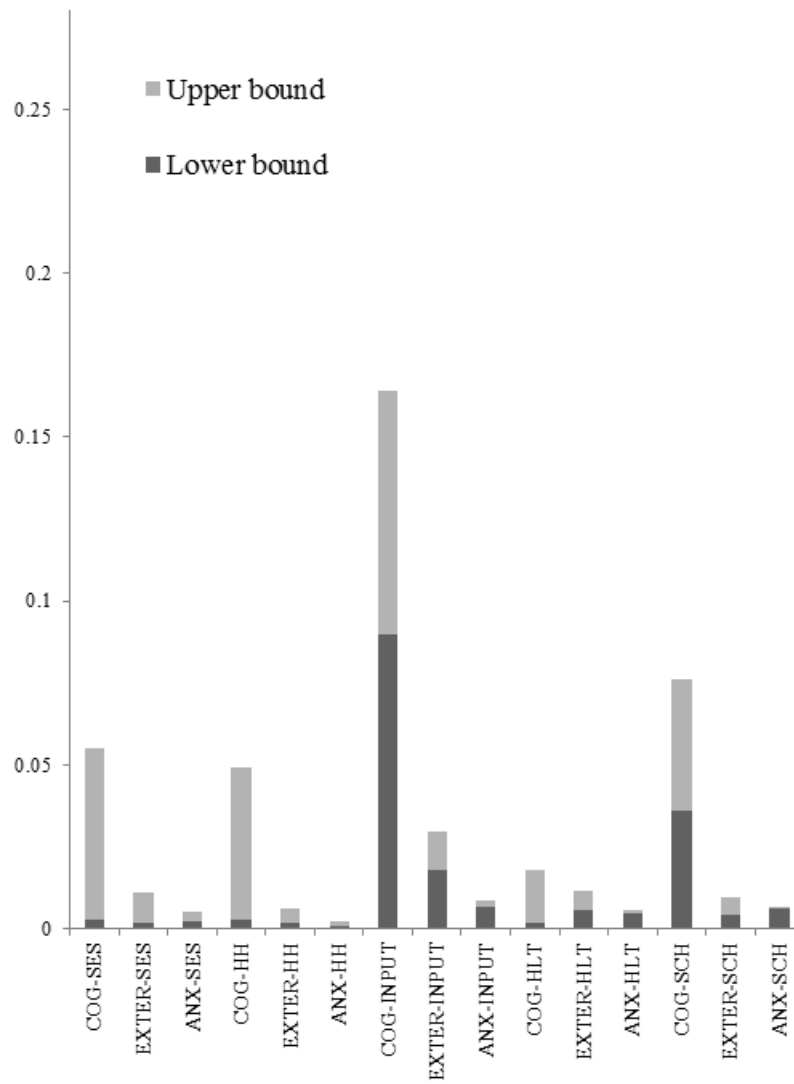
FIGURE 2.6: Marginal contribution of childhood characteristics on adj-R^2 of outcomes at age 16
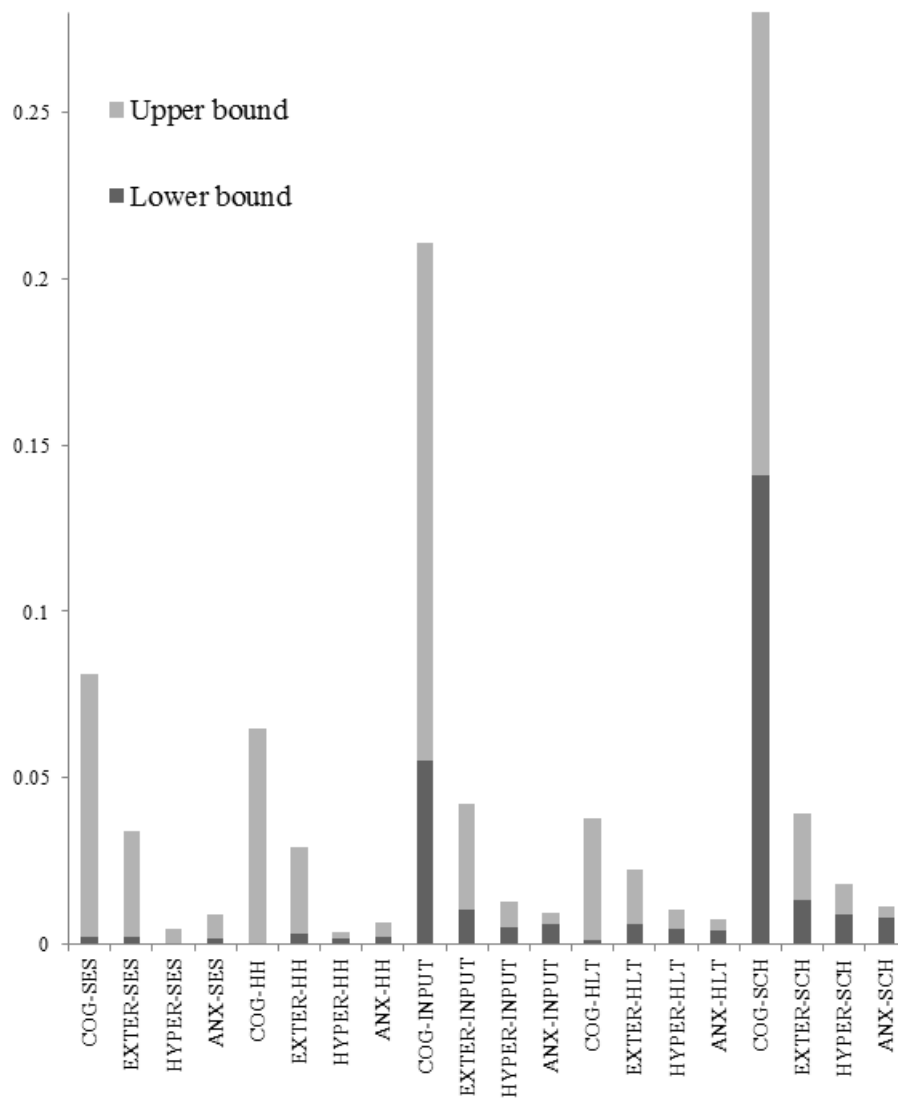
FIGURE 2.7: Marginal contribution of childhood characteristics on adj-R^2 of outcomes at age 7 using the MCDS
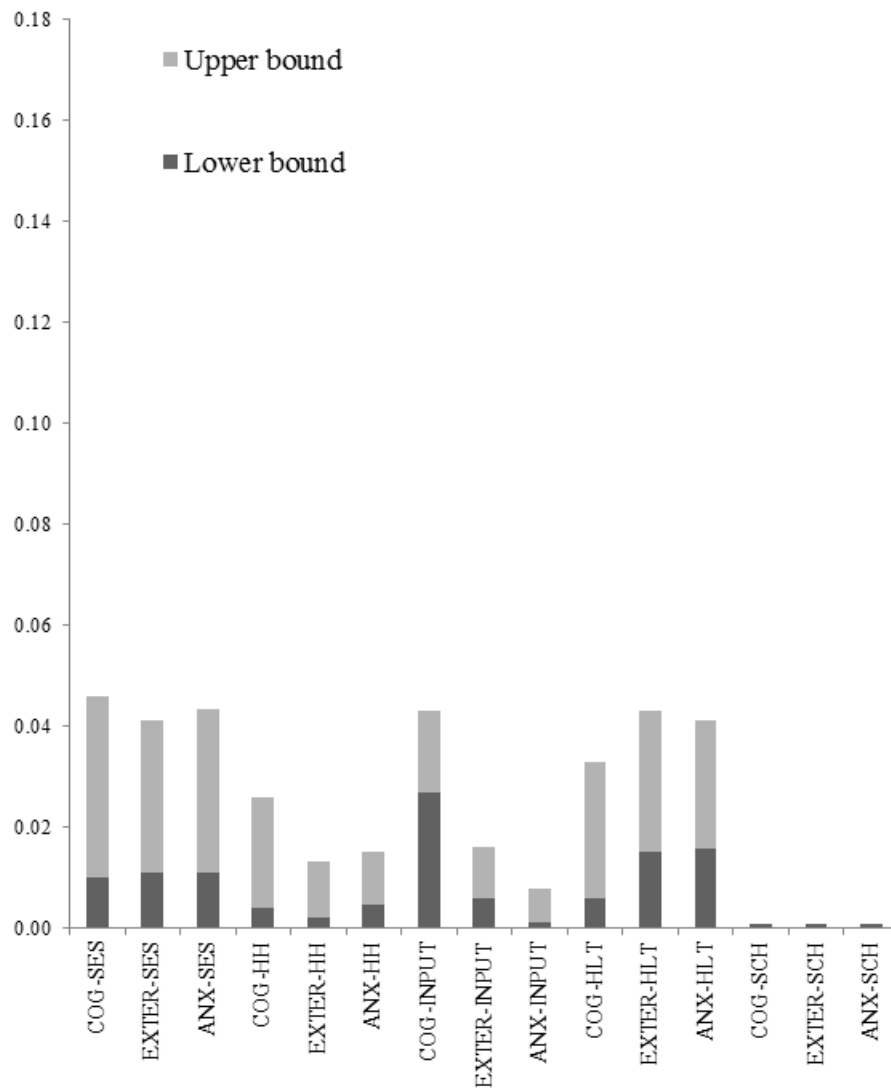
Tables

TABLE 2.1: NCDS variable description

Age 0	Age 7	Age 11	Age 16	Group	Description
x				Baseline	Birth weight (grams)
x				Baseline	Gender (male =1)
x				Baseline	Region at birth (11 regions)
x				Baseline	Mother's age
x				Baseline	Father's age
x				Baseline	First born child (1=yes)
x				Baseline	Gestation weeks
x				Baseline	English language spoken (1=yes)
x				Baseline	Mother compulsory school age (in years)
	x			Baseline	Father compulsory school age (in years)
x	x	x	x	SES	Social class of father (fixed effects indicating professional, skilled and unskilled)
		x	x	SES	Father employment status (working =1)
x	x	x	x	SES	Mother employment status (working =1)
		x	x	SES	Council house status (council =1)
		x	x	SES	Own house status (own house =1)
x	x	x	x	SES	Crowdedness (persons per room)
		x	x	SES	Number of times moved house
	x	x	x	SES	Financial difficulties (yes =1)
		x	x	SES	Whether child gets free school meals (yes =1)
		x	x	SES	Whether family on some benefit (yes = 1)
			x	SES	Father monthly net pay (banded from 1-12, used as continuous. If father is unemployed, the variable is assigned value 1)
			x	SES	Mother monthly net pay (banded from 1-12, used as continuous. If mother is unemployed, the variable is assigned value 1)
x	x	x	x	HH	Whether live with natural father (yes = 1)
x	x	x	x	HH	Number of siblings

Age 0	Age 7	Age 11	Age 16	Group	Description
x				Input	Duration of separation from mother (in months)
		x		Input	Mother time away from home (hours)
		x		Input	Mother time away from home for work (hours)
	x	x		Input	Father involvement with child rearing (0 'left to mother 1 'mother more' 2 'big or equal to mother')
	x	x	x	Input	Teacher's assessment of mother interested in child education (0 'little interest' 1 'some' 2 'very' 3 'over-concerned')
	x	x	x	Input	Teacher's assessment of father interested in child education (0 'little interest' 1 'some' 2 'very' 3 'over-concerned')
	x	x	x	Input	Whether parent discuss child with teacher (yes =1)
	x	x		Input	Outing with Mother (0 'hardly ever' 1 'occasionally' 2 'every week')
	x	x		Input	Outing with Father (0 'hardly ever' 1 'occasionally' 2 'every week')
	x			Input	Mother reads to the child (0 'hardly ever' 1 'occasionally' 2 'every week')
	x			Input	Father reads to the child (0 'hardly ever' 1 'occasionally' 2 'every week')
	x			Input	Cognitive habit: Mother read newspaper (0 'hardly ever' 1 'occasionally' 2 'most days')
	x			Input	Cognitive habit: Father read newspaper (0 'hardly ever' 1 'occasionally' 2 'most days')
		x		Input	Cognitive habit: Mother goes to library (yes =1)
		x		Input	Cognitive habit: Father goes to library (yes =1)

Age 0	Age 7	Age 11	Age 16	Group	Description
x	x	x	x	Health	Whether mother has any illness (yes = 1)
		x	x	Health	Whether father has any illness (yes = 1)
x		x		Health	Mother weight (in stones)
x		x		Health	Mother height (in inches)
		x		Health	Father weight (in stones)
		x		Health	Father height (in inches)
			x	Health	Mother number of cigarettes per day (0 'do not smoke' 1 'less than 1' 2 '1-5' 3 '6-10' 4 '11-20' 5 '21-30' 6 '31 or more')
			x	Health	Father number of cigarettes per day (0 'do not smoke' 1 'less than 1' 2 '1-5' 3 '6-10' 4 '11-20' 5 '21-30' 6 '31 or more')
x	x	x	x	School	Whether child goes to LEA school (yes = 1)
	x	x	x	School	Total number pupils in school
	x	x	x	School	Class size (number of pupils in a class)
			x	School	% of pupils in the class with father from non-manual job
		x	x	School	% pupils suitable for O-level only
			x	School	% pupils suitable for A-level
			x	School	% pupils suitable for a university degree
			x	School	No. pupils stay in school beyond compulsory school
		x	x	School	No. full time teachers
	x	x	x	School	Whether in a class with ability streaming (yes = 1)
	x	x	x	School	No. child's half-day attendance (school reported)
	x	x	x	School	No. child's half-day absence (school reported)
		x	x	School	How long altogether the child's absence due to bad health in last 12 months (0 'less than a week' 1 '1 week-1 month' 2 '1-3 months' 3 'over 3 months')

TABLE 2.2: Outcomes at age 50

	Cognitive		Positivity		Malaise	
	Lower	Upper	Lower	Upper	Lower	Upper
SES at 0	0.000	0.006	0.000	0.000	0.000	0.002
HH at 0	0.001	0.010	0.000	0.000	0.000	0.002
INPUT at 0	0.000	0.000	0.000	0.000	0.000	0.000
HLT at 0	0.000	0.002	0.000	0.000	0.000	0.001
SCH at 0	0.000	0.000	0.000	0.000	0.000	0.000
SES at 7	0.001	0.009	0.000	0.001	0.001	0.004
HH at 7	0.000	0.008	0.000	0.000	0.000	0.000
INPUT at 7	0.001	0.012	0.001	0.003	0.001	0.004
HLT at 7	0.000	0.001	0.000	0.001	0.000	0.001
SCH at 7	0.001	0.003	0.001	0.001	0.002	0.003
SES at 11	0.000	0.008	0.000	0.001	0.000	0.004
HH at 11	0.001	0.008	0.000	0.001	0.001	0.004
INPUT at 11	0.004	0.019	0.000	0.001	0.000	0.003
HLT at 11	0.000	0.002	0.000	0.000	0.000	0.000
SCH at 11	0.003	0.013	0.000	0.001	0.001	0.004
SES at 16	0.000	0.005	0.000	0.000	0.000	0.002
HH at 16	0.001	0.005	0.001	0.000	0.001	0.001
INPUT at 16	0.003	0.013	0.000	0.001	0.001	0.002
HLT at 16	0.000	0.003	0.000	0.000	0.000	0.001
SCH at 16	0.02	0.038	0.001	0.004	0.005	0.010
Complete adj-R^2	0.113		0.009		0.045	

TABLE 2.3: Outcomes at age 7

	Cognitive		Externalising Behaviour		Anxiety	
	Lower	Upper	Lower	Upper	Lower	Upper
SES at 0	0.000	0.017	0.000	0.002	0.001	0.002
HH at 0	0.002	0.034	0.001	0.001	0.001	0.004
INPUT at 0	0.001	0.002	0.000	0.001	0.000	0.000
HLT at 0	0.001	0.005	0.004	0.007	0.000	0.000
SCH at 0	0.000	0.002	0.002	0.002	0.000	0.000
SES at 7	0.002	0.033	0.002	0.008	0.001	0.003
HH at 7	0.000	0.03	0.001	0.004	0.000	0.002
INPUT at 7	0.084	0.127	0.025	0.032	0.01	0.011
HLT at 7	0.002	0.006	0.001	0.003	0.002	0.001
SCH at 7	0.01	0.016	0.000	0.000	0.002	0.002
Complete adj-R^2	0.285		0.088		0.05	

TABLE 2.4: Outcomes at age 11

	Cognitive		Externalising Behaviour		Anxiety	
	Lower	Upper	Lower	Upper	Lower	Upper
SES at 0	0.001	0.021	0.000	0.002	0.000	0.001
HH at 0	0.001	0.042	0.000	0.002	0.000	0.002
INPUT at 0	0.001	0.002	0.001	0.000	0.000	0.000
HLT at 0	0.001	0.009	0.003	0.006	0.000	0.000
SCH at 0	0.000	0.001	0.003	0.003	0.000	0.001
SES at 7	0.000	0.033	0.000	0.007	0.000	0.004
HH at 7	0.000	0.035	0.000	0.004	0.000	0.002
INPUT at 7	0.02	0.087	0.005	0.018	0.001	0.004
HLT at 7	0.001	0.005	0.000	0.001	0.001	0.001
SCH at 7	0.002	0.010	0.000	0.000	0.001	0.002
SES at 11	0.002	0.039	0.001	0.011	0.001	0.004
HH at 11	0.000	0.030	0.001	0.006	0.000	0.002
INPUT at 11	0.05	0.131	0.008	0.021	0.004	0.006
HLT at 11	0.000	0.009	0.002	0.005	0.004	0.005
SCH at 11	0.031	0.073	0.002	0.007	0.004	0.005
Complete adj-R^2	0.375		0.085		0.033	

TABLE 2.5: Outcomes at age 16

	Cognitive		Externalising Behaviour		Hyperactivity		Anxiety	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
SES at 0	0.000	0.028	0.000	0.008	0.000	0.000	0.000	0.000
HH at 0	0.001	0.055	0.001	0.013	0.001	0.002	0.000	0.001
INPUT at 0	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
HLT at 0	0.000	0.014	0.000	0.005	0.000	0.002	0.000	0.000
SCH at 0	0.000	0.001	0.001	0.002	0.001	0.001	0.001	0.001
SES at 7	0.000	0.046	0.000	0.018	0.000	0.003	0.000	0.003
HH at 7	0.000	0.041	0.000	0.016	0.000	0.000	0.000	0.001
INPUT at 7	0.005	0.087	0.003	0.024	0.001	0.004	0.001	0.003
HLT at 7	0.000	0.004	0.000	0.001	0.000	0.001	0.000	0.000
SCH at 7	0.000	0.011	0.000	0.000	0.000	0.000	0.000	0.001
SES at 11	0.000	0.05	0.000	0.02	0.000	0.003	0.000	0.004
HH at 11	0.000	0.036	0.000	0.021	0.000	0.002	0.001	0.002
INPUT at 11	0.009	0.103	0.001	0.017	0.001	0.006	0.001	0.003
HLT at 11	0.000	0.011	0.001	0.003	0.000	0.002	0.000	0.002
SCH at 11	0.005	0.062	0.001	0.007	0.001	0.005	0.001	0.004
SES at 16	0.000	0.034	0.001	0.027	0.000	0.003	0.001	0.007
HH at 16	0.000	0.036	0.001	0.027	0.001	0.003	0.001	0.006
INPUT at 16	0.026	0.137	0.006	0.018	0.003	0.007	0.004	0.005
HLT at 16	0.000	0.022	0.005	0.019	0.003	0.009	0.003	0.007
SCH at 16	0.119	0.267	0.011	0.035	0.006	0.015	0.005	0.009
Complete adj-R^2	0.556		0.11		0.054		0.047	

TABLE 2.6: MCS variable description

Age 0	Age 7	Main group	Description
x		Baseline	Sex (Male =1)
x		Baseline	Mother's age at birth
x		Baseline	Father's age at birth
x		Baseline	1 'city' 2 'fringe' 3 'rural'
x		Baseline	Country (E,W,S,NI)
x		Baseline	Gestation weeks
x		Baseline	Whether MCS is first born (yes = 1)
x		Baseline	Birth weight (kg)
x		Baseline	Mother's age when left school
x		Baseline	Father's age when left school
x		Baseline	Whether father left school after 16 years old (yes = 1)
x	x	SES	Whether mother works (yes = 1)
x	x	SES	Whether father works (yes = 1)
x	x	SES	Whether hh lives in a council house (yes = 1)
x	x	SES	Predicted OECD equivalised weekly hh income
x	x	SES	Mother's social class (fixed effect: 1 'manager' 2 'intermediate' 3 'skilled and semi-skilled' 4 'low technical' 5 'routine and semi-routine')
x	x	SES	Father's social class (fixed effect: 1 'manager' 2 'intermediate' 3 'skilled and semi-skilled' 4 'low technical' 5 'routine and semi-routine')
x	x	HH	No. siblings
x		HH	No. all household members
x	x	HH	Whether lives with natural father (yes = 1)

Age 0	Age 7	Main group	Description
x		Health	Current frequency of drinking (0 'never'- 6 'everyday')
x	x	Health	Whether mother smokes currently (yes = 1)
x	x	Health	Whether father smokes currently (yes =1)
x	x	Health	Mother's Body Mass Index (BMI)
x	x	Health	Mother's self-assessed general health (0 'poor' 1 'fair' 2 'good' 3 'excellent')
x	x	Health	Father's Body Mass Index (BMI)
x	x	Health	Father's self-assessed general health (0 'poor' 1 'fair' 2 'good' 3 'excellent')
	x	Emotional health	Mother's self-assessed Kessler score (24 points)
	x	Emotional health	Father's self-assessed Kessler score (24 points)
x	x	Input	Mother's rate time spend with child (0 'not enough' 1 'not quite' 2 'just enough' 3 'plenty of time')
x	x	Input	Father's rate time spend with child (0 'not enough' 1 'not quite' 2 'just enough' 3 'plenty of time')
	x	Input	Freq. mother reads to child this month (0 'not at all'- 5 'every day')
	x	Input	Freq. father reads to child this month (0 'not at all'- 5 'every day')
		Input	Freq. child goes to library (0 'not at all' - 5 'every week')
		Input	Freq. child helped with learning alphabet (0 'not at all'- 7 'every day')
		Input	Freq. child helped with counting (0 'not at all'- 7 'every day')
		Input	Freq. child taught songs (0 'not at all'- 7 'every day')
	x	Input	Freq. child helped with reading (0 'not at all'- 7 'every day')
	x	Input	Freq. child helped with writing (0 'not at all'- 7 'every day')
	x	Input	Freq. child helped with maths (0 'not at all'- 7 'every day')
	x	School	Class size (no. pupils in a class)
	x	School	Whether school has class streaming at all (yes = 1)
	x	School	No. classes with streaming
	x	School	Class teacher's tenure at school

TABLE 2.7: MCS outcomes at age 7

	Cognitive		Externalising Behaviour		Anxiety	
	Lower	Upper	Lower	Upper	Lower	Upper
SES at 0	0.002	0.036	0.001	0.028	0.002	0.028
HH at 0	0.002	0.022	0.002	0.01	0.004	0.005
INPUT at 0	0.000	0.003	0.001	0.001	0.000	0.001
HLT at 0	0.000	0.019	0.003	0.027	0.002	0.024
SES at 7	0.003	0.04	0.005	0.038	0.006	0.04
HH at 7	0.000	0.018	0.000	0.009	0.004	0.013
INPUT at 7	0.027	0.041	0.005	0.015	0.001	0.007
HLT at 7	0.002	0.028	0.007	0.035	0.008	0.034
SCH at 7	0.001	0.001	0.001	0.001	0.001	0.001
Complete adj-R^2	0.215		0.153		0.101	

2.6 Appendix A

TABLE 2.8: Transition matrix for father's occupational types

	Professional	Managerial	Skilled	Semi-Skilled	Unskilled
Panel A: Age 0 & Age 11					
Professional	73.42	12.61	10.81	2.70	0.45
Managerial	66.78	17.63	9.69	4.99	0.91
Skilled	31.25	35.10	20.03	11.90	1.71
Semi-Skilled	9.76	5.92	64.20	16.47	3.65
Unskilled	6.40	3.37	42.92	38.24	9.08
Panel B: Age 11 & Age 16					
Professional	79.73	7.88	9.49	0.58	2.32
Managerial	22.35	62.10	10.99	1.36	3.21
Skilled	6.37	2.79	81.49	0.62	8.73
Semi-Skilled	5.76	6.59	34.91	4.79	47.95
Unskilled	4.81	3.70	53.70	4.81	32.96

TABLE 2.9: Summary statistics for each sample of NCDS

	Imputed Sample		Sample with complete age 0's variables		Sample with complete age 7's variables		Sample with complete age 11's variables		Sample with complete age 16's variables	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Birth weight	3295	[551.3]	3351	[508.4]	3358	[500.8]	3338	[497.7]	3367	[479.2]
Male	0.52	[0.5]	0.51	[0.5]	0.52	[0.49]	0.52	[0.5]	0.50	[0.5]
Mother's age at birth	27.5	[5.54]	27.62	[5.54]	27.51	[5.27]	27.29	[5.44]	27.96	[4.99]
Father's age at birth	30.6	[6.12]	30.57	[6.25]	30.52	[5.90]	30.16	[5.91]	31.06	[5.6]
Whether first born	0.38	[0.49]	0.38	[0.48]	0.39	[0.49]	0.39	[0.49]	0.40	[0.49]
Gestation weeks	39.99	[1.9]	40.15	[1.68]	40.16	[1.63]	40.12	[1.60]	40.20	[1.45]
Mother speaks English	0.9	[0.3]	0.90	[0.29]	0.89	[0.31]	0.90	[0.3]	0.90	[0.3]
Mother ¿ compulsory school	0.25	[0.43]	0.27	[0.44]	0.32	[0.47]	0.23	[0.42]	0.49	[0.49]
Father ¿ compulsory school	0.23	[0.42]	0.25	[0.43]	0.32	[0.47]	0.21	[0.41]	0.44	[0.49]
Total observations	18558		10445		5755		3074		619	

TABLE 2.10: Factor loadings for cognitive measures at age 50, 16, 11 and 7 (NCDS)

	Age 50	Age 16	Age 11	Age 7
Letter cancellation (speed)	0.155			
Animal naming	0.377			
Words correctly recalled	0.801			
Words recalled after delay	0.8			
Maths teacher-assessed		0.89		
English teacher-assessed		0.902		
Language teacher-assessed		0.813		
Science teacher-assessed		0.867		
Practical teacher-assessed		0.739		
Social studies teacher-assessed		0.887		
Reading score		0.778	0.822	0.742
Maths score		0.799	0.83	0.651
Numeracy teacher-assessed			0.818	0.766
Copy score			0.375	0.427
Oral teacher-assessed			0.794	0.747
Awareness teacher-assessed			0.868	0.804
Reading teacher- assessed			0.837	0.828
Drawing score				0.456
Creativity teacher-assessed				0.715

TABLE 2.11: Factor loadings (after oblique rotation) for non-cognitive measures at age 50 (NCDS)

	Positivity	Malaise
Been feeling optimistic about the future	0.56	0.061
Been feeling useful	0.603	0.043
Been feeling relaxed	0.681	0.002
Been feeling interested in other people	0.369	0.07
Had energy to spare	0.594	0.036
Been dealing with problems well	0.669	0.009
Been thinking clearly	0.7	0.03
Been feeling good about myself	0.818	0.065
Been feeling close to other people	0.574	0.091
Been feeling confident	0.8	0.051
Been able to make up my own mind about things	0.57	0.021
Been feeling loved	0.52	0.036
Been interested in new things	0.596	0.06
Been feeling cheerful	0.822	0.055
Feels tired most of the time	-0.222	0.616
Feels miserable and depressed	-0.241	0.72
Often gets worried about things	-0.259	0.584
Often gets into a violent rage	0.185	0.879
Often suddenly scared for no good reason	0.028	0.845
Is easily upset or irritated	-0.155	0.684
Is constantly keyed up and jittery	0.024	0.876
Every little thing gets on nerves	0.017	0.87
Heart often races like mad	0.055	0.826
Emotional problems led less time spent on activities in past 4 wks	0.425	-0.145
Emotional problems led to accomplish less in past 4 wks	0.494	-0.13
Emotional problems led to less care with activities in past 4 wks	0.459	-0.133
Felt full of life (reversed)	-0.765	0.003
Have a lot of energy (reversed)	-0.706	0.022
Felt worn out (reversed)	0.588	-0.11
Felt tired (reversed)	0.555	-0.096
Been a very nervous person (reversed)	0.474	-0.166
Felt so down in the dumps nothing could cheer up (reversed)	0.615	-0.168
Felt calm and cheerful (reversed)	-0.788	0.033
Felt downhearted and low (reversed)	0.697	-0.122
Been a happy person (reverse)	-0.744	0.009

TABLE 2.12: Factor loadings (after oblique rotation) for non-cognitive measures (SDQ equivalent) at age 16, 11 and 7 (NCDS)

	Age 16			Age 11		Age 7	
	Externalising behaviour	Hyperactive	Anxiety	Externalising behaviour	Anxiety	Externalising behaviour	Anxiety
Irritable, flies off the handle	0.423	0.089	0.203	0.533	0.078	0.52	0.102
Often destroys others property	0.415	0.101	-0.066	0.406	-0.037	0.462	-0.083
Often disobedient	0.606	0.062	-0.018	0.58	-0.077	0.582	-0.069
Frequently fights, quarrelsome	0.623	-0.051	0.014	0.477	-0.151	0.478	-0.16
Bullies other children	0.564	-0.066	-0.055				
Often tells lies	0.562	0.05	-0.013				
Squirmy or fidgety	0.01	0.723	0.002	0.483	0.077	0.505	0.117
Difficulty settling to anything	0.189	0.448	0.051	0.455	0.062	0.47	0.063
Restless, difficulty staying seated	-0.03	0.804	-0.007				
Continually worried	-0.038	0.006	0.68	-0.003	0.738	0	0.741
Miserable or tearful	0.301	-0.01	0.398	0.377	0.225	0.34	0.237
Upset by new situation	-0.041	0.022	0.501	0.017	0.48	0.024	0.465

TABLE 2.13: Confirmatory factor analysis for factor variables at age 50

Age	Factor Variable	Item	Coef.	SE
50	Cognitive	Letter cancellation (speed)	0.174	0.01
		Animal naming	0.424	0.008
		Words correctly recalled	0.902	0.001
		Words recalled after delay	0.901	0.001
50	Positivity	Been feeling optimistic about the future	0.554	0.007
		Been feeling useful	0.603	0.006
		Been feeling relaxed	0.696	0.005
		Been feeling interested in other people	0.355	0.009
		Had energy to spare	0.596	0.006
		Been dealing with problems well	0.681	0.005
		Been thinking clearly	0.707	0.005
		Been feeling good about myself	0.816	0.003
		Been feeling close to other people	0.559	0.007
		Been feeling confident	0.802	0.003
		Been able to make up my own mind about things	0.576	0.007
		Been feeling loved	0.521	0.007
		Been interested in new things	0.591	0.006
		Been feeling cheerful	0.824	0.003
		Emo probs led less time spent on activities in past 4 wks	0.481	0.008
		Emo porbs led to accomplish less than liked in past 4 wks	0.547	0.007
		Emo probs led to less care with activities in past 4 wks	0.512	0.007
		Felt full of life (reversed)	-0.783	0.003
		Have a lot of energy (reversed)	-0.729	0.004
		Felt worn out (reversed)	0.636	0.006
		Felt tired (reversed)	0.598	0.006
		Been a very nervous person (reversed)	0.538	0.007
		Felt so down in the dumps nothing could cheer up (reversed)	0.682	0.005
		Felt calm and cheerful (reversed)	-0.817	0.003
		Felt downhearted and low (reversed)	0.752	0.004
		Been a happy person (reverse)	-0.764	0.004
50	Malaise	Feels tired most of the time	0.704	0.005
		Feels miserable and depressed	0.818	0.003
		Often gets worried about things	0.683	0.005
		Often gets into a violent rage	0.845	0.002
		Often suddenly scared for no good reason	0.86	0.002
		Is easily upset or irritated	0.753	0.004
		Is constantly keyed up and jittery	0.893	0.002
		Every little thing gets on CM's nerves	0.889	0.002
		Heart often races like mad	0.832	0.003

TABLE 2.14: Confirmatory factor analysis for cognitive factor variables at age 7, 11 and 16

Age	Factor Variable	Item	Coef.	SE
7	Cognitive	Reading score	0.779	0.003
		Drawing score	0.505	0.006
		Copying score	0.467	0.006
		Maths score	0.687	0.004
		Oral ability (teacher-assessed)	0.786	0.003
		Awareness (teacher-assessed)	0.846	0.002
		Reading (teacher-assessed)	0.868	0.002
		Creativity (teacher-assessed)	0.752	0.003
		Numeracy (teacher-assessed)	0.803	0.002
11	Cognitive	Reading score	0.851	0.002
		Maths score	0.86	0.002
		Oral ability (teacher-assessed)	0.823	0.002
		Awareness (teacher-assessed)	0.899	0.001
		Reading (teacher-assessed)	0.867	0.002
		Numeracy (teacher-assessed)	0.847	0.002
		Copying score	0.388	0.007
16	Cognitive	Reading score	0.79	0.003
		Maths score	0.83	0.002
		Maths (teacher-assessed)	0.915	0.001
		English (teacher-assessed)	0.921	0.001
		Science (teacher-assessed)	0.914	0.001
		Social studies (teacher-assessed)	0.928	0.001
		Practical (teacher-assessed)	0.857	0.002
		Language (teacher-assessed)	0.85	0.002

TABLE 2.15: Confirmatory factor analysis for non-cognitive factor variables at age 7, 11 and 16

Age	Factor Variable	Item	Coef.	SE
7	Externalising behaviour	Squirmy or fidgety	0.642	0.004
		Difficulty concentrating	0.583	0.005
		Irritable	0.655	0.004
		Generally destructive	0.525	0.006
		Disobedient	0.674	0.004
		Fight with other children	0.52	0.006
7	Anxiety	Continually worried	0.931	0.001
		Miserable or tearful	0.413	0.007
		Upset by new situation	0.592	0.005
11	Externalising behaviour	Squirmy or fidgety	0.611	0.005
		Difficulty settling to anything	0.569	0.005
		Irritable	0.68	0.004
		Destroys own, others things	0.466	0.006
		Disobedient at home	0.668	0.004
		Fight with other children	0.513	0.006
11	Anxiety	Continually worried	0.95	0.001
		Miserable or tearful	0.395	0.007
		Upset by new situation	0.583	0.005
16	Externalising behaviour	Irritable	0.596	0.005
		Often destroys others property	0.504	0.006
		Disobedient	0.722	0.004
		Frequently fights, quarrelsome	0.699	0.004
		Bullies other children	0.601	0.005
		Often tells lies	0.666	0.005
16	Hyperactivity	Difficulty settling to anything	0.613	0.005
		Squirmy or fidgety	0.828	0.002
		Restless, difficulty staying seated	0.899	0.001
16	Anxiety	Continually worried	0.855	0.002
		Miserable or tearful	0.614	0.005
		Upset by new situation	0.631	0.005

TABLE 2.16: Comparing individual questionnaire items on parent-assessed childhood behaviours: a consistent list between the NCDS and the MCS

Strengths-and-Difficulties Questionnaire (MCS)	MCS (3, 5, 7)	NCDS (7, 11)	NCDS (16)	Rutter-Behaviour-Score (NCDS)
HYPERACTIVE				
Restless, over-active, cannot stay still for long	x		x	Cannot settle more than a few moments
Constantly fidgeting or squirming	x	x	x	Squirmy, fidgety child
Easily distracted, concentration wanders	x	x	x	Restless, difficulty staying seated
Thinks things out before acting	x			
Sees tasks through to the end, good attention span	x			
EMOTIONAL				
Often complains of headaches, stomach-aches or sickness	x			
Many worries, often seems worried	x	x	x	Often worries about things
Often unhappy, down-hearted or tearful	x	x	x	Appears miserable, unhappy and tearful
Nervous or clingy in new situations, easily loses confidence	x	x	x	Fearful of new situations or things
Many fears, easily scared	x			
CONDUCT				
Often has temper tantrums or hot tempers	x	x	x	Irritable, flies off the handle
			x	Often destroys others property
Generally obedient, usually does what adults request	x	x	x	Is often disobedient
Often fights with other children or bullies them	x	x	x	Frequently fights, quarrelsome
			x	Bullies other children
Often lies or cheats			x	Often tells lies
Steals from home, school or elsewhere				
PEER PROBLEM				
Rather solitary, tends to play alone	x			Does things on own, rather solitary
Has at least one good friend	x			
Generally liked by other children	x			Not much liked by other children
Picked on or bullied by other children	x			
Gets on better with adults than with other children	x			

TABLE 2.17: Factor loadings (after oblique rotation) for cognitive measures at age 7 for the MCS

	Cognitive
Proficiency: speaking and listening	0.821
Proficiency: reading	0.889
Proficiency: writing	0.885
Proficiency: science	0.853
Proficiency: maths	0.848
Proficiency: ICT	0.743
Proficiency: art	0.597
BAS Reading Assessment	0.716
BAS Pattern	0.433
Progress in Maths	0.579

TABLE 2.18: Factor loadings (after oblique rotation) for non-cognitive measures (NCDS equivalent) at age 7 for the MCS

	Externalising behaviour	Anxiety
Constantly fidgeting or squirming	0.677	0.013
Easily distracted	0.592	0.069
Restless, cannot stay still for long	0.813	-0.057
Often has temper tantrums	0.427	0.211
Generally obedient	0.396	0.035
Many worries, often seems worried	-0.035	0.67
Often unhappy, down-hearted or tearful	0.053	0.533
Nervous or clingy in new situations	0.1	0.374

TABLE 2.19: Confirmatory factor analysis for factor variables at age 7 in the MCS

Age	Factor variable	Item	Coef.	SE
7	Cognitive	Proficiency: speaking and listening	0.847	0.003
		Proficiency: reading	0.902	0.002
		Proficiency: writing	0.902	0.002
		Proficiency: science	0.881	0.002
		Proficiency: maths	0.873	0.002
		Proficiency: ICT	0.782	0.004
		Proficiency: art	0.632	0.006
		BAS Reading Assessment	0.72	0.005
		BAS Pattern	0.442	0.009
		Progress in Maths	0.589	0.007
7	Externalising behaviour	Constantly fidgeting or squirming	0.768	0.003
		Easily distracted	0.696	0.004
		Restless, cannot stay still for long	0.879	0.002
		Often has temper tantrums	0.589	0.005
		Generally obedient	0.467	0.006
7	Anxiety	Many worries, often seems worried	0.771	0.003
		Often unhappy, down-hearted or tearful	0.742	0.003
		Nervous or clingy in new situations	0.511	0.006

FIGURE 2.8: Scree plot for cognitive factors at age 50, using Principal Component Analysis
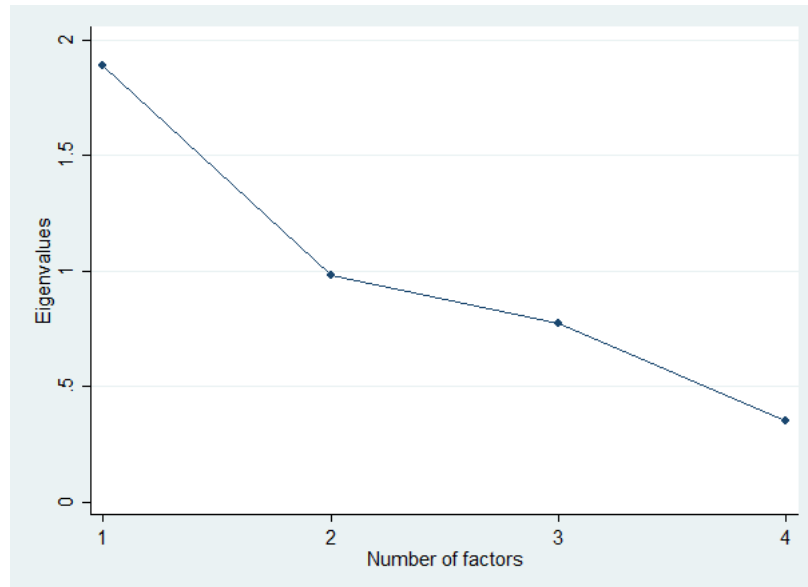
FIGURE 2.9: Scree plot for non-cognitive factors at age 50, using Principal Component Analysis
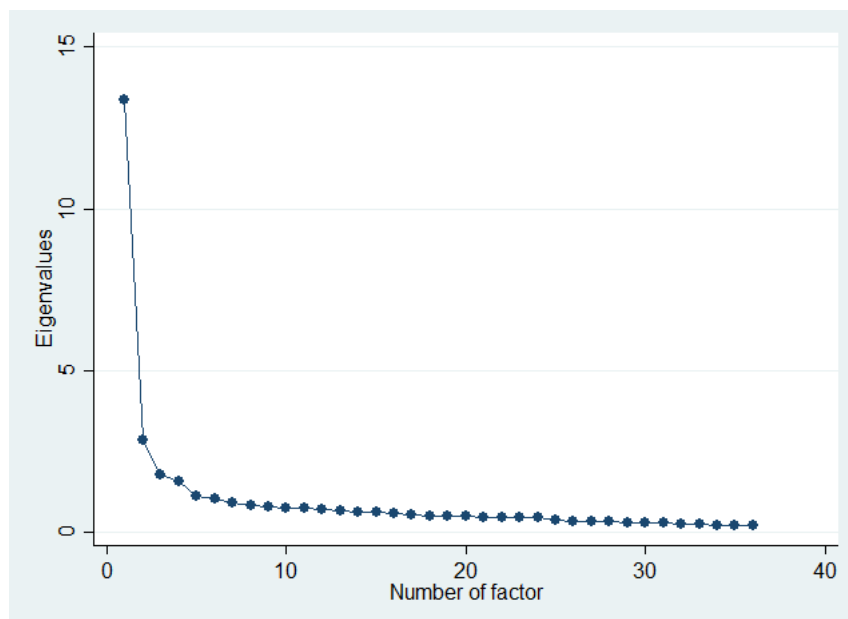
2.7 Appendix B

TABLE 2.20: Log of own net annual pay at various adult ages (NCDS)

	Age 33		Age 42		Age 46		Age 50	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
SES	0.001	0.008	0.001	0.005	0.002	0.007	0.003	0.008
HH	0.001	0.007	0.000	0.002	0.000	0.003	0.001	0.003
INPUT	0.005	0.018	0.004	0.013	0.004	0.014	0.004	0.014
HLT	0.000	0.002	0.000	0.001	0.000	0.002	0.000	0.001
SCH	0.008	0.018	0.01	0.017	0.012	0.021	0.012	0.022
Complete adj-R^2	0.304		0.256		0.276		0.227	

Note: This is calculated as a log of net annual net income of the cohort members (52 week) at age 33, 42, 46 and 50. The value of income is assigned as zero when a cohort member is unemployed at each age.

TABLE 2.21: Rutter Malaise at various adult ages (NCDS)

	Age 23		Age 33		Age 42		Age 46		Age 50	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
SES	0.002	0.016	0.002	0.009	0.002	0.006	0.002	0.006	0.002	0.005
HH	0.002	0.014	0.002	0.008	0.001	0.002	0.001	0.003	0.001	0.004
INPUT	0.005	0.023	0.004	0.014	0.001	0.006	0.001	0.007	0.002	0.003
HLT	0.000	0.006	0.000	0.004	0.000	0.003	0.000	0.002	0.000	0.003
SCH	0.014	0.03	0.006	0.015	0.009	0.014	0.009	0.013	0.009	0.009
Complete adj-R^2	0.119		0.061		0.048		0.046		0.045	

Note: Malaise score is calculated using the Malaise Inventory (Rutter et al. [1970]). It is a set of self-completion questions which combine to measure levels of psychological distress, or depression. The 24 'yes-no' items of the inventory cover emotional disturbance and associated physical symptoms. When administered in its standard format, scores range from 0 to 24. In the NCDS in 2008, the score is calculated from 9 out of the original 24 items namely (i) whether he feels tired most of the time (ii) whether he often feels miserable and depressed (iii) whether he often gets worried about things (iv) whether he often gets into a violent rage (v) whether he often suddenly scared for no good reason (vi) whether he is easily upset or irritated (vii) whether he is constantly keyed up and jittery (viii) whether every little thing gets on his nerves and (ix) whether his heart often races like mad.

TABLE 2.22: MCS outcomes at age 7, with parental emotional health variables

	Cognitive		Externalising Behaviour		Anxiety	
	Lower	Upper	Lower	Upper	Lower	Upper
SES at 1	0.002	0.036	0.000	0.028	0.001	0.028
HH at 1	0.002	0.022	0.001	0.01	0.003	0.005
INPUT at 1	0.000	0.003	0.000	0.001	0.000	0.001
HLT at 1	0.000	0.019	0.001	0.027	0.002	0.024
SES at 7	0.003	0.04	0.002	0.038	0.002	0.04
HH at 7	0.000	0.018	0.000	0.009	0.004	0.013
INPUT at 7	0.027	0.041	0.004	0.015	0.001	0.007
HLT at 7	0.002	0.028	0.002	0.035	0.002	0.034
SCH at 7	0.001	0.001	0.000	0.001	0.001	0.001
EMOT at 7	0.001	0.01	0.027	0.059	0.051	0.092
Complete adj-R^2	0.216		0.178		0.152	

2.8 Appendix C

Cognitive measures at age 50 in the NCDS

Word List Recall is a test of verbal fluency and recall where participants are required to learn a list of 10 common words. Once the list has been read out, cohort members have up to two minutes to recall as many words as they can. This is essentially a test for verbal or memory span. This type of memory is what allows us to remember what we hear or read long enough to use the information, either right then and there, or by transferring it to long-term memory.

Animal Naming Test measures phonemic and semantic verbal fluency. Specifically, it measures how quickly participants can think of words from a particular category and in this case the category is animals. This test has been widely used, and the present version was taken from the cognitive assessment section of the Cambridge Mental Disorders of the Elderly Examination (CAMDEX) (Roth et al., 1986).

Letter Cancellation is a test of attention, mental speed and visual scanning whereby the participant is given a page of random letters of the alphabet, set out in rows and columns, and is asked to cross out as many "Ps" and "Ws" as possible within one minute. The total number of letters searched provides a measure of speed of processing. The number of target letters missed (P and W) up to the letter reached provides a measure of accuracy.

Delayed Word List Recall tests the participant's delayed memory. Here, the respondent is asked to recall as many words as they can from an original list presented to them, after a short distraction period is interpolated between the final list item and the start of the recall period (Brown and Dodgeon, 2010.

Non-cognitive measures at age 50 in the NCDS

Short-Form Quality of Life Scoring System (SF-36) is a 36 item, self-administered questionnaire that was constructed to fill the gap between much more lengthy surveys and relatively coarse single-item measures of quality of life. It consists of 36 questions, 35 of which are compressed into eight multi-item scales: (i) physical functioning is a ten-question scale that captures abilities to deal with the physical requirement of life, such as attending to personal needs, walking, and flexibility; (ii) role-physical is a four-item scale that evaluates the extent to which physical capabilities limit activity; (iii) bodily pain is a two-item scale that evaluates the perceived amount of pain experienced during the previous 4 weeks, and the extent to which that pain interfered with normal work

activities; (iv) general health is a five-item scale that evaluates general health in terms of personal perception; (v) vitality is a four-item scale that evaluates feelings of pep, energy, and fatigue; (vi) social functioning (SF) is a two-item scale that evaluates the extent and amount of time, if any, that physical health or emotional problems interfered with family, friends, and other social interactions during the previous 4 weeks; (vii) role-emotional (RE) is a three-item scale that evaluates the extent, if any, to which emotional factors interfere with work or other activities; and (viii) mental health is a five-item scale that evaluates feelings principally of anxiety and depression. Hence, in the SF36 scoring system, the scales are assessed quantitatively, each on the basis of answers to two to ten multiple choice questions, and a score between 0 and 100 is then calculated on the basis of well-defined guidelines, with a higher score indicating a better state of health. The scales of SF36 are summarized into two groups. The first five scales make up the "physical health" dimension, and the last five form the "mental health" dimension. The scales vitality and general health are parts of both groups. Hence, each dimension includes three specific and two overlapping scales (Ware Jr and Sherbourne [1992]).

Warwick-Edinburgh Mental Well-Being Scale is a 14-item scale of positive mental well-being including subjective well-being and psychological functioning. For example, the respondent is asked to rate the frequency of her feeling optimistic about the future in the past two weeks. The scale is scored by summing responses answered on a 5 Item Likert-scaled with the minimum score being 14 and the maximum score 70 (Stewart-Brown and Janmohamed [2008]).

Quality of Life Score CASP-12 and CASP-19 are scales designed to measure quality of life in the *third age* by using Likert-scaled questions which cover four theoretical domains: control, autonomy, self-realisation and pleasure (Wiggins et al., 2008).

Malaise Score is calculated using the Rutter Malaise Inventory (Rutter et al. [1970]). It is a set of self-completion questions which combine to measure levels of psychological distress, or depression. The 24 'yes-no' items of the inventory cover emotional disturbance and associated physical symptoms. When administered in its standard format, scores range from 0 to 24. In the NCDS in 2008, the score is calculated from 9 out of the original 24 items namely (i) whether he feels tired most of the time (ii) whether he often feels miserable and depressed (iii) whether he often gets worried about things (iv) whether he often gets into a violent rage (v) whether he often suddenly scared for no good reason (vi) whether he is easily upset or irritated (vii) whether he is constantly keyed up and jittery (viii) whether every little thing gets on his nerves and (ix) whether his heart often races like mad.

Cognitive measures at age 16 in the NCDS

The Teacher Rating Score is obtained from the teacher's rating on the cohort member's performance in subjects, including mathematics, English, modern languages, science, social studies and practical subjects. For each subject, the rating ranges from (1) little ability, (2) below average, (3) CSE grades 2-4 (4) O-Level and (5) A-level ability equivalent.

Mathematics Test contains both numerical and geometric questions with 27 multiple-choice questions and 4 true-or-false questions, with a total score between 0 and 31.

Reading Comprehension Test measures reading comprehension ability. The child was required to choose from a selection of 5 words which appropriately completed sentences. There were 35 questions in total with the total score a total score between 0 and 35.

Cognitive measures at age 11 in the NCDS

General Ability Test measures mental ability. It contains verbal and non-verbal items. It consists of 40 verbal and 40 non-verbal items tested and recorded individually by the child's teacher to measure mental ability (Douglas, 1964). For the verbal items, children were presented with an example set of four words that were linked either logically, semantically, or phonologically. For the non-verbal tasks, shapes or symbols were used. The children were then given another set of three words or shapes or symbols with a blank. Participants were required to select the missing item from a list of five alternatives. Each correct answer was rewarded with a mark, giving intermediate verbal and non-verbal scores (between 0 and 40), and a total score (between 0 and 80).

Reading Comprehension Test is constructed by the National Foundation for Educational Research in England and Wales (NFER) specifically for use in this study. There are 35 items in the test and 20 minutes in which to complete the test. One mark was awarded for each correctly completed sentence, giving a total score between 0 and 35.

Arithmetic/Mathematics Test constructed by NFER especially for use in the NCDS. There are 40 items in the test. One mark was awarded for each correctly completed sentence, giving a total score between 0 and 40.

Copying Design Test is to measure perceptual and motor ability. Six designs were presented: a circle, square, triangle, diamond, cross and star. The children were asked to copy each design twice. Not all children completed two drawings of each design; therefore a score was given if at least one good copy was made of a given design. The

total score was the sum of the scores obtained on each design, thus giving a range of 0-8. Zero score was obtained when a child attempted to copy at least one design but all attempts were judged to be poor copies (Pringle et al., 1966).

Cognitive measures at age 7 in the NCDS

The Southgate Reading Test is a measure of word recognition and comprehension particularly suited to identifying poor readers. In the test the children were given a picture/drawing and a list of five words. They had to put a circle round the word that correctly described the picture. There were 30 items in the test (Southgate, 1962).

Arithmetic Ability Test is a 10-item Problem Arithmetic Test for children to work out in the test (Pringle et al., 1966). Ten problems graded in level of difficulty. In order to avoid penalizing the poor readers, the teachers were asked to read the problems to the children if necessary.

Copying Design Test is to measure perceptual and motor ability. Six designs were presented: a circle, square, triangle, diamond, cross and star. The children were asked to copy each design twice. Scoring is as at age 11.

Drawing-a-Man Test asks the child to draw a picture of a man. It is awarded a mark out of 100 according to the features that were included. It measures general mental and perceptual ability.

Teacher Rating Score is obtained from a teacher's rating on the cohort member's performance in numeracy, oral ability, reading ability, awareness of the world around him and creativity (e.g. in free writing, telling a story handwork, painting, drawing, dramatic work). In all items, the rating ranges from (1) being exceptional, (2) above average, (3) average, (4) below average and (5) very limited.

Non-cognitive measures at age 16 in the NCDS

Parent-Assessed Rutter Behaviour Score is a measure of behavioural-emotional problem. Teachers are asked whether a list of behaviours do not apply (1), applies somewhat (2), or certainly applies (3) to the NCDS child. The listed behaviours include the behaviours in the parent assessed index at age 16, and also includes: (i) Truants from school; (ii) Tends to be absent from school for trivial reasons; (iii) Has stolen things on one or more occasions in the past 12 months; (iv) Unresponsive, inert or apathetic; (v) Often complains of aches or pains; (vi) Has had tears on arrival at school or has

refused to come into the building in the past 12 months; (vii) Has a stutter or stammer; and (viii) Resentful or aggressive when corrected.

Non-cognitive measures at age 7 and 11 in the NCDS

Parent-assessed Rutter Behaviour Score is a measure of behavioural-emotional problem. Parents are asked whether a list of behaviours never happen (1), sometimes happen (2), or frequently happen (3) at the current time. The listed behaviours are: (i) Has difficulty in settling to anything for more than a few moments; (ii) Prefers to do things on his/her own rather than with others; (iii) Is bullied by other children; (iv) Destroys own or others belongings; (v) Is miserable or tearful; (vi) Is squirmy or fidgety; (vii) Worries about many things; (viii) Is irritable, quick to fly off the handle; (ix) Sucks thumb or finger during day; (x) Is upset by new situation, by things happening for first time; (xi) Has twitches or mannerisms of the face, eyes or body; (xii) Fights with other children; (xiii) Bites nails; and (xiv) Is disobedient at home.

Labour market outcomes at adulthood in the NCDS

Net Annual Income is a log of net annual income of the cohort members (52 week) at age 33, 42, 46 and 50. Whenever a cohort is unemployed, the log of net annual income is assigned as zero.

Emotional health at adulthood in the NCDS

Sub-Malaise Score is calculated using the Malaise Inventory (Rutter et al, 1970). It is a set of self-completion questions which combine to measure levels of psychological distress, or depression. The 24 'yes-no' items of the inventory cover emotional disturbance and associated physical symptoms. When administered in its standard format, scores range from 0 to 24. Since at age 50, the NCDS only collect 9 out of the original 24 items, we also construct a consistent index of malaise at age 23, 33, 42 and 46. The index score is a unweighed average from all nine items. The nine items selected are (i) whether he feels tired most of the time (ii) whether he often feels miserable and depressed (iii) whether he often gets worried about things (iv) whether he often gets into a violent rage (v) whether he often suddenly scared for no good reason (vi) whether he is easily upset or irritated (vii) whether he is constantly keyed up and jittery (viii) whether every little thing gets on his nerves and (ix) whether his heart often races like mad.

Cognitive measures at age 7 for the Millennium Cohort Study

British Ability Scales Pattern Construction is a test of non-verbal reasoning and spatial visualisation in which children construct patterns using flat squares or solid cubes. The raw score is transformed into an ability score. The BAS Pattern was also assessed in earlier ages in the MCS (age 5).

The Progress in Mathematics (PiM) Test assesses the child's skills on all UK National Curricula mathematics content. Children complete a variety of mathematical problems covering numbers, shape, space, measures and data handling.

British Ability Scales Word Reading assesses children's English reading ability. The child reads aloud a series of words presented on a card. The assessment consists of 90 words in total. The words are organised into 9 blocks of 10 words in ascending order of difficulty. The child is asked to read each word in a block out loud to the interviewer. The number of blocks of words the child is asked to attempt to read is dependent on the child's performance during the assessment. This assessment is designed to be used with children aged from 5 to 17 years and 11 months. All of the children in Wave 4 of the MCS started at the first item, as this was the starting point for children of their age. A child's progression through the assessment is dependent on the number of words they read correctly. If a child makes 8 errors in a block of 10 words, then the assessment stops.

Teacher-Assessed Proficiency is a collection of teacher-reported on performance in reading, speaking, writing, science, numeracy, ICT and creative art. In each question, the teacher is asked to rate the child's ability of the 5-point scale (well above average, above average, average, below average and well below average). The scores are added up with equal weight.

Non-cognitive measures at age 7 for the Millennium Cohort Study

Strengths and Difficulties Questionnaire is a parent-responded measure of child behavioural assessment. It contains 25 items, which can be divided into five sub-scales: emotional symptoms, conduct problems, hyperactivity, peer problems and pro-social behaviour. The first four sub-scales are used to construct the SDQ Total Difficulties score (Goodman, 1997).

Chapter 3

Causal Effect of Sibship Size on Child Development: Evidence from Young Lives Dataset

Abstract

This paper presents new causal evidence on the child quantity-quality trade-off using pooled longitudinal data from four developing countries. Our empirical strategy exploits exogenous variation in sibship size due to parental preferences for sibling-sex composition. We construct measures of the discrepancy between the ideal and the actual number of sons and daughters. These variations capture heterogeneous fertility stopping rules amongst families from different backgrounds. Our instrumental variables are no longer restricted by the assumption that parents homogeneously prefer having two children at optimal. We then examine the causal effect of sibship size on children's human capital development and investigate any potential intra-household responses that may influence the findings. Our 2SLS results show no evidence of a short-term quantity-quality trade-off but detect the trade-off three years later, at 8 years old. Children's own time allocation, where a child spends more time caring for younger siblings and less time on schooling, is a potential key driver of our results.

3.1   Introduction

This work examines the effect of family size on outcomes of an older sibling. More precisely, we look at the effect of having additional younger siblings on the early cognitive development of an older sibling from the family of two children and above. Early

theoretical work on the quantity-quality trade-off model suggests that when sibship size increases, parents would subsequently scale down their resources and investments per child, and that this adversely affects the children's human capital accumulation (Becker and Lewis, 1973; Becker and Tomes, 1976; Galor and Weil, 2000). Statistical studies from both developed and developing countries have documented a negative correlation between family size and child welfare, both in the short and long-term (Leibowitz, 1974; Hanushek, 1992; Desai, 1995).

Despite the widely observed relationship between sibship size and the quality of outcomes of an individual, it does not imply a causal link. This is because of how large families end up with children of lower quality may not have anything to do with the trade-off per se. In contrast, it may only reflect unobserved variables linking fertility decisions and parental investment behaviour as well as home environment, for example parental education, socio-economic status and earning potential. The task of examining if the Q-Q trade-off has a causal interpretation is exceptionally important to public policy. In order to shed light on causality, our empirical strategies rely on two-stage least squared estimates. Our analysis exploits the exogeneity of a birth of a given gender in order to obtain a set of instrument variables which explain the fertility variation.

Our design of the first-stage is a sharp modification of the conventional specification, which uses sibling sex-composition and family preferences for balanced-sex children as a key driver of the fertility decision. This empirical strategy has been elaborated in Angrist and Evans [1998] and Angrist et al. [2010]. However, we find that, especially in a developing country context, the direct application of the conventionally defined sibling sex-composition instruments may not be suitable. This is due to a weak instrumental variable problem. There are two main explanations, both related to the fertility stopping-rules in developing countries' context. First, evidence from Demographic Health Surveys has shown that family size in developing countries, particularly in Africa, is larger than the average of two children in most developed countries. Hence, this affects the binding power of the sex-composition instrument, which relies largely on the first two children in a family. With an average family size of around 5 children, this implies that a family may continue to have more children regardless of the sex-composition of the older children (Kana, 2010).

Second, it is known that in many of these countries, families do not state preferences for balanced-gender children. That is, unlike evidence from US and other developed countries (Ben-Porath and Welch, 1976), families do not achieve their optimal family composition when they have one boy and one girl. In fact, for many Asia countries son preferences are exceptionally strong. Many studies incorporate this culturally specific

fertility pattern by resorting to using having a boy in the last birth as an alternative instrument (e.g. Chun and Oh, 2002; Jensen and Chintan, 2003 and Lee, 2008).

In this paper, we introduce an alternative instrumental variable, which directly takes into account the heterogeneity of the fertility-stopping rule by exploiting the information on the ideal number of sons and daughters stated by families themselves in our developing country dataset.

Note that the specified ideal number of sons and daughters are endogenous to other household behaviours. However, the actual number of sons and daughters are primarily driven by the exogeneity of a conception of a specific gender. Therefore, we obtain an alternative instrumental variable using the discrepancy between the stated ideal number and the actual number of sons (daughters) in a family. This empirical strategy allows for a set of instrumental variables that depart from the imposition of homogeneous preferences of children on the households from different cultural background. With a conditional expectation, our instruments satisfy the exclusion restriction. We also support this with validity tests on our instruments and confirm that our instrumental variables are exogenous.

We investigate the effect of family size on the short-term outcomes of the index child, using the Young Lives dataset (the younger cohort sub dataset). The dataset follows 8,000 children from 4 countries- Peru, Vietnam, Ethiopia and India (Andhra Pradesh) since 2000. With the longitudinal nature of the data, we are able to study a longer-term effect of additional young siblings on outcomes later in life. Whilst our main focus is on the cognitive development of the index child, we also explore the effect of family size on health outcomes and attitudinal outcomes- proxies for socio-emotional competencies. To analyse this, we pool the data from all four countries, using only the Young Cohort sample. Given the empirical design, our sample is of index YL children who have at least one older sibling in Wave 1 (when they were 9 months old on average).

In contrast to the strong and negative effect found using an OLS specification, our 2SLS analysis does not find much evidence to support that having more younger siblings causally leads to lower development in the short run (at age 5). However, the effect of increased family size on child's cognitive development become significant and negative in the later wave (age 8), measured by PPVT and Maths. Using 2SLS, we find no negative effect of family size on physical health as opposed to negative ones under OLS.

We then attempt to understand if families also adjust their behaviours given more children to take care off. On parental labour market activities, we find no effect on maternal employment (in hours, days, months) when the index children are 5 years old. In contrast, under 2SLS, we see a positive effect of increased family size on father's employment

at the same age. By age 8, we find no labour supply compensation from the father in response to a drop in maternal employment.

The most interesting finding is of time allocation of the YL index child. Having increased family size causally leads to the index child spending more time looking after younger siblings when they are 5 years old. The negative effect remains when they were 8 years old. Moreover, the index child spends more time working on unpaid family business, and less time on schooling activities.

Our paper is related to an empirical literature exploiting the accident of multiple births and gender-specific birth as exogenous variation in fertility to causally estimate the Q-Q trade-off in children welfare. While the OLS estimates of the effect of sibship on child quality tend to present strong negative links, the empirical findings using IV estimation from these studies are however mixed. While many studies find no effect of large family size (Black et al., 2005), some find negative implications in certain aspects of children's welfare (Cáceres-Delpiano, 2006; Grawe, 2008). In a developing country context, some studies do find evidence of the Q-Q trade-off (Lee, 2008; Dang and Rogers, 2009; Rosenzweig and Wolpin, 1980b) whereas others find no evidence (Angrist et al., 2010; Fitzsimons and Malde, 2014) along with positive benefit of large family size in some cases (Rosenzweig and Zhang, 2009; Qian, 2009).

The paper is structured as follows: Section 3.2 outlines the Young Lives dataset and the construction of the instrumental variables. Section 3.3 describes the empirical strategy. Section 3.4 reports estimation results and Section 3.5 examines different pathways. Section 3.6 concludes.

3.2 Young Lives Dataset and Variable Description

3.2.1 Dataset

Young Lives Longitudinal Dataset: Young Lives is a long-term international study focused on childhood poverty which is coordinated by the University of Oxford. The dataset is tracking the development of 12,000 children in Ethiopia, India (in the state of Andhra Pradesh only), Peru and Vietnam through quantitative and qualitative research over a 15-year period. Young Lives has been following two cohorts of children per country since the beginning of the project. In this paper, we make use of the Younger Cohort dataset which comprises of 2,000 children in each country who were born in 2001/02. Three rounds of surveys have been administered when the YL cohort was 6-18 months old (2002), 4-5 years old (2006) and 7-8 years old (2009). Despite the

longitudinal structure of the data, the attrition rate is found to be less than 5 per cent (Outes-Leon and Dercon, 2008). No evidence of attrition bias has been found.

Using the pooled data across four countries, the full sample has 8,065 children. Given the empirical strategies, we restrict the sample to only index children with at least one older sibling when Round 1 was administered. Therefore, the sample is reduced to 4,493 children (accounted for 56 % of the sample). We retain children in which we have information on ideal and actual fertility outcomes. Amongst these families, approximately 40 % reported to have more children between Round 1 and Round 2 of the survey. Depending on each outcome of interest, our finalised, non-imputed sample ranges between 2,714 and 3,779 children in the fully specified models [1].

Measures of family size: As we question if there is any effect of additional minor sibling(s) on the older one, we obtain this variation from the information provided in Round 2, when the YL index children were 5 years on average. We construct two variables of interest: (a) the number of younger siblings born after Round 1 and (b) the probability of having at least one younger sibling born after Round 1. These measures of sibship size allow our analysis to capture both the intensity and the extensive margin of having younger siblings.

We first show background characteristics of the Young Lives children and their families when the YL cohorts were 9 months old on average at the time the longitudinal data was first administered. Table 3.1 compares the characteristics between the full sample (8065 children) from the four-country pooled data and the sub-sample of which the families have at least 2 children, inclusive of the YL index children) in Round 1 (the 2+ sub-sample).

Amongst the 2+ sub-sample, 40 per cent of the families eventually have at least one more child between Round 1 and Round 2. During this 4-year period, 85 per cent of these families have one more child whilst 15 percent have two or more children. Across all characteristics, our 2+ sub-sample are closely similar to the full sample. Note that the 2+ sub-sample who continue to have more child(ren) by Round 2 are more likely to have parents with lower education attainment, come from agricultural households and more relative less well-off, given the wealth index measure.

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[1]One main concern for using the complete sample is that it might be biased. We check to ensure that the probability of being the complete sample (having the full set of covariates) does not correlate to (i) ideal number of sons and daughters (ii) outcomes of interest (iii) sibship size. We run OLS with only geographical indicators (robust and clustered) and find no statistical relationship between being in the complete sample and those main characteristics, which may bias our findings.

3.2.2 Measures of Children's Human Capital Accumulation

To estimate the causal effect of an increase of minor sibship size on the older child's human capital development and welfare, we look at various measures of cognitive achievement as well as health status. Additionally, we will exploit the longitudinal nature of the date and examine potential dynamic effect of extra sibship size on contemporaneous outcomes as well as those in later time horizon. In sum, our outcomes of interest are derived from the following:

Cognitive achievement: Round 1 did not include any measures of children's development for the Younger Cohort. In Round 2 (5 years old), the Peabody Picture Vocabulary Test (PPVT) was administered to measure cognitive development [2]. For Mathematical skills, the Cognitive Development Assessment (CDA, of which only the Quantitative sub-test) was utilised. In Round 3, PPVT was repeated when the children were 9 years old on average. For measuring quantitative skill, a Young Lives Maths Test was administered. Reading ability in Round 3 was measured by the Early Grade Reading Assessment (EGRA), which consists of two modules on word recognition and reading fluency. See the Appendix for more detail.

Physical health and socio-emotional competencies: Measure of the YL children's body mass index (BMI), height-for-age z score (for stunting), weight-for-age z score (for underweight) and a subjective measure of carer's assessed healthy status are available for both Round 2 and 3. We also have carer's reported number of health issues of the YL children in at age 5 (Round 2). For socio-emotional competencies, we have self-assessed measures of self-esteem, trust, own locus of control and subjective well-being (using ladder of life score) at age 9 (Round 3)

Parental labour supply: In Round 2 and 3, the children's parents provide information on maternal and paternal time in employment. The variables consist of number of hours spend per day, number days spent working per week and number of months spent working in the past calendar year. We code non-working as zero unit for all employment variables.

---

[2]It was originally developed in English in 1959 and has been updated several times. In this study we used version III (204 items) (Dunn and Dunn, 1996) in Ethiopia, India and Vietnam; this was the version available for Round 2 and 3. In Spanish we used the PPVT-R (125 items) adapted for Latin America (Dunn et al., 1986). Several studies have found that the PPVT has a positive strong correlation with some commonly used intelligence measures, such as the Wechsler and the McCarthy Scales (e.g. Campbell et al., 2001; Gray et al., 1999; Campbell, 1998).

Household expenditure on YL: In Round 3, the carer of each YL children provide information on how much the household spend on different items in the past 12 months, both in total monetary expenditure and also the proportion allocated to the YL children. The items are clothes, shoes, uniform, medical treatments, school fee, extra schooling, books and transport to school.

YL Children's time allocation: In Round 2 and 3, YL children were asked to indicate the number of hours in a typical day spent on sleeping, caring for others, doing domestic tasks, doing family farm or business, being at school, studying outside school time and doing leisure activities. In Round 3, they also indicate how many hours spent in paid work as well as whether or not they had ever missed school more than 1 week in the past 12 months.

3.2.3 Instrumental Variables: Heterogeneous Preferences for Children-Sex Composition

To account for the reversed causality between fertility preferences and children's outcomes, as well as the omitted variable bias, the typical approach in the recent literature exploits the exogenous variation of a birth of a gender-specific child and applies instrumental variable strategies to gain causal interpretation.

The validity of the instruments is based on two crucial assumptions. First, parents do not have influence on the actual gender mix of their children. Second, all parents prefer the optimal children composition of one son and one daughter. Therefore, the families who do not achieve this exogenously determined balanced gender composition would be more likely to continue to have the third child or more and vice versa. Followed AE, we use the information on family members from the household module in Round 1 to construct dummies for boys born at first ($B1_i$) and second birth ($B2_i$). A dummy for same-sex sibling pairs ($SS12_i$), a dummy indicating two sons ($BB12_i$) and a dummy indicating two daughters ($GG12_i$) are subsequently derived.

As a key contribution of this paper, we introduce an alternative set of instrumental variables. As before, we exploit the exogenous variation of gender-specific birth and explicitly take into account heterogeneity of fertility preferences of families from different cultural backgrounds. To do so, we make use of the information of ideal number of sons and daughters provided by the carers in the Young Lives data. We combine this information with the actual number of sons and daughters in the YL index children's family. Note that the specified ideal number of sons and daughters are fully endogenous

to other household behaviours. However, the actual number of sons and daughters are predominantly driven exogenously by the natural chance of a conception.

Therefore, our alternative instrumental variables can be derived using the discrepancy between the ideal and the actual number of sons (daughters) for each family. Most importantly, these are a set of instrument variables that depart from the implicit imposition of homogeneous preferences of children on the households with a different cultural background. The stated ideal total number of sons and daughters are explicit proxies for the optimal fertility stopping rule, specifically to each family.

In the Young Lives dataset, the carer of the YL index child, generally the natural mother, was asked to state the ideal total number of sons and daughters the family wishes to have (IDB_i, IDG_i). The actual number of sons and daughters, ACB and ACG, are obtained the stated fertility information in each round. Thus, we construct the ratio of ideal total to the actual number of sons (and of daughters) in Round 1 (ZB_i, ZG_i).

Each of the ratios below indicates the distance a family is from achieving their optimal fertility goal. Given the average age of 9 months old, it is most likely that the YL index children were the most recent born in the family [3].

$$ZB_i = \frac{IDB_i}{ACB_i}$$

$$ZG_i = \frac{IDG_i}{ACG_i}$$

Because our *optimal fertility discrepancy* variables account explicitly for heterogeneous preferences for sibling-sex composition, in the first-stage regressions, it is necessary to directly account for the stated fertility preferences, the ideal total number of sons and daughters. And having controlled for the stated heterogeneous fertility stopping rule, our instrumental variables satisfy the exclusion restriction under a conditional expectation[4].

Table 3.2 shows mean ideal total as well as the actual number of sons and daughters indicated in the YL data, using the full sample. We compare these numbers to the

---

[3]For technical reason, to prevent the zero denomination, which occurs when a household does not have a son or a daughter, we add the value of 1 to both ideal total number and actual number of sons and daughters. $ZB_i = \frac{IDB_i + 1}{ACB_i + 1}$ and $ZG_i = \frac{IDG_i + 1}{ACG_i + 1}$.

[4]See Appendix for the proof.

information available in larger, representative surveys at the country level and the sub-continent level. The ideal numbers are derived from the Demographic Health Surveys and the actual numbers of children come from the United Nation Population Division[5].

Table 3.3 lists the mean value of instrument variables being used in this paper and make comparison across the full sample, the 2+ sub-sample with more children by Round 2 and the 2+ sub-sample without more children by Round 2. On the one hand, the 2+ sub-sample indeed desires to have similar number of children to the full sample. On the other hand, within the 2+ sub-sample, families who desire to have more children eventually have higher fertility than the rest. Also, notice that the probability of each sibling-sex composition variable in our YL sample reflects the true likelihood when a birth of a given gender is naturally determined (Panel B of Table 3.3)[6]. We believe that this is supporting evidence of lack of fertility manipulation in the average YL sample, namely selective abortion or fertility treatment.

Figure 3.1 plots raw correlation pattern, using the 2+ sub-sample, between the average likelihood of having more children (by Round 2) and the distance away from achieving the desired level (defined as the difference between ideal and actual number). For both sons and daughters, the upward trend indicates that our *optimal fertility discrepancy* instruments would satisfy the relevance assumption of the instrument variable technique. We will formally test this in a subsequent section.

3.3 Empirical Strategies

First, we describe the basic model used to estimate the effect of having more minor siblings on the outcomes of an older sibling. We then outline the empirical strategies for two-stage least squared regressions. The results from first-stages using different choice of instruments are discussed. Subsequently, the IV estimates from the most preferred specification, which uses the combination of (a) conventional children-sex composition and (b) *optimal fertility discrepancy* variables, are reported.

3.3.1 Basic model

The basic model to be estimated is as follows:

---

[5]For the ideal total number of sons and daughters, we make use of the Demographic Health Surveys during the years nearest to 2000. The exact information of ideal total number of children by gender is not directly available. Instead, informants provide the ideal total number of children overall. We combine this number with the information on the proportion of households who prefer balanced-gender, only sons, only daughters, or indifferent and calculate the ideal number by each gender.

[6]That is the unconditional probability of having a son (daughter) at each birth in a random draw is equal to 0.5 Therefore, the probability of having two sons (daughters) consecutively is 0.25.

$$Y_{i,t+n} = \alpha_f F_{i,t} + X'_{i,t}\pi + \mu_{i,t} \tag{3.1}$$

where the outcome variables, $Y_{i,t+n}$, including child i's human capital (cognitive abilities, physical health and socio-emotional well-being) at survey round $t+n$ and $n \geq 0$. X_t is a vector of covariates in Round 1, which comprise of the child's, parents' and household's characteristics. $F_{i,t}$ is the variable of interest indicating the increase of sibship size during the 5 years period after the child was born. $F_{i,t}$ is defined in two ways: (a) the number of siblings born after the index child, measured in Round 2 and (b) a dummy variable for whether any siblings born after the child at all by Round 2. The error term, $\mu_{i,t}$, denotes unobserved factors which influence $Y_{i,t+n}$ whilst can be correlated with $F_{i,t}$. The family size effect, α_F, is estimated using Ordinary Least Squares (OLS). Given the characteristic of $\mu_{i,t}$, α may suffer from omitted variable bias.

3.3.2 First-Stage Specifications

To obtain consistent estimate of the sibship size effect, an instrumental variable technique is employed. This subsection illustrates three specifications of first-stage regressions. We perform validity tests for each set of instrumental variables and make comparison so as to select a preferred choice of instrument variables for family size within a context of developing countries in our data.

First-stage using sibling-sex composition in the 2+ Sample : We start our first-stage regressions by estimating sibship size on sibling-sex composition variables. This set of instrumental variables is identically defined as in Angrist and Evans (1998) (AE thereafter). The first-stage specification using the sample of children with at least one older sibling in the family in Round 1 (the 2+ sample) are based on the following models:

$$F_{i,t} = \beta_1 B1_{i,t-n} + \beta_2 B2_{i,t-n} + \beta_s SS12_{i,t-n} + X'_t\eta + \varepsilon_{i,t} \tag{3.2}$$

$$F_{i,t} = \beta_1 B1_{i,t-n} + \beta_b BB12_{i,t-n} + \beta_g GG12_{i,t-n} + X'_t\eta + \varepsilon_{i,t} \tag{3.3}$$

where $B1_{i,t-n}$, $B2_{i,t-n}$, $SS12_{i,t-n}$, $BB12_{i,t-n}$ and $GG12_{i,t-n}$ are a set of dummies for sibling-sex composition of first two children in a family, which are constructed from a period prior to the fertility outcome.

First-stage using optimal fertility discrepancy in the 2+ sub-sample: Our alternative first-stage specification replaces the sibling-sex composition variables with the heterogeneous variation of family-specific *optimal fertility discrepancy*. We run the first-stage estimations using only this set of variables (Equation 3.4) as well as the specifications which include the sibling-sex composition as well (Equation 3.5). Under this alternative first-stage specification, the variables on family-specific ideal number of sons and ideal number of daughters are included. This is to ensure under a conditional expectation, our derived *optimal fertility discrepancy* instrumental variables satisfy the exclusion restrictions. (See Appendix for the proof.) The regression equations are described as follows:

$$
\begin{aligned}
F_{i,t} = {} & \theta_{gg} ZG_{i,t-n} + \theta_{gb} ZB_{i,t-n} \\
& + \theta_{dg} IDB_{i,t-n} + \theta_{db} IDB_{i,t-n} + X_t' \eta + \omega_{i,t}
\end{aligned}
\tag{3.4}
$$

$$
\begin{aligned}
F_{i,t} = {} & \theta_{gg} ZG_{i,t-n} + \theta_{gb} ZB_{i,t-n} \\
& + \theta_{dg} IDG_{i,t-n} + \theta_{db} IDB_{i,t-n} \\
& + \theta_1 B1_{i,t-n} + \theta_b BB12_{i,t-n} + \theta_g GG12_{i,t-n} + X_t' \eta + \omega_{i,t}
\end{aligned}
\tag{3.5}
$$

where $ZG_{i,t-n}$ is a ratio of the total ideal number to the actual number of daughters in Round 1 for the family of child i and $Gapboy_{i,t-n}$ is the ratio for sons. $IDG_{i,t-n}$ and $IDB_{i,t-n}$ are the mother's stated number of ideal daughters and sons. θ_{gg} and θ_{gb} indicate an effect the distance away from achieving the ideal size of daughters and sons has on the fertility decision in the next period respectively. Note that while each family is free to decide on the ideal size of children from each gender, it is beyond their control to dictate an arrival of a son or a daughter in each pregnancy. Therefore, conditional on the family's stated preferences for children from each gender, $ZG_{i,t-n}$ and $ZB_{i,t-n}$, are exogenous to characteristics of the family and the older siblings.

First-stage using optimal fertility discrepancy with country-interactions in the 2+ sub-sample: Similar to Angrist et al., 2010, we decide to incorporate cultural heterogeneity into our first-stage specifications by adding the country-instrumental variable interactions to our analysis using the pooled four-country data. We describe Equation 3.6 as follows:

$$
\begin{aligned}
F_{i,t} ={}& \rho_{gg} ZG_{i,t-n} + \rho_{gb} GB_{i,t-n} + \rho_{dg} IDG_{i,t-n} + \rho_{db} IDB_{i,t-n} \\
&+ \rho_1 B1_{i,t-n} + \rho_b BB12_{i,t-n} + \rho_g GG12_{i,t-n} \\
&+ \sum_{m=1}^{3} \rho_{ggm} ZG_{i,t-n} C_i^m + \sum_{m=1}^{3} \rho_{ggb} ZB_{i,t-n} C_i^m \\
&+ \sum_{m=1}^{3} \rho_{1m} B1_{i,t-n} C_i^m + \sum_{m=1}^{3} \rho_{bm} BB12_{i,t-n} C_i^m + \sum_{m=1}^{3} \rho_{gm} GG12_{i,t-n} C_i^m \\
&+ \sum_{m=1}^{3} \rho_m C_i^m + X_t' \eta + \phi_{i,t}
\end{aligned}
\tag{3.6}
$$

where C_i^m is a set of dummies for each four countries of residence in the pooled data, namely Vietnam, India, Peru and Ethiopia [7].

In the next section, we provide evidence relating to the issue of instrument validity. We make comparison among the specifications described in Equations 3.2 to 3.6 and subsequently select the preferred model before proceeding to the second-stage of 2SLS estimation.

3.3.3 Causal effect of sibship size on children's human capital

To estimate the causal effect of having younger siblings on children's cognitive abilities, the second-stage estimation follows the OLS specification previous whilst replacing $F_{i,t}$ with the predicted value of additional sibship size, $F_{i,t}$, from the first-stage. The causal estimation under Two-Stage Least Squared is outlined as follows:

$$
Y_{i,t+n} = \gamma_y \hat{F}_{i,t} + X_{i,t}' \kappa + \mu_{i,t}
\tag{3.7}
$$

where $\hat{F}_{i,t}$ is a predicted family size when the average YL children turn 5 years old. $X_{i,t}$ is a equivalent of covariates used in the OLS and first-stages. They include a full set of control variables and dummies for YL's gender, geographical characteristics (rural, region within a country), number adults in household in Round 1, male as head of household, mother's age (Round 1), father's age (Round 1), whether father's education is higher than primary school, whether mother's education is higher than primary school, whether YL was born prematurely (before 37th week of gestation), housing quality index (Round 1), services index (Round 1), wealth index (Round 1), home ownership (Round

---

[7]Technically, the specification omits the Peru country dummy so as to avoid multi-collinearity problems.

1) and industry of employment in Round 1. To account for maternal' personalities, we include mother' s self-efficacy index (Round 1)and mothers self-pride index (Round 1). These variables are some personality traits, which we hope would capture a degree heterogeneous fertility preferences of the mother as well as her overall self-control.

Also, the set of variables on maternal health and conditions of pregnancy are included (namely mother with any disabilities, size of YL at birth, mother's rating of her pregnancy with YL, mother's assessment of labour difficulty). This is to capture a degree of heterogeneous fertility constraints, which may be correlated to the states fertility preferences [8]. More important, in the fully specified model, we include a set of birth order indicators so as to account for differences in the outcomes across different parity (Black et al. [2005]; Bagger et al. [2013]).

$Y_{i,t+n}$ is the variable of child's welfare. The outcomes were measured when the YL index child was, on average, 5 years old (Round 2) and 8 years old (Round 3). As described in the data section, in Round 2, we have measures for the child's achievement assessment (cognitive and maths) and physical health (objective measure of height and weight; mother's assessed health status). In Round 3, child's welfare measures comprise of the achievement assessment (cognitive, Maths and reading ability), physical health (as in Round 2) and attitudinal outcomes (self-efficacy index, trust index, pride index and subjective well-being).

The IV estimate, γ_y, from 2SLS is a causal effect of having an increased size of sibship on the older child's human capital accumulation. If there is omitted variable bias and the Q-Q trade-off exists, we expect γ to be negative, possibly with a larger estimate than the OLS.

3.4 Main Results

In this section, we first show the estimates from our first-stage regressions between our variables of family size and the instruments. We also report some validity tests of the instrument variables. Then, we show the estimates from the 2SLS using the preferred choice of instruments. Throughout, we will compare the results from the 2SLS estimates with the OLS estimates.

---

[8]It is possible that the ideal number of children may be correlated to fertility constraints. Without accounting for this, our variable of interest may not reflect the true preferences and therefore the estimations may suffer from biases.

3.4.1 First-Stage Regressions and Validity Tests

Using the YL's 2+ sub-sample, we run first-stage equations and compare the results between each specification (namely Eq. 3.2,3.3, 3.4, 3.5 and 3.6). We define the increase of sibship size as (i) total number of younger siblings born to the same family by Round 2 and (ii) whether or not the family have at least one additional sibling born by Round 2. For the binary outcome, we assume a linear probability model therefore the OLS models are used throughout. All regressions have robust standard error. We also cluster the standard errors at country level for the specifications in Eq. 3.2,3.3, 3.4 and 3.5.

Table 3.4 reports the first-stage estimates between the sibship size and the sibling-sex composition as described in AE and Angrist et al. (2010). The estimates show that having first two children from a same gender makes the YL families 4 percent more likely to have at least one more child by Round 2 (Column I and III). And the effect comes from families which have two daughters as their oldest children (Column II and IV). Given that the significant levels of the coefficients, it is not surprising that the F-test on the excluded variables is considerably low, at 2.3. On the one hand, the magnitude of the effect of $Samesex12_{i,t-n}$ is similar to what AE found using a US sample. On the other hand, we find that the effect from having two daughters is much larger with much higher t-statistics than having two sons.

Table 3.5 reports the first-stage estimates in the model that uses *optimal fertility discrepancy* variations as instruments. Without other covariates, a unit away from achieving the ideal number of sons is related to 9 percent increase in the probability of family having more children. For daughters, it is related to 5.6 percent increase in the probability (Column I). These are related to an increase on the number of younger children by 0.14 (from the son-discrepancy) and 0.087 (from the daughter-discrepancy) (Column V). When all covariates (inclusive of birth order indicators) as well as AE's instruments are included, a unit increase in son-discrepancy and daughter-discrepancy are linked to an increase of fertility probability at 5 and 4 percent respectively. The F-test on the excluded variables under this specification is at 33.9.

Table 3.6 reports estimation findings from the first-stage specification which the country-interaction terms are included. Controlling for all covariates, country-specific effect of daughter-discrepancy is negative but statistically insignificant for Ethiopia and India. A unit increase in son-discrepancy raises the fertility in Vietnam and India by 9 and 17 percent. These estimates reflect culturally difference in fertility preferences whereby son-bias preferences are more prominent in Asia. Our Peru's estimates which indicate

that families' fertility decision is not driven by children-sex preferences is also well documented in DHS surveys (Arnold, 1997). Above all, the magnitude of F-tests on the excluded variables satisfies the instrumental variable's relevance assumption.

In sum, having compared the estimates and some validity tests for instrumental variables across all potential specifications, we decide to use Eq. 3.5 as our preferred first-stage model. In the next section, we report our empirical findings from the second-stages to estimate the effect of having minor siblings on measures of child's human capital.

3.4.2 Second-Stage Estimations: Child Outcomes

We use the two-stage least squares (2SLS) to estimate the effect of sibship size on the older sibling's welfare. For comparison, we also present alongside the empirical findings from the linear probability model (when sibship size is measured as the fertility probability) and the OLS model (when sibship size is measured as number of minor siblings). All outcomes reported here are standardised with mean equals to zero and standard deviation equals to one. All regressions controls for socio-economic characteristics of the family and the child (see Table 3.1). To make regression estimates comparable, we use the YL 2+ sub-sample and decide to keep only those observations with the full set of covariates. The estimates from all 2SLS are robust. Results are shown separately for three groups of human capital outcomes: cognitive development, physical health and socio-emotional well-being. Whenever possible, we report and compare the outcomes measured in Round 2 (age 5) and in Round 3 (age 8) respectively. For brevity, we report the 2SLS estimates when sibship size is measured as number of minor siblings [9]. We also assess our identification assumption by computing the Sargan over-identification test for the 2SLS models below. The p-value for the χ^2 statistics for each main outcome is reported in the adjacent column of the 2SLS estimates (Table 3.7-3.9). Overall, the p-values are high and therefore we do not reject the null hypothesis that our optimal fertility discrepancy instruments are valid [10].

Cognitive development : We see from the estimates in Table 3.7 that the OLS estimates are negative and statistically significant from zero in all assessments at age 5 as well as age 8. An extra minor sibling is related to 0.74 sd. increase in PPVT at age 5 and a further 0.12 sd. increase of PPVT assessed again at age 8. In quantitative

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[9]Results from other specifications are available on request.

[10]A point of concern is that in this specification, the ideal number of sons and of daughters are indeed endogenous to individual family preferences. The same concern is valid for having birth order variables in many conventional models in the QQ literature. Bagger et al (2013) shows that when independent variables (birth order in their case) are potentially correlated to the key variable (family size), the estimate of the family size effect can face an issue of biased-towards-zero and thus a false rejection of the QQ trade-off.

assessments, the adverse effect of sibship size reduces score in CDA assessment by 0.6 sd. and the effect is slightly larger at age 8. The negative association in the language ability is observed at a 0.05 sd. decrease in EGRA at age 8.

When we instrument for the increase of sibship size with both *optimal fertility discrepancy* and sibling-sex composition IV, the magnitude of the effect of sibship size on cognitive development at age 5 have higher negative magnitude. However, all cognitive assessments at age 5 have low t-statistics. When we look at cognitive abilities at age 8 (3 years later), the results from our 2SLS model shows a strong negative effect where an extra minor sibling leads to a decrease in PPVT score at age 8 by 0.62 sd. Similarly, the Maths score declines by 0.4 sd. These negative effects are robust to the addition of the full set of covariates.

The absence of an adverse effect on cognitive development at 5 years old suggests that having an extra sibling, who might be in her infancy at the time, does not pose a Q-Q trade-off on the older child. This finding seems to be in line with previous studies. (for example Hauser and Kuo, 1998; Fitzsimons and Malde, 2014). On the other hand, the evidence of a strong negative effect on cognitive development in later age (8 years old) indicates that the Q-Q trade-off may have some dynamic patterns.

There are a number of explanations why we observe the time lag between the period when the minor sibling was added to the family and the period where a decline in cognitive performance is detected.

First, the production function of child human capital itself takes time. Therefore, the change in child's outcomes from a potential decrease in parental input may not be detected instantaneously (e.g. Weiling, 2003; Price, 2008). Second, a family's behavioural responses to having an extra child may vary across time. Credit constraints can limit the length of time a family can afford to do things differently (e.g. Chesnokova and Vaithianathan, 2008; Locay, 1990). Lastly, as the YL child turns from 5 to 8 years old, her time spending may change in response to her domestic work as well as market work abilities (e.g. Ejrnæs and Pörtner, 2004; Edmonds, 2006). In a later section, we formally investigate all of these plausible channels in which the adverse effect of having minor siblings may potentially feed through over time.

Physical health : Table 3.8 compares the estimates from the OLS and 2SLS on physical health outcomes. In the OLS, we find that sibship size is positively associated with higher body mass index (BMI) and negatively linked to the probability of the YL child being stunted at age 5. By age 8, we only find a negative and statistically significant association of sibship size (when 5 years old) and stunting. That is, a larger

sibship size is linked to better physical health of the child. However, we do not observe any significant relationship in term of weight-for-age and in particular, the underweight status. In term of subjective health measure, we find that mothers from families with more minor sibling tend to report worse health status of the YL child (by 0.04 sd. at age 8).

Using 2SLS, the estimates on the sibship size effect on objective physical health (weight and height) become statistically insignificant, both the immediate outcomes at age 5 and later outcomes at age 8. Our 2SLS findings are closely related to Lordan and Frijters [2013] who also look at Q-Q effects using the YL's Peru sub-sample. They find that when the minor siblings are unplanned, there is no health effect (weight and height) on the older children.

Socio-emotional competencies : Previous studies from health sciences have often emphasised the negative impacts of large sibship size on childhood psycho-emotional conditions whilst few researchers have assessed how siblings may influence indicators of mental health. For instance, social interactions with siblings may have a positive influence, in particular children's social and interpersonal skills (e.g. Downey and Condron, 2004; Lawson and Mace, 2010). Table 3.9 reports the regression results from the OLS and 2SLS specifications using child's subjective outcomes on socio-emotional status when she was 8 years old. Using the OLS, we do not observe statistically significant relationship between having an extra minor sibling with all four measures. Self-evaluated trust index and self-esteem index are positive correlated with larger sibship size. On the other hand, self-efficacy (a measure for how much she believes her own actions matter to how her life turns out) and the ladder of life scale (a subjective well-being measure) are negative linked to more number of minor siblings.

Using 2SLS specification, the effect on an extra sibling leads to an increase of the Trust index by 0.1 sd. In contrast, it leads to a decrease of the self-esteem scale by 0.09 sd. The sibship size effect on self-efficacy and the ladder of life scale become smaller than the OLS estimates but remain insignificantly different from zero. Having a younger sibling seems to present a positive attitude on social capital and community on the older child. Note that self-pride index comprise of resources provided to the child, for example clothes and books, this may signal an adverse effect on having a younger sibling on the quality as well as quantity of resources parents being able to provide to the older child. We investigate this channel further in the next section when we look at family expenditure on the YL child.

3.5 Young Lives Dataset and Variable Description

3.5.1 Parental Labour Supply and Family Expenditure using 2SLS

In this section, we investigate how might the expansion of sibship size in our four-developing country data do not pose immediate negative effect on welfare on the old child and why we find selected negative effects at outcomes measured three years after.

First, we examine labour market activities on both mother and father and how they might adjust their labour supply in the immediate term (when the YL children age 5 years old) and two years later (YL at age 8). Formally, the parental labour supply model we estimate is the following equation.

$$L_{i,t+n} = \gamma_l \hat{F}_{i,t} + X_{i,t} \kappa_L + \mu_{i,t} \tag{3.8}$$

where $L_{i,t+n}$ is a measure of labour supply of parents (mother and father separately) from the family of the YL child i when her age is $t + n = 5$ and 8. $\hat{F}_{i,t}$ is the predicted minor sibling size from the first-stage regression. Given the data, we are able look at the sibship effect on labour supply, $L_{i,t+n}$), at three levels: hours per day, days per week and months in a year.

Table 3.10 reports consistent 2SLS estimates of the effect of sibship size on parental labour supply, γ_l, and compare the findings with the estimates from the OLS model, when the YL child was 5 years old. Using the OLS, maternal labour supply when YL was 5 years old is reduced by approximately 0.09 sd. when the family has an extra minor sibling. We, however, observe positive relationship of sibship size in some measures of paternal labour supply. However, they are statistically insignificant. In contrast, the more consistent estimates from 2SLS show that there is in fact no change in maternal labour supply when the family recently have an extra child. Interestingly, the positive effect of sibship size on paternal labour supply (increase of approximately 0.2 sd. for number of days in a week and 0.4 sd. for number of months annually) suggest that there is intra-household labour supply adjustment in respond to having more children. Across the board, the reduction of maternal labour supply is compensated by more time spent working by the father. In term of hours per day, the result indicates equal compensation between the mother and the father. The 2SLS estimates suggest that an average father puts in approximately twice the amount of time reduced by the mother when we consider the number of days per year.

This is evidence of how a family with an extra child may be able to finance the extra expenditure. As a result, this suggests how the Q-Q trade-off was not detected when

examining the child's welfare at age 5. When we look at parental labour supply when the YL child aged 8 years old, the estimates from 2SLS suggest that an average mother who had at least an extra child from 3 years ago reduces her weekly work time by 0.32 sd. These effects are larger than the magnitudes found in the OLS model. Our 2SLS detects a positive effect of sibship size on paternal labour supply as previously found when the YL child was 5 years old (months per year).

Overall, our estimates of maternal labour supply models using the YL sample of developing countries share similar patterns to what had previously been found (e.g. Rosenzweig and Wolpin, 1980a; Angrist and Evans, 1998; Cruces and Galiani, 2007). The results also suggest that the negative effect of having younger children on maternal labour supply amongst the 2+ families in developing countries can be long-lasting. Subsequently, this may pose further constraints on the family's financial situation. Even if we observe that there is a reshuffling of intra-household labour supply, with positive change on paternal labour supply, around the time when extra children were added to the family, this pattern did not continue three years after. We believe this is a possible channel why we observe a Q-Q trade-off in term of YL's cognitive assessment at 8 years old.

In the next step, we formally examine possible effects in which the extra sibship size may pose on household's expenditure. We estimate the following model:

$$EXP_{i,t+n} = \gamma_e \hat{F}_{i,t} + X_{i,t}\kappa_E + \mu_{i,t} \tag{3.9}$$

where $EXP_{i,t+n}$ is a standardised measure of log of household expenditure spent on YL child i when she is 8 years old ($n = 3$). As before, $\hat{F}_{i,t}$ is the predicted minor sibling size from the first-stage regression. At Round 3, we have information on $EXP_{i,t+n}$ includes school-relating expenditure (books, transport, tuition fee, uniform) and health expense (doctor, medicine). This allows us to investigate how the intra-household allocation of resources are adjusted as a respond to having had an extra minor child at least three years ago. Given its component, $EXP_{i,t+n}$) is essentially a monetary measure of parental inputs of the child's human capital development at 8 years old.

The estimates of γ_e are reported in Table 3.11. In the OLS models, we observe the negative pattern of the sibship size effect on almost all measures of parental inputs. An extra minor sibling is related to a decrease in spending on school books (0.12 sd.), school fee (0.08 sd.) and medical expenses (0.11 sd.) In contrast, transport-to-school expense and extra-schooling spending are found to be positive correlated but statistically insignificant.

Using the 2SLS models for more consistent estimates, we find a negative effect of sibship size on almost all household expenditure measures. We find the negative effect on medical expenditure (0.23 sd.) and a larger negative effect on schooling expenses (0.6 sd for school fee and 0.43 sd. for extra-classes fee). Note that their magnitudes are much larger in compare to the OLS estimates. Our findings are somewhat contradictory to the absence of the effect shown recently by Fitzsimons and Malde, 2014. Their empirical test, which used the Mexico's Progessa sample, is to demonstrate that economies of scale (e.g. Rosenzweig and Zhang, 2009) from having same is not an important concern in the Q-Q trade-off analysis. Unlike our study, the family expenditure used in their investigation was the total value spent on all children instead of on a specific child.

Together with the estimates from the parental labour supply models, it is suggestive that YL families undergo intra-household adjustment in response to having an extra child. In the short run, because fathers increase their working time twice the size of the time the mother takes out, the Q-Q trade-off measured in immediately at age 5 is therefore undetected. At age 8, however, negative effect of additional fertility on mother's labour supply is not compensated by the father's. At the same time, we observe adverse effects on the allocation of household resources. An explanation to this is that the scope of economies of scale (for example *hand-me-downs*) is very limited in developing countries (Attanasio et al., 2009, Fitzsimons and Malde, 2014). Hence, if families are not able perfectly adjust their finance in respond to the additional young child, some resources directed to older children may be affected. Subsequently, the decrease in parental inputs may help explain how we observe the Q-Q trade-off in the medium term when the child is 8 years old.

3.5.2   Child's Own Time Spending Using 2SLS

To investigate this further, we turn our attention to another important for which families can adjust their intra-household tasks in respond to an exogenous increase of sibship size. In many developing countries, the lack of government-sponsored childcare provision means that family members are usually in charge of caring for young children. Together with the absence of legal rights to maternal leave for women, the task of childcare is taken up by older siblings in the family (Engle, 1991; Leslie and Paolisso, 1989; Levison and Moe, 1998). On the one hand, there are both positive effect of being looked after by own siblings on the young child themselves (e.g. Downey et al., 1999). On the other hand, the opportunity cost of looking after a younger sibling is the amount of time the older child could have spent learning and accumulating their own human capital (Ejrnæs and Pörtner, 2004). Moreover, sibling care may lead to a lack of verbal

stimulation, which subsequently reduces cognitive development of both the older and younger siblings (Belsky et al., 1980; Royce et al., 1983).

To obtain a consistent estimate of the effect of extra sibship size on the time allocation of the older child, we formally estimate the following model:

$$H_{i,t+n} = \gamma_h \hat{F}_{i,t} + X_{i,t}\kappa_H + \mu_{i,t} \tag{3.10}$$

where $H_{i,t+n}$ is a measure of hours in a typical day that the YL child i spent doing an activity. We have the information on child's daily time use, including time associated to schooling, to household chores and own leisure, when the child is 5 and 8 years old. γ_h is the consistent estimate on the effect of sibship size on the older child's time spending.

Table 3.12 reports the estimates from the OLS and 2SLS models. When the child is 5 years old an extra minor sibling has a statistically significant negative relationship with leisure time (0.06 sd. for sleeping, 0.12 sd. for playing) whilst a positive relationship with household chores (0.4 sd. for caring for others, 0.07 sd. for domestic tasks and 0.7 sd. for taking care family business). We find the similar pattern when the time-use is measured when the child turns 8 years old. For school-related activities, at age 5, the association are negative but with low t-statistics (0.002 sd. for being at school, 0.04 sd. for studying outside classes). When measured at age 8, the relationship becomes more negative and statistically significant (0.07 sd. for being at school and 0.09 sd. for studying outside classes).

For the 2SLS models, each estimate at age 5 maintains the same direction of the relationship as the OLS. We find the effect of sibship size on schooling to be statistically significant. An extra minor sibling leads to an immediate reduction of schooling time per day by 0.21 sd. At this age, we also observe a Q-Q trade-off in time spent at doing household-related tasks and caring for others. Looking at the activities at age 8, we also do not see the trade-off in term of own leisure time. However, having an extra minor sibling when the child aged 5 leads to a rise of 0.53 sd. of the child's time spent on caring for others when she is 8 years old. Simultaneously, it leads to a fall by 0.33 sd. in schooling time as well as 0.18 sd. of time spent studying outside classroom. This indicates that the YL child is tasked with looking after her younger siblings as a result of the intra-household resource organisation. And the way she can manage this is by trading off her schooling time to do so. This implies that, as a medium term effect of having extra minor siblings the older child invests less towards her own human capital accumulation in order to maintain the welfare of her younger sibling. And this may be a reason for the Q-Q trade-off in the child's cognitive abilities, assessed at 8 years old. Our findings offer a deeper understanding why children from lower birth-order are found

to perform worse scholarly in comparison to their younger siblings (Downey et al., 1999; Zajonc, 1976; Butcher and Case, 1994; Booth and Kee, 2009).

3.6 Discussions

3.6.1 Interpretation of ideal number of children

In our analysis, we rely solely on the stated number of ideal sons and daughters by the mothers as the proxy for the true fertility preferences of the collective households. However, since the similar data from the father's perspective is not available in the Young Lives Dataset, it is difficult to prove that this number represents only the mother's preferences or it is a consequence of the intra-household bargaining process (for instance Thomas [1990]; Browning and Chiappori [1998]; Rasul [2008]). The data from Demographic Health Surveys provide additional sub-sample of men's reproductive preferences for selected countries [11] .

This allows us to check whether or not men and women share common ideal number of sons and daughters. The evidence suggests for most Asia and Latin American countries (where the data on men's preferences is available), the average ideal number of children of women and men are aligned (with average men indicate only a fraction higher number of children than the women). The exception is sub-Sahara African countries whereby married men, on average, prefer higher ideal number of children (3 children higher) than the female counterparts (DHS, 2015) Therefore, we are more confident that the stated ideal number of sons and daughters by the mother in our Vietnam, India and Peru sample are most likely to reflect the preferences of the couples. However, we are less confident that this is the case in our Ethiopia sample, (where the male sample from DHS in 2005 indicates that they do prefer, on average, 1.3 children more than an average female.)

3.6.2 Non-linear effect of sibship size and birth order

In so far, our analysis have assumed that the effect of sibship size on child development and parental behaviours is linear. When the sibship size is modelled as a probability of having at least one more sibling, we do not distinguish between different magnitude of

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[11]In the DHS, the desired number of children is based on responses to the survey question: "if you could go back in the time you did not have any children and could choose exactly the number of children to have in your life, how many would that be?" This initial question is then followed by "How many of these children would you like to be boys, how many would you like to be girls, and for how many would the sex not matter?"

sibship size. Much of the early literature on the QQ model which find no evidence of the trade-off also rely heavily on the imposition of constant marginal effect of additional sibship size (see for example Black et al. [2005]; Cáceres-Delpiano [2006]). To circumvent the theoretical ambiguity, Mogstad and Wiswall (2011) estimate a model that allows for non-linear, non-parametric structure and show an evidence of a u-shape relationship between family size and outcomes. To account for this, we run an alternative OLS specification with indicators of different family size (controlling also for parity indicator) (Mogstad and Wiswall [2011]; Bagger et al. [2013])[12]. Table 3.13 shows that there is an evidence of non-linear effect of sibship size whereby the negative correlation is found in the first additional sibling whilst do not find statistically significant evidence for higher sibship size. However, we urge the readers to interpret our findings with caution. This is because due to the short duration between Round 1 and Round 2 of the survey, we only observe very few households who have more than one additional child. (only 15 % of those who have more children have two extra children or more). In additional, with the lack of twins in our Young Lives Data, our analysis is unable to follow the instrumental variable method in Mogstad and Wiswall (2011).

3.7 Conclusions

We study the causal relationship between sibship size and human capital development of children from four developing countries. Our empirical design exploits variation in fertility due to the discrepancy between the desired numbers and the actual numbers for sons and daughters in each individual family, along with the conventional sibling-sex composition. We are able track the effect of having extra minor siblings across time periods. This allows us to detect possible dynamic patterns of the Q-Q trade-off on the child's welfare and its underlying pathways. Our instruments, which explicitly allow for heterogeneous preferences for sibling-sex composition, exhibit strong first-stage relationship. Our findings from the OLS models indicate that the endogeneity of fertility plays a prominent role in the negative link between child quantity and quality. While we do not detect significant adverse effect of increased sibship size on cognitive outcomes at 5 years old, we later observe a strong negative effect on child's abilities when she turned 8 years old.

The results reported here provide a broader pattern which may not necessarily align with previous studies using data from the US, Norway, Mexico or Israel. For the families in our sample, even if parents prefer equality among their children *ex ante*, a possibility

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[12]We estimate $Y_{i,t+n} = \alpha_{d1}D_{1i,t} + \alpha_{d2}D_{2i,t} + ... + \alpha_{ds}D_{si,t} + X'_{i,t}\pi + +\mu_{i,t}$ whereby $D_{si,t} = 1\{s_i = s\}$. Given the data structure, we are not able to conduct family fixed effect model, as seen in Black et al. [2005]; Bagger et al. [2013]

of resource constraints may limit the quality parents are able to invest in the child's human capital ex post. We observe that in the short-run, parents do adjust their labour supply at the margin whereby fathers are able to over-compensate the reduction in mothers' working hours. At age 8, we, however, observe reduced expenditure on the older sibling at the same time when paternal employment no longer increases as much. An explanation for this is that older family members (including the older siblings) are required to reallocate their resources in order to maintain the quality of the extra minor sibling. This might explain a negative effect on child's own time spent learning and a positive effect on domestic responsibilities at age 8. The extent to which this may lead to further adverse implication on human capital development of the older child is of a great concern as cognitive abilities are known driver of many later success in life. With the on-going data collection in the Young Lives Dataset, we will be able examine this in future work.

Figures

FIGURE 3.1: Correlation between fertility probability and optimal fertility discrepancy, by sons and daughters
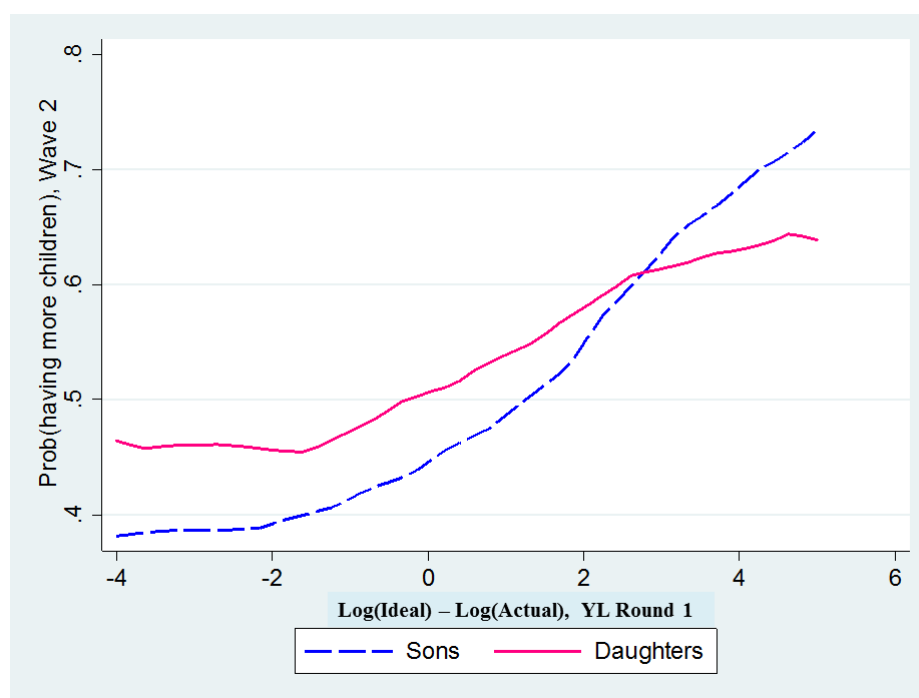
Tables

TABLE 3.1: Summary statistics

	Full sample (N=8065)		2+ Sub-sample			
			Have more children in Round 2 (N=1773)		Not have more children in Round 2 (N=2720)	
	Mean	SD	Mean	SD	Mean	SD
Male YL	0.52	0.5	0.51	0.5	0.53	0.5
Rural	0.63	0.48	0.72	0.45	0.62	0.48
No. adults (Round 1)	3	1.56	2.62	1.29	2.78	1.32
Male head of household	0.87	0.33	0.92	0.28	0.88	0.32
Mother's age (Round 1)	26.3	6.13	27.67	5.5	29.61	6.07
Father's age (Round 1)	31.62	7.62	34.14	7.8	34.56	7.57
Father ¿ primary school	0.49	0.5	0.3	0.46	0.53	0.5
Mother ¿ primary school	0.39	0.49	0.19	0.4	0.42	0.49
Mother with disability	0.04	0.19	0.05	0.22	0.04	0.19
Birth weight (grams)	3081.38	544.18	3113.42	594.13	3175.06	535.3
Birth size	3.03	0.92	2.97	0.95	3	0.91
Good pregnancy	0.79	0.41	0.75	0.43	0.77	0.42
Difficulties during labour	0.31	0.46	0.29	0.45	0.29	0.45
premature birth	0.04	0.2	0.03	0.17	0.04	0.19
Housing quality index (Round 1)	0.42	0.29	0.29	0.26	0.45	0.29
Services index (Round 1)	0.44	0.29	0.31	0.27	0.45	0.28
Wealth index (Round 1)	0.37	0.22	0.26	0.2	0.39	0.21
Home ownership (Round 1)	0.77	0.42	0.82	0.38	0.79	0.41
Mother:self-efficacy (Round 1)	3.11	0.52	3.11	0.5	3.08	0.5
Mother:self-pride (Round 1)	3.14	0.5	3.1	0.49	3.11	0.49
Agriculture	0.66	0.47	0.77	0.42	0.66	0.47
Mining & quarrying	0.02	0.12	0.02	0.13	0.01	0.12
Manufacturing	0.2	0.4	0.16	0.36	0.2	0.4
Electricity, gas & water	0	0.04	0	0.05	0	0.04
Construction	0.1	0.3	0.06	0.24	0.11	0.31
Wholesale & retail trade	0.24	0.43	0.2	0.4	0.25	0.43
Transport & communications	0.1	0.3	0.05	0.22	0.1	0.3
Finance & business services	0.1	0.3	0.08	0.27	0.09	0.29
Community & personal services	0.25	0.43	0.23	0.42	0.26	0.44

TABLE 3.2: Fertility preferences and actual fertility behaviour, comparing YL dataset, DHS at national level and DHS at sub-continent level

	Vietnam	India	Peru	Ethiopia
Ideal sons				
Young Lives	1.32	1.35	1.78	3.07
DHS	1.4	1.56	1.2	3.19
Sub-continent	1.41	1.89	1.36	2.44
Ideal daughters				
Young Lives	1.19	1.15	1.63	2.53
DHS	1.1	1.05	1.4	2.49
Sub-continent	1.52	1.16	1.6	2.43
Actual sons				
Young Lives	1.12	1.15	1.46	1.87
Actual daughters				
Young Lives	1.23	1.21	1.45	1.75
Actual children				
Young Lives	2.35	2.36	2.91	3.62
UNPD (Total fertility rate)	2.4	3.2	3.1	5.9
UNDP Sub-continent	2.4	3.6	2.7	6

Notes: DHS is the Demographic Health Surveys for each country. We compute the summary statistics from DHS between 1998-2010 depending on data availability. The data from United Nations Development Programme (UNDP) are taken from the same periods. The sub-continent associate to Vietnam is South-East Asia, to India is South Asia, to Peru is Latin American and to Ethiopia is East Africa.

TABLE 3.3: Ideal, actual and optimal fertility discrepancy of sons and daughters by sub-sample

| | Full sample (N=8065) | | 2+ Sub-sample | | | |
| | | | Have more children in Round 2 (N=1773) | | Not have more children in Round 2 (N=2720) | |
	Mean	SD	Mean	SD	Mean	SD
Panel A: Optimal fertility discrepancy instruments						
Ideal sons (1)	1.88	1.26	2.63	1.54	1.84	1.2
Ideal daughters (2)	1.63	1.03	2.22	1.28	1.63	1
Actual sons in Round 1 (3)	1.42	1.06	1.67	1.3	1.52	1.14
Actual daughters in Round 1 (4)	1.43	1.06	1.68	1.23	1.5	1.17
Gap Son = (1)/(3)	0.59	1.26	0.99	1.52	0.33	1.2
Gap Daughter = (2)/(4)	0.32	1.17	0.56	1.43	0.13	1.14
Panel B: AE instruments						
Same sex as 1st and 2nd born	0.53	0.5	0.56	0.5	0.51	0.5
Sons as 1st and 2nd	0.26	0.44	0.27	0.44	0.26	0.44
Daughters as 1st and 2nd	0.27	0.44	0.29	0.45	0.26	0.44
Son as 1st born	0.51	0.5	0.48	0.5	0.5	0.5
Son as 2nd born	0.49	0.5	0.49	0.5	0.5	0.5

TABLE 3.4: First-stage estimates between the sibship size and the sibling-sex composition as described in AE

	Prob of having more minor sibling(s) in Round 2		Number of minor sibling(s) born after the index child, in Round 2	
	I	II	III	IV
Son as 1st born	-0.014	-0.007	-0.001	0.029
	[0.015]	[0.022]	[0.020]	[0.030]
Son as 2nd born	-0.007		-0.03	
	[0.015]		[0.020]	
Same sex as 1st and 2nd born	0.037**		0.043**	
	[0.015]		[0.020]	
Sons in 1st and 2nd parity		0.031		0.012
		[0.022]		[0.030]
Daughters in 1st and 2nd parity		0.044**		0.073***
		[0.022]		[0.028]
Additional controls	N	N	N	N
Observations	4,018	4,018	4,018	4,018
R-squared	0.002	0.002	0.002	0.002
F-test	2.29	2.29	2.362	2.362

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. F-statistic tests show the jointly significance of the excluded instrumental variables.

TABLE 3.5: First-stage estimates in the model when instruments are optimal fertility discrepancy variables

	Prob(more minor sibling(s) in Round 2)				Number of minor sibling(s) born after the index child, in Round 2			
	I	II	III	IV	V	VI	VII	VIII
G-son	0.090***	0.085***	0.108***	0.049***	0.136***	0.135***	0.156***	0.083***
	[0.012]	[0.015]	[0.022]	[0.019]	[0.016]	[0.021]	[0.030]	[0.026]
G-Daugh	0.056***	0.061***	0.084***	0.040**	0.087***	0.095***	0.112***	0.061**
	[0.012]	[0.017]	[0.022]	[0.019]	[0.016]	[0.023]	[0.031]	[0.027]
Son 1st born		-0.012	-0.013	-0.013		0.02	0.02	0.02
		[0.022]	[0.021]	[0.020]		[0.029]	[0.028]	[0.026]
Son 1st and 2nd born		-0.003	-0.014	-0.002		-0.035	-0.041	-0.033
		[0.028]	[0.028]	[0.026]		[0.038]	[0.038]	[0.035]
Daughter 1st and 2nd born		0.006	-0.01	0.039		0.001	-0.016	0.045
		[0.027]	[0.029]	[0.026]		[0.034]	[0.037]	[0.034]
Ideal daughters	0.048***	0.047***	0.034***	0.007	0.064***	0.062***	0.052***	0.021
	[0.010]	[0.011]	[0.013]	[0.011]	[0.014]	[0.015]	[0.018]	[0.015]
Ideal sons	0.054***	0.056***	0.045***	0.020*	0.064***	0.065***	0.055***	0.028*
	[0.009]	[0.011]	[0.013]	[0.011]	[0.012]	[0.014]	[0.018]	[0.015]
Birth order indicators	N	N	Y	Y	N	N	Y	Y
Additional controls	N	N	N	Y	N	N	N	Y
Observations	3,789	3,789	3,779	3,749	3,789	3,789	3,789	3,749
R-squared	0.12	0.12	0.258	0.262	0.126	0.126	0.131	0.259
F-test	91.06	52.74	38.4	33.9	82.47	47.15	32.9	27.09

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. F-statistic tests show the jointly significance of the excluded instrumental variables. G-son is a ratio of ideal number of sons and actual number of sons. G-Daugh is the equivalent ratio for number of daughters.

TABLE 3.6: First-stage specification which the country-interaction terms are included

	Prob of having more child(ren) in Round 2			Number of younger child(ren) after the index child, in Round 2		
	I	**II**	**III**	**IV**	**V**	**VI**
G-Son*Peru	0.089***	0.074**	0.045	0.123***	0.101**	0.061
	[0.033]	[0.036]	[0.033]	[0.047]	[0.051]	[0.046]
G-Daugh*Peru	0.041	0.021	0.024	0.059	0.029	0.039
	[0.034]	[0.037]	[0.034]	[0.047]	[0.053]	[0.047]
G-Son*Ethiopia	-0.027	-0.026	-0.025	-0.003	-0.003	0.001
	[0.038]	[0.038]	[0.035]	[0.054]	[0.054]	[0.049]
G-Daugh*Ethiopia	0.024	0.029	0.008	0.046	0.0526	0.016
	[0.039]	[0.039]	[0.036]	[0.055]	[0.055]	[0.05]
G-Son*Vietnam	0.093*	0.092*	0.099**	0.075	0.0781	0.086
	[0.051]	[0.051]	[0.046]	[0.068]	[0.068]	[0.061]
G-Daugh*Vietnam	0.081	0.078	0.055	0.088	0.09	0.049
	[0.055]	[0.056]	[0.055]	[0.072]	[0.073]	[0.071]
G-Son* India	0.051	0.048	0.084	0.12	0.123	0.171**
	[0.057]	[0.058]	[0.055]	[0.081]	[0.082]	[0.078]
G-Daugh*India	-0.046	-0.04	-0.035	-0.052	-0.037	-0.038
	[0.082]	[0.081]	[0.084]	[0.10]	[0.10]	[0.102]
Additional controls	N	N	Y	N	N	Y
Birth orders	N	Y	Y	N	Y	Y
Country fixed effect	Y	Y	Y	Y	Y	Y
Observations	3,789	3,789	3,789	3,789	3,789	3,789
R-squared	0.179	0.182	0.272	0.17	0.173	0.268
F-test	36.83	32.16	27.98	28.31	24.85	21.61

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. F-statistic tests whether the instruments are jointly significant. G-son is a ratio of ideal number of sons and actual number of sons. G-Daugh is the equivalent ratio for number of daughters.

TABLE 3.7: Child cognitive outcomes, Round 2 and 3

	OLS		2SLS			Obs
	Coeff	SE	Coeff	SE	P-value	
Dependent variable for Round 2:						
PPVT	-0.074***	[0.021]	-0.229*	[0.129]	0.015	3,790
CDA	-0.087***	[0.027]	-0.085	[0.163]	0.099	3,954
Dependent variable for Round 3:						
PPVT	-0.121***	[0.024]	-0.620***	[0.139]	0.02	3,819
Maths	-0.097***	[0.025]	-0.383***	[0.141]	0.49	3,848
EGRA Total	-0.046*	[0.025]	-0.031	[0.133]	0	3,749
EGRA: Word	-0.053**	[0.022]	-0.128	[0.148]	0.001	3,901
EGRA: Reading	-0.006	[0.018]	-0.055	[0.068]	0.68	3,761

Notes: All standard errors are robust and clustered at country level with *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Column 5 reports the p-value from the Sargan over-identification test statistic for the 2SLS model. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.8: Child health outcomes, Round 2 and 3

	OLS		2SLS		Obs
	Coeff	SE	Coeff	SE	
Dependent variable for Round 2:					
Not stunted	0.055**	[0.028]	-0.071	[0.141]	4,002
Underweight	-0.004	[0.029]	-0.221	[0.143]	4,004
BMI	0.067***	[0.025]	0.055	[0.134]	4,002
Health compared to others	-0.022	[0.028]	0.126	[0.148]	4,016
No.health issues	-0.016	[0.015]	-0.186	[0.138]	4,019
Dependent variable for Round 3:					
Not stunted	0.062**	[0.029]	-0.19	[0.147]	3,955
Underweight	0.018	[0.031]	-0.209	[0.148]	4,004
BMI	0.017	[0.025]	0.106	[0.127]	3,951
Health compared to others	-0.044	[0.036]	0.128	[0.220]	4,019
LT health: vision	0.015	[0.025]	-0.055	[0.112]	3,157
LT health: hearing	0.027	[0.031]	0.062	[0.093]	3,158
LT health: respiratory	-0.018	[0.031]	-0.09	[0.135]	3,157

Notes: All standard errors are robust and clustered at country level *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.9: Child socio-emotional outcomes, Round 2 and 3

	OLS		**2SLS**		Obs
	Coeff	SE	Coeff	SE	
Trust	0.057**	[0.026]	0.103	[0.134]	3,941
Self-efficacy	-0.011	[0.027]	-0.122	[0.138]	3,936
Self-esteem	-0.060**	[0.028]	-0.091	[0.140]	3,943
Ladder of life	-0.038	[0.028]	-0.064	[0.138]	3,913

Notes: All standard errors are robust and clustered at country level *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.10: Parental labour supply, Round 2 and 3

	OLS		**2SLS**		Obs
	Coeff	SE	Coeff	SE	
Dependent variable for Round 2:					
Mother's hrs work/day	-0.093***	[0.029]	-0.129	[0.155]	2,889
Father's hrs work/day	0.048*	[0.027]	0.211	[0.132]	3,710
Mother's days/ week	-0.080***	[0.031]	-0.208	[0.161]	2,889
Father's days/week	0.021	[0.026]	0.281**	[0.137]	3,710
Mother's months/year	-0.085***	[0.031]	-0.149	[0.164]	2,890
Father's months/year	-0.012	[0.029]	0.483***	[0.141]	3,711
Dependent variable for Round 3:					
Mother's hrs work/day	-0.090***	[0.030]	-0.178	[0.157]	2,860
Father's hrs work/day	-0.029	[0.031]	-0.062	[0.138]	2,748
Mother's days/ week	-0.090***	[0.029]	-0.306**	[0.155]	2,861
Father's days/week	0.013	[0.031]	0.039	[0.156]	2,750
Mother's months/year	-0.060**	[0.030]	-0.151	[0.163]	2,858
Father's months/year	0.002	[0.031]	0.339**	[0.153]	2,750

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.11: Household expenditure on the YL child, Round 3

	OLS		2SLS		Obs
	Coeff	SE	Coeff	SE	
School books	-0.124***	[0.029]	-0.251*	[0.129]	0.021
Transport costs to school	0.04	[0.037]	0.024	[0.126]	2,997
School fee	-0.081***	[0.028]	-0.645***	[0.136]	3,984
Extra schooling	0.008	[0.030]	-0.339***	[0.126]	3,041
Medical consultation	-0.135***	[0.027]	-0.293**	[0.134]	3,336
Medicine and treatment	-0.107***	[0.030]	-0.231*	[0.137]	3,566

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.12: Child own time-use, Round 2 and 3

	OLS		2SLS		Obs
	Coeff	SE	Coeff	SE	
Dependent variable for Round 2:					
Leisuring	-0.121***	[0.028]	-0.041	[0.144]	3,482
Sleeping	-0.055*	[0.029]	0.099	[0.148]	3,482
Caring for others	0.438***	[0.040]	0.367***	[0.112]	3,472
Domestic tasks	0.071**	[0.031]	-0.093	[0.154]	3,482
Family business	0.071**	[0.033]	-0.050*	[0.028]	3,482
Schooling	-0.002	[0.025]	-0.17	[0.117]	3,482
Studying	-0.043*	[0.025]	-0.212*	[0.124]	3,482
Dependent variable for Round 3:					
Leisuring	-0.115***	[0.029]	0.207	[0.143]	3,956
Sleeping	-0.017	[0.028]	-0.363**	[0.145]	3957
Caring for others	0.413***	[0.034]	0.532***	[0.122]	3,942
Domestic tasks	0.063**	[0.028]	0.107	[0.147]	3,996
Family business	0.064*	[0.033]	-0.161	[0.107]	3,955
Schooling	-0.069**	[0.028]	-0.330**	[0.137]	3,957
Studying	-0.087***	[0.024]	-0.18	[0.126]	3,954

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised.

TABLE 3.13: Non-linear effect of sibship size and birth order

	PPVT(R2)	CDA(R2)	PPVT (R3)	Maths(R3)
$S \geq 1$	-0.107***	-0.122***	-0.146***	-0.119***
	[0.029]	[0.035]	[0.032]	[0.033]
$S \geq 2$	-0.042	-0.038	-0.088	-0.097*
	[0.045]	[0.068]	[0.054]	[0.056]
$S \geq 3$	0.131	0.037	-0.12	0.106
	[0.136]	[0.214]	[0.190]	[0.160]
Birth order 1st	0.09	0.268*	-0.137	-0.015
	[0.107]	[0.148]	[0.101]	[0.124]
Birth order 2nd	-0.049	0.191	-0.187*	-0.096
	[0.108]	[0.149]	[0.103]	[0.125]
Birth order 3rd	-0.14	0.153	-0.258**	-0.231*
	[0.109]	[0.151]	[0.106]	[0.126]
Birth order 4th	-0.015	0.131	-0.277**	-0.236*
	[0.117]	[0.155]	[0.113]	[0.132]
Birth order 5th	0.004	0.184	-0.233**	-0.178
	[0.117]	[0.163]	[0.116]	[0.135]
Birth order 6th	-0.135	0.144	-0.532***	-0.297**
	[0.120]	[0.165]	[0.118]	[0.142]
Observations	3,806	3,971	3,834	3,865
R-squared	0.302	0.186	0.309	0.302

Notes: Robust standard errors with *¡10 %; **¡5 % ; ***¡1%. All regressions are controlled for the full set of covariates of background characteristics at age 1. Each cell is for each regression specification where the outcomes of interest are standardised. $s \geq 1$, $s \geq 2$ and $s \geq 3$ are indicators for having additional sibling of 1 or more, 2 or more and 3 or more by wave 2, respectively.

3.8 Appendix

3.8.1 Proof of IV exclusion restriction

To estimate the effect of sibship size on child's outcomes, we begin with Equation 3.11 where families' heterogeneous preferences for ideal sibling sex-composition, in term of the ideal number of sons and daughters, are explicitly controlled for.

$$Y_{i,t+n} = \alpha_f F_{i,t} + X'_{i,t}\pi + \theta_{dg}IDG_{i,t-n} + \theta_{db}IDB_{i,t-n} + \mu_{i,t} \tag{3.11}$$

Under the OLS model, α_f will be an inconsistent estimate because $corr(F_{i,t}, \mu_{i,t})$ is not zero(Rosenzweig and Wolpin [1980b]; Schultz [2007]). One way to solve this problem is to find instrumental variables for $F_{i,t}$. Our choices of instrumental variables are the heterogeneous distance away from achieving the ideal sibling-sex composition, separately for sons and daughters. Our optimal fertility discrepancy variables are defined as $ZB_{i,t-n} = \frac{IDB_{i,t-n}}{ACB_{i,t-n}}$ and $ZG_{i,t-n} = \frac{IDG_{i,t-n}}{ACG_{i,t-n}}$. Therefore, our first-stage regression is described in Equation 3.12 as follows:

$$\begin{aligned} F_{i,t} = &\theta_{gg}ZG_{i,t-n} + \theta_{gb}ZB_{i,t-n} \\ &+ \theta_{dg}IDG_{i,t-n} + \theta_{db}IDB_{i,t-n} + X'_t\eta + \omega_{i,t} \end{aligned} \tag{3.12}$$

Under a conditional expectation where ideal sibling sex-composition variations are explicitly controlled for, we formally show that our instruments satisfy the exclusion restriction in the following statements:

Exclusion restriction requires that the conditional covariance between $ZB_{i,t-n}$ and $\mu_{i,t}$ is zero (same for $ZG_{i,t-n}$ and $\mu_{i,t}$). That is $E(ZB_{i,t-n}, \mu_{i,t} \mid IDB_{i,t-n})$ must be zero. Our derivation relies on the fact that the fertility probability of having a son or a daughter is naturally random. That is the covariance between $ACB_{i,t-n}$ and $\mu_{i,t}$ is zero. Therefore, the exclusion restriction is derived as

$$E(ZB_{i,t-n}, \mu_{i,t} \mid IDB_{i,t-n}) = E(\frac{IDB_{i,t-n}}{ACB_{i,t-n}}, \mu_{i,t} \mid IDB_{i,t-n}) \tag{3.13}$$

Under a conditional expectation using $IDB_{i,t-n}$, it implies that

$$E(\frac{IDB_{i,t-n}}{ACB_{i,t-n}}, \mu_{i,t} \mid IDB_{i,t-n}) = E(ACB_{i,t-n}, \mu_{i,t} \mid IDB_{i,t-n})IDB_{i,t-n}$$

And because of the randomness of fertility probability of having a child from a given gender, we get that

$$
\begin{aligned}
E(ZB_{i,t-n}, \mu_{i,t} \mid IDB_{i,t-n}) &= E(ACB_{i,t-n}, \mu_{i,t} \mid IDB_{i,t-n})IDB_{i,t-n} \\
&= 0
\end{aligned}
\tag{3.14}
$$

3.8.2 Data Appendix

TABLE 3.14: Variable Description

Variable	Rd 2	Rd 3	Scoring/Description
Achievement outcomes			
Peabody Picture Vocabulary Test (Cognitive)	X	X	A test for receptive vocabulary. PPVT-III (204 items) for VN, ET and IN in both Wave 2 and Wave 3. PPVT-R (Spanish, 125 items) is used for PE. The test is individually administered, orally administered, untimed and norm-referenced. Corrected raw scores are used.
Cognitive Development Assessment (Maths)	X		The test was developed by the International Evaluation Associate for pre-school age (4 year old) children. Several subtests are: spatial relations (notions of on, under, behind, etc), quantity (notions of a few, many, equal, etc.), time (notions of days of the weeks, night, before, etc.). For Maths, only the quantity subtest was administered. Each correct answer was score 1 and 0 to wrong or non-response. The maximum score is 15 on the CDA quantity subscale. The test was translated in own languages. Corrected raw scores are used.
Early Grade Reading Assessment (Reading): global raw score		X	The test developed under USAID. It is "an oral assessment designed to measure the most basic foundation skills for literacy acquisition in the early grades. The test was administered in several sub-tests: letters and alphabet recognition, reading simple words, understanding sentences and paragraphs and listening comprehension. The tests are conducted in local languages.
EGRA: word recognition (words per minute)		X	YL was presented that 60 words and asked to read them in order within 60 seconds.
EGRA: reading fluency (words per minute)		X	YL was presented with a small text and asked to read it. Number of words read in 60 seconds is the score.
EGRA: reading comprehension		X	YL read a small text in silent and answer orally 8 questions
EGRA: listening comprehension		X	YL was read a short text and is then asked 6 questions orally.
Maths Test: raw score		X	The test has 2 sections: (1) 9 items to measure basic quantitative and number notions and (2) 20 items using numbers for addition, subtraction, multiplication and divisions to measure ability to perform basic maths operations with numbers. All tests discontinued after 8 minutes.

Variable	Rd 2	Rd 3	Scoring/Description
Health outcomes			
YL total num of health issues	X		Mother reported total number of health issues since Wave 1.
Height-for-age z-score	X	X	Stunted when the z-score is below 2 standard deviation
Weight-for-age z-score	X	X	Underweight when the z-score is below 2 standard deviation
BMI-for-age z-score	X	X	body mass index
YL's health compare to others.	X	X	(0)worse (1) same (2)better
YL's stunted status	X	X	(1) height-for-age lower than 2 sd. (0) otherwise
YL's underweight status	X	X	(1) weight for age lower than 2 sd. (0) otherwise
Attitude outcomes			
YL's Trust index		X	Average score (1-5): trust the neighbours, safety perception with go outside; believe the government does the right things for children like YL
YL's Locus of control (Efficacy) index		X	Average score (1-5): can try to improve own situation, make own decisions on time spending, make own plan for future studies and work, believe in studying hard will reward, own choice about the work doing
YL's Pride index		X	Average score (1-5): proud of shoes, proud of clothes, feel own clothing is right for all occasions, never embarrassed if not have the right books or stationary, proud of work, proud if have correct uniform.
YL's Life Ladder		X	Nine steps of ladder where the ninth step, at the very top, represent the best possible life for you and the bottom represents the worst possible life for you. The YL indicates where on the ladder she feels personally she stands at the present time.

Variable	Rd 2	Rd 3	Scoring/Description
Expenditure			
Spending on YL's school books		X	Log of hh expenditure allocated to YL
Spending on YL's transport cost to school		X	Log of hh expenditure allocated to YL
Spending on YL's medical consultation		X	Log of hh expenditure allocated to YL
Spending on YL's medicine and treatment		X	Log of hh expenditure allocated to YL
Spending on YL's school fee		X	Log of hh expenditure allocated to YL
Spending on YL's expense on extra schooling		X	Log of hh expenditure allocated to YL
Spending on school fee & extra tuition		X	Log of reported expenditure of school fee and extra tuition
Parental time spending & employment			
No. activities parents do with YL	X		No. activities parents indicate to participate with YL.
Fraction of activities parents do with YL	X		Percentage of activities parents do with YL to total number of activities with anyone (and self) indicated.
Mother's hrs work per day	X	X	Hours (0-24) YL's mother reported to work per day
Father's hrs work per day	X	X	Hours (0-24) YL's father reported to work per day
Mother's days work per week	X	X	Days (0-7) YL's mother reported to work per week
Father's days work per week	X	X	Days (0-7) YL's father reported to work per week
Mother's months work per year	X	X	Months (0-12) YL's mother reported to work per year
Father's months work per year	X	X	Months (0-12) YL's father reported to work per year

Variable	Rd 2	Rd 3	Scoring/Description
Child's time allocation			
Hrs sleeping on a typical day	X	X	Hours (0-24)
Hrs caring for others on a typical day	X	X	Hours (0-24)
Hrs on domestic tasks on a typical day	X	X	Hours (0-24)
Hrs on family farm or business on a typical day	X	X	Hours (0-24)
Hrs at school on a typical day	X	X	Hours (0-24)
Hrs spent studying outside school on a typical day	X	X	Hours (0-24)
Hrs on general leisure on a typical day	X	X	Hours (0-24)

Chapter 4

Mortality Risk and Human Capital Investment: the Legacy of Landmines in Cambodia

Abstract

Life expectancy plays a key role in determining households' optimal investment in children's human capital accumulation. This paper examines this relationship by looking at a unique case of Cambodia and its prevalence of landmines. Extensive usage of landmines during its long civil conflict in the 1970s was followed by large international effort of landmine clearance operation. A two-fold increase in landmine clearance effort during the periods 2004-2005 in affected areas, has led to a subsequent sharp fall in landmine casualty rates. Together with the male-biased characteristic of landmine accidents, all three variations allow me to estimate the human capital impact of working-age mortality risk using a difference-in-difference-in-difference model. To deal with the unobservable, landmine casualty rates are also instrumented by the stock of dangerous land in neighbouring areas. I find a strong negative effect of landmine mortality on both schooling and health investment outcomes. When the mortality risk from such a fearful event as landmine accidents is replaced by a more common incident of traffic accidents, any mortality effect on schooling outcomes is no longer detected. This is evidence that the optimal schooling decision is determined by subjective life expectation.

4.1   Introduction

Earlier theoretical literature predicts that an increase in life expectancy raises the optimal level of human capital accumulation (**?**; Ben-Porath, 1967). Lower mortality is thought to raise the expected return to the investment by increasing the expected total lifetime productive gains from labour market and also the horizon over which the benefits from investments earlier in human capital can be enjoyed (e.g. Galor and Weil, 1999; Soares, 2005; De la Croix and Licandro, 1999; Cervellati and Sunde, 2005; Hazan, 2012). To test this theory, many empirical studies provide analysis investigating the relationship between mortality and education outcomes.

Using cross-country data in a context of comparative development, mortality is found not to be associated with higher education attainment in some studies (Acemoglu and Johnson, 2007; Lorentzen et al., 2008) whilst others (Bils and Klenow, 2000 and Manuelli and Seshadri, 2007) find a significant positive relationship. Beyond inclusive findings, statistical estimations using cross-sectional - data have proven difficult to pin down the causal relationship between life expectancy and human capital development.

Recent literature focuses on the circumstance of a specific health condition, which can pose an effect on mortality outside infancy, to investigate its role on household investments in their children. In a developing country context, many recent studies exploit regional variation in health conditions and identity causal effects of life expectancy on individual human capital development (e.g. Fortson, 2011 on HIV in African; Jayachandran and Lleras-Muney, 2009 on maternal mortality in Sri Lanka). Oster et al. [2013] and Stoler and Meltzer [2013] also find positive effect of individual-level impact of personal health-related mortality risks on individuals' own human capital investment decisions. They were able to find that not only does mortality risk negatively affect human capital investment, but, more importantly, that it is the timing of the realisation of the risk that led to a reduction in human capital investment.

In this study, I step aside from a conventional focus on the types of mortality risk that come from deadly diseases, illnesses or breakthroughs in healthcare innovation. Instead, this paper examines the role of a non-medical source of mortality risk on human capital investment. More precisely, I will focus on the human capital implications of mortality risk occurring from usage of warfare weaponry and other materials that are capable of terminating lives. Mortality risk derived from warfare weaponry is distinct from that of general deadly diseases in two ways. First, it is a source of mortality risk that is very much capable of directly and instantaneously changing an individual's lifespan. Second, in comparing to catching common diseases, the risk of dying from warfare weaponry carries heavily an element of fright and fear.

A number of studies (e.g. Kahneman and Tversky, 1979; Slovic et al., 1982) argue that an availability heuristic may exaggerate the level of risk beyond its statistical level in the cases where substantial publicity of the event or emotions are at play. Therefore, it is possible that individuals' investment decisions may not homogeneously response to mortality risk from low probability events vis-á-vis high probability ones. A key contribution of this research is to provide empirical evidence of the causal effect of non-health mortality risk on human capital accumulation. Another contribution is that this paper will pay attention a role in which fear and fright perception may have on individuals' evaluation of their subjective life expectancy. I will show that under an influence of heuristic probability, individuals may not necessarily allocate equal weighting to equivalent mortality risks of the same statistical magnitude. As a result, individuals may adjust their economic behaviours differently when facing with different sources of mortality risk.

To tackle these questions, this paper takes on the case of landmines in Cambodia and examines how the variation of mortality risk as a result of this lethal ordinance affects human capital investment behaviours. More precisely, it will compare the schooling outcomes among adjacent birth cohorts who would otherwise be analogous, but otherwise are faced with different magnitude of landmine-induced mortality risk. Cambodia fits the research agenda for a number of reasons. First of all, prime-age adults remain the main sufferers of mine casualties in Cambodia, accounting for 80 percent of total casualties (CMVIS, 2012). Precisely, this is the type of mortality risk that does not affect the whole lifespan of an individual but more specifically at the ages where individuals are active in the labour market. This allows the analysis to concentrate on working ages survival probability, which is argued to be more relevant than the risk early on in the life-cycle to determining schooling decisions (Cervellati and Sunde, 2013; De la Croix and Licandro, 2013; Strulik and Vollmer, 2013).

The identification strategy in this paper exploits three key variations of landmine-related mortality risk: spatial, temporal and gender variation. First, landmine prevalence are spatially differently across Cambodia where the western part is more heavily affected due to retreat strategies of Khmer Rouge at the end of the civil conflict in the 1980s. The temporal variation of mortality risk is benefited from the international collaboration of landmine clearance operations, as a major post-conflict recovery action. The two-fold expansion of landmine clearance operations during the periods of 2004-2005 has led to a sharp decline in landmine casualties. This implies that suddenly adjacent birth cohorts of equivalent backgrounds are faced with very different levels of prime-age mortality risk. That is, to them and their parents, the younger cohorts then gain a higher expected lifetime working hours and a longer horizon to enjoy these benefits. As

a result, for the affected households, this discontinuous change will directly affect their optimal investment decision in terms of the schooling for their children.

The third variation is derived from the male-bias nature of landmine casualties in Cambodia whereby adult males account for around 90 percent of total landmine casualties in the past 20 years (CMVIS; Roberts, 2011). Therefore, the changes in the variation of landmine mortality, particularly in the decline in year 2005, contribute directly to life expectancy of the males whilst leave that of the females unchanged. This, in effect, allows the empirical strategy to use the females as a main comparison group in analysing the mortality effect on human capital development.

Using data from the 1998 and 2008 Cambodia census (IPUMS), my initial empirical exercise uses a difference-in-difference-in-difference (DDD) specification. The data on landmine casualties by district and province level between 1979- 2010 is obtained from Cambodia Mine Action Authority database. The outcome of interest is an individual's school attainment. Using the full specification, I find that a unit increase in the landmine casualty rate (per 1000 local prime-age population) relates to a 4.5 percentage point (pp.) decrease in the probability of having attained a primary school level. For secondary school level, the effect is higher at 6.1 pp.

To account for any potential omitted variable bias, landmine casualty rate at district level is instrumented by the average stock of dangerous land (from landmine prevalence) in surrounding provinces. This is because landmine clearance operation is found to be directly related to landmine casualties in the area. Under the instrument variable specification, the effect of landmine mortality becomes 5.5 pp. under the full specification for primary school level and 13.6 pp. for secondary school level.

Next, I investigate a potential role of heuristic probability in influencing human capital investment decision. I compare the effect on schooling outcomes in Cambodia between the event with low probability, available heuristic characteristic (landmine accidents) and that with high probability (road traffic accidents). Most of all, both of these mortality sources are non-health, prime-age and male-biased. To do so, the same DDD analysis is repeated, with the road accident as the source of mortality variation. In addition, we instrument for road accidents by using averaged neighbouring province road network. Whilst the findings at the province-level shows a negative and significant effect of mortality risk on human capital investment behaviour when landmine casualty rate is the mortality variation, I do not find the same results in the specification with road traffic accidents. With reference to the literature and the arguments we illustrated above, we therefore believe that a possible key mechanism driving our findings on the effect of landmine mortality on schooling decision is the subjectively quantified variation in life expectancy, and not the objective one.

This paper is related to growing literature which tries to understand the legacy of civil conflict on economic development (see Justino, 2009 and Blattman and Miguel, 2010 for the review). I show that an active recovery plan, the landmine clearance operation in this case, can help set a nation both directly (via the improvement of physical capital) and indirectly (via reduction in mortality risk) to a more enhancing growth path. Moreover, this study also contributes to the understanding of the legacy of armed conflicts on human capital development. A number of micro-studies have shown a key mechanism in which the prevalence of weaponry usage reduces investments in human capital is through the contemporary level of local violence (Akresh and de Walque, 2008); Shemyakina, 2011; Leon, 2012; Gerardino, 2013; Millán, 2014), with mortality risk as a possible pathway (Gerardino, 2013). In this study, the periods of interest are post-conflict and are the time when Cambodia has been relative peaceful. In this case, this study will be more able in identifying solely the role of mortality risk on human capital development.

The paper is organised as follows: the next section discusses the context surrounding landmines in Cambodia. Section 4.2 describes historical background of landmines in Cambodia and gives an overview of educational institutions in the country. Section 4.3 explores a simple conceptual framework and theoretical hypothesis. Section 4.4 and 4.5 describe the data. Section 4.6 discusses the empirical strategy and estimation findings. Section 4.7 presents robustness checks and explores on possible mechanisms. Section 4.8 concludes.

4.2   Background of Landmines in Cambodia

4.2.1   Historical Background of Landmines in Cambodia

Landmines had been laid in Cambodia since the 1950s during the years of civil conflicts. However, it became more heavily used as a weapon of choice towards the end of the Khmer Rouge era by 1979. The areas in the Northern and North-western parts of the country, especially along borders with Thailand, are where the predominant amount of landmines were laid and later recovered. It is estimated that nearly 44 percent of Cambodia's land is affected by landmines (CMAA, 2001). This is 4,460 km^2 or equivalently 3,037 suspected mined areas. Approximately 10 percent of the mined land directly affect the livelihood of communities (equivalent to 446 km^2).

The practice of landmine laying is indeed non-random as it is one of the main strategies during the Khmer Rouge civil war. During its retreat away from the Vietnamese invasion, Khmer Rouge army laid landmines to prevent the invaders' advance from the Eastern and South-eastern regions. Given the nature of the war, most of the mine laying

activities occurred outside the capital city, Phnom Penh. Despite being strategically laid to block out the enemies, it is worth noting that landmines are not found either strictly in remote parts of the country, or the most infertile parts. A number of towns, for example Battambang and Rattana Mondul situated in the western part of the country, were rather much prosperous areas prior to 1979 (Davies and Dunlop, 1994). Moreover, given that Khmer Rouge profoundly imposed a restructuring of a fundamentally agrarian utopian state across the country, differential economic conditions were thus neutralised across the country during their brutal reign (Etcheson, 1984; Kiernan, 2001; Weitz, 2009).

This suggests that contemporary economic conditions were not determinant factors of landmine laying decision. In additional, it is safe to say that we expect no link between spatial correlation between mine prevalence and educational inputs. Khmer Rouge's ruling had led to a complete eradication of the educated class along with the educational infrastructure during its era (MoEYS, ious; Kiernan, 2001)

The magnitude of landmine usages began to decline along with the on-going internal violence as a result of the Paris peace treaty, signed in 1991. However, it is not until the sign of Mine Ban Treaty in 1997 that the fresh laying of landmines came to a virtual end. Since the departure of the UN care-taker (UNTAC) in 1993, Cambodian societies have been relatively free from violent conflicts. Most of all, the relatively peaceful society in Cambodia after the ceasefire allows the analysis to rule out the entailing effect of violence associated with weapon usage in other contexts (Camacho, 2008; Leon, 2012, Mansour and Rees, 2012; Gerardino, 2013) [1].

4.2.2   Landmine Clearance Operations and Landmine Casualties

Landmine clearance operations: Humanitarian landmine clearance efforts began in 1992, during the period of UNTAC peacekeeping presence in spite of existing on-going minor fighting in the region. Up to now, there are 3 main agencies: CMAC, Halo Trust, MAG operating in Cambodia [2]. By 2004, the total areas of 162 km^2 have been cleared, at an approximate rate of 15 km^2 per year. In the years 2004/2005, a number of fundamental changes of techniques and methods of landmine clearance were introduced. These included the utilisation of non-technical and technical survey in order to facilitate the landmine-marking process, in prior to a full clearance (CMAA).

As a consequence, by the end of the year 2005, mine clearance agencies achieved highest productivity at 32 km^2 per year- equivalent to over 100 percent increase in productivity

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[1] One of the advantages of this setting is that without on-going fightings during the period of interest, we are able separately identify landmine casualties as a sole variation of mortality risk.

[2] Over 90 percent of the funding is internationally financed (Authority, ious).

(Authority, 2005). Subsequently, this results in the rise of 100% in the number of landmines recovered nationally, of which the rate remains stable thereafter up to 2010. Figure 4.1 shows the magnitude of landmine clearance productivity at the national level over the years. There is a noticeably sharp decline of the level of clearance around the year 2005 [3].

Landmine casualties: CMVIS collects and maintains the full list of landmine-related casualties in Cambodia from 1979 until present. The information of an incident contains its precise location, profile of the victim, the activity performed at the time as well as the victim's intention. Prior to the ceasefire in the early 1990s, the majority of casualties were found to be of military exercise. In contrast, the data from the recent decade indicates that landmine accidents are more likely to occur either during travelling or working in the field (CMVIS). More importantly, the statistics shows that landmine casualties over time are found to be male-biased. Working-age men are among the heavily affected, with on average 80-90% of the total casualties across regions (CMAA; CMVIS).

The level of landmine casualties in Cambodia (defined as deaths and injuries) has been on a steady decline over time. Prior to 1999, the decrease of landmine casualties was a by-product of the peace treaty and a subsequent ending of the armed conflict. During 1999-2004, the casualty level became more constant, at an average of 800 casualties per year. During the same time in 2004-2005 when a sharp increase in landmine clearance productivity is observed, the level of landmine casualties nationally experienced a sharp, simultaneous decline (see Figure **??**).

Figure 4.3 presents the spatial distribution (at district level) of landmine clearance productivity and landmine casualty rate for the periods before and after 2005. Together with the evidence from Figure 4.1 and Figure **??**, this indicates a negative correlation whereby the increase in clearance productivity is corresponded to a decrease in landmine casualties [4].

Furthermore, all districts in Cambodia are ranked in percentile by the averaged intensity of its landmine casualty prevalence during 2001-2004 (prior to the change in 2005). Figure 4.4 show time-series plots of landmine casualty rates between the districts below

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[3]I run tests for structural breaks with the data on clearance productivity at province level, and find evidence supporting the break around the years 2004 to 2006 (Chow, 1960; Jayachandran and Lleras-Muney, 2009).

[4]Alternatively, a variable for stocks of *dangerous* land at district level is constructed from the data. Then, a fixed effect model regresses the stocks *dangerous* land on landmine casualties at district level.)

the 45th percentile and those above 65th percentile [5] . The figure shows that amongst the districts with already low intensity of landmine casualty rates in the years before 2005, not much changes are observed after 2005. On the other hand, the districts with high casualty intensity show dramatic decline in the years post-2005. In Figure 4.4, the similar findings are found when the landmine clearance productivity rate is considered instead [6].

Landmine casualties and life expectancy: Over the years, an average life expectancy in Cambodia increases from 57 years in 1998 to 64 years in 2011 for females and similarly from 54 to 62 years during the same period for males. Many factors have contributed to such a change, including a decline in child mortality as well as maternal mortality (World Bank (2013)).

The landmine casualty census from CMVIS indicates that between the years 2005-2011, males in their prime ages account for the largest share of the casualties. By comparing the effect of the change of landmine clearance productivity in 2005 and a nation-wide decrease in landmine casualties around the same time, almost a twofold decrease of landmine casualties for Cambodian adult males is observed. In contrast, there is not much changes for the Cambodian adult females. At the same time, the younger age groups do not at all experience that same decline in the casualty level (Table 4.2).

To evaluate how sizeable the impact of landmine casualties has on the overall life expectancy, Table 4.1 compares landmine casualties from 2005-2011 to the total mortality at province level. Precisely, the denominator is the total mortality level is calculated as the average across all provinces, constant at 2008 [7]. For adult males, the size of province-level landmine casualties in 2005 is equal to 17.4 percent of the total province-average male mortality. On the other hand, landmine casualties counts for only 1.23% for females. Among working-age males, the relative size of landmine casualties declines by 80 percent between the years 2005 and 2008, in contrast to less than 20 percent for females.

These numbers can be interpreted as the marginal effect of landmine casualties on total life expectancy in a year-on-year basis on a hypothetical event where the entire level of

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[5]I choose the $45^{th}/65^{th}$ cut-off criteria to separate between the low and high intensity groups while omitting the middle group (instead of at the median) in order to make the distinction more obvious. All in all, similar patterns are also found when I vary the cut-off points

[6]Districts are grouped by low clearance intensity (below the 45th percentile) and high intensity (above the 65th percentile).

[7]Ideally, landmine casualties would be compared to total mortality in the province at the same corresponding year. Unfortunately, Cambodia do not keep record of vital statistics. Therefore, the landmine casualty data is compared with the total mortality level from the year 2008.

landmine casualties is eradicated in a certain year. The findings show that landmine-mortality risk faced by males have seen an approximate twofold decrease nationally whereas it remains considerably stable and unchanged for the female counterpart. This also contributes to the reduction in males' mortality risk overall. As an implication, the empirical identification will also rely on this gender-bias characteristic of landmine casualties. Given that they come from the same locality, a male individual would get to experience a decline in mortality risk whilst his female equivalent would not.

4.2.3 Educational Institutions: Costs and Benefits of Schooling in Cambodia

Costs of education: After the Khmer Rouge regime ended in 1979, Cambodia's educational institutions were restarted from zero, and have since been gradually developed. The educational system had a major reform in 1996 and the education years were set to a 12-year formula of 6+3+3. Since 2000, a National Education Strategic Plan of Education-for-All has been in place to implement a universal education policy. It introduced a *free* education of 6 years of basic education for all children of certain age cohorts in the country. The main aim was to reduce cost burdens to schooling by primarily abolishing the start of school year fees in primary schools.

In spite of the efforts, children education in Cambodia remains somewhat costly for the majority of households in the country [8]. Data from Cambodia Household Socio-Economic Survey indicates that costs of education get more expensive the higher the level of qualification. In 2004, with relation to the median level of household disposable income, costs of schooling at primary school level accounts for 13 percent for a rural household. It rises to 132 percent at upper secondary school when schooling is no longer free and it reaches almost 700 percent an undergraduate degree (Cambodia National Institute of Statistics).

Forgone earning from the child's labour market activity plays another key contribution to the total costs of schooling. And indeed, child labour remains a key issue in Cambodia. The Cambodia Child Labour Survey (CCLS) in 2001 indicates that approximately 50% of children aged 7-14 were economically active. This rate is slightly higher than the low income countries' average. Nonetheless, only 9 percent of these children worked exclusively. That means most Cambodian children in the 2001 survey both worked and went to school.

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[8]MoEYS [2005] and Bray and Bunly [2005] calculate that despite the exclusion of school fees, direct costs of primary school per pupil in 2004 is at 160,000 riels for urban household and 71,000 riels for rural household (USD 1 is exchanged from Cambodia Riels 4,000). Especially in urban areas, the bulk of these expenses come from costs of uniform and equipment as well as supplementary tutoring.

Statistics on schooling: Official statistics show a steady rise of the enrolment rate of primary school children, with a completion rate shows much stronger improvement. Net enrolment rate at primary school education stands at 90 percent in 2008. On the other hand, the rate for secondary school remains low at 38 percent (World Bank (2008)), with a marginally smaller for girls. It is reported that among the 15-17 years old age group, the share of economically active children far exceeds those remain in education. While enrolment ratio at primary school is similar across regions, the drop-out rates during primary school level in remote and rural area stand approximately 50 percent higher than urban areas. Similarly, in 2005, 91 percent of primary school students in urban area progress to a secondary school level whilst only 26 percent did so from remote areas.

When the provinces are ranked and grouped by the intensity of landmine casualty rate, the evolution of educational characteristics over time do not differ between each group. However, the differences are in the levels where the provinces with low landmine intensity have higher educational outcomes than the provinces from the high intensity group. Figure 4.5 shows that they share a similar pattern over time. Moreover, Figure 4.6 shows that within each group, there is no gender difference in term of the trends in the educational statistics prior to the change of landmine mortality risk in 2005.

4.3 Conceptual Framework

Parents in Cambodian households are faced with children's schooling decision. Public funded education at the primary school makes it less costly than other qualifications for a parent to invest in the child's human capital. The rising returns of outside options in the labour market also makes is less attractive to send the child, especially the older ones, to school. The Ben-Porath mechanism (Ben-Porath, 1967; ?) predicts that parents' investment decisions will response to an increase in the expected net lifetime return to schooling. Therefore, parents will invest more when children's life expectation increases, allowing a longer horizon of productive life as well as the duration in which the benefits can be enjoyed (Hazan, 2009; Cervellati and Sunde, 2013).

However, the extent to which parents can adjust their optimal investments depends heavily on the ability to transfer credit over the life-cycle. The role of financial market imperfections is expected to be important for Cambodia households. Financial constraints could mean that the same change in mortality may not have a homogeneous effect on human capital outcomes in different schooling qualifications [9].

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[9] See a simple theoretical framework with and without financial market imperfections in the Appendix 4.9.1. Given the education structure in Cambodia, the role of financial constraints are expected to be

In this framework, the decline in mortality is exogenous and the forward-looking parents response instantaneously to the change. With no uncertainty, parental investment is translated directly to the observed outcome of human capital accumulation. There is no gender-bias in parental response. In sum, the effects of mortality risk on the returns of human capital investments are homogeneous for boys and girls. However, when the risk is gender-specific mortality, only parents of a particular gender adjust their investments [10]. Therefore, a decrease in landmine mortality risk in Cambodia will affect the pay-off of schooling and consequently an increase in human capital investment for Cambodian boys, with no changes amongst the girls.

4.4 Description of the Data

4.4.1 Individual Schooling Data

Individual education outcomes are taken from Cambodia IPUMS 1998 and 2008, a 10 percent sample of the census record. The main outcome of interest is individuals' probability of attaining a particular level of school qualification.

In order to examine to causal relationship between mortality risk and education decision of the households, the age cohorts of interest in the 2008 census are selected according to two main criteria (depending also on a school qualification in question: (i) primary school or (ii)secondary school level)). To be defined as the so-called *treated* cohorts, first, the child' s age in 2005 cannot exceed the maximum age of a typical student at that educational level. In details, her age is not more than 12 or 18 years old for a primary school a secondary school in 2005, respectively. This condition implies that when her parents observe the sharp local change of landmine mortality in the year 2005, they are able to credibly react to the change by adjusting their investment response. Second, for econometricians to detect any behavioural response in the data, an individual must be old enough for her schooling status to be observable in the data in 2008. In sum, the *treated* cohorts are individuals aged 3-12 in 2005 (that is age cohorts of 6-15 years old in the 2008 census) for the primary school analysis and aged 9-17 years old in 2005 (equivalent to aged 12-20 in the 2008 census) for the secondary school.

The *control* cohorts are the cohorts with the identical ages as the *treated* cohorts, but are taken from the 1998 census. These are the individuals who are faced with the level of landmine mortality risk in the years prior to the change in landmine mortality. In the

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more severe in higher education levels. This is because primary school education in Cambodia is publicly sponsored.

[10]Because each parent only has one child, the conceptual framework presented here is abstract from an additional effect of the subsequent intra-household reallocation of resources.

empirical analysis, I sub-divide each *treated* and *control* cohorts into as sub-groups of three consecutive ages. In total, there are three sub-groups for each of the *treated* and *control* cohorts. The main empirical exercise will focus on the difference in the outcomes across these two census.

Alternatively, the analysis will focus only on the individuals from the 2008 census. Note that the *control* cohorts from the 1998 are the exact birth cohorts as those who are ten years older in the 2008 census. Therefore, the alternative *control* cohorts are equivalent to the cohorts of 16-25 year old in 2008 for the primary school and 22-30 years old in 2008 for the secondary school. Analogously, these individuals would have faced landmine mortality risk of the years prior to the discontinuity in 2005 when their schooling decisions are finalised (see Appendix 4.9.2 for an illustration.) [11].

An individual's probability of attaining a qualification is constructed as follows. At a given level, I assign a value of 1 to those whose school status is classified as *completed* and zero otherwise. This criterion is also applied to those who only obtain an incomplete level of the qualification. For those attending school at the time of a census, I assign a value of 1 for being at school at the particular qualification or higher and zero otherwise. Note that, by construction, I assume that someone with a final year of a qualification is as good as someone in their first year.

4.4.2 Landmine Casualties

The Cambodia Mine Victims Information System (CMVIS) provides the data for landmine casualties in Cambodia. The Cambodian Mine Action and Victim Assistance Authority (CMAA) collects the census of casualties nationwide from 1979. This study focuses on the dataset from the year 1997 to 2010. I calculate landmine casualty rates at the province level (24) and the district level (156). Additionally, I am able to distinguish the rates between different ages and genders. Note that landmine casualties are defined inclusively the deaths as well as the injuries from a landmine accident. For now, we decide to combine all the counts and refer to it as *landmine mortality*.

The individual-level data from IPUMS is then matched with CMVIS landmine datasets at 2 levels of current residence locality: district and province. Then, the mortality rate (LMR hereafter) is normalised by dividing total landmine mortality level by the total adult population age (defined as between 18 and 35 years old) within a locality [12].

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[11] The larger period gap (i.e. going back 20 years) had been initially considered for another alternative control group. However, the control group from 1988 census would not have fitted the common trend assumption, as these children were living through the height of the Khmer civil war conflict.

[12] The reason why adult population is used is because this is the ages with at least 80 percent share of landmine accidents in Cambodia.

To minimise measurement error of the mortality rate, I calculate a three-year running average of LMR for the years after 2005 (2007-2009) and a similar rate of 10 years before (1997-1999), for each locality (Jayachandran and Lleras-Muney, 2009) [13]. Subsequently, the post-2005 rate is assigned to the *treated* cohorts while the pre-2005 rate is matched with the *control* cohorts. All rates are thus presented in a unit of per 1,000 adult population in a given locality. Provided that there are no other changes from other mortality risks at the locality in the same manner during the period of interest, this is equivalent to assigning the children from the *treated* cohorts with an unexpected, positive shock on their life expectancy, in relation to the control ones from the same area.

4.4.3   Other Related Datasets

CMAA provides measures of district-level landmine clearance productivity year-on-year. Also, it keeps the current states of *dangerous* lands in each locality by 2013. The Yale' s Cambodia Genocide Database for GIS bombing locations during the Vietnam War and mass graves during the 1970s Civil War period in Cambodia is also consulted for more district-level characteristics.

We seek other year-on-year variables at locality levels from Commune Database (Cambodia Ministry of Planning), series of annual reports from Ministry of Education and Sports and Socio-Economic Surveys from National Institute of Statistics. Data on health-related mortality is obtained from Ministry o Public Health' s reports and the 2008 Cambodia Mortality database. In sum, we have variables on education infrastructure, health-related conditions, and related economic circumstances (for example poverty rate and rice production activities).

4.5   Descriptive Statistics

4.5.1   Summary Statistics and Balancing Test

In this section, we start by presenting summary statistics of key characteristics of individuals and households. Using Cambodia IPUMS 1998 Cambodia Commune Data from the nearby year (SEILA, 2002), we compares some characteristics between households from high intensity of landmine casualty rate (averaged of the 1997-1999 rate) and households living areas with low intensity. We further divide each intensity group into

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[13]Low frequency data of mortality rate is preferred in order to avoid noise from the data and also allow for a clearer distinction between our *control* and *treated* cohorts.

outcomes for males and females when available. The findings from spatial comparison in Table 4.3 show that low intensity areas had slightly preferred socio-economic conditions than the high intensity areas. Across areas, education attainment look higher in low intensity area. However, within the area, we observe comparable education outcomes between males and females, especially within the areas with high intensity of *pre-treatment* LMR.

The domination of Khmer Rouge regime in Cambodia and in particular its implementation of equal agrarian society ensures that there should not be any statistical correlation between the spatial choices of landmines usages with the education endowments across areas. Nevertheless, we need to ensure that the local development conditions in recent years had not influenced decisions regarding landmine clearance effort and subsequently landmine mortality risk. We perform another balancing test exercise with data at district level to find evidence that the increase of landmine clearance productivity around the year 2005 was not determined by human capital conditions in the area at the time. To do this, we group all districts in Cambodia according to its level of total landmine clearance during 2005-2007. Table 4.3 compares some observable characteristics between districts with landmine clearance below the 45th percentile and those with above the 65th percentile.

4.5.2 Accounting for Common Trend Assumption

The exercise in this section is to make certain that the crucial Common Trend assumption is maintained. That is, each confounding variable between the *treated* and *control* cohorts share similar time-variant behaviours. In the context of this paper, we focus on the time trend of each key factor that may directly affect the education outcomes (from both the demand and supply side) or indirectly influence the level of aggregate mortality risk. Precisely, we present evidence of the common trends of these factors across two interacted dimensions namely (i) landmine casualty rate intensity (high and low); and (ii) gender (male and female) [14].

Figure 4.8 presents aggregate health-related mortality rates from the 2008 census for males and females across different age levels. Across all ages, Cambodian females have marginally lower mortality rate than males. Nonetheless, the variations from both groups look to synchronize over time. The similar pattern is found when all four sub-groups are compared (at province level) suggesting the absence of potential structural change in general mortality risk during the time and provides support of a common trend of general mortality across the groups.

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[14]Eventually, four groups are constructed: high-male; high-female; low-male and low-female.

To validate the common trend assumption on education variables, we conduct a similar exercise with schooling outcomes across school age cohorts, comparing among four sub-groups. Figure shows that at each level of education, whilst female school attendance is lower than males. The levels of school attendance among four sub-groups fluctuate over time in the same manner. On the supply side, the same exercise is applied to the level of educational infrastructure, for example, the number of schools. The findings demonstrate that there is no trend difference between areas of high and low intensity of LMR [15]. In sum, No sharp change in the supply side of education is observed around the year 2005 when theses localities experienced an abrupt change in LMR (Figure 4.5).

One potential caveat is that landmine clearance operation may also change general economic well-being of a locality. Note that the level differences in the economic gains between areas of low and high LMR intensity do not invalidate our identification design when use triple differences strategy ([16]). Nonetheless, the economic trend is investigated to make sure that changes of economic circumstances among localities did not have any discontinuities, if at all around the year 2005. Using poverty rates as a proxy for economic well-being, Figure 4.7 shows that the local poverty rates between both groups changed with a similar trend over time (2002-2012). Most of al, no discontinuity of the poverty rates is observed over time.

4.6   Empirical Analysis

This section presents estimation strategies to identify a causal effect of a change in a non-health mortality risk on parents' optimal investment decisions on child's schooling.

4.6.1   Difference-in-Difference-in-Difference

To do so, a *difference-in-difference-in-difference* method (DDD hereafter) is used as the main empirical strategy. Three variations (spatial, temporal and gender) are exploited in order to identify a causal effect of mortality risk on human capital accumulation. First, the spatial variation of landmine prevalence and casualties in Cambodia is derived from the historical retreat strategies the Khmer Rouge away from the Vietnamese invasion at the end of the turbulent civil conflict in the 1980s. To block and slow down the invasion from the Cambodia-Vietnam borders, the Khmer Rouge troop exercised landmine-laying

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[15]It is plausible that with the on-going effort nationally to achieve the targets set by Millennium Development Goals, certain localities may have experienced different trends in other confounding effects.

[16]On an assumption that there is no gender-bias effects from general economic well-being, girls and boys from the same locality will experience the evolution of their human capital equally. Therefore, once this confounding effect is differenced out following a difference-in-difference strategy, the mortality risk effect will be identified.

as its preferred military option. As an implication, the western part of Cambodia is much more heavily affected by landmines than its eastern region (see Figure 4.3). Second, the temporal variation is obtained from the landmine clearance operations and the two-fold expansion their productivity around the years 2004-2005. As shown previously in Figure 4.1 and 4.2, the increase in the number of landmines being recovered is directly linked to a subsequent sharp decline in landmine casualties, particularly in the affected areas. This event implies that amongst the landmine-affected areas, adjacent birth cohorts from the same locality would suddenly face with a much different level of mortality risk. For the unaffected areas, in contrast, they do not experience such a change in their expected longevity.

The timing of the abrupt decline of landmine casualties allows for any differences in schooling decisions amongst adjacent birth cohorts from the same locality to be examined. A key identifying assumption for a causal interpretation is that whilst facing a different magnitude of the reduction in their exposure to mortality risk, these individuals are otherwise comparable. And that, upon observing such a change in the objective mortality risk in their locality, the parents update their perception of prime-age life expectancy of their children at an instance. Thus, to the affected households, this discontinuous change will directly affect their optimal investments in their children's schooling.

The gender variation is obtained from the unique pattern of landmine casualties in Cambodia that they are predominately males. In the past 20 years, adult males accounts for 90 percent of total landmine casualties (CMVIS, Roberts, 2011). And as shown in the previous section (see Table 4.1), the expansion of landmine clearance effort in 2005 had led to a sharp decline in the male's level of risk whilst not much changes for the females'. This gender differential of landmine mortality risk is exploited as the final variation for the empirical exercise.

The main analysis uses individual schooling information from the 1998 and 2008 Cambodia census. Altogether, the data comprises of 624 grouped observations, which are derived from gender (2), district of residence (156) and census year (2) [17].

The DDD estimation is as follows:

$$
\begin{aligned}
HC_{L,G,Y} = \beta_0 &+ \beta_1 Mine_{L,Y} Male_G \\
&+ \theta_1[\mu_L Male_G] + \theta_2[\mu_L \gamma_Y] + \theta_3[\gamma_Y Male_G] + \epsilon_{L,G,Y}
\end{aligned}
\tag{4.1}
$$

---

[17]Alternatively, the analysis the data can also be done at the province level to supplement the key findings. In which case, the data is made up of 96 grouped observations (24 provinces of residence).

where $HC_{L,G,Y}$ is our outcome of interest- a probability of attaining a level of qualification (primary school level and secondary school level) for each cohort (3-age grouping), living in a locality (L) and is found in a census year (Y). The variable of interest, $Mine_{L,Y}$, is a rate of landmine casualties per 1000 adult population (aged 18-35) in a locality. In the main regressions when the comparison is between the same age cohorts from two different census, $Mine_{L,Y}$ takes two values. For the *control* cohorts, they are assigned a three-year running average rate of 1997-1999 as the LMR before the sharp change in 2005. For the *treatment* age cohorts, they are assigned the three-year running average LMR of 2007-2009 as the rate of casualties after the sharp change in 2005. The specification includes a dummy for male ($Male_G$), all double interactions between gender ($Male_G$), province (μ_L) and IPUMS census year (γ_Y) and a random error term ($\epsilon_{L,G,Y}$). Note that among the age cohorts at each schooling outcome of interest, the analysis subsequently puts together each age into a group of three consecutive age cohorts in the regression exercises (Jayachandran and Lleras-Muney, 2009).

As described previously, the first difference comes from the geographical difference of the changes in LMR. The second difference is derived from comparing the same age cohorts across the census years. And the third difference is the male-female comparison, given the same census and locality of residence. We obtain our estimates using linear probability models with the robust standard errors and clustered at province of residence. Given the prediction from the theoretical framework, we expect β_1 to have a negative sign, indicating that mortality risk has a negative impact of human capital investment decision. And if the model is correctly specified, β_1 is a consistent estimate of the effect of having one unit increase in mortality rate on schooling probability.

Key identification assumptions for a causal interpretation of β_1 are (i) education institutions and endowment in localities was not a predetermination of the location choice of landmine laying activities in the first place; (ii) that the sharp, two-fold increase of landmine clearance and subsequently the fall of LMR in 2005 was not anticipated by Cambodian households many years before; (iii) that households response instantaneously to changes in mortality risk; and (iv) we are able to observe the direct consequence of households' investment decision in our schooling measures in the data.

Given the empirical design, females from the same locality and same census are required to act as a good *control* for the equivalent males. More precisely, the comparable males and females should share common behaviour responses to inputs (of human capital production).[18] Note also that in Equation 4.1, by using the dummy ($Male_G$) in the

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[18] It is advocated that conditional on locality and census, it must be ensured that $\frac{\Delta HC_{male}}{\Delta Mortality_{male}} = \frac{\Delta HC_{female}}{\Delta Mortality_{male}}$ and that for other confounding factors, X, we expect to see $\frac{\Delta HC_{male}}{\Delta X_{male}} = \frac{\Delta HC_{female}}{\Delta X_{male}}$

treatment assignment, we assume that landmine casualties affect only the male population in the area. On the other hand, the effect of LMR on females is assumed away when a zero value is assigned to the female population. In the next step, this assumption will be relaxed and allow the mortality risk exposed by each gender to come directly from the casualty rates which are specific to each group. Therefore, $Mine_{L,Y}Male_G$ is replaced with $Mine_{L,Y,G}$ and the alternative estimation equation becomes:

$$
\begin{aligned}
HC_{L,G,Y} = \beta_0 &+ \beta_1 Mine_{L,Y,G} \\
&+ \theta_1[\mu_L Male_G] + \theta_2[\mu_L \gamma_Y] + \theta_3[\gamma_Y Male_G] + \epsilon_{L,G,Y}
\end{aligned}
\tag{4.2}
$$

This specification also includes confounding variables, X which potentially vary across locality, gender and time. Note that the variations in LMR in Cambodia are direct implications of the on-going landmine clearance operation. Therefore, I account for the confounding effect from income by controlling for average poverty at province level-with the years corresponding to each census cohort. In addition, another variable, *rice income*, is constructed to capture direct gains from having more agricultural lands as a result of landmine clearance. To do this, I use the knowledge that the main source of income to Cambodia households, particularly in the rural area, is rice production. Approximately 80 percent of all available land in Cambodia are used for rice growing activity (Cambodia Socio-Economic Survey; Cambodia Commune Database). It is reported that after the allocation of de-mined land for resettlements, the second largest proportion of de-mined land (approximately 30 percent) are returned to the local population for agricultural activities (CMAA). Therefore, we calculate annual income of rice harvesting for each district, using the information on annual land clearance, yield productivity for each geography and average rice prices from the nearest trading market. We finally calculate the three-year average income for the periods corresponding to LMR at the district level.

Estimates from two-census comparison: Table 4.5 shows the estimation results from the specification which compare the same age cohorts but across different census years. The baseline model finds that a unit increase in LMR is related to 6 pp. decrease in the probability of attaining primary school education. The magnitude of the mortality effect reduces slightly when we add extra controls in order to account for confounding factors.

The inclusion of potential rice income from having more safe land reduces the size of LMR to 5.4 pp. In the models with time-varying poverty rates and other health-related mortality rates at province level (namely malaria infection rate, child mortality and maternal mortality), the effect of LMR is at 4.5 pp for the primary school outcome.

For secondary school, the baseline model finds that a unit rise in landmine casualty leads to 4.2 pp decrease in schooling. By adding more controls as previously, the effect is at 6.1 pp. Note that there is a difference in the size of the mortality effect between the two levels of schooling. This finding is aligned with the conceptual framework where the effect of mortality risk is hypothesised to be larger under the condition with higher financial constraint.

Estimates from within-census comparison: Table 4.6 presents the analysis where the *treated* cohorts are compared with the *control* cohorts from the same census year (in 2008 census). Precisely, this *control* group is the exact same group (same birth cohorts) as in the previous exercise. For the *control* group, I basically track the same birth cohorts from the 1998 census ten years forward and locate them again in the 2008 census. The analysis in this part compares schooling behaviours of the *children* in the same census who, however, faced rather different mortality risk at the time when their parents make schooling investments.

For primary school level, one unit increase in LMR is related to 1.5 pp. in baseline model and at 1 pp. in the full model. For the secondary school level, the effect is higher at 3.5 pp in the full specification. Again, the difference in the magnitude between *free* school qualification (primary school) and costly secondary school is observed in this Cambodia sample.

Estimates from using gender-specific LMR: To allow landmine risk to have non-zero effect on both males and females, we run our estimation according to Equation 4.2 by using gender-specific landmine casualty rates with the two-census approach. Essentially, this specification permits spatial and time variation of LMR within the female population, even if their life expectancy are only minimally affected by landmine prevalence. Table 4.7 shows that, given the relaxed assumption, the magnitude of LMR is robust at 4.24 pp. for the primary school outcome. On the other hand, the negative effect on LMR on the probability of having some secondary school when parents are allowed to response to changes in the variation of female's expected longevity, the effect of landmine mortality risk is reduced to 3.1 pp. in the full specification.

4.6.2 Instrumental Variable

The causal interpretation of the findings from the DDD specification relies heavily on the fact that other changes apart from LMR over this decade is gender-neutral. In the

previous analysis, we are able to control for all the changes that is gender-locality, gender-time, and locality-time using our double interaction fixed effects. As seen in the previous section, the specification also takes into account the possibility of gender-bias income effect which may bias the results. A main caveat is that households may also adjust their behaviours in a more heterogeneous manner, as a result of having experienced landmine incidence in their area. And if such a change happens simultaneous with gender, locality and time, the findings may be biased. In order to mitigate this omitted variable bias, I incorporate the technique of Two-Stage Least Square (2SLS) to the DDD model.

An ideal instrumental variable (IV) is required to be strongly correlated with the changes of LMR over time, but does not have any other influences on households education decisions. Given that the pattern of LMR is influenced directly by the landmine clearance operation, I therefore exploit this variable to construct an instrumental variable. To do so, I exploit the information from the 2012 Cambodia Baseline Survey (of landmine prevalence in communes) as well as the landmine clearance database from CMAA. The level of *dangerous* lands, which were not yet de-mined by landmine agencies, is calculated for each province-year. We then calculate the proportion of uncleared, *dangerous* areas per total area in a province. However, using the variation directly may invalidate the exclusion restriction. It is because landmine clearance operations are likely to lead to changes in other confounding factors, which may affect educational decisions of households in the area aside the change in mortality risk.

Therefore, for each province, the *dangerous* area of its neighbouring provinces (defined as having shared border) is constructed. This is a valid instrumental variable based on two main identifying assumptions (Bai et al., 2013; Bartik, 1991; Bound and Holzer, 2000). First, it is assumed that the pattern of landmine clearance at each province is determined by the clearance operation planning at the national level. Therefore, this aggregate *shock* ensures that there is spatial correlation between the province of interest and its neighbours. The second assumption is that, however, how landmine casualties are influenced by the landmine clearance and the remains of *dangerous* land areas at each point in time are a province-specific event. That is there is no spillovers of landmine mortality risk between neighbouring provinces. Households' decisions are not affected by what happened in other provinces. Given that our instrument is constructed at the province level, we argue the large spatial area size will mitigate spillovers across its neighbouring regions. Statistical evidence indicate that migration in Cambodia is indeed high. However, around 80-90 percent of the migration movement is within province. Therefore, we believe that using the averaged *dangerous* land areas of neighbouring provinces do not violate the exclusion restriction in this analysis.

The first-stage regression for the Two-Stage Least Square specification is as follows:

$$Mine_{L,Y}Male_G = \omega_0 + \omega_1 NeighbourDangerLand_{L,Y}Male_G + \varepsilon IV_{L,G,Y} \qquad (4.3)$$

Mortality effect under 2SLS models: First, I run the 2SLS regressions with the specification in Equation 4.1, using two-census comparison. In Table 4.5, the first-stage regressions show a strong and positive relationship between stock of *dangerous* land in neighbouring provinces and LMR of the locality of interest (F-test on the excluded variables are at 20.75 for the primary school models and 20.50 for the secondary school models).

For the primary school models, by accounting for omitted variable bias, the effect of LMR becomes 9.9 pp. in the baseline specification and 5.5 pp. under the full specification (controlling for health and economic conditions). For the secondary school models, we find that a unit rise in LMR leads to 13.6 pp in the probability of having had some secondary school education [19].

Next, we repeat the 2SLS exercise with Equation 4.2 using gender-specific landmine casualties. The first-stage specification is similar to Equation 4.3 but with $Mine_{L,Y,G}$ instead. The findings are presented in Table 4.7. Under the full specification, the negative effect of LMR on the probability of primary school attainment is estimated at 3.1 pp. For secondary school level, the effect is found to be larger at 6.8 pp. in the full model. In addition, the size of the mortality risk effect is higher for the costly education level (i.e. secondary school) than that found at *free* school level (i.e. primary school). Additionally, by comparing the results between the specification using a *male dummy* and the specification with gender-specific LMR, it is found by allowing parents' decisions to also response to the variation of female's landmine mortality risk, the *intention-to-treat* effect becomes smaller.

4.7   Robustness Checks

4.7.1   Health Investments as Alternative Measures

In this section, the empirical specifications (looking at the age cohorts from different survey years) to the Cambodia Demographic Health Surveys (CDHS thereafter). The main objective here is to test if mortality risk, using LMR as a proxy, displays a negative effect on other measures of human capital as well as at a different stage of development. In particular, parental investment in child's physical health capital will be analysed.

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[19]See results from other specification modification can be found in the Online Appendix.

The data from the CHDS allows for the focus on the age cohorts of 1-5 years old from 3 different years of the CDHS (2000, 2005 and 2010). Considering the timing of the change in LMR, the cohorts from 2000 and 2005 are classified as the *control* group whilst the same age cohorts from 2010 are the *treament* group [20]. The outcomes of interest is the probability of the child having been vaccinated (a list of vaccination types) and received micro-nutrition treatment. I apply the DDD specification analogously to Equation 4.1 in the previous section.

From Table 4.10, an increase in mortality risk, defined as LMR, leads to a decrease in healthy behaviours of the household. More precisely, the DDD analysis shows a reduction of the probability of a child being vaccinated. In the specification A, where the children from the CDHS 2000 (*control*) and the CDHS 2010 (*treated*) are being compared, a unit increase in landmine casualty rate (at district level) leads to 4 pp. decline in the probability of a child receiving BCG vaccination; 4.3 pp. decline in polio vaccination; and 3.9 pp decline in measles vaccination. There is a weaker but insignificant effect of landmine mortality of the probability of a child receiving vitamin A dosage before 5 years old. When the children cohorts from CDHS 2005 are included as an additional control group (and are assigned the 2001-2003 average of LMR), the magnitude of effect of mortality risk gets larger by twofold and more significant in the full specification (controlling for time-varying economic conditions and health-related mortality rates). In sum, the analysis using the CDHS provides supportive evidence that mortality risk (with LMR as a proxy) has a negative significant effect on human capital investment.

4.7.2   Comparing the Effect of Mortality Risk between Landmine Accidents and Road Accidents

As said, a key research interest in analysing the role of landmine-mortality risk on human capital development is that this risk is caused by the event that is orthogonal to healthcare improvements or medical breakthroughs. Therefore, the empirical exercises in this study have provided evidence that such a mortality risk, in form of LMR in Cambodia, do poses a negative effect on households' decisions of human capital investment. This section turns to another source of mortality risk, *road traffic accidents*, which shares many closely-related features to landmine mortality, but with one stark contrast. Analogous to landmine accidents, it is a non-health source of mortality risk. Across various causes of death in Cambodia, road accidents are the top reason for casualties, especially among the prime-age population. Most of all, the statistics show that males

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[20]In the main specification, cohorts from CDHS 2010 are assigned LMR of the averaged 2007-2009 and those from CDHS 2000 and CDHS 2005 are assigned the rate of the averaged 1997-1999. Alternatively, for CDHS 2005, I assign the three-year average of LMR during 2001-2003 so that the cohorts from each survey year are faced with a different level of landmine mortality risk

are the dominant victims of such accidents (see Figure 4.9). In sum, these characteristics of road traffic accidents allow for the application of the same empirical strategy, using DDD, in order to test if such a source of mortality risk influences human capital investment decisions of the Cambodian households.

Nevertheless, there is a stark difference between landmine accidents and road traffic accidents- the fundamental of dread and the role of *availability heuristic*(Kahneman and Tversky, 1979; Slovic et al., 1982; Slovic, 1987). The risk of being exposed to explosive warfare weaponry like landmines have two keys features that road accidents do not possess. First, as many other causes of death, road accidents are more likely to be controllable or, to the least, avoidable. In contrast, landmines are much less observable by being buried underground. In many areas in Cambodia, minefields are still being recovered. Despite being cleared marked in a lot of areas, landmine accidents continue to occur while the victims are travelling or working in the field (CMAA; CMVIS). Given the severity of *unobservable* manifestation of harm, it becomes much more difficult for households to adapt or adjust their behaviours in the prevalence of landmines in the area. Second, because road accidents happen more frequently, the events become more common. Therefore, such a source of risk is perceived to be less salient than a rarer but more psychologically traumatic event of landmine accidents Slovic, 1987.

On the one hand, the subjective survival probability of the households responses to new updated information from all sources of mortality (Hurd and McGarry, 2002). On the other hand, the same magnitude of mortality rate from landmine accident and road traffic accident may not be translated equally to the same level of mortality risk perceived by the Cambodian households. Being a *low probability event*, the households are more likely to assign higher *subjective* mortality risk to a landmine accident whilst subjectively attenuate the risk from a common road traffic accident (Kahneman and Tversky, 1979). And if households' decisions on investment are influenced by the subjective mortality risk, we expect, in our empirical exercise, that the effect of road traffic accident on education outcome would be smaller or attenuated to zero.

Hence, we modify our previous DDD specification and estimate a possible causal effect of road traffic accident mortality risk on education attainment in Cambodia. Figure 4.10 displays the distribution of road accident at province level for the years 1997-1999 and 2007-2009. And we compare the schooling outcomes under the event of *low probability* (landmine accidents) with events of *high probability* (road traffic accidents) (Slovic, 1987). The main estimation equation using DDD for road traffic accidents is as follows:

$$HC_{L,G,Y} = \beta_0 + \beta_1 Roadacc_{L,Y} Male_G$$
$$+ \theta_1[\mu_L Male_G] + \theta_2[\mu_L \gamma_Y] + \theta_3[\gamma_Y Male_G] + \epsilon_{L,G,Y} \tag{4.4}$$

where $Roadacc_{L,Y}$ is road accident rate per 10,000 adult population in a locality L in census year Y. Again, the empirical analysis uses individual schooling characteristics from the 1998 and 2008 Cambodia census [21]. Given the data availability, the analysis is performed at the province level. Additional covariates are number of motor vehicles and population across time for each locality [22].

Road accident data with DDD: The traffic accident rates at each province are computed over the same period as the LMR, using the data from Cambodia Road Traffic and Victim Information System (RTAVIS). The data contains all reported incidents and fatalities by traffic police and hospitals in the country. Given the data availability, the level of locality is at province-level The road traffic casualty rates are calculated from the share of fatalities amongst the prime-age adult population (18-35 years old). Again, the three-year average casualty rates at province level from the years 1997-1999 are assigned to the *control* age cohorts and the 2007-2009 average rates are assigned to the *treated* cohorts [23]. The analysis focuses on the same two school cohorts- primary school and secondary school level as before [24].

In contrast to the findings using LMR, the estimates from the regressions with road accident mortality are not statistically significant at any level of education- although it indicates a negative relationship between them (see Table 4.11) If, as in the conceptual framework, all causes of mortality risk are perceived objectively equivalent by the households, it is expected to observe a negative and significant result as found in the specifications with LMR. On the other hand, if the investment decision is, in fact, influenced by subjective mortality risk, it is possible that different conclusions may be drawn from different causes of death.

Before coming to a conclusion, I investigate if the insignificant effect of traffic accidents is caused by potential omitted variable bias or attenuation bias. To do so, I run the DDD specification whilst use an instrumental variable for $Road_{L,Y}$. The ideal instrument will need to have a strong correlation with changes road traffic casualty rates and it will not have any other influences on education decision of the household in the locality. Given

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[21]Key variables defined analogously to our initial specification with landmine mortality rate.

[22]The data sources are census data, SEILA and Cambodia Commune Database

[23]This is the exact assignment rule as previously conducted with LMR.

[24]That is, the empirical exercise compares individuals aged 6-15 year old between the 1998 and the 2008 census for primary school attainment and the 12-20 year old for secondary school attainment.

reports from Cambodia authorities [25], it is shown that straight roads and road junctions are key causes of road accidents within a province (RTAVIS). However, it is possible that own road networks may be correlated to other confounding variables, for example economic prosperity of the province, which may violate the exclusion restriction.

To overcome this, measures of road networks are constructed [26] at a given time (1997 for *before* and 2007 for *after*) of neighbouring provinces (with shared borders). Under two key assumptions that the road constructions in each province is led by national agenda but road accidents themselves are province-specific, this is the instrumental variable for road $Road_{L,Y}$. The first stage regression of the Two-Stage Least Square for the road traffic accident specification is:

$$Roadacc_{L,Y}Male_G = \omega_0 + \omega_1 NeighbourRoadnetwork_{L,Y}Male_G + \varepsilon_{L,G,Y}^{IV} \qquad (4.5)$$

Road accident with 2SLS: Table 4.12 reports the results using 2SLS with traffic accident. The first stage result shows a strong significant relationship between the magnitude of road networks of neighbouring provinces and the traffic accident rate in the province in a given year (F-test on the excluded variable are 34.18 and 33.40). In the second-stage, after controlling for time-varying covariates (economic conditions, motor vehicles), it shows that there is no significant relationship between road traffic accident and education outcomes, in both primary and secondary school level. To allow comparison with landmine accidents, I re-run the 2SLS with DDD specification (Equation 4.1 and 4.3) using LMR at province level. See Table 4.13 for the findings [27].

In sum, whilst the analysis provides evidence for a negative and significant effect of mortality risk on human capital investment behaviour when LMR is considered, the same results are no longer found road traffic accidents are used. With reference to the literature and the arguments illustrated above, it shows that a possible key mechanism driving the findings on the effect of landmine mortality on schooling decision in this study is the subjectively quantified variation in life expectancy, and not the objective one (e.g. Krimsky and Golding, 1992; Kilka and Weber, 2001).

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[25]Cambodia Road Traffic Accident and Victim Information System provide annual reports on traffic accidents across Cambodia. By compiling data from hospitals and police authorities, its data contains information includes causes and location of accidents.

[26]the variable is constructed from data maintained by Cambodia Ministry of Planning and Cambodia Land and Environment Atlas and Resource (CLEAR) project.

[27]we also run the DDD specification at province level with CDHS data and find significant results with landmine mortality risk.

4.8   Discussions

4.8.1   Landmine Clearance Operation and Gains in Household Wealth

Here, I investigate whether landmine clearance operation leads to improvement in households wealth or income. I test this proposition with asset data, available in the CDHS 2000, 2005 and 2010. This exercise is important to the identification strategy in this study. Given evidence that income itself can have a gender-bias effect (that is households tend to spend or invest more in boys than girls when their wealth or income increase) (e.g. Strauss and Thomas, 1995; Behrman, 1988 ; Gupta, 1987), a common trend assumption between males and females may be challenged.

The asset regression is similar to the previous exercise with the CDHS datasets. THe households from the CDHS 2000 and the CDHS 2005 are considered as the *control* group while the CDHS 2010 as the treatment group. The LMR are assigned correspondingly (see the previous section on health outcomes). The households of interest are those with children age 8-22 years old (at the survey year) [28] .

$$Asset_{L,Y} = \lambda_0 + \lambda_1 Clearance_{L,Y} + \varepsilon_{L,Y}^{asset} \tag{4.6}$$

where $Asset_{L,Y}$ is a measure of asset in a household (DHS-constructed Household Wealth Index and total household asset) and $Clearance_{L,Y}$ is the productivity rate of landmine clearance operation in a specific district L, for a given survey year Y. From the estimations (using repeated cross-section at district level), landmine clearance productivity does not seem to have a statistical significant effect on household wealth. I also run Equation 4.6 with a Two-Stage Least Square specification in order to mitigate omitted variable problems. By instrumenting $Clearance_{L,Y}$ with $NeighbourClearance_{L,Y}$, a three-year average rate of landmine clearance of neighbouring provinces, I do not find evidence supporting changes in household wealth using CDHS dataset (see Table 4.14).

4.8.2   Incentives for Schooling Investments

This section examines what benefits a Cambodia household may gain from investing in child's higher schooling, particularly in an agrarian economy.

A reason is that education allows higher mobility for children to get out of the agricultural sector and move into alternative sectors with higher pays (e.g. **?**; Wozniak, 2010; Machin et al., 2012). Furthermore, this may also encourage higher spatial mobility and

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[28]Therefore, they are of the equivalently same birth cohorts as the census cohorts.

thus an urbanisation, away from the previous resided area and thus allows lower mortality risk from landmines. The expected lifetime utility would be greater not only because of an additional decrease in landmine mortality at adulthood but also other gains from education (see Oreopoulos and Salvanes, 2011 for a review).

Even when individuals do not end up moving out of the agricultural section, earning distributions from Cambodia Labour Force surveys over the years suggest that there are returns to be gain from a higher education without migration. Moreover, statistics from the Cambodia Socio-Economic surveys show that around 20 percent of urban individuals with secondary school education are in the agriculture section, with nearly 40 percent amongst those who live in rural areas. Figure 4.11 compare the earning distributions between working in agriculture and other occupations available in more urban areas (for example, food manufacturing, retail and services in hotels and restaurants). The earning distribution of agriculture does exhibit the right tail, indicating over 30 percent chance of high earning (being in higher than the 40th percentile of average wage in Cambodia in 1998-2001).

4.9 Conclusions

Economic theories of human capital development assert that life expectancy plays a key role in determining households' optimal level of schooling investments. So far, this study has investigated a causal relationship and illustrated supporting evidence by using landmines in Cambodia as the measure of mortality risk. Landmine casualties differ from previous studies in the literature in a way that this is a mortality risk variation which is not derived from a conventional improvement in health environment. Instead, the study examined a key variation of mortality risk that is caused by a powerful lethal device, namely landmines.

This study use DDD specifications to estimate the corresponding change in schooling and health investment. The decrease in LMR led to an increase in the probablity of school attendance. Furthermore, in a 2SLS specification where LMR is instrumented by stock of *dangerous* lands among neighbouring provinces, a unit decrease in LMR caused a 5.5 percentage points increase in the probabiity at primary school level and a 13.6 percentage points increase at secondary school level. For physical health investment, there is a sizeble negative effect of LMR on the likelihood of vaccination amongst children age under-five in the CDHS sample.

In the next step, LMR is replaced with road traffic accident rates and run with the identical analysis. This exercise is as if substituting the same level of one objective

mortality risk by another. If it is the objective mortality risk that drives households' investment behaviours and thus the outcomes, a similar effect under road traffic accident will be expected. However, in both the DDD and IV specification, no statistically significant effect of road traffic mortality risk on educational outcomes is detected.

Provided that (i) households do exaggerate the risk from landmine casualty rate but instead attenuate the risk caused by a much common, less terrorised event of road accident and (ii) it is *subjective* mortality risk that influences investment behaviour, it is not expected to see a strong relationship between road accident mortality and human capital outcomes. The empirical exercises in this study present supportive evidence for this mechanism. To conclude, this paper and its findings from the causal analysis advocate for a role of life expectancy on optimal decision making, particularly in human capital investment.

More strongly, there is evidence that different findings between various causes of mortality risk demonstrate a strong consideration for differentiating between objective and subjective risk or probability within the framework of household optimisation (e.g. see Dominitz and Manski, 1996; Attanasio and Kaufmann, 2009).

Figures

FIGURE 4.1: National level of landmine clearance productivity: 2000-2008
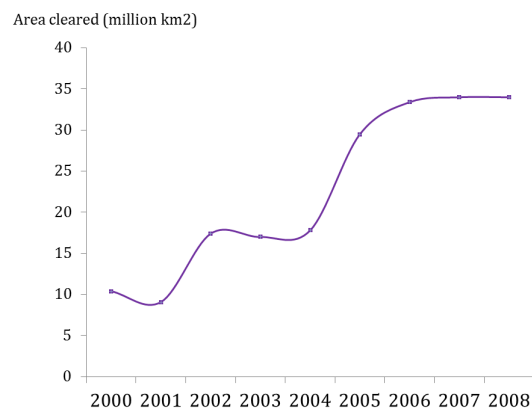
FIGURE 4.2: National level of landmine casualty rate: 2000-2008
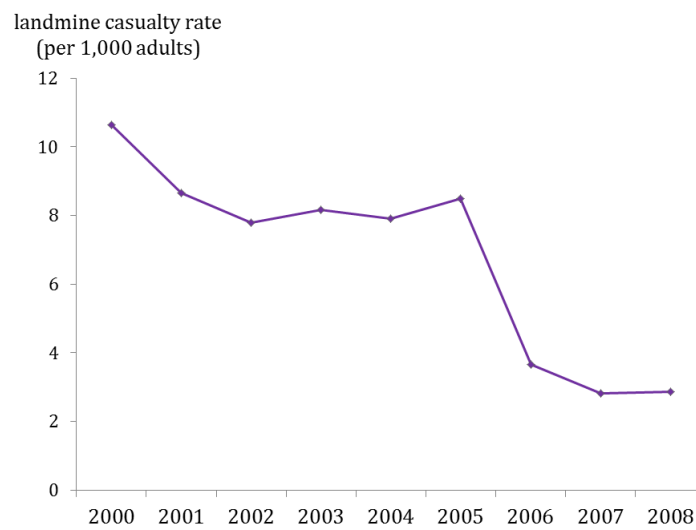
FIGURE 4.3: Spatial distribution of landmines productivity and landmine casualty rate: before and after 2005
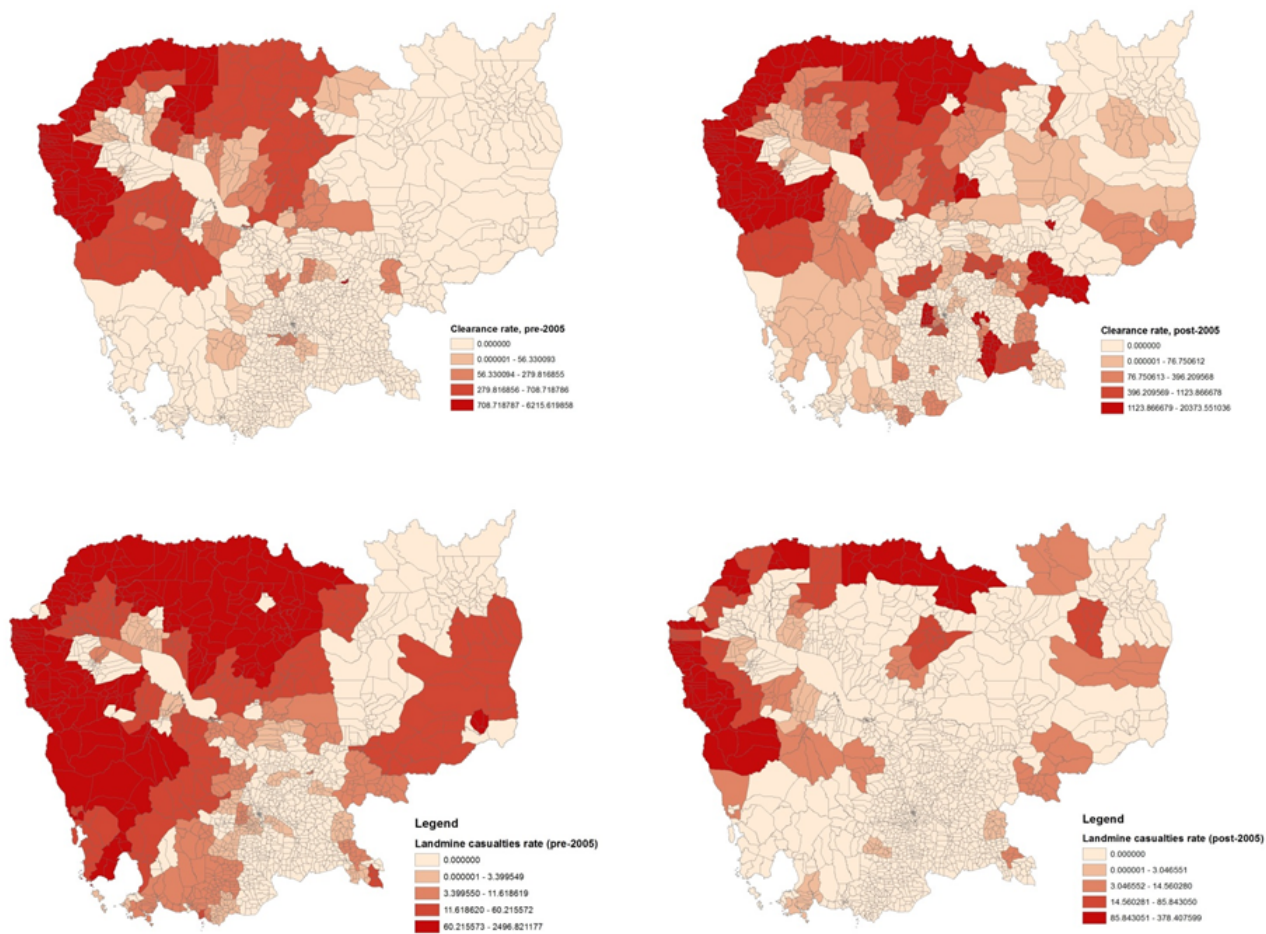
FIGURE 4.4: Trends of landmines productivity and landmine casualty rate by average intensity of landmine casualty rates in 2001-2004
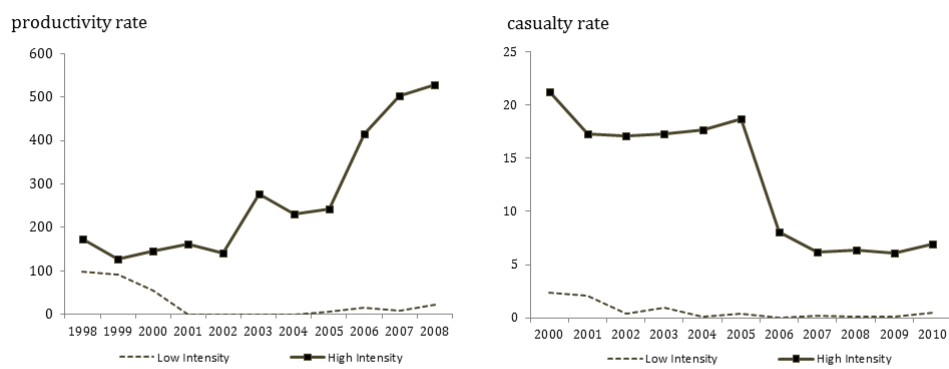
FIGURE 4.5: Average number of schools by average intensity of landmine casualty rates in 2001-2004 (province-level)
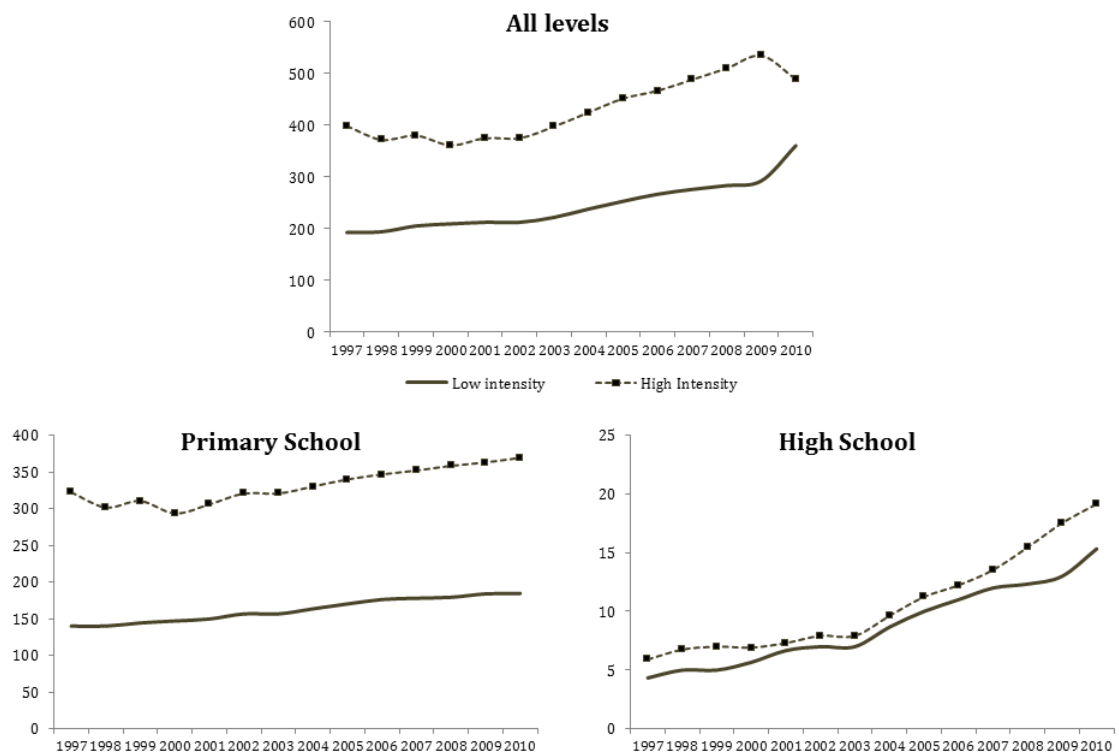
FIGURE 4.6: School attendance characteristics by average intensity of landmine casualty rate in 2001-2004 (province-level)
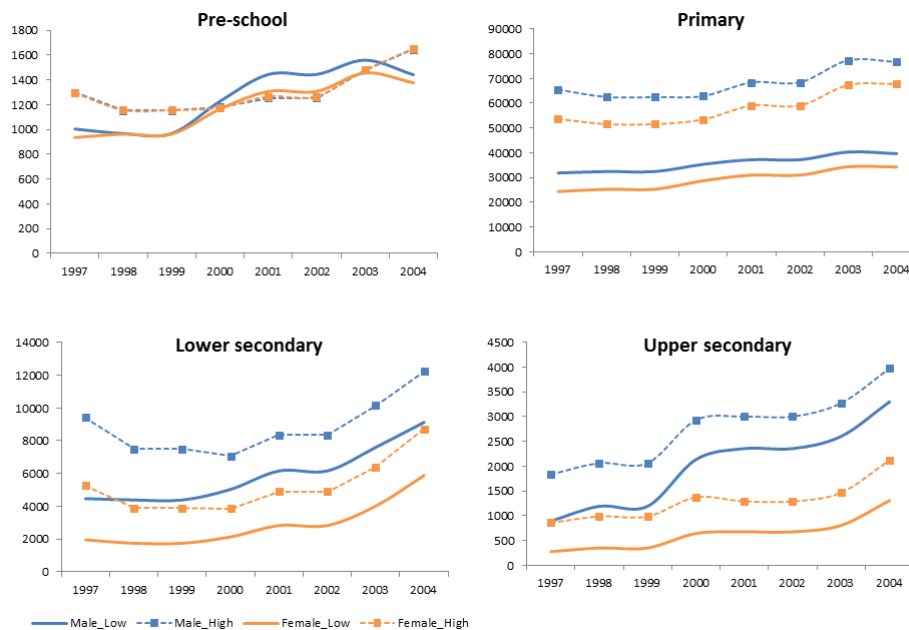
FIGURE 4.7: Poverty rate by intensity of landmine clearance productivity in 2005-2007
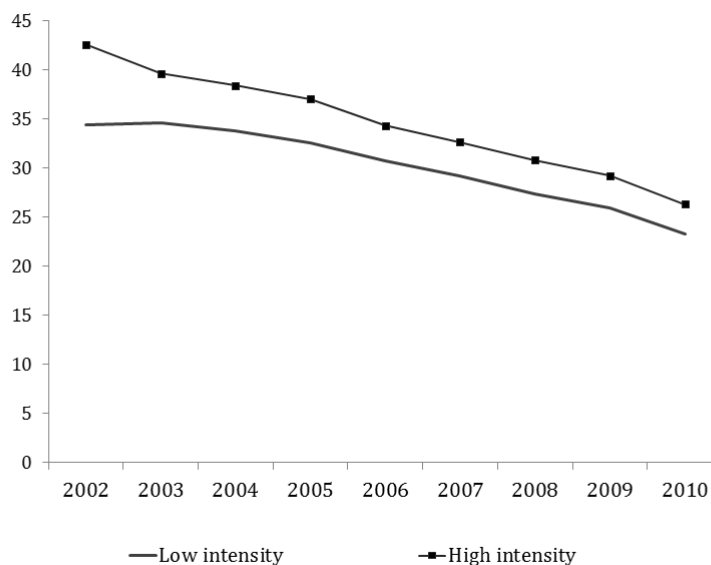
FIGURE 4.8: Age-gender specific mortality rates at province level, by intensity of clearance productivity in 2005-2007
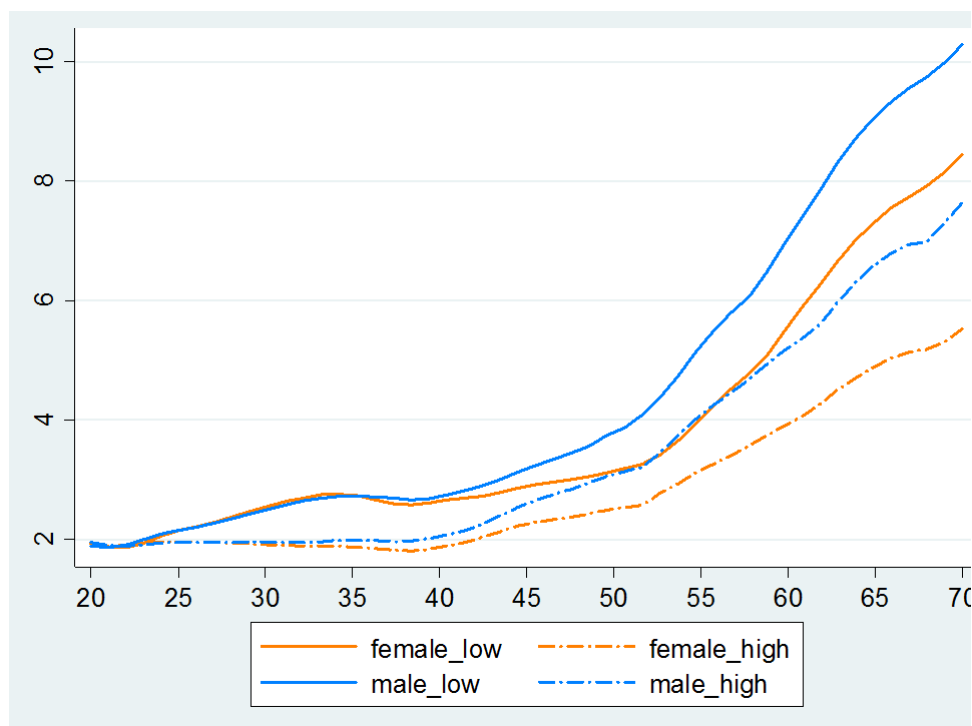
FIGURE 4.9: Causes of death in Cambodia (national average)

Male-female ratio, by cause of death (2010)
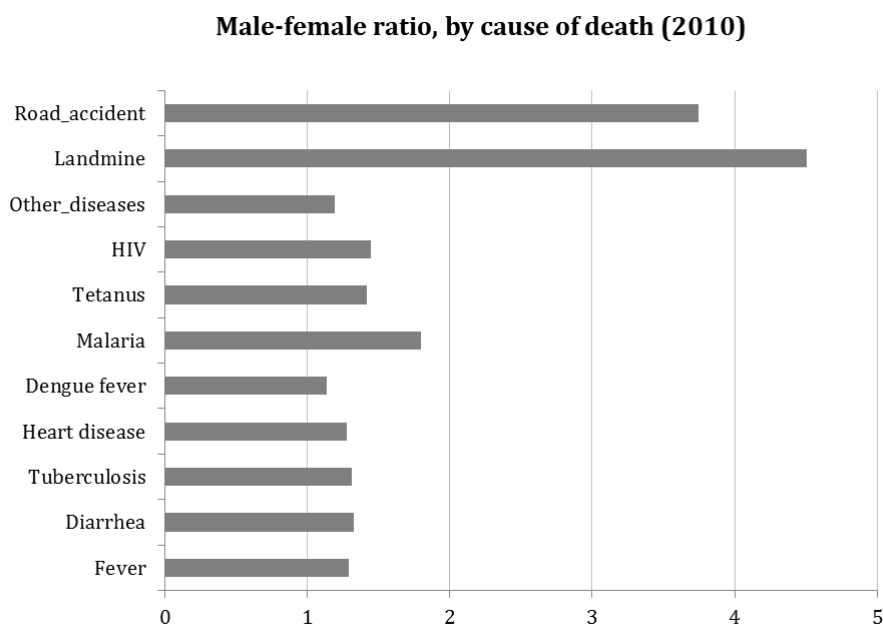
FIGURE 4.10: Causes of death in Cambodia (national average)
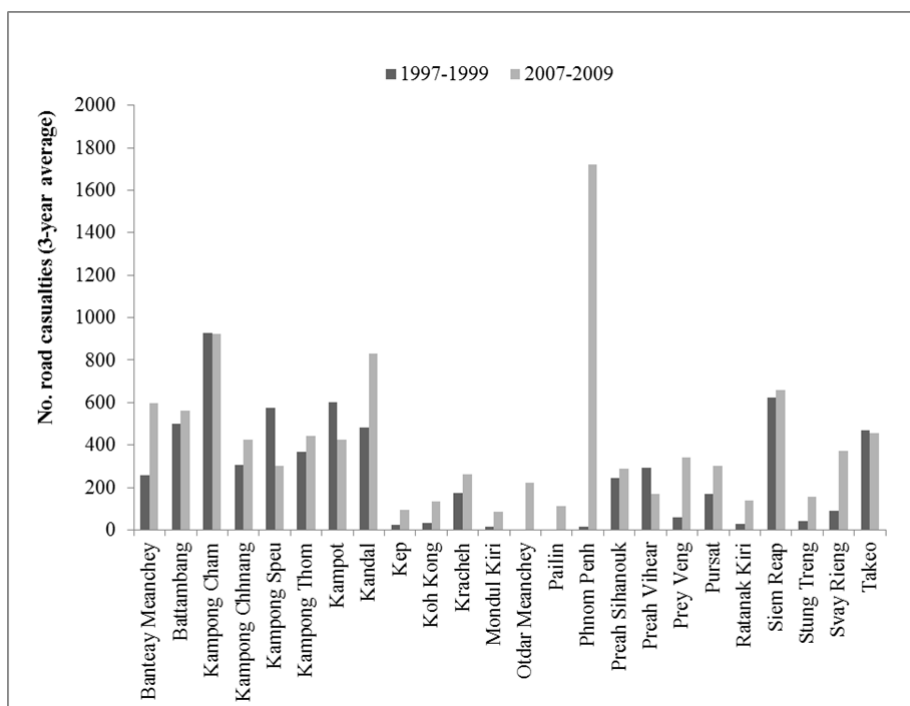
FIGURE 4.11: Wage distribution by decile in 2001 (national average)
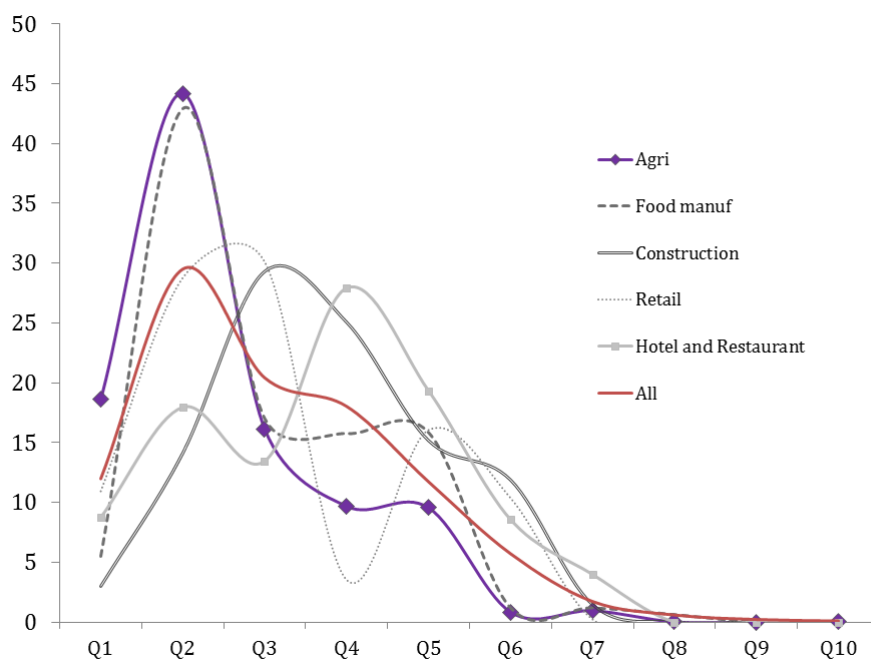
Tables

TABLE 4.1: Share of landmine casualties to total mortality (province average) by age and gender, 2008

Age:	Under 0	0-5	0-14	15-40
Panel A: Males				
2005	22.28	9.00	6.45	17.40
2006	9.8	3.77	2.56	6.41
2007	6.54	2.54	1.77	4.59
2008	4.98	1.94	1.35	3.34
2009	4.82	1.80	1.22	3.09
2010	6.9	2.79	1.96	5.4
2011	6.58	2.52	1.66	4.31
Panel B: Females				
2005	1.80	0.68	0.46	1.23
2006	0.88	0.33	0.23	0.57
2007	0.33	0.11	0.07	0.15
2008	1.37	0.42	0.27	0.91
2009	0.56	0.23	0.16	0.04
2010	2.98	1.34	1.04	2.63
2011	0.30	0.11	0.06	0.14

Source: CMAA. The numbers indicate percentage share among different age groups with each calendar year, for males (Panel A) and females (Panel B)

TABLE 4.2: Province-average number of landmine casualties, by age group and gender

	Age 0-15		Age 15-40	
	Male	Female	Male	Female
2005	1	0	17.8	3.6
2006	1	2	11.1	2.4
2007	3.5	1	8.7	4.0
2008	2	0	8.0	2.6
2009	1	3	8.1	2.3
2010	3	1.5	7.2	4.5
2011	1	1	9	3.0

Notes: the data on landmine casualties come from CMAA database. The numbers above are the total number of reported landmine casualties the province level between 2005-2011 in Cambodia.

TABLE 4.3: Summary statistics by intensity of landmine casualties (1998)

	Low Intensity		High Intensity	
	Male	Female	Male	Female
Educational characteristics in 1998				
Primary (age 6-15)	0.63	0.60	0.83	0.84
Secondary (age 12-20)	0.26	0.20	0.47	0.46
Literacy (age 6-15)	0.59	0.57	0.84	0.85
Literacy (age 12-20)	0.84	0.77	0.93	0.92
School attendance (age 6-14)	0.78	0.77	0.77	0.76
School attendance (age 15-17)	0.62	0.58	0.59	0.55
Other characteristics in 1998				
Rural(%)		0.82		0.87
With electricity(%)		0.17		0.14
With piped water(%)		0.09		0.04
With toilets(%)		0.17		0.13
Home ownership(%)		0.92		0.93
Female as household head(%)		0.25		0.25
No. health centres per commune		0.5		0.5
Poverty rate (%)		34.15		38.17
Landmine mortality rate		14.52		169.84
Annual landmine clearance rate(km^2)		0.85		355.0

Notes: Data are derived from various sources (IPUMS 1998, 2008; Cambodia Commune Database 2006; Seila-CARERE2 1998; CMAA 2010). Low intensity districts are defined as the districts with the rate of landmine casualty (per 1000 adults) below the 45th percentile in the years 2002-2004. High intensity districts are those with the casualty rate above the 65th percentile.

TABLE 4.4: District-level summary statistics by the intensity of landmine clearance operation productivity in the years 2005-2007

Characteristics	High Productivity	Low Productivity	P-value
Male illiteracy (age 36-45)	47.8	53.7	0.54
Female illiteracy (age 36-45)	57.4	59.6	0.96
Male illiteracy (age 46-60)	49.0	53.8	0.62
Female illiteracy (age 46-60)	60.4	64.6	0.68
No. all schools	0.6	0.5	0.23
No. primary schools	3.0	3.7	0.08
No. lower-secondary schools	0.6	0.7	0.36
No. upper-secondary schools	0.2	0.2	0.98
No. health clinics	0.3	0.3	0.73
Child mortality rate	160	171	76
Maternal mortality rate	0.8	0.7	0.60
Poverty rate (%)	30.83	27.35	0.04
No. large-size markets	0.1	0.1	0.40
No. small-size markets	0.4	0.4	0.47

Notes. Data are derived from various sources (Cambodia Commune Database 2006; Seila-CARERE2 1998; CMAA 2010). Illiteracy variables are the percentage per population of a given age-gender group. Number of school (total and by each level) are the number at district level, child mortality rate is under-five year mortality per 1,000 live births, maternal mortality rate is per 100,000 birth. The P-values are obtained from a t-test from the null hypothesis that there is no difference between the districts from high and low clearance productivity. Low productivity districts are defined as the districts receiving the aggregate landmine clearance operation (per km^2) during the years 2005-2007 below the 45th percentile. High productivity districts are those with the landmine clearance operation rate above the 65th percentile.

TABLE 4.5: DDD at district level using the 1998 and 2008 census

	(I)	(II)	(III)	(IV)
Panel A: primary school (age 6-15 in 1998 and 2008)				
*Mine * Male*	-0.061***	-0.054***	-0.045***	-0.045***
	[0.011]	[0.014]	[0.014]	[0.014]
Additional controls				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.0929	0.0933	0.0934	0.0934
Obs	620497	620497	620497	620497
Panel B: secondary school (age 12-20 in 1998 and 2008)				
*Mine * Male*	-0.042***	-0.056***	-0.056***	-0.061***
	[0.009]	[0.008]	[0.008]	[0.009]
Additional controls:				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.1114	0.125	0.125	0.1269
Obs	518638	518638	518638	518638

Notes: Dependent variable is the probability of having at least a primary school education for Panel A and the probability of having at least secondary school for Panel B. Each cell reports the coefficient from each separate regression. *Mine* is landmine casualty rate per 1,000 prime age adult population in a district of interest. In Panel A, the cohorts of interest aged 6-25 years old in IPUMS 2008. Panel B, the cohorts of interest aged 12-30 years old in IPUMS 2008. All regressions include district-age cohort, age cohort-gender, district-gender and age fixed effect. Robust standard errors clustered at province level are reported in square brackets.* significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4.6: DDD at district level using two groups of age cohorts in the 2008 census

	(I)	(II)	(III)	(IV)
Panel A: primary school (age 6-15 and 16-25 in 2008)				
$Mine * Male$	-0.015***	-0.012**	-0.012**	-0.010**
	[.007]	[.007]	[.007]	[.007]
Additional controls:				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.0275	0.1668	0.1668	0.1668
Obs	567350	567350	567350	567350
Panel B: secondary school (age 12-20 and 22-30 in 2008)				
$Mine * Male$	-0.031***	-0.033***	-0.032***	-0.035***
	[0.009]	[0.008]	[0.008]	[0.01]
Additional controls:				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.133	0.1246	0.1246	0.1253
Obs	359992	359992	359992	359992

Notes: Dependent variable is the probability of having at least a primary school education for age 6-15. Dependent variable is the probability of having at least a secondary school education for age 12-20. Each cell reports the coefficient from each separate regression. *Mine* is landmine casualty rate per 1,000 prime age adult population in a district of interest. The cohorts of interest aged 6-15 years old in IPUMS 2008 and similarly in IPUMS 1998. Similarly, they are aged 12-20 for Panel B. All regressions include district-year, year-gender and district-gender fixed effects. Robust standard errors clustered at province level are reported in square brackets.* significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4.7: DDD at district level using gender-specific rate, with the 1998 and 2008 census

	(I)	(II)	(III)	(IV)
Panel A: primary school (age 6-15 in 1998 and 2008)				
$Mine_G$	-0.046***	-0.042***	-0.042***	-0.043***
	[0.009]	[0.009]	[0.009]	[0.009]
Additional controls:				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.0943	0.0947	0.0947	0.0947
Obs	621066	621066	621066	621066
Panel B: secondary school (age 12-20 in 1998 and 2008)				
$Mine_G$	-0.029***	-0.029***	-0.029***	-0.031***
	[0.007]	[0.005]	[0.005]	[0.005]
Additional controls:				
Rice income	N	Y	Y	Y
Poverty rate	N	N	Y	Y
Health conditions	N	N	N	Y
R-Sq	0.1119	0.1247	0.1247	0.1266
Obs	518638	518638	518638	518638

Notes: Dependent variable is the probability of having at least a primary school education for Panel A and the probability of having at least secondary school for Panel B. Each cell reports the coefficient from each separate regression. $Mine_G$ is gender-specific landmine casualty rate per 1,000 prime age adult population in a district of interest. In Panel A, the cohorts of interest aged 6-25 years old in IPUMS 2008. Panel B, the cohorts of interest aged 12-30 years old in IPUMS 2008. All regressions include district-age cohort, age cohort-gender, district-gender and age fixed effect. Robust standard errors clustered at province level are reported in square brackets.* significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4.8: 2SLS with neighbouring provinces' stock of *dangerous* areas as instruments, 1998 and 2008 census

	Primary School Age 6-15			Secondary School Age 12-20		
	Mine	Prob(Primary)		*Mine*	Prob(Secondary)	
First-stage						
NeighDangerland $*$ *Male*	2.326**			2.234***		
	[0.06]			[0.035]		
Second-stage						
MineHat $*$ *Male*		-0.099**	-0.055**		-0.087**	-0.136*
		[0.002]	[0.002]		[0.007]	[0.017]
Additional controls:						
Rice income	N	N	Y	N	N	Y
Poverty rate	N	N	Y	N	N	Y
Health conditions	N	N	Y	N	N	Y
F-test (only excluded)	20.75			20.50		
R-Sq	0.7633	0.092	0.093	0.728	0.111	0.126
Obs	621066	621066	621066	567350	567350	567350

Notes: Each cell reports the coefficient from each separate regression. For the main regression, dependent variable is the probability of having at least a primary school education. In the first stage, the dependant variable is $Mine * Male$ is a given period. $NeighDangerland$ is averaged level of proportion of lands in neighbouring provinces that are not yet cleared by landmine operations per 1000 squared meters. $MineHat$ is predicted landmine casualty rate per 1,000 prime age adult population in a province of interest from the first stage. In the second stage, the dependent variable is probability of having a qualification of interests (primary school, secondary school). The datasets used are from Cambodia IPUMS 1998 and 2008. Robust standard errors clustered at age cohort are reported in square brackets with * significant at 10%; ** significant at 5%; *** significant at 1%. F-statistic tests whether the instruments are jointly significant.

TABLE 4.9: 2SLS using gender-specific landmine casualty rates, 1998 and 2008 census

	Primary School Age 6-15			Secondary School Age 12-20		
	Mine	Prob(Primary)		*Mine*	Prob(Secondary)	
First-stage						
$NeighDangerland*$ $Male$	2.59**			4.04***		
	[0.52]			[1.026]		
Second-stage						
$\widehat{Mine_G}$		-0.055***	-0.031***		-0.048***	-0.068***
		[0.01]	[0.01]		[0.01]	[0.007]
Additional controls:						
Rice income	N	N	Y	N	N	Y
Poverty rate	N	N	Y	N	N	Y
Health conditions	N	N	Y	N	N	Y
F-test (on the excluded)	19.15			19.12		
R-Sq	0.7029	0.0923	0.0931	0.639	0.1112	0.126
Obs	621066	621066	621066	567350	567350	567350

Notes: Each cell reports the coefficient from a separate regression. For the main regression, dependent variable is the probability of having at least a primary school education. In the first stage, the dependant variable is $Mine*Male$ is a given period. $NeighDangerland$ is averaged level of proportion of lands in neighbouring provinces that are not yet cleared by landmine operations per 1000 squared meters. $\widehat{Mine_G}$ is predicted gender-specific landmine casualty rate per 1,000 prime age adult population in a province of interest from the first stage. In the second stage, the dependent variable is probability of having a qualification of interests (primary school, secondary school). The datasets used are from Cambodia IPUMS 1998 and 2008. Robust standard errors clustered at age cohort are reported in square brackets with * significant at 10%; ** significant at 5%; *** significant at 1%. F-statistic tests whether the instruments are jointly significant.

TABLE 4.10: Health capital investments, using DDD with CDHS datasets

	BCG	Polio	Measles	Vitamin A
Panel A: age 1-5, DHS 2000 and 2010				
Mine ∗ Male	-0.040*	-0.043*	-0.039**	-0.022
	[0.024]	[0.019]	[0.018]	[0.015]
R-Sq	0.173	0.111	0.107	0.569
Obs	15550	15559	15427	15371
Panel B: age 1-5, DHS 2000, 2005 and 2010				
Mine ∗ Male	-0.093***	-0.082***	-0.062***	-0.037
	[0.025]	[0.018]	[0.021]	[0.020]
R-Sq	0.092	0.090	0.268	0.155
Obs	23067	23060	22849	22921

Notes: Dependent variables are the probability of the individual having received vaccination or micro-nutrition treatment by the observed age. Each cell reports the coefficient from a separate regression. *Mine* is landmine casualty rate per 1,000 prime age adult population in a district of interest. The cohorts of interest aged 1-5 years old in each Cambodia DHS (2000, 2005 and 2010). All regressions include district-age cohort, age cohort-gender, district-gender and age fixed effect. Robust standard errors clustered at province level are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4.11: Probability of schooling and road accident mortality: DDD analysis

	Prob(Primary School)		Prob(Secondary School)	
	(I)	(II)	(III)	(IV)
*Roadaccident * Male*	-0.106	-0.071	-0.148*	-0.13
	[0.13]	[0.11]	[0.084]	[0.19]
Additional controls				
No. motor vehicles	N	Y	N	Y
Rice income	N	Y	N	Y
Poverty rate	N	Y	N	Y
R-Sq	0.081	0.085	0.091	0.112
Obs	621066	621066	518638	518638

Notes: Roadaccident is road traffic casualty rate per 10,000 prime age adult population (aged 18-35) in a province of interest. Individuals of interest for the primary school outcome are 6-15 years old in 1998 and 2008. For secondary school outcomes, they aged 12-20 in 1998 and 2008. The datasets used are from Cambodia IPUMS 1998 and 2008. Robust standard errors are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4.12: Probability of schooling and road accident mortality: 2SLS analysis

	Primary School (age 6-15)			Secondary School (age 12-20)		
	Road Accident	Prob(Primary)		Road Accident	Prob(Secondary)	
First-stage						
RoadNetworks * *Male*	0.014**			0.015***		
	[0.0024]			[0.0025]		
Second-stage						
AccidentHat * *Male*		-0.178	-0.066		-0.271	-0.607
		[0.314]	[0.442]		[0.280]	[0.650]
Additional controls:						
No. motor vehicles	N	Y	Y	N	Y	Y
Rice income	N	N	Y	N	N	Y
Poverty rate	N	N	Y	N	N	Y
Health conditions	N	N	Y	N	N	Y
F-test (only excluded)	34.18			33.40		
R-Sq	0.746	0.087	0.091	0.755	0.090	0.069
Obs	651760	651760	651760	555999	555999	555999

Notes: Roadaccident is road traffic casualty rate per 10,000 prime age adult population (aged 18-35) in a province of interest. Individuals of interest for the primary school outcome are 6-15 years old in 1998 and 2008. For secondary school outcomes, they aged 12-20 in 1998 and 2008. *RoadNetworks* is the sum of distance (in 100 km) of major highways going through the neighbouring provinces in 1997 (*for control*) and 2007 (*for treated* cohorts). The datasets used are from Cambodia IPUMS 1998 and 2008. Robust standard errors are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. F-statistic tests whether the instruments are jointly significant.

TABLE 4.13: 2SLS landmine casualty rates at province level), the 1998 and 2008 census

	Primary School (age 6-15)			Secondary School (age 12-20)		
	Mine	Prob(Primary)		*Mine*	Prob(Secondary)	
First-stage						
NeighDangerland * *Male*	2.203**			2.126***		
	[0.024]			[0.026]		
Second-stage						
MineHat * *Male*		-0.087**	-0.033**		-0.096**	-0.13*
		[0.002]	[0.002]		[0.005]	[0.014]
Additional controls:						
Rice income	N	N	Y	N	N	Y
Poverty rate	N	N	Y	N	N	Y
Health conditions	N	N	Y	N	N	Y
F-test (only excluded)	20.65			20.50		
R-Sq	0.353	0.085	0.090	0.348	0.088	0.109
Obs	621066	621066	621066	518637	518637	518637

Notes: Each cell reports the coefficient from a separate regression. For the main regression, dependent variable is the probability of having at least a primary school education. In the first stage, the dependant variable is *Mine* * *Male* is a given period. *NeighDangerland* is averaged level of proportion of lands in neighbouring provinces that are not yet cleared by landmine operations per 1000 squared meters. *MineHat* is predicted landmine rate per 1,000 prime age adult population in a province of interest from the first stage. In the second stage, the dependent variable is probability of having a qualification of interests (primary school, secondary school). The datasets used are from Cambodia IPUMS 1998 and 2008. Robust standard errors clustered at age cohort are reported in square brackets with * significant at 10%; ** significant at 5%; *** significant at 1%. F-statistic tests whether the instruments are jointly significant.

TABLE 4.14: Landmine clearance and household wealth, using Cambodia DHS

	Household Wealth Index		Total Household Asset	
	(I)	(II)	(III)	(IV)
OLS repeated cross-section				
Clearance	-0.018		-0.046	
	[0.023]		[0.057]	
2SLS				
ClearanceHat		0.191		12.97
		[0.37]		[7.22]
R-Sq	0.3515	0.3475	0.3403	3343
Obs	41741	41741	41741	41741

Notes: The data used are CDHS 2000, 2005 and 2010. $Clearance_{L,Y}$ is 3-year average district-level landmine clearance area per total area in 1997-1999, 2001-2003, 2007-2009 for each corresponding Y. $ClearanceHat$ is the predicted clearance rate from the first stage where the instrument is $NeighbourClearance_{L,Y}$- the average rate of clearance of neighbouring provinces for the corresponding year. Robust standard errors clustered at province level are reported in square brackets * significant at 10%; ** significant at 5%; *** significant at 1%.

4.9.1   A Simple Theoretical Framework

I present a simple framework to illustrate the role of mortality risk on optimal children schooling. The framework is built upon standard human capital investment theories. I adopt a simple two-period static model of paternalistic parents (Ben-Porath, 1967; **?**; Acemoglu and Autor, 2009). For now, the model assumes a perfect capital market [29] and no uncertainty.

Let a unitary household consists of a parent and a young child. The parent works and earns Y_1. He consumes C_1 for both him and the child in Period 1. The parent will decide how much to invest in the child's schooling in this period. Let H_1 equals 1 when the parent decides to invest and zero otherwise. The total cost of schooling is θ_1, summing all official costs, for example school fee (F_1), and foregone costs. In the context of Cambodia, we can think of foregone costs is the child's earning from his labour market activities (W_C). At the end of Period 2, the parent dies and the child becomes a working adult. In this period, an educated adult earns W_E in the labour market whilst an uneducated adult receives W_U. In any case, she consumes C_2 in Period 2. The per-period utility take log-functions

Note that the unitary household discounts the future with the rate, ρ). To account for mortality risk, we add that the child faces a probability of not surviving to adulthood, m, at the end of Period 1 (Fortson, 2011). With a perfect capital market, the parent is able to borrow to invest, with the interest rate, r. The parent makes decision on the value of C_1, C_2 and H_1 so as to optimise the household lifetime utility given the budget constraint as the followings:

$$\max_{C_1, C_2, H_1} lnC_1 + exp(-(\rho + m))lnC_2 \tag{4.7}$$

subject to

$$C_1 + \frac{C_2}{1+r} = Y_1 - \theta_1 H_1 + \left[\frac{W_u}{1+r} + \frac{H_1(W_e - W_u)}{1+r}\right] \tag{4.8}$$

Under a perfect capital market, $1 + r$ is equivalent to $exp(-(\rho + m))$. The findings from the optimisation show that the parent will invest ($H_1 = 1$) only if $\theta_1 \leq ((W_e - W_u))/exp(-(\rho + m))$. This implies that a fall in mortality risk gives the parent more incentive to invest in the child's schooling. However, the effect gets more positive

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[29]Nevertheless, some borrowing constraints will be introduced later in order to reflect a more typical capital market in developing economies. With costs of schooling borne to the household become increasingly larger with a higher level of qualification, the role of financial constraints will become more determinant on the optimal level of household investments.

when the heterogeneous schooling premium $(W_e - W_u)$ gets larger or when the costs on schooling falls.

Given the context of Cambodia, the assumption on perfect capital market may be far from true. To account for that, I introduce a borrowing constraint in which inter-temporal budget transfer is no longer possible (Acemoglu and Autor, 2009). Hence, the budget constraint of Period 1 and of Period 2 becomes the follows respectively:

$$C_1 - S_1 + \theta_1 H_1 \leq Y_1 \tag{4.9}$$

$$C_2 \leq W_u + (W_e - W_u)H_1 + (1 + r)S_1 \tag{4.10}$$

The parent compares between (i) the lifetime utility when they decide to invest in schooling and (ii) the lifetime utility when they do not invest. Denotes β as $exp(-(\rho + m))$, under imperfect capital market, H_1 is equal to one only if net utility gain from investment is strictly greater than net gain from not investing. This is equivalent to Equation (4.11) and subsequently Equation (4.12) below:

$$ln(Y_1 - \theta_1) + \beta ln(W_e) \geq ln(Y_1) - ln(W_u) \tag{4.11}$$

$$Y_1 \left(1 - \left[\frac{ln(W_e)}{ln(W_u)} \right]^{exp(-(\rho + m))} \right) \geq ln(\theta_1) \tag{4.12}$$

The inequality in Equation (4.12) shows that the effect of mortality risk on human capital investment remains negative under a credit constraint assumption. Compare to the perfect capital setting, in order to induce parents to invest, the magnitude of gains from human capital investment when facing with limited borrowing ability is required to be much larger *ceteris paribus*. A unit increase in m will pose a stronger negative response on the optimal investment decision under an imperfect capital market setting. Likewise, household's decision is more sensitive to a rise in costs of schooling in this context.

4.9.2 Supplementary Figures

FIGURE 4.12: Definition of treated and control cohorts in the 1998 and 2008 census
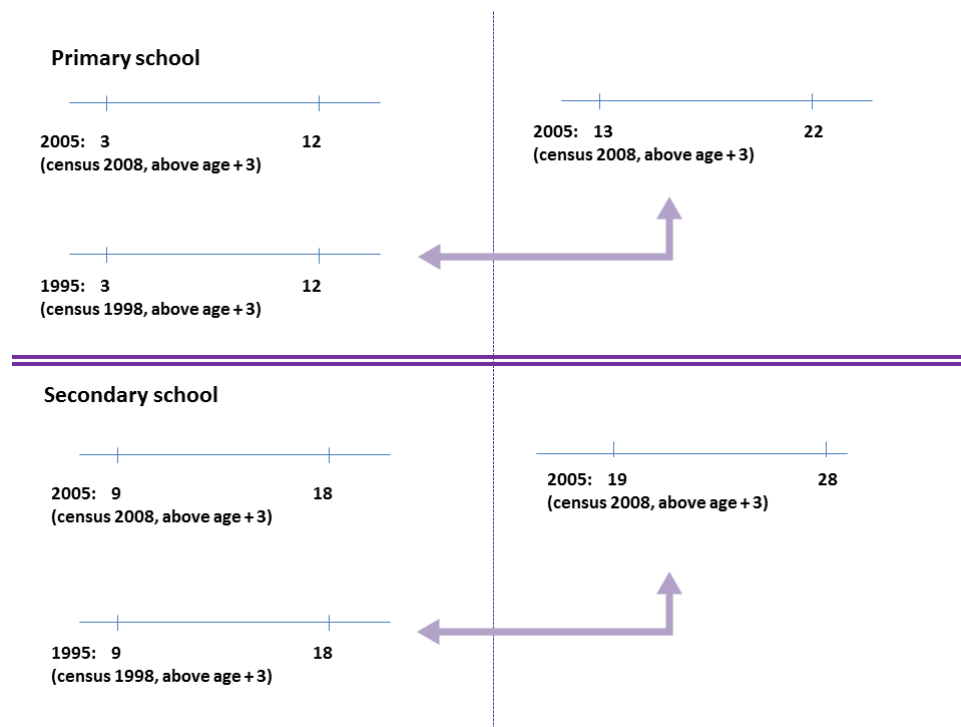
Note: For each panel (primary school and secondary school panel), the top left figure indicates the treated cohorts from the 2008 census. The bottom left in each separate panel shows the age of the controlled cohorts from the 1998 census. The top right figures in each panel is the cohorts in the 2008 census that are the equivalent birth cohorts to the controlled group in the 1998 census. In each figure, the horizontal line outlines the actual ages of the cohorts of interest in a given calendar year. To link them to a related census year, three years need to be added to a given age.

Chapter 5

Direct and Indirect Effects of Education on Life Satisfaction: A Lesson from Australia.

Abstract

Many economists and educators favour public support for education on the premise that education improves the overall quality of life of citizens. However, little is known about the different pathways through which education shapes people's satisfaction with life overall. One reason for this is because previous studies have traditionally analysed the effect of education on life satisfaction using single-equation models that ignore inter-relationships between different theoretical explanatory variables. In order to advance our understanding of how education may be related to overall quality of life, the current study estimates a structural equation model using nationally representative data for Australia to obtain the direct and indirect associations between education and life satisfaction through five different adult outcomes: income, employment, marriage, children, and health. Although we find the estimated direct (or net) effect of education on life satisfaction to be negative and statistically significant in Australia, the total indirect effect is positive, sizeable and statistically significant for both men and women. This implies that misleading conclusions regarding the influence of education on life satisfaction might be obtained if only single-equation models were used in the analysis.

5.1 Introduction

Many educators favour public support for education on the premise that education improves the overall quality of life of citizens. However, relatively little is known about the mechanisms and the relative impacts of these different mechanisms through which more education actually contributes to people's overall life satisfaction. Much of the research in this area typically reports only the estimated contemporaneous relationship between education and life satisfaction once income and other socio-economic variables are controlled for (Frey and Stutzer [2000]; Blanchflower and Oswald [2004]; Headey et al. [2008]; Powdthavee [2008]). Unfortunately, since income and other indicators of socio-economic status (e.g., employment and marital status) are themselves a function of education, simply running a single-equation model in which both education and other adult outcomes are entered on the right-hand side tells us little about the relative importance of the different pathways through which education can enhance (or even in some cases, reduce) overall life satisfaction.

While income is naturally viewed as the main mediating factor of education on a person's well-being (Diener et al. [1993]; Clark et al. [2008]; Powdthavee [2010c]), many scholars have argued that education plays a much more important role in influencing individual's life satisfaction through non-monetary channels than through its impact on one's financial status (Brighouse [2006]; Michalos [2008]). In a comprehensive review of the non-pecuniary benefits of education, Oreopoulos and Salvanes [2011] concluded that education was one of the most important predictors of one's health status, employability, and probability of being married, all well-known predictors of life satisfaction (Oswald [1997]; Layard [2011]; Layard et al. [2013]) [1]. In a more direct test of the indirect effects of education on happiness, Chen [2012] used data from four East Asian countries to show that the statistical association between education and happiness is mediated more by non-pecuniary factors, such as the strength of social networks and cosmopolitan experiences, than income. Empirical evidence in this area, however, remains scarce, and the extent of any indirect effects of education on life satisfaction remains imperfectly understood.

We aim to fill this research gap by testing whether findings on the overall effect of education on life satisfaction are sensitive to the choice of estimation strategy, and in particular the use of a structural equation model rather than the more conventional single-equation approach. We propose that, in order to better understand the different

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[1]They also acknowledged that more education might also bring along with it added stress and constraints on time, thus leading to the possibility that education could also have a negative impact on overall life satisfaction.

pathways through which education predicts people's overall quality of life, an empirical test has to have a number of special features. First, we must be able to estimate the amount of variation in the potential mediating factors (which, in our case, are contemporaneous adult outcomes measured at the same time as life satisfaction) explained by education. Second, we must also be able to simultaneously determine how these variations in the potential mediating factors explain life satisfaction.

Using longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, and covering the period 2001 to 2010, we estimate a structural equation model that allows us to simultaneously compare the relative indirect associations between education and life satisfaction through five different adult outcomes: income, employment, marriage, children, and health. In addition to this, we also want to be able to shed some lights on the following two questions. First, are the pathways through which education influences life satisfaction the same for men and women? Second, how stable are these estimated indirect effects over time?

By answering these questions we provide powerful, new and more comprehensive insights into how education can be associated with having a more satisfying life and what matters most in that process.

There is also another important reason for choosing the HILDA Survey for our analysis. Previous studies that have used this popular data set have often found education to be correlated negatively and statistically significantly with life satisfaction in regression equations where income, health, and other socio-economic variables are controlled for in a single-equation model (e.g., Shields et al. [2009]; Green [2011]; Allen and Van der Velden [2001],Ambrey and Fleming [2014]), which could potentially lead to a loose and largely incorrect interpretation of education being welfare reducing in Australia. Hence, one of our objectives is to test the hypothesis that the combined indirect effect of education on life satisfaction is positive, sizeable and statistically significant even though the direct (or net) effect is not [2].

The paper is structured as follows. Section 5.2 summarises previous relevant literature. Section 5.3 briefly discusses the data and the empirical strategy. Results are reported in Section 5.4. Section 5.5 discusses and concludes.

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[2]The negative correlation between education and life satisfaction has also often been found in studies that used the British Household Panel Survey (BHPS). For example, see Powdthavee (2008, 2010a).

5.2 Background

5.2.1 Previous research on the relationship between education and life satisfaction

Previous studies have used single-equation models to establish the link between education and measures of life satisfaction and have produced mixed results. Using highest education qualification dummies as control variables in cross-section regression equations, many scholars have found a positive and statistically significant association between education and self-rated life satisfaction across different international data sets and time periods (e.g. Blanchflower and Oswald, 2004; Easterlin, 2001; Ferrer-i Carbonell, 2005). Yet there have also been other studies that have documented either a negative or a statistically insignificant effect of education on the way people report their satisfaction with life overall (e.g. Melin et al., 2003; Flouri, 2004; Powdthavee, 2008; Shields et al., 2009).

One explanation for these mixed findings is that both direction and magnitude of the coefficient on education in a life satisfaction regression equation are often sensitive to the inclusion of other variables in the model (Dolan et al., 2008). For example, controlling for potential outcomes of education, such as income and health, in a life satisfaction regression equation will tend to produce a coefficient that underestimates the full contribution which education is making to life satisfaction.

While most researchers know this to be the case, little attempt has been made to decompose the overall effect of education on life satisfaction into direct and indirect effects and study them individually. Consequently, previous research tends to refrain from over-interpreting the coefficient on education in a life satisfaction regression equation, citing it only as a control variable that needs to be interpreted with caution given the presence of other endogenous variables in the model.

5.2.2 Accounting for the links between education and different adult outcomes

Previous research, especially by economists, has highlighted financial returns as one of the main benefits that people receive from investing in additional human capital (e.g. Angrist and Krueger, 1991; Harmon and Walker, 1995; Leigh and Ryan, 2008). Using data sets across countries and time periods, researchers have often reported the rate of financial return to education to be economically sizeable, statistically significant, and to have causal interpretations; for example, education allows individuals to become (or at

least, be *perceived* as) more efficient and productive in the labour market, leading them to earn more than their less educated counterparts (for a comprehensive review of this literature, see Psacharopoulos and Patrinos*, 2004).

However, many educational philosophers and researchers (e.g. Brighouse, 2006; Michalos, 2008) have argued that monetary gains are not the main benefit from education. Rather, it is the non-pecuniary gains, such as better health and stability in family life, where the real value of investment in human capital lies. These sentiments are reflected in recent empirical work in economics. According to a review by Oreopoulos and Salvanes (2011, p. 159):

"*In the traditional investment model, [education] itself is treated as a black box: individuals enter, something happens, and productivity (usually defined in terms of one-dimensional skill) increases. A look inside the box, however, reveals that [education] generates many experiences and affect multiple dimensions of skill that, in turn, may affect central aspects of individual's lives both in and outside the labour market.*"

What researchers in this area have found is that education affects not only individual income, but also enables individuals to make better decisions about health, marriage and family life. For example, studies have found individuals with more schooling to have, on average, better mental and physical health outcomes (Lleras-Muney, 2005; Powdthavee, 2010a). More educated individuals are also significantly less likely to be unemployed and when unemployed, do not remain unemployed for very long (Mincer, 1991; Kettunen, 1997).

Some researchers have also found that education not only makes individuals more attractive in the labour market, but also in other settings. Men and women with more earnings potential or with higher prestige jobs are typically seen as relatively more appealing in a competitive marriage market (Chiappori et al., 2009; Lafortune, 2013). There is also evidence of substantially lower divorce rates among those with more completed years of schooling of similar age and family background, thus suggesting that the critical thinking and social skills acquired from more education may also translate to more stable marriages (Oreopoulos and Salvanes, 2011).

With respect to the effect of education on people's decision to start a family, the existing empirical evidence mostly seems to suggest that education has a negative effect on women's fertility rate (Sander, 1992; Martin, 1995; Isen and Stevenson, 2010). One of the reasons for this could be that education increases the value of time in the labour market, thereby significantly raising the opportunity cost of child rearing for women (Becker and Becker, 2009) or simply reducing women's preferences for children (Easterling et al., 1987).

There are certainly many other non-pecuniary effects of education on life that could also be potentially welfare enhancing, including its effects on the extent of social networks, attitudes towards work and job satisfaction, and even the ability to trust other people (e.g. Oreopoulos and Salvanes, 2011), as well as potentially welfare reducing, including its effects on income aspirations, the tendency to migrate, and the average commuting time to and from work (e.g. McLafferty, 1997). Education can also be welfare reducing for the individuals in countries where, holding other things constant, there is widespread skill mismatch and/or over-education (Allen and Van der Velden, 2001; Chevalier, 2003). However, the current study will focus only on adult outcomes that are both objectively measured and have been found to have some influence on adult life satisfaction in previous research. These are: income, employment, marriage, the number of children, and health.

5.2.3 Accounting for the links between adult outcomes and life satisfaction

In a typical life satisfaction regression equation a standard set of control variables will include, among other things, income, employment status, marital status, the number of children, and the health status of the respondent (Layard, 2011; Powdthavee, 2010b).

Based on previous studies, income has generally been found to have a positive and statistically significant relationship with life satisfaction (Diener et al., 1993; Oswald, 1997; Clark et al., 2008; Powdthavee, 2010c). The association, however, is often depicted as small when compared with the effects of other potential mediating factors of education. For example, Blanchflower and Oswald, 2004 showed that it would take, on average, US$100,000 extra income per annum to compensate for a marital separation, and US$60,000 extra income per annum to compensate for unemployment.

These estimated compensation variations for marital separation and unemployment are also typically larger for men than for women, consistent with previous evidence that men usually have more to gain than women from marriage (perhaps through better lifestyle changes; Gardner and Oswald, 2004) and more to lose from joblessness (especially in terms of loss of self-esteem; Goldsmith et al. 1997). This broad pattern of comparatively large non-pecuniary effects of marriage and unemployment on life satisfaction holds across different data sets and analytical methods (e.g. Winkelmann and Winkelmann, 1998; Helliwell, 2003; Powdthavee, 2008).

Much of the evidence on the relationship between having children and life satisfaction suggests that parents are either less satisfied with life or report the same level of life satisfaction as non-parents (Di Tella et al., 2003; Shields et al., 2009; Clark et al., 2008;

Powdthavee, 2008). One likely explanation for this is the negative impact of children on financial satisfaction, which is a common finding across many different countries around the world (Stanca, 2012). There are, however, a few exceptions to this finding. For example, using data from the 1995-1997 round of the World Values Survey, Haller and Hadler, 2006 report a positive and statistically significant effect on life satisfaction after controlling for income and financial satisfaction. Their explanation is that children put demands on day-to-day positive emotions but nonetheless people still regard them as a positive contribution when providing a cognitive evaluation of well-being [3]. Other studies suggest that the relationship between children and life satisfaction may depend significantly upon broader cultural and social factors. For instance, it has been found that the presence of children has a stronger negative effect on subjective well-being in the UK and the US compared to Europe and Russia (Di Tella et al., 2003; Smith, 2003). The relationship may also depend on how the children variable is coded in the life satisfaction equation. A study by Shields et al. [2009], for example, finds that the negative relationship between children and life satisfaction is driven more by the children living at home and less by those living elsewhere.

Finally, health, both psychological and physical, has been found to represent one of the largest and most significant contributing factors to higher levels of life satisfaction in many data sets. While different specific health conditions, such as heart attacks and strokes, can have differential negative effects on evaluations of overall quality of life (Shields and Price, 2005; Powdthavee and Van den Berg, 2011), having a long-term incapacitating health problem or disability is generally found to be associated with relatively low levels of life satisfaction. Further, adaptation over time to the onset of such serious conditions has been found to be far from complete (Oswald and Powdthavee, 2008).

Based on the review above, different rates of return can be expected in the relationships between education and different adult outcomes, and between different adult outcomes and life satisfaction. The indirectly channelled educational benefits through each of the five adult outcomes may even vary significantly across genders and time periods. The overall direction and the magnitude for each of the indirect effects are, however, unclear on a priori grounds. For example, it is entirely possible that the marginal effect of education on the probability of being employed is higher for women than for men. Yet it is also possible that the marginal effect of employment on life satisfaction is higher for men than for women, thus making it difficult to predict whether the indirect effect of education on life satisfaction via employment will be larger for men or for women. Hence, it seems important to analyse these channels simultaneously and estimate the

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[3]For a discussion of the potential effects of children on day-to-day positive experiences, see White and Dolan, 2009.

relative importance of each of these pathways in order to make sense of how education really affects people's satisfaction with life overall.

5.3 Data and Empirical Strategy

5.3.1 Data

As already noted, the data used in this analysis come from the HILDA Survey, a longitudinal survey that has been tracking members of a nationally representative sample of Australian households since 2001. A total of 7,682 households participated in Wave 1, providing an initial sample of 19,914 persons (Wooden et al. 2002). The members of these participating households form the basis of the panel pursued in subsequent annual survey waves. Interviews are conducted with all adults (defined as persons aged 15 years or older) who are members of the original sample, as well as any other adults who, in later waves, are residing with an original sample member. Annual re-interview rates (the proportion of respondents from one wave who are successfully interviewed the next) are reasonably high, rising from 87% in wave 2 to over 96% by wave 9 (see Watson and Wooden, 2012).

Our main dependent variable comes from responses to a question about overall life satisfaction. The question reads: *"All things considered, how satisfied are you with your life? Again, pick a number between 0 and 10 to indicate how satisfied you are."* A visual aid is used in the administration of these questions, which involves a pictorial representation of the scale with the extreme points labelled "totally dissatisfied" and "totally satisfied".

The measure of education is a continuous variable representing the number of years spent in education, which is commonly used as a proxy of education in the field of labour economics (e.g. Oreopoulos and Salvanes, 2011). This "Years of education" variable is derived from respondents' highest educational attainment. Thus a respondent reporting having completed secondary school (Year 12) is assumed to have completed 12 years of education, a person completing an ordinary university degree is assumed to have completed 15 years of education, and so on. As is conventional, we are not measuring actual years spent in education (which would vary with the time with which qualifications are completed, the number of qualifications obtained, and time spent studying that did not lead to a qualification) but instead the time typically taken to obtain the highest qualification reported.

Turning to the other adult outcomes that are also potentially mediating factors of education on life satisfaction, we have income being represented by the log of real equivalised household income [4]. Employment is a binary variable representing whether the person was employed or not during the week preceding interview (0 = not employed; 1 = employed). Marriage is also a binary variable representing whether or not the person is currently married, where marriage is defined to include both registered and *de facto* unions (0 = not married; 1 = married). Number of children is the total number of children the respondent has, including children that no longer live at home. And health status is a binary variable identifying whether the respondent has no long-term health condition, disability or impairment (0 = has long-term health problems; 1 = has no long-term health problems).

Our control variables in all regression equations include gender, birth year, and regional (or state) dummies [5]. This permits comparisons of effects to be made within the same gender, same cohort, and same Australian state.

The analysis of indirect effects of education is restricted to individuals aged 20 to 64 who were not participating in full-time education in the year of the survey, participated in any of the first ten survey waves, and responded to the questions from which the life satisfaction and the five adult outcome variables (income, employment, marriage, children, and health) were constructed. The age range selected is when the majority of individuals would be in the labour market, under general circumstances. Pooling data across ten survey waves, this produces 73,504 observations; 34,662 males and 38,842 females. Table 5.1 presents the mean unadjusted scores on life satisfaction and other adult outcomes. However, to aid the interpretation of our results we standardize all variables in the regression equation to have a mean of zero and a standard deviation of one.

5.3.2 Empirical strategy

We adopt the multiple mediation analysis method (Baron and Kenny, 1986; Hayes, 2009) to study the indirect effects of education on life satisfaction through the five different channels of income, employment, marriage, children, and health (see Figure 5.1). A standard structural equations model (SEM) is estimated, thereby allowing a non-zero correlation between the residuals of the equations for each dependent variable. Note that failure to allow for the interdependence across equations could be benign or it

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[4]Equivalised real annual household income is calculated using the following formula: $\frac{real\,annual\,household\,income}{(1 + 0.5 * (adult\,members - 1) + 0.3 * (children\,under\,15))}$.

[5]Note that the broad results are unaffected without controlling for these variables.

could confound the correlation of residuals with the effects of the independent variables (Greene, 2003).

The model is:

$$LS_{it} = \alpha_0 + \sum_{s=1}^{5} \beta_s X_{sit} + \gamma_0 EDUC_{it} + Z'_{it}\theta_0 + \mu_{0i} + u_{0it} \qquad (5.1)$$

$$X_{1it} = \alpha_1 + \gamma_1 EDUC_{it} + Z'_{it}\theta_1 + \mu_{1i} + u_{1it}$$

$$.$$

$$.$$

$$X_{5it} = \alpha_5 + \gamma_5 EDUC_{it} + Z'_{it}\theta_5 + \mu_{5i} + u_{5it}$$

where LS_{it} denotes standardized life satisfaction, with a mean of zero and a standard deviation of 1, of individual i at time t; X_{sit} represents the standardized adult outcome s, where $1 =$ log of real equivalised household income, $2 =$ in employment, $3 =$ married, $4 =$ number of children, and $5 =$ no long-term health problems; is standardized years of education; represents a vector of control variables; μ_{si} represents the unobserved individual-specific effect; and u_{sit} denotes the error term in each equation. The SEM equation was estimated with robust standard errors, which also allowed for clustering at the individual level. Assuming that the adult variables and the education variable are not correlated with μ_{si} and u_{sit}, unbiased estimates of β and γ_s can be obtained from running the SEM model on the pooled sample.

Based on the equations above, the indirect effect of $EDUC_{it}$ on LS_{it} through X_{sit} for each s is given by $\beta_s\gamma_s$. Following Hayes (2009), bootstrapping (with 200 replications) is used to estimate the standard errors for all of the estimated indirect effects [6].

One objection to the naïve estimation of Eq.5.1 is that both education and other adult outcomes are likely to be correlated with the unobserved individual-specific component, μ_{si}. This includes, for example, personality traits and/or ability. It is well known that if researchers fail to appropriately controlling for these important heterogeneous factors, then ordinary least squares (OLS) can produce biased estimates (Ferrer-i Carbonell and Frijters, 2004).

A typical approach to correct for the unobserved heterogeneity bias is to exploit panel data and estimate a fixed effects (FE) model on the pooled sample. The FE model works by focusing solely on the within-person variation in the data set and thus eliminating any

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[6]The model is estimated using the SEM command in STATA 13.

variables that do not have any within-person information from the estimation process. Consequently, it is not possible to obtain any reliable estimates on characteristics that have zero or little within-person variation, such as gender or education, using the typical FE estimator (Plümper and Troeger, 2007).

Hence, the second part of our empirical analysis applies the empirical strategy outlined in Boyce [2010] and estimates Plümper and Troeger [2007]'s fixed effects vector decomposition (FEVD) model with personality traits as additional determinants of individual fixed effects in an SEM setting. More formally, the FEVD method allows researchers to estimate a FE model without the loss of information on variables that have zero or little within-person variation via the three following steps. The first step involves estimating a conventional FE model of LS_{it} with no other covariates and obtaining the estimate of the FE residual ($\hat{\mu}_{i,t}$) from the model. In principal, this FE residual includes all observable and unobservable between-person information. From Equation 1, we can represent $\hat{\mu}_{i,t}$ as

$$\hat{\mu}_{0i} = \bar{LS}_i - \sum_{s=1}^{5} \pi_s \bar{X}_{si} - \pi E\bar{DUC}_i \bar{Z}'_i \tau - \bar{u}_{0i} \tag{5.2}$$

where $\bar{LS}_i$ is a within-person average of LS_{it} , $\bar{X}_{si}$ is a within-person average of X_{ist}, $E\bar{DU}_i$ is a within-person average of EDU_{it} and $\bar{X}_i$ is a within-person average of Z_{it} , from each wave, t.

The second step of the FEVD involves decomposing the fixed residual into a part that is observable and a part that is not. The inclusion of personality variables, P_i at this stage then helps to reduce the size of the unobservable component of the FE residual, which will effectively reduce the correlation between any covariates with potentially low within-person variation and the true unobservable component, thus allowing many slow moving variables to be favourably estimated using the FEVD model (Boyce, 2010). The decomposition can then take place using observable characteristics and a set of personality traits in a pooled OLS setting to predict the FE residual obtained from Eq.5.2.

$$\hat{\mu}_{0i} = \sum_{s=1}^{5} \sigma_s X_{sit} + \vartheta EDUC_{it} + Z'_{it}\varphi + P'_i\zeta + \eta_{0i} \tag{5.3}$$

where the vector of personality variables, P_i, are taken from measures of Big-5 personality traits from Wave 5 in the survey. This model therefore leaves the true unobservable component of $\hat{\mu}_{0i}$ captured in the predicted error term of Equation 5.3 and denoted here as $\hat{\eta}_{0i}$

The third and last stage involves using $\hat{\eta}_{0i}$ as an explanatory variable in a pooled OLS regression:

$$LS_{it} = \alpha_0 + \sum_{s=1}^{5} \beta_s X_{sit} + \gamma_0 EDUC_{it} + Z'_{it}\theta_0 + \omega_0\hat{\eta}_{0i} + u_{0it} \tag{5.4}$$

Although education may be correlated with μ_{0i}, it is not correlated with $\hat{\eta}_{0i}$. Therefore, by including $\hat{\eta}_{0i}$, we can obtain reliable estimates on both zero within-person variation covariates, such as gender, and very slow moving variables, such as education (as well as other time-varying variables, such as income and employment). The same steps are then repeated for other equations in the SEM model. Hence, the FEVD version of Equation 5.1 is

$$LS_{it} = \alpha_0 + \sum_{s=1}^{5} \beta_s X_{sit} + \gamma_0 EDUC_{it} + Z'_{it}\theta_0 + \omega_0\hat{\eta}_{0i} + u_{0it} \tag{5.5}$$

$$X_{1it} = \alpha_1 + \gamma_1 EDUC_{it} + Z'_{it}\theta_1 + \omega_1\hat{\eta}_{1i} + u_{1it}$$

$$.$$

$$.$$

$$X_{5it} = \alpha_5 + \gamma_5 EDUC_{it} + Z'_{it}\theta_5 + \omega_5\hat{\eta}_{5i} + u_{5it}$$

5.4 Results

5.4.1 Direct and indirect associations between education and life satisfaction

Table 5.2 first reports single-equation model of life satisfaction with education and other variables appearing on the right-hand side. Here, we include as control variables gender, age, age-squared, state of residence dummies, and wave dummies.

Looking at the estimates taken from the full sample(males and females combined), we can see that years of education is negatively and statistically significantly correlated with life satisfaction (column 1). The coefficients on the other variables of interest are all positive, with the largest coefficient coming from being married; a one standard deviation (sd. hereafter) increase in the marriage variable is associated with a 0.173 sd. increase in life satisfaction. This is followed, in order of size of association, by health (the absence of long-term health problems), household income, employment, and

the total number of children (the coefficient for which is insignificant and close to zero in magnitude). Note that the negative and statistically significant coefficient on years of education is consistent with previous studies employing HILDA Survey data (e.g. Shields et al., 2009).

Splitting the sample into male and female sub-samples, we can see that, consistent with previous studies, men generally derive more satisfaction from being employed and from being married than women. Women, on the other hand, report a slightly higher level of life satisfaction from the same increase in log of real equivalised household income than men. In addition, having no long-term health problems is associated with more satisfaction for women than for men. Further, the total number of children is positively associated with life satisfaction for women but negatively associated with life satisfaction for men, although both correlations are not statistically significantly different from zero. More importantly, years of education enter both gender-specific life satisfaction equations in a negative and statistically significant manner.

Table 5.3 moves on to present the estimates obtained from running the SEM model specified in the previous section. We begin by observing that the first panel of Table 5.3 (i.e., Equation 5.1) is an exact replication of Table 5.2's single-equation estimates. With respect to Equation 5.1 (or equations in which variations in different adult outcomes are explained by education), an increase in years of education is associated positively and statistically significantly with income, the likelihood of being employed, and the likelihood of having no long-term health problems in the combined samples. By contrast, there is strong evidence to suggest that more educated Australian adults tend to have fewer children on average. Moreover, there is evidence that more years of education is associated with a higher probability of being married in the combined sample. The largest positive contribution from an increase of one standard deviation in the years spent in education is in the income domain, then employment, health, and the probability of being married.

When splitting the sample by gender, we can see that a one standard deviation increase in education is associated with a greater increase in the likelihood of being employed for women than for men. In contrast, education is found to be a good predictor of the probability of being married for men but not women. Men also typically enjoy a slightly higher rate of return to education when it comes to health. On the other hand, there is very little gender difference in the effect of education on the log of real equivalised household income. Finally, the previously observed negative association between standardized years of education and standardized total number of children is negative and statistically significant for both men and women, although the estimated coefficient size is larger for women than for men.

By combining all of the above estimates together we are able to estimate and report each of the indirect effect of years of education on life satisfaction. These indirect effects are reported in Table 5.4.

Looking across columns, we can see that all but one of the estimated indirect effects are positive and statistically significant. Only the indirect associations between education and life satisfaction via income (0.021), employment (0.006), marriage (0.013), and health (0.014) are statistically well determined at conventional statistical levels in the combined sample.

Interesting results emerge when we compare these indirect relationships between men and women. For men, the largest indirect association between education and life satisfaction is through income (0.018). For women, the largest indirect association between education and life satisfaction is also through income (0.022). Further, while men seem to have enjoyed the indirect benefit of education through its positive effect on the probability of being employed, the same cannot be said for women. Indeed, the indirect effect of education through being employed is insignificantly different from zero for women.

A closer look at the estimates in Table 5.4 also suggests a noticeable gap in the size of the total indirect effects between men and women (total indirect relationship for men = 0.058; total indirect relationship for women = 0.036).

As explained earlier, to deal with potential heterogeneity bias, we adopt Boyce's (2010) FEVD model and use it in the SEM setting. On the assumption that personality is mostly stable across ten waves, we used the personality traits variables collected in wave 5 of the HILDA Survey (measuring the Big Five personality traits of extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience) to assist us in the second step of the FEVD estimation [7]. The estimates obtained from this second stage are reported in Table 5.8 in the Appendix. Consistent with Boyce, 2010, we find that personality explains a great deal of the individual heterogeneity in life satisfaction (as well as in other outcomes). Interestingly, it is worth noting that, other things held constant, the years of education variable is not strongly correlated with the FE residual obtained from the life satisfaction equation. This implies that, given a specification that includes other individual characteristics and personality variables, education is unlikely to have suffered from unobserved heterogeneity bias in a pooled OLS estimation.

We report the third stage FEVD estimates in the SEM setting in Table 5.5 and the implied indirect effects in Table 5.6. Inclusion of the estimated η_{si} in each SEM equation

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[7]Qualitatively the same results can be obtained using the personality data collected in Wave 9 (or the averages from both waves) in the second stage of FEVD.

has very little impact on the size of the estimated coefficients and the relative trade-offs between coefficients in the same equation. For example, in Table 5.5 (Equation 5.1), the coefficient on education is only slightly more negative than the coefficient reported in Table 5.3; -0.034 compared to -0.028. Although part of these differences in the SEM estimates is attributed to the smaller sample used in the FEVD estimation (not everyone who appeared in Wave 1 to Wave 10 was surveyed in Wave 5), it is reassuring to see in Table 5.6 that qualitatively similar indirect effects can still be obtained with or without the use of FEVD method. For instance, the total indirect effects of education on life satisfaction in the combined sample with and without the use of FEVD are 0.049 and 0.048, respectively. The only clear difference is that for men, the total indirect effects with the use of FEVD are higher (0.049, in compare to 0.58) In contrast, the use of FEVD for the female sample gives 0.048 versus the value of 0.036 when used only simple SEM (without fixed effect)

Finally, as a robustness check, we tested whether our results were sensitive to the specification of the education variable, replacing years of education with a dummy variable representing whether the individual had completed at least a university degree. The estimated indirect effects on life satisfaction from this alternative specification are reported in Table 5.7. As can be seen, it makes virtually no difference to our results whether one uses years of education or a *Graduates versus non-graduates* dummy as a proxy of education. For example, a large part of the positive indirect effect of education on life satisfaction still comes from the higher levels of incomes being earned among the graduates compared to the non-graduates.

5.4.2 Time-profiles of the indirect effects by gender

To obtain a complete picture of the direct and indirect associations between education and life satisfaction, we next explore the time-profiles of these estimated coefficients, using data for each year over the period 2001 to 2010. This involves re-estimation of the SEM equations with FEVD presented in Table 5.5 and 5.6 for each of the ten survey waves used here. A graphical summary of the results is presented in Figure 5.2.

What we learn from looking at these figures can be summarised as follows: First, not all positive indirect associations are positive in all years, and vice versa for the negative indirect associations. By controlling for other adult outcomes, the negative direct association between education and life satisfaction has been declining over time (Figure 5.2). We are not certain why this is, given that we cannot directly explain the direct effect. It could have simply been caused by the time effect, cohort effect, or changes in the unobserved relationship between education and life satisfaction. Third, the indirect

association between education and life satisfaction through employment is U-shaped for women. Also, there is an increasing trend in the indirect effect of education through marriage for both men and women over time. Lastly, there appears to be relatively little difference in the estimated indirect effects between men and women, and this mostly does not change over time.

5.5   Discussions and Conclusions

According to the traditional human capital model, people invest in education in hopes of greater lifetime wealth and consumption. While evidence of a significant financial return to schooling is well documented in the education literature, we still know very little about how this effect might contribute to individual evaluations of overall quality of life.

In this paper, we empirically demonstrate that, for adults living in Australia between 2001 and 2010, education is likely to be positively related to overall life satisfaction through many different channels even when *ceteris paribus* education itself has a negative and statistically significant relationship with overall life satisfaction. For both men and women, the largest estimated indirect effect of education on life satisfaction is through income. This is followed by its positive effect on long-term health. On average, men tend to benefit slightly more than women from education, in part because education is more strongly associated with a greater likelihood of employment for men. There is no statistically important indirect benefit (or cost) from what education does to either men's or women's decision over the number of children to have on life satisfaction.

Why are these results important? First, if an aim of educational policy is to maximize well-being, the pre-requisite is a model that captures in a quantitative way the relative impact of all the main influences of education on subsequent well-being. Separate studies of the effect of education on life satisfaction with different choices of control variables are of little use in helping us understand how education operates in a well-being function. These indirect effects need to be estimated together and then compared. Second, our results provide important information for people who have been thinking about whether or not to invest in more education if their ultimate goal is not in a particular area but to have a satisfied life as a whole.

The analyses presented here are, of course, not without limitations. In this work, we assume that for the findings to be interpreted as causal, there is no correlation between each and every error term with our variables of interest. It is clear to see this is a very strong assumption imposed on the model. Ideally what we would like to present

is a fully causal model of education on life satisfaction. The ability to overcome the issue of unobserved heterogeneity is simply not enough. It requires running controlled experiments on a grand scale, not only on education, but also on every other aspect of a person's life. This is both expensive and requires long time horizons. Future research will have to return to address the issues of causality related to these estimated direct and indirect effects [8]. Further, the conventional issue of sampling attrition in panel structure is another point of concern. The size of the estimated association between each outcome and education will be over-estimated if the sample is positively selected (that is, for example only highly educated or healthy individuals or good emotional-health stay on in later waves of the survey).

Another potential shortcoming is in the model's assumption of how different mechanisms work. Here, we assume that there are only two distinct channels through which education can separately influence life satisfaction: (i) the financial channel, and (ii) the non-financial channel. Yet in reality, the two channels are likely to be interwoven. For example, there is a large literature in economics showing income to be a strong predictor of health and mortality, holding education constant (e.g. Gardner and Oswald, 2004). Given the complex relationships between financial and non-financial pathways of education, a multilevel mediation analysis, which is beyond the scope of this paper, might be more suitable for analysing the direct and indirect effects of education on life satisfaction. Finally, it might also be worthwhile for future researchers to test whether these direct and indirect effects of education on life satisfaction can be found in data from countries other than Australia.

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[8] In the previous version of this paper, we attempted to instrument for years of education by using the change of the schooling leaving age laws in Australian as well as using windfall income to instrument for the income measure. However, without being able to find exogenous variables for other key adult outcomes, we decide that the study will benefit more from a more tractable but simpler modelling. Our use of the FEDV method enables our analysis to account for some time-invariant confounders but the problem of omitted variable bias yet persist.

Tables

TABLE 5.1: Descriptive statistics, HILDA 2001 and 2010

	All	**Men**	**Women**
Life satisfaction	7.82	7.76	7.87
	(1.46)	(1.46)	(1.47)
Years of education	12.45	12.45	12.40
	(2.32)	(2.24)	(2.39)
Log of real HH income per capita	10.19	10.23	10.15
	(0.68)	(0.67)	(0.69)
Employment	0.71	0.71	.70504
	(0.45)	(0.45)	(0.45)
Married	1.67	1.56	1.76
	(1.43)	(1.44)	(1.43)
Number of children	0.77	0.85	0.70
	(.42)	(.35)	(.45)
No long-term health problems	0.80	0.80	0.80
	(.39)	(.39)	(.39)
Female	0.53		
	(.49)		
Age	41.23	41.24	41.22
	(12.07)	(12.09)	(12.04)
N	73,504	34,662	38,842

Notes: Standard deviations are in brackets. All figures are unadjusted (i.e. not standardized).

TABLE 5.2: Single-equation model of the relationship between education and life satisfaction, HILDA Survey 2001-2010

Dependent variable: Life satisfaction	All	Men	Women
Years of education	-0.029***	-0.026**	-0.027***
	[0.008]	[0.011]	[0.010]
Log of real equivalised household income	0.065***	0.056***	0.069***
	[0.007]	[0.010]	[0.009]
Employed	0.029***	0.095***	0.001
	[0.007]	[0.014]	[0.008]
Married	0.173***	0.172***	0.170***
	[0.008]	[0.012]	[0.010]
Total number of children	0	-0.02	0.011
	[0.009]	[0.014]	[0.013]
No long-term health problems	0.134***	0.099***	0.156***
	[0.007]	[0.010]	[0.009]
Female	0.102***		
	[0.015]		
Age	-0.068***	-0.079***	-0.059***
	[0.004]	[0.006]	[0.006]
Age-squared	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]
N	73,076	34,434	38,642

Notes: ***¡1%; **¡5%; *¡10%. Robust standard errors are in parentheses. All regressions controlled for gender, age and age-squared, state of residence dummies, and wave dummies. All regressions also allow for clustering at individual level. All variables are standardized with a mean of zero and a standard deviation of one.

TABLE 5.3: Structural equation modelling of the indirect effects of years of education on life satisfaction, HILDA Survey 2001-2010

	All	Men	Women
Eq. 1: Life satisfaction			
Years of education	-0.029***	-0.026**	-0.027***
	[0.007]	[0.010]	[0.010]
Log of real equivalised household income	0.065***	0.056***	0.069***
	[0.007]	[0.010]	[0.009]
Employed	0.029***	0.095***	0.001
	[0.007]	[0.014]	[0.008]
Married	0.173***	0.172***	0.170***
	[0.008]	[0.012]	[0.010]
Total number of children	0.00	-0.02	0.011
	[0.009]	[0.014]	[0.013]
No long-term health problems	0.134***	0.099***	0.156***
	[0.007]	[0.01]	[0.009]
Eq. 2: Log of real equivalised household income			
Years of education	0.321***	0.325***	0.32***
	[0.008]	[0.011]	[0.010]
Eq. 3: Employed			
Years of education	0.199***	0.141***	0.25***
	[0.007]	[0.010]	[0.011]
Eq. 4: Married			
Years of education	0.043***	0.078***	0.006
	[0.007]	[0.010]	[0.013]
Eq. 5: Total number of children			
Years of education	-0.131***	-0.047***	-0.205***
	[0.009]	[0.013]	[0.012]
Eq.6: No long-term health problems			
Years of education	0.105***	0.123***	0.096***
	[0.007]	[0.011]	[0.010]
Observations	73,076	34,434	38,642

Notes: ***¡1%; **¡5%; *¡10%. Robust standard errors are in parentheses. All regressions controlled for gender, age and age-squared, state of residence dummies, and wave dummies. All regressions also allowed for clustering at individual level. All variables are standardized with a mean of zero and a standard deviation of one.

TABLE 5.4: Implied indirect associations between years of education and life satisfaction, HILDA Survey 2001-2010

	All	**Men**	**Women**
Indirect effects			
Log of real equivalised household income	0.021***	0.018***	0.022***
	[0.002]	[0.002]	[0.002]
Employed	0.006***	0.013***	0.001
	[0.001]	[0.001]	[0.001]
Married	0.007***	0.013***	0.001
	[0.001]	[0.001]	[0.001]
Total number of children	0	0.001**	-0.002*
	[0.001]	[0.000]	[0.001]
No long-term health problems	0.014***	0.012***	0.015***
	[0.001]	[0.001]	[0.001]
Total indirect effects	**0.048*****	**0.058*****	**0.036*****
	[0.002]	**[0.002]**	**[0.002]**

Notes: ***¡1%; **¡5%; *¡10%. Bootstrap standard errors (200 replications) are in parentheses. The t-statistics are based on the test that the two coefficients between males and females within the same year are equal. All variables are standardized with a mean of zero and a standard deviation of one.

TABLE 5.5: Structural equation modeling with the application of the fixed effects vector decomposition method, HILDA Survey 2001-2010

	All	**Men**	**Women**
Eq.1: Life satisfaction			
Years of education	-0.034***	-0.037***	-0.031***
	[0.003]	[0.005]	[0.004]
Log of real equivalised household income	0.072***	0.068***	0.076***
	[0.004]	[0.005]	[0.005]
Employed	0.020***	0.031***	0.015***
	[0.004]	[0.007]	[0.005]
Married	0.172***	0.175***	0.169***
	[0.004]	[0.005]	[0.005]
Total number of children	-0.002	-0.005	0.001
	[0.004]	[0.005]	[0.005]
No long-term health problems	0.131***	0.127***	0.134***
	[0.003]	[0.005]	[0.005]
Fixed effect residual (life satisfaction)	0.984***	0.990***	0.978***
	[0.005]	[0.007]	[0.006]
Eq.2: Log of real equivalised household income			
Years of education	0.32***	0.317***	0.322***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (income)	0.994***	0.992***	0.996***
	[0.002]	[0.003]	[0.003]
Eq.3: Employed			
Years of education	0.194***	0.193***	0.195***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (employed)	0.993***	0.988***	0.995***
	[0.002]	[0.003]	[0.002]

Table 5.5 cont.

	All	Men	Women
Eq.4: Married			
Years of education	0.043***	0.043***	0.043***
	[0.002]	[0.002]	[0.002]
Fixed effect residual (married)	0.996***	0.992***	0.999***
	[0.002]	[0.003]	[0.002]
Eq.5: Total number of children			
Years of education	-0.126***	-0.125***	-0.128***
	[0.001]	[0.001]	[0.001]
Fixed effect residual (children)	0.994***	0.995***	0.992***
	[0.001]	[0.001]	[0.001]
Eq.6: No long-term health problems			
Years of education	0.102***	0.102***	0.101***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (health)	0.999***	0.995***	1.001***
	[0.002]	[0.003]	[0.003]
Observations	57,871	26,821	31,050

Notes: ***¡1%; **¡5%; *¡10%. Robust standard errors are in parentheses. All regressions controlled for gender, age and age-squared, state of residence dummies, and wave dummies. All regressions also allowed for clustering at individual level. All variables are standardized with a mean of zero and a standard deviation of one.

TABLE 5.6: Implied indirect associations between years of education and life satisfaction obtained from Table 5's FEVD estimates, HILDA Survey 2001-2010

	All	**Men**	**Women**
Indirect effects			
Log of real equivalised household income	0.023***	0.022***	0.024***
	[0.001]	[0.002]	[0.002]
Employed	0.004***	0.006***	0.003***
	[0.001]	[0.001]	[0.001]
Married	0.007***	0.007***	0.007***
	[0.000]	[0.000]	[0.001]
Total number of children	0	0.001	0
	[0.0004]	[0.001]	[0.001]
No long-term health problems	0.013***	0.013***	0.013***
	[0.000]	[0.001]	[0.001]
Total indirect effects	**0.048*****	**0.049*****	**0.048*****
	[0.001]	**[0.002]**	**[0.002]**

Notes: ***¡1%; **¡5%; *¡10%. Bootstrap standard errors (200 replications) are in parentheses. The t-statistics are based on the test that the two coefficients between males and females within the same year are equal. All variables are standardized with a mean of zero and a standard deviation of one.

TABLE 5.7: Implied indirect associations between completing at least a university degree and life satisfaction, HILDA Survey 2001-2010

	All	**Men**	**Women**
Indirect effects			
Log of real equivalised household income	0.018***	0.016***	0.019***
	[0.001]	[0.001]	[0.001]
Employed	0.002***	0.004***	0.002***
	[0.000]	[0.001]	[0.001]
Married	0.006***	0.006***	0.006***
	[0.000]	[0.001]	[0.001]
Total number of children	0	0	0
	[0.000]	[0.001]	[0.001]
No long-term health problems	0.009***	0.008***	0.009***
	[0.000]	[0.001]	[0.001]
Total indirect effects	**0.035***	**0.035***	**0.035***
	[0.001]	**[0.002]**	**0.001**

Notes: ***¡1%; **¡5%; *¡10%. Bootstrap standard errors (200 replications) are in parentheses. The t-statistics are based on the test that the two coefficients between males and females within the same year are equal. All variables are standardized with a mean of zero and a standard deviation of one.

Figures

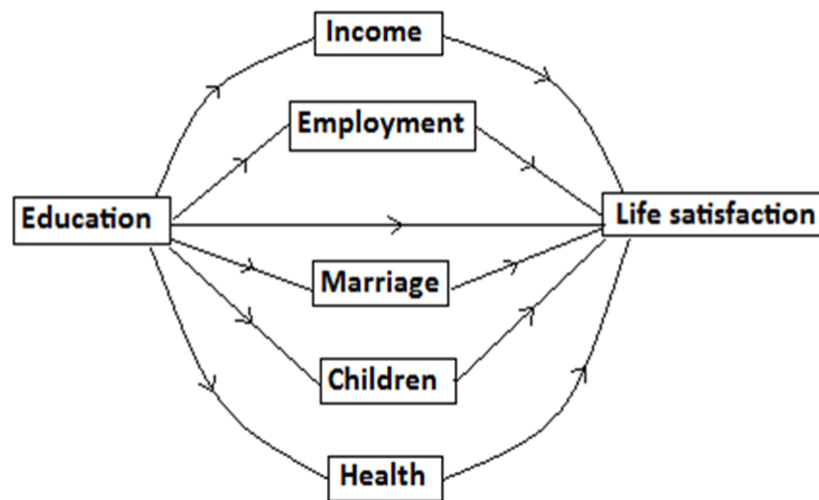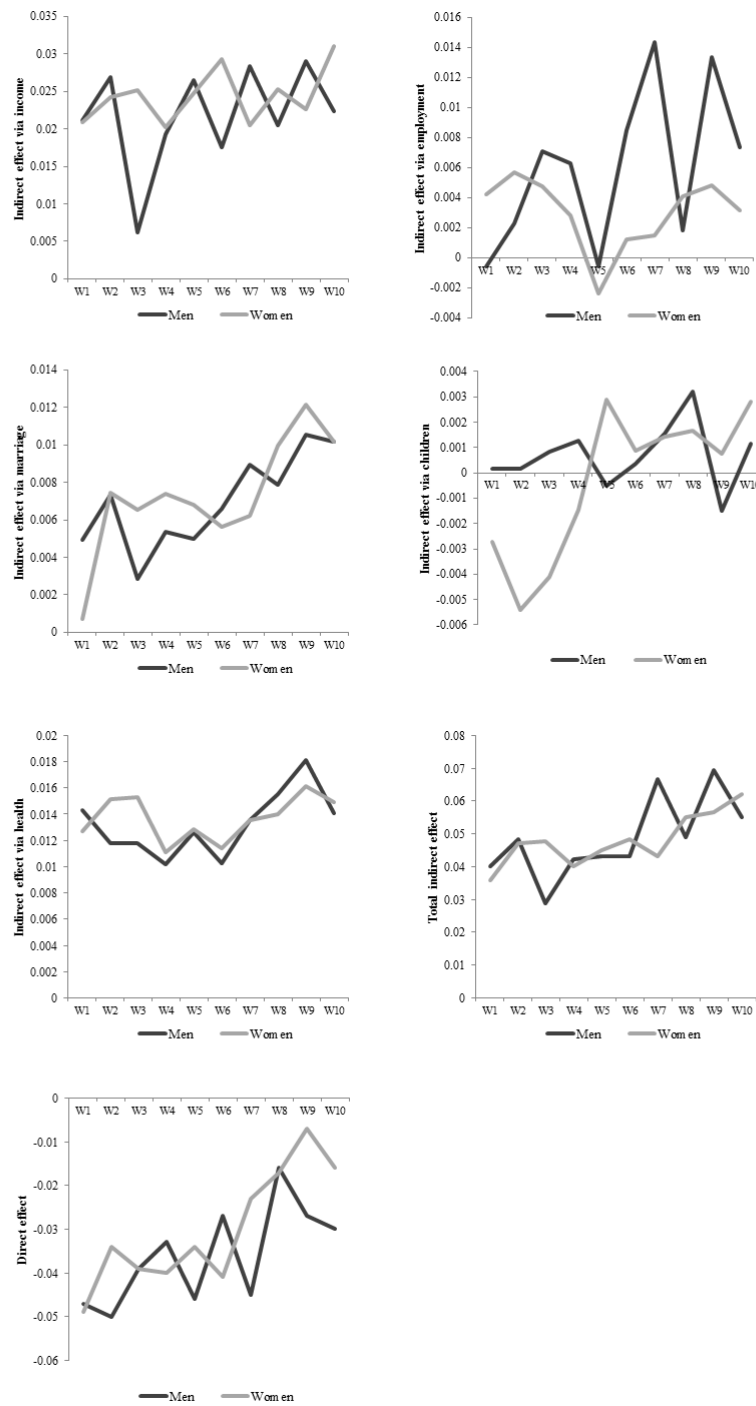FIGURE 5.1: A multiple mediation model of education on life satisfaction

FIGURE 5.2: Time profiles of the estimated implied indirect effects of a one standard deviation increase in the standardized years of education on standardized life satisfaction

5.6 Appendix

TABLE 5.8: Predicting the fixed effect residuals using various objective characteristics and personality variables

	Fixed effect residual obtained for each dependent variable					
	Life Satisfaction	Log(Real HH Income)	Employment	Married	No. Children	No LT health
Years of education	-0.031***	0.326***	0.201***	0.064***	-0.110***	0.112***
	[0.009]	[0.009]	[0.009]	[0.011]	[0.011]	[0.009]
Log of real equivalised household income	0.055***					
	[0.007]					
Employed	0.003					
	[0.008]					
Married	0.134***					
	[0.008]					
Total number of children	0.003					
	[0.010]					
No long-term health problems	0.103***					
	[0.007]					
Other control variables (non-standardized)						
Female	-0.004	-0.133***	-0.397***	-0.066***	0.118***	-0.012
	[0.017]	[0.018]	[0.018]	[0.022]	[0.022]	[0.018]
Age	-0.049***	0.011**	0.068***	0.080***	0.127***	0.007
	[0.005]	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]
Age-squared	0.001***	-0.000**	-0.001***	-0.001***	-0.001***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table 5.8 continued.

	Life Satisfaction	Log(Real HH Income)	Employment	Married	No. Children	No LT health
Personality measures from W5 (non-standardized)						
Extraversion	0.062***	0.042***	0.039***	0.039***	0.034***	0.023***
	[0.008]	[0.008]	[0.008]	[0.010]	[0.010]	[0.008]
Agreeableness	0.105***	-0.019*	0.006	-0.01	0.011	-0.016
	[0.011]	[0.011]	[0.011]	[0.014]	[0.013]	[0.011]
Conscientiousness	0.061***	0.067***	0.043***	0.065***	-0.012	0.051***
	[0.009]	[0.009]	[0.009]	[0.011]	[0.011]	[0.009]
Emotional stability	0.125***	0.008	0.009	-0.023**	-0.014	0.030***
	[0.009]	[0.009]	[0.009]	[0.011]	[0.011]	[0.009]
Openness	-0.058***	-0.051***	-0.054***	-0.092***	-0.046***	-0.071***
	[0.009]	[0.009]	[0.010]	[0.011]	[0.011]	[0.010]
Observations	57,589	57,627	57,871	57,859	57,871	57,844
R-squared	0.194	0.207	0.2	0.052	0.228	0.113

Notes: ***¡1%; **¡5%; *¡10%. Robust standard errors are in parentheses. All regressions controlled for state of residence dummies and wave dummies, and allowed for clustering at individual level. All variables are standardized with a mean of zero and a standard deviation of one. Personality traits come from Wave 5 in the HILDA Survey and assumed to be mostly stable across all ten waves. Log(Real HH Income) is log of real annual household equivalised income; employment =1 if an individual is employed; married = 1 if an individual is married; no LT health equals to one if an individual has no long term health problem.

TABLE 5.9: Structural equation modeling with the application of the fixed effects vector decomposition method and completing at least a university as a proxy for education, HILDA Survey 2001-2010

	All	**Men**	**Women**
Equation 1: Life satisfaction			
Completed at least a university degree	-0.021***	-0.022***	-0.019***
	[0.003]	[0.004]	[0.004]
Log of real equivalised household income	0.068***	0.063***	0.072***
	[0.003]	[0.005]	[0.005]
Employed	0.018***	0.028***	0.013***
	[0.004]	[0.007]	[0.005]
Married	0.172***	0.175***	0.169***
	[0.004]	[0.005]	[0.004]
Total number of children	0.001	-0.003	0.002
	[0.004]	[0.005]	[0.005]
No long-term health problems	0.13***	0.127***	0.132***
	[0.003]	[0.005]	[0.005]
Fixed effect residual (life satisfaction)	0.984***	0.990***	0.979***
	[0.005]	[0.007]	[0.006]

Table 5.9 continued	**All**	**Men**	**Women**
Equation 2: Log of real equivalised household income			
Completed at least a university degree	0.26***	0.257***	0.261***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (income)	0.995***	0.995***	0.995***
	[0.003]	[0.005]	[0.005]
Equation 3: Employed			
Completed at least a university degree	0.135***	0.134***	0.135***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (employed)	0.993***	0.992***	0.996***
	[0.002]	[0.003]	[0.002]
Equation 4: Married			
Completed at least a university degree	0.034***	0.034***	0.035***
	[0.002]	[0.002]	[0.002]
Fixed effect residual (married)	0.996***	0.987***	0.998***
	[0.002]	[0.003]	[0.002]
Equation 5: Total number of children			
Completed at least a university degree	-0.103***	-0.102***	-0.103***
	[0.001]	[0.001]	[0.001]
Fixed effect residual (children)	0.994***	0.992***	0.994***
	[0.001]	[0.003]	[0.002]
Equation 6: No long-term health problems			
Completed at least a university degree	0.066***	0.067***	0.066***
	[0.001]	[0.002]	[0.002]
Fixed effect residual (health)	0.999***	0.994***	1.001***
	[0.002]	[0.002]	[0.003]
Observations	57,876	26,826	31,050

Notes: ***¡1%; **¡5%; *¡10%. Robust standard errors are in parentheses. All regressions controlled for gender, age and age-squared, state of residence dummies, and wave dummies. All regressions also allowed for clustering at individual level. All variables are standardized with a mean of zero and a standard deviation of one.

Chapter 6

Conclusion

This thesis has explored three aspects of human capital development. Firstly, it has provided evidence of whether childhood characteristics, from family and school environments, may have a long-term legacy on cognitive and non-cognitive skills in adulthood. Using the NCDS 1958 cohort, it has shown that childhood factors can predict more of the variation in cognitive skills than in non-cognitive skills. The most important variable groups for capturing the variation in cognitive skills at adulthood are early parental investment (for example engaging in reading activities, spending time with the child) and schooling environment in late teenage years. In contrast, the legacy of early parental inputs on non-cognitive skills (measured by emotional health conditions) is small, with no other group of childhood characteristics being particularly predictive. The additional analysis using the MCS 2000 cohort leads to a similar conclusion. In additional, the analysis has shown that parental emotional health during childhood plays an important role in determining the child's emotional health status.

Overall, the analysis of the British cohorts from two different generations suggests that childhood matters more for cognitive skills when compared to non-cognitive skill attainment. This is consistent with evidence that suggests non-cognitive traits such personality traits are more malleable in later life (Frijters et al., 2014; Layard et al., 2013; Borghans et al., 2008), whereas cognitive skills (in particular IQ) stabilize much earlier in childhood (Schuerger and Witt, 1989; Hopkins and Bracht, 1975).

With respect to policy, the results suggest that it is more feasible to try and change a person's non-cognitive skills when compared to their cognitive skills in adulthood. In addition, it suggests that policies that aim to change a child's trajectory at age 7 and age 16 are likely to be different. That is, policy-makers should pay attention to parenting skills at age 7, and consider the schooling environment at age 16. Overall, the analysis highlights that while the legacy of childhood on life satisfaction may be

small (Frijters et al., 2014; Layard et al., 2013), to the extent that a government would want an adult population that is income generating and cognitively aware, investments in childhood are not wasted. Furthermore, this work has highlighted that during early years, childhood characteristics matter for both cognitive and non-cognitive skills, even if the legacy in later years is small.

The second aspect of human capital development is to understand the role of parents and their investment decisions. In this thesis, I have explored two complementary topics: (i) a factor that influences parents to make higher investments and (ii) the implication of parental investment decision for skill formation. Chapter 4 considered life expectancy and its role in determining the optimal level of schooling. The main empirical strategy exploited an external change in adult mortality risk derived from the variation of landmine prevalence in Cambodia. Under a difference-in-difference-in-difference specification, this chapter showed that an increase in life expectancy leads to a sizeable positive effect on schooling outcomes. Nevertheless, by replacing the mortality risk from such a fearful event as landmine accidents by a more common incident of traffic accidents, the effect of mortality risk on schooling outcomes is no longer detectable. This chapter ended by posing an important agenda for future research to examine individuals and whether their decisions are influenced equally and objectively by different types of risk. Alternatively, they may be affected differently depending on how the objective magnitude of the risk is subjectively translated in the rational calculation.

Next, the thesis considered family size, in particular the number of younger siblings. It examined if there is a trade-off between the quantity and the quality of children in developing-country households. In order to obtain a causal interpretation, the identification strategy in Chapter xx exploited the exogeneity of a birth of a given gender. For a set of instrumental variables for fertility variations of households from four different cultural backgrounds, I constructed measures of the discrepancy between the ideal and the actual number of sons and daughters. These instrumental variables are no longer confined by the assumption that parents homogeneously prefer the optimal number of two children.

In contrast to the strong and negative effect found under the OLS specification with the Young Lives Datasets, the 2SLS analysis did not find much evidence to support the contention that more younger siblings causally lead to lower development in the short run (at age 5). However, the sibship effect on cognitive development became negative and sizeable at a later age in childhood. It was found that there was a degree of intra-household allocation of responsibilities and resources. Although there was no evidence of any change in maternal labour supply, paternal labour supply increased (at least in the short run). What was most affected by an increase in sibship size was a reduction of

the time the older child spends on his own activities along with an increase in the time spent on caring for others.

The findings in this chapter demonstrate a degree of complexity in the full understanding of the Quantity-Quality trade-off. An important avenue of further research may examine potential differentiation in the degree of the trade-off amongst children from (i) different birth orders and (ii) different age groups. In a context where households make simultaneous decisions on investments in children and fertility choices, the intra-household's reallocation of tasks and resources may also incorporate older children as contributing members. As a result, it is important that the trade-off is examined in the human capital accumulation of the existing older children as well as the more recent-born. Future updates of the Young Lives datasets will allow research to examine this potential aspect. In addition, it will be possible to investigate further the dynamic of sibship size effects in future survey rounds into the adolescence years.

The last chapter considered the third aspect of human capital development: a broader perspective on gains from human capital accumulation beyond the typical financial returns. It showed that, using the HILDA dataset from Australia, education is likely to be positively related to overall life satisfaction through many different channels, even when, *ceteris paribus*, education by itself has a negative relationship with life satisfaction. The largest indirect effect of education (measured as years of schooling) on life satisfaction is via income, followed by a positive effect on long-term physical health status. A caveat in the specification in this chapter is that it is far from a fully causal model of education on life satisfaction. Even with the fixed effect model, the issue of unobserved heterogeneity is not completely resolved. For a causal interpretation, exogenous variation, not only of education, but also on every other indirect pathway, is required. Future research will have to address the issues of bias when re-estimating direct and indirect effects.

Lastly, it is worthwhile for future research to examine these direct and indirect benefits of education for life satisfaction using data drawn from alternative cultural contexts. The findings are important for a number of reasons. First, if educational policy aims to maximise overall welfare of individuals, the SEM method will be able to capture and compare the relative impact of all of the main pathways of education on well-being. Second, the results provide important information about any potential returns to investments in human capital above and beyond the financial sphere.

Bibliography

Aaronson, D. (1998). Using sibling data to estimate the impact of neighborhoods on children's educational outcomes. *Journal of Human Resources*, 915–946.

Acemoglu, D. and D. Autor (2009). Lectures in labor economics. *Unpublished manuscript, Department of Economics, Massachusetts Institute of Technology, Cambridge, MA. Retrieved from http://economics. mit. edu/files/4689*.

Acemoglu, D. and S. Johnson (2007). Disease and development: The effect of life expectancy on economic growth. *Journal of Political Economy 115*(6).

Akbulut, M. and A. D. Kugler. Inter-generational transmission of health status in the us among natives and immigrants.

Akresh, R. and D. de Walque (2008). Armed conflict and schooling: Evidence from the 1994 rwandan genocide.

Allen, J. and R. Van der Velden (2001). Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. *Oxford economic papers 53*(3), 434–452.

Ambrey, C. L. and C. M. Fleming (2014). Life satisfaction in australia: Evidence from ten years of the hilda survey. *Social Indicators Research 115*(2), 691–714.

Angrist, J. and W. Evans (1998). Children and their parents' labor supply: Evidence from exogenous variation in family size. *The American Economic Review 88*(3), 450–477.

Angrist, J., V. Lavy, and A. Schlosser (2010). Multiple experiments for the causal link between the quantity and quality of children. *Journal of Labor Economics 28*(4), 773–824.

Angrist, J. D. and A. B. Krueger (1991). Does compulsory school attendance affect schooling and earnings? *Quarterly Journal of Economics 106*(4), 979–1014.

Angrist, J. D. and V. Lavy (1999). Using maimonides' rule to estimate the effect of class size on scholastic achievement. *The Quarterly journal of economics 114*(2), 533–575.

Arnold, F. (1997). Gender preferences for children. *Demographic and Health Surveys Comparative Studies 23*.

Attanasio, O., V. DiMaro, V. Lechene, and D. Phillips (2009). The welfare consequence of increases in food prices in rural mexico and colombia. Technical report, Mimeo, UCL.

Attanasio, O. and K. Kaufmann (2009). Educational choices, subjective expectations, and credit constraints. Technical report, National Bureau of Economic Research.

Authority, C. M. A. (2005). *Cambodia Mine Action Authority Annual Report*.

Authority, C. M. A. (various). *Cambodia Mine Action Authority Annual Report*.

Bagger, J., J. A. Birchenall, H. Mansour, and S. Urzúa (2013). Education, birth order, and family size. Technical report, National Bureau of Economic Research.

Bai, J., S. Jayachandran, E. J. Malesky, and B. A. Olken (2013). Does economic growth reduce corruption? theory and evidence from vietnam. Technical report, National Bureau of Economic Research.

Baron, R. M. and D. A. Kenny (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology 51*(6), 1173.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Becker, G. S. (1994). Human capital. *University of Chicago Press Economics Books*.

Becker, G. S. and G. S. Becker (2009). *A Treatise on the Family*. Harvard university press.

Becker, G. S. and H. G. Lewis (1973). On the interaction between the quantity and quality of children. *Journal of Political Economy 81*(2), S279–88.

Becker, G. S. and N. Tomes (1976). Child endowments and the quantity and quality of children. *Journal of Political Economy*, S143–S162.

Becker, G. S. and N. Tomes (1986). Human capital and the rise and fall of families. *Journal of Labor Economics 4*(3), S1–39.

Behrman, J. R. (1988). Intrahousehold allocation of nutrients in rural india: Are boys favored? do parents exhibit inequality aversion? *Oxford Economic Papers*, 32–54.

Belsky, J., M. K. Goode, and R. K. Most (1980). Maternal stimulation and infant exploratory competence: Cross-sectional, correlational, and experimental analyses. *Child Development*, 1168–1178.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *The Journal of Political Economy*, 352–365.

Ben-Porath, Y. and F. Welch (1976). Do sex preferences really matter? *The Quarterly Journal of Economics*, 285–307.

Berlinski, S. and P. Carneiro (2012). Comparing the predictive power of early tests for adolescence tests,. *mimeo*.

Bils, M. and P. J. Klenow (2000). Does schooling cause growth? *American economic review*, 1160–1183.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2005). The more the merrier? the effect of family size and birth order on children's education. *The Quarterly Journal of Economics 120*(2), 669–700.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2007). From the cradle to the labor market? the effect of birth weight on adult outcomes. *The Quarterly Journal of Economics 122*(1), 409–439.

Blackwell, D. L., M. D. Hayward, and E. M. Crimmins (2001). Does childhood health affect chronic morbidity in later life? *Social science & medicine 52*(8), 1269–1284.

Blanchflower, D. G. and A. J. Oswald (2004). Well-being over time in britain and the usa. *Journal of public economics 88*(7), 1359–1386.

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic Literature*, 3–57.

Blau, D. M. (1999). The effect of income on child development. *Review of Economics and Statistics 81*(2), 261–276.

Booth, A. L. and H. J. Kee (2009). Birth order matters: the effect of family size and birth order on educational attainment. *Journal of Population Economics 22*(2), 367–397.

Borghans, L., A. L. Duckworth, J. J. Heckman, and B. Ter Weel (2008). The economics and psychology of personality traits. *Journal of Human Resources 43*(4), 972–1059.

Bound, J. and H. J. Holzer (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of labor Economics 18*(1), 20–54.

Boyce, C. J. (2010). Understanding fixed effects in human well-being. *Journal of Economic Psychology 31*(1), 1–16.

Bray, M. and S. Bunly (2005). *Balancing the books: Household financing of basic education in Cambodia*. Comparative Education Research Centre, University of Hong Kong Hong Kong.

Brighouse, H. (2006). *On education.* Psychology Press.

Brooks-Gunn, J., G. J. Duncan, P. K. Klebanov, and N. Sealand (1993). Do neighborhoods influence child and adolescent development? *American journal of sociology*, 353–395.

Brown, M. and B. Dodgeon (2010). Ncds cognitive assessments at age 50: initial results.

Browning, M. and P.-A. Chiappori (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, 1241–1278.

Butcher, K. F. and A. Case (1994). The effect of sibling sex composition on women's education and earnings. *The Quarterly Journal of Economics*, 531–563.

Cáceres-Delpiano, J. (2006). The impacts of family size on investment in child quality. *Journal of Human Resources 41*(4), 738–754.

Camacho, A. (2008). Stress and birth weight: evidence from terrorist attacks. *The American Economic Review*, 511–515.

Campbell, J. (1998). Book review: Peabody picture vocabulary test. *Journal of Psychoeducational Assessment 16*(4), 334–338.

Campbell, J. M., S. K. Bell, and L. K. Keith (2001). Concurrent validity of the peabody picture vocabulary test-as an intelligence and achievement screener for low ses african american children. *Assessment 8*(1), 85–94.

Carrell, S. E. and M. L. Hoekstra (2010). Externalities in the classroom: How children exposed to domestic violence affect everyone's kids. *American Economic Journal: Applied Economics 2*(1), 211–228.

Carrell, S. E. and J. E. West (2010). Does professor quality matter? evidence from random assignment of students to professors. *Journal of Political Economy 118*(3), 409–432.

Case, A., A. Fertig, and C. Paxson (2005). The lasting impact of childhood health and circumstance. *Journal of health economics 24*(2), 365–389.

Case, A., D. Lubotsky, and C. Paxson (2002). Economic status and health in childhood: The origins of the gradient. *The American Economic Review 92*(5), 1308–1334.

Case, A. and C. Paxson (2010). Causes and consequences of early-life health. *Demography 47*(1), S65–S85.

Case, A. and C. Paxson (2011). The long reach of childhood health and circumstance: Evidence from the whitehall ii study. *The Economic Journal 121*(554), F183–F204.

Cervellati, M. and U. Sunde (2005). Human capital formation, life expectancy, and the process of development. *American Economic Review*, 1653–1672.

Cervellati, M. and U. Sunde (2013). Life expectancy, schooling, and lifetime labor supply: Theory and evidence revisited. *Econometrica 81*(5), 2055–2086.

Chen, W.-c. (2012). How education enhances happiness: Comparison of mediating factors in four east asian countries. *Social indicators research 106*(1), 117–131.

Chesnokova, T. and R. Vaithianathan (2008). Lucky last? intra-sibling allocation of child labor. *The BE Journal of Economic Analysis & Policy 8*(1).

Chetty, R., J. N. Friedman, and J. E. Rockoff (2011). The long-term impacts of teachers: Teacher value-added and student outcomes in adulthood. *NBER Working Paper* (w17699).

Chevalier, A. (2003). Measuring over-education. *Economica 70*(279), 509–531.

Chiappori, P.-A., M. Iyigun, and Y. Weiss (2009). Investment in schooling and the marriage market. *The American Economic Review*, 1689–1713.

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica 28*(3), 591–605.

Chun, H. and J. Oh (2002). An instrumental variable estimate of the effect of fertility on the labour force participation of married women. *Applied Economics Letters 9*(10), 631–634.

Clark, A. E., E. Diener, Y. Georgellis, and R. E. Lucas (2008). Lags and leads in life satisfaction: a test of the baseline hypothesis. *The Economic Journal 118*(529), F222–F243.

Clark, A. E., P. Frijters, and M. A. Shields (2008). Relative income, happiness, and utility: An explanation for the easterlin paradox and other puzzles. *Journal of Economic Literature*, 95–144.

CMAA (2001). *Cambodia Mine Action Authority Level 1 Survey Report*.

CMVIS (2012). *Cambodia Mine Victims Information System Report*.

Connolly, S., J. Micklewright, and S. Nickell (1992). The occupational success of young men who left school at sixteen. *Oxford Economic Papers*, 460–479.

Conti, G. and C. Hansman (2013). Personality and the education–health gradient: A note on understanding differences in health behaviors by education. *Journal of health economics 32*(2), 480–485.

Conti, G., J. Heckman, and S. Urzua (2010). The education-health gradient. *The American Economic Review*, 234–238.

Conti, G. and J. J. Heckman (2010). Understanding the early origins of the education–health gradient a framework that can also be applied to analyze gene–environment interactions. *Perspectives on Psychological Science 5*(5), 585–605.

Conti, G. and J. J. Heckman (2014). *Economics of Child Well-Being*. Springer.

Corcoran, M., R. Gordon, D. Laren, and G. Solon (1992). The association between men's economic status and their family and community origins. *Journal of Human Resources*, 575–601.

Cruces, G. and S. Galiani (2007). Fertility and female labor supply in latin america: New causal evidence. *Labour Economics 14*(3), 565–573.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *The American Economic Review*, 31–47.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica 78*(3), 883–931.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of Economic Literature*, 87–122.

Currie, J. and R. Hyson (1999). Is the impact of health shocks cushioned by socioeconomic status? the case of low birthweight. *American Economic Review 89*(2), 245–250.

Currie, J. and M. Stabile (2003). Socioeconomic status and child health: Why is the relationship stronger for older children? *American Economic Review 93*(5), 1813–1823.

Dang, H.-A. and H. Rogers (2009). The decision to invest in child quality over quantity: Has declining fertility increased household investment in education in vietnam? In *Annual Meeting of the Population Association of America, Princeton*, Volume 2.

Datcher, L. (1982). Effects of community and family background on achievement. *The review of Economics and Statistics*, 32–41.

Davies, P. and N. Dunlop (1994). *War of the Mines: Cambodia, Landmines and the Impoverishment of a Nation*. Pluto Press London.

De la Croix, D. and O. Licandro (1999). Life expectancy and endogenous growth. *Economics Letters 65*(2), 255–263.

De la Croix, D. and O. Licandro (2013). The child is father of the man: Implications for the demographic transition. *The Economic Journal 123*(567), 236–261.

Delaney, L., M. McGovern, and J. P. Smith (2011). From angela's ashes to the celtic tiger: Early life conditions and adult health in ireland. *Journal of Health Economics 30*(1), 1–10.

Desai, S. (1995). When are children from large families disadvantaged? evidence from cross-national analyses. *Population Studies 49*(2), 195–210.

Di Tella, R., R. J. MacCulloch, and A. J. Oswald (2003). The macroeconomics of happiness. *Review of Economics and Statistics 85*(4), 809–827.

Diener, E., E. Sandvik, L. Seidlitz, and M. Diener (1993). The relationship between income and subjective well-being: Relative or absolute? *Social Indicators Research 28*(3), 195–223.

Dolan, P., T. Peasgood, and M. White (2008). Do we really know what makes us happy? a review of the economic literature on the factors associated with subjective well-being. *Journal of economic psychology 29*(1), 94–122.

Dominitz, J. and C. F. Manski (1996). Eliciting student expectations of the return to schooling. *Journal of Human Resources 31*(1), 1–26.

Douglas, J. W. B. (1964). *The home and the school.* MacGibbon & Kee London.

Downey, D. B. and D. J. Condron (2004). Playing well with others in kindergarten: The benefit of siblings at home. *Journal of Marriage and Family 66*(2), 333–350.

Downey, D. B., B. Powell, L. C. Steelman, and S. Pribesh (1999). Much ado about siblings: Change models, sibship size, and intellectual development: Comment on guo and vanwey. *American Sociological Review*, 193–198.

Dunn, L., E. Padilla, D. Lugo, and L. Dunn (1986). Manual del examinador para el test de vocabulario en imágenes peabody (peabody picture vocabulary test)–adaptación hispanoamericana (hispanic-american adaptation). *Circle Pines (MN): AGS*.

Dunn, L. M. and L. Dunn (1996). Peabody picture vocabulary test. *American Guidance Service*.

Easterlin, R. A. (2001). Income and happiness: Towards a unified theory. *The economic journal 111*(473), 465–484.

Easterling, R., J. Eatwell, M. Milgate, and P. Newman (1987). *Fertility: The New Palgrave.* WW Norton & Company.

Edmonds, E. V. (2006). Understanding sibling differences in child labor. *Journal of Population Economics 19*(4), 795–821.

Ejrnæs, M. and C. C. Pörtner (2004). Birth order and the intrahousehold allocation of time and education. *Review of Economics and Statistics 86*(4), 1008–1019.

Elovainio, M., L. Pulkki-Råback, M. Jokela, M. Kivimäki, M. Hintsanen, T. Hintsa, J. Viikari, O. T. Raitakari, and L. Keltikangas-Järvinen (2012). Socioeconomic status and the development of depressive symptoms from childhood to adulthood: A longitudinal analysis across 27 years of follow-up in the young finns study. *Social Science & Medicine 74*(6), 923–929.

Engle, P. L. (1991). Maternal work and child-care strategies in peri-urban guatemala: Nutritional effects. *Child development 62*(5), 954–965.

Epple, D., E. Newlon, and R. Romano (2002). Ability tracking, school competition, and the distribution of educational benefits. *Journal of Public Economics 83*(1), 1–48.

Etcheson, C. (1984). *The rise and demise of Democratic Kampuchea.* Westview.

Ferrer-i Carbonell, A. (2005). Income and well-being: an empirical analysis of the comparison income effect. *Journal of Public Economics 89*(5), 997–1019.

Ferrer-i Carbonell, A. and P. Frijters (2004). How important is methodology for the estimates of the determinants of happiness?*. *The Economic Journal 114*(497), 641–659.

Ferrie, J. and K. Rolf (2011). Socioeconomic status in childhood and health after age 70: A new longitudinal analysis for the us, 1895–2005. *Explorations in Economic History 48*(4), 445–460.

Finn, J. D., D. Fulton, J. Zaharias, and B. A. Nye (1989). Carry-over effects of small classes. *Peabody Journal of Education 67*(1), 75–84.

Finn, J. D., G. M. Pannozzo, and C. M. Achilles (2003). The why's of class size: Student behavior in small classes. *Review of Educational Research 73*(3), 321–368.

Fitzsimons, E. and B. Malde (2014). Empirically probing the quantity–quality model. *Journal of Population Economics 27*(1), 33–68.

Flouri, E. (2004). Subjective well-being in midlife: The role of involvement of and closeness to parents in childhood. *Journal of Happiness Studies 5*(4), 335–358.

Fortson, J. G. (2011). Mortality risk and human capital investment: The impact of hiv/aids in sub-saharan africa. *The Review of Economics and Statistics 93*(1), 1–15.

Frey, B. S. and A. Stutzer (2000). Happiness, economy and institutions. *The Economic Journal 110*(466), 918–938.

Frijters, P., T. J. Hatton, R. M. Martin, and M. A. Shields (2010). Childhood economic conditions and length of life: evidence from the uk boyd orr cohort, 1937–2005. *Journal of health economics 29*(1), 39–47.

Frijters, P., D. W. Johnston, and M. A. Shields (2014). Does childhood predict adult life satisfaction? evidence from british cohort surveys. *The Economic Journal*.

Galor, O. and D. N. Weil (1999). From malthusian stagnation to modern growth. *American Economic Review*, 150–154.

Galor, O. and D. N. Weil (2000). Population, technology, and growth: From malthusian stagnation to the demographic transition and beyond. *American economic review*, 806–828.

Galster, G., D. E. Marcotte, M. Mandell, H. Wolman, and N. Augustine (2007). The influence of neighborhood poverty during childhood on fertility, education, and earnings outcomes. *Housing Studies 22*(5), 723–751.

Gardner, J. and A. Oswald (2004). How is mortality affected by money, marriage, and stress? *Journal of health economics 23*(6), 1181–1207.

Gerardino, M. P. (2013). The effect of violence on the educational gender gap. Technical report.

Gibb, S. J., D. M. Fergusson, and L. J. Horwood (2012). Childhood family income and life outcomes in adulthood: Findings from a 30-year longitudinal study in new zealand. *Social Science & Medicine 74*(12), 1979–1986.

Goodman, R. (1997). The strengths and difficulties questionnaire: a research note. *Journal of child psychology and psychiatry 38*(5), 581–586.

Gorsuch, R. (1983). Factor analysis. *LEA, Hillsdale, NJ*.

Grawe, N. D. (2008). The quality–quantity trade-off in fertility across parent earnings levels: a test for credit market failure. *Review of Economics of the Household 6*(1), 29–45.

Gray, S., E. Plante, R. Vance, and M. Henrichsen (1999). The diagnostic accuracy of four vocabulary tests administered to preschool-age children. *Language, Speech, and Hearing Services in Schools 30*(2), 196–206.

Green, F. (2011). Unpacking the misery multiplier: How employability modifies the impacts of unemployment and job insecurity on life satisfaction and mental health. *Journal of Health Economics 30*(2), 265–276.

Greene, W. H. (2003). Econometric analysis, 5th. *Ed.. Upper Saddle River, NJ*.

Guo, G. and K. M. Harris (2000). The mechanisms mediating the effects of poverty on children's intellectual development. *Demography 37*(4), 431–447.

Gupta, M. D. (1987). Selective discrimination against female children in rural punjab, india. *Population and development review*, 77–100.

Haas, S. (2008). Trajectories of functional health: the "long arm" of childhood health and socioeconomic factors. *Social Science & Medicine 66*(4), 849–861.

Haller, M. and M. Hadler (2006). How social relations and structures can produce happiness and unhappiness: An international comparative analysis. *Social indicators research 75*(2), 169–216.

Hanushek, E. A. (1992). The trade-off between child quantity and quality. *Journal of political economy*, 84–117.

Harmon, C. and I. Walker (1995). Estimates of the economic return to schooling for the united kingdom. *The American Economic Review*, 1278–1286.

Harris, D. N. and T. R. Sass (2011). Teacher training, teacher quality and student achievement. *Journal of public economics 95*(7), 798–812.

Hatch, S. L., P. B. Jones, D. Kuh, R. Hardy, M. E. Wadsworth, and M. Richards (2007). Childhood cognitive ability and adult mental health in the british 1946 birth cohort. *Social science & medicine 64*(11), 2285–2296.

Hauser, R. M. and H.-H. D. Kuo (1998). Does the gender composition of sibships affect women's educational attainment? *Journal of Human Resources*, 644–657.

Hayes, A. F. (2009). Beyond baron and kenny: Statistical mediation analysis in the new millennium. *Communication Monographs 76*(4), 408–420.

Hazan, M. (2009). Longevity and lifetime labor supply: Evidence and implications. *Econometrica 77*(6), 1829–1863.

Hazan, M. (2012). Life expectancy and schooling: new insights from cross-country data. *Journal of Population Economics 25*(4), 1237–1248.

Headey, B., R. Muffels, and M. Wooden (2008). Money does not buy happiness: Or does it? a reassessment based on the combined effects of wealth, income and consumption. *Social Indicators Research 87*(1), 65–82.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–86.

Heckman, J. J. (2012). The developmental origins of health. *Health economics 21*(1), 24–29.

Heckman, J. J. and T. Kautz (2012). Hard evidence on soft skills. *Labour Economics 19*(4), 451–464.

Helliwell, J. F. (2003). How's life? combining individual and national variables to explain subjective well-being. *Economic Modelling 20*(2), 331–360.

Hopkins, K. D. and G. H. Bracht (1975). Ten-year stability of verbal and nonverbal iq scores. *American Educational Research Journal 12*(4), 469–477.

Hurd, M. D. and K. McGarry (2002). The predictive validity of subjective probabilities of survival*. *The Economic Journal 112*(482), 966–985.

Isen, A. and B. Stevenson (2010). Women's education and family behavior: Trends in marriage, divorce and fertility. In *Demography and the Economy*, pp. 107–140. University of Chicago Press.

Jayachandran, S. and A. Lleras-Muney (2009). Life expectancy and human capital investments: Evidence from maternal mortality declines. *The Quarterly Journal of Economics 124*(1), 349–397.

Jensen, R. T. and B. Chintan (2003). *Equal Treatment, Unequal Outcomes?: Generating Sex Inequality Through Fertility Behaviour*. Bazaar Chintan.

Johnson, J., R. Rosenberg, L. Platt, and S. Parsons (2011). Millennium cohort study fourth survey: A guide to the teacher survey dataset.

Justino, P. (2009). Poverty and violent conflict: A micro-level perspective on the causes and duration of warfare. *Journal of Peace Research 46*(3), 315–333.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291.

Kana, F. (2010). Variations in attitudinal gender preferences for children across 50 less-developed countries. *Demographic Research 23*, 1031–1048.

Kettunen, J. (1997). Education and unemployment duration. *Economics of Education Review 16*(2), 163–170.

Kiernan, B. (2001). Myth, nationalism and genocide. *Journal of Genocide Research 3*(2), 187–206.

Kilka, M. and M. Weber (2001). What determines the shape of the probability weighting function under uncertainty? *Management science 47*(12), 1712–1726.

Krimsky, S. and D. Golding (1992). Social theories of risk.

Krueger, A. B. (1999). Experimental estimates of education production functions. *The Quarterly Journal of Economics 114*(2), pp. 497–532.

Lafortune, J. (2013). Making yourself attractive: Pre-marital investments and the returns to education in the marriage market. *American Economic Journal: Applied Economics 5*(2), 151–178.

Lawson, D. W. and R. Mace (2010). Siblings and childhood mental health: Evidence for a later-born advantage. *Social Science & Medicine 70*(12), 2061 – 2069.

Layard, R. (2011). Happiness: lessons form a new science.

Layard, R., A. E. Clark, F. Cornaglia, N. Powdthavee, and J. Vernoit (2013). What predicts a successful life? a life-course model of well-being.

Lee, C.-I. and G. Solon (2009). Trends in intergenerational income mobility. *The Review of Economics and Statistics 91*(4), 766–772.

Lee, J. (2008). Sibling size and investment in childrens education: An asian instrument. *Journal of Population Economics 21*(4), 855–875.

Leibowitz, A. (1974). Home investments in children. *The Journal of Political Economy*, S111–S131.

Leigh, A. and C. Ryan (2008). Estimating returns to education using different natural experiment techniques. *Economics of Education Review 27*(2), 149–160.

Leon, G. (2012). Civil conflict and human capital accumulation the long-term effects of political violence in perú. *Journal of Human Resources 47*(4), 991–1022.

Leslie, J. and M. Paolisso (1989). Women work and child welfare in the third world.

Levison, D. and K. S. Moe (1998). Household work as a deterrent to schooling: An analysis of adolescent girls in peru. *The Journal of Developing Areas*, 339–356.

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the united states. *The Review of Economic Studies 72*(1), 189–221.

Lordan, G. and P. Frijters (2013). Unplanned pregnancy and the impact on sibling health outcomes. *Health economics 22*(8), 903–914.

Lorentzen, P., J. McMillan, and R. Wacziarg (2008). Death and development. *Journal of Economic Growth 13*(2), 81–124.

Luo, Y. and L. J. Waite (2005). The impact of childhood and adult ses on physical, mental, and cognitive well-being in later life. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 60*(2), S93–S101.

Machin, S., K. G. Salvanes, and P. Pelkonen (2012). Education and mobility. *Journal of the European Economic Association 10*(2), 417–450.

Mansour, H. and D. I. Rees (2012). Armed conflict and birth weight: Evidence from the al-aqsa intifada. *Journal of Development Economics 99*(1), 190–199.

Manuelli, R. E. and A. Seshadri (2007). Human capital and the wealth of nations.

Martin, T. C. (1995). Women's education and fertility: results from 26 demographic and health surveys. *Studies in family planning*, 187–202.

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the united states using social security earnings data. *Review of Economics and Statistics 87*(2), 235–255.

McLafferty, S. (1997). Gender, race, and the determinants of commuting: New york in 1990. *Urban Geography 18*(3), 192–212.

Melin, R., K. S. Fugl-Meyer, and A. R. Fugl-Meyer (2003). Life satisfaction in 18-to 64-year-old swedes: in relation to education, employment situation, health and physical activity. *Journal of rehabilitation medicine 35*(2), 84–90.

Michalos, A. C. (2008). Education, happiness and wellbeing. *Social Indicators Research 87*(3), 347–366.

Millán, J. A. (2014). Crime and labour market, choice under uncertainty model and an application for colombian cities. *University College London mimeo*.

Mincer, J. (1991). Education and unemployment. Technical report, National bureau of economic research.

MoEYS (2005). Education strategic plan 2006-2010.

MoEYS (various). *Cambodia Ministry of Education and Sports Annual Report*.

Mogstad, M. and M. Wiswall (2011). Testing the quantity-quality model of fertility: estimation using unrestricted family size models. *Quantitative Econoomics*.

Neidell, M. and J. Waldfogel (2010). Cognitive and noncognitive peer effects in early education. *The Review of Economics and Statistics 92*(3), 562–576.

Oreopoulos, P. and K. G. Salvanes (2011). Priceless: The nonpecuniary benefits of schooling. *The Journal of Economic Perspectives*, 159–184.

Oster, E., I. Shoulson, and E. Dorsey (2013). Limited life expectancy, human capital and health investments. *The American Economic Review 103*(5), 1977–2002.

Oswald, A. J. (1997). Happiness and economic performance. *The Economic Journal*, 1815–1831.

Oswald, A. J. and N. Powdthavee (2008). Does happiness adapt? a longitudinal study of disability with implications for economists and judges. *Journal of public economics 92*(5), 1061–1077.

Outes-Leon, I. and S. Dercon (2008). Survey attrition and attrition bias in young lives. *Young Lives Technical Note 5*.

Page, M. E. and G. Solon (2003). Correlations between sisters and neighbouring girls in their subsequent income as adults. *Journal of Applied Econometrics 18*(5), 545–562.

Plümper, T. and V. E. Troeger (2007). Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. *Political Analysis 15*(2), 124–139.

Portrait, F., R. Alessie, and D. Deeg (2010). Do early life and contemporaneous macro-conditions explain health at older ages? *Journal of Population Economics 23*(2), 617–642.

Powdthavee, N. (2008). Putting a price tag on friends, relatives, and neighbours: Using surveys of life satisfaction to value social relationships. *The Journal of Socio-Economics 37*(4), 1459–1480.

Powdthavee, N. (2010a). Does education reduce the risk of hypertension? estimating the biomarker effect of compulsory schooling in england. *Journal of Human Capital 4*(2), 173–202.

Powdthavee, N. (2010b). *The happiness equation: The surprising economics of our most valuable asset*. Icon Books.

Powdthavee, N. (2010c). How much does money really matter? estimating the causal effects of income on happiness. *Empirical Economics 39*(1), 77–92.

Powdthavee, N. and B. Van den Berg (2011). Putting different price tags on the same health condition: Re-evaluating the well-being valuation approach. *Journal of health economics 30*(5), 1032–1043.

Powdthavee, N. and A. Vignoles (2008). Mental health of parents and life satisfaction of children: A within-family analysis of intergenerational transmission of well-being. *Social Indicators Research 88*(3), 397–422.

Price, J. (2008). Parent-child quality time: Does birth order matter? *Journal of human resources 43*(1), 240–265.

Pringle, M. L. K., N. R. Butler, and R. Davie (1966). *11,000 Seven-year-olds*, Volume 1. Longmans.

Psacharopoulos, G. and H. A. Patrinos* (2004). Returns to investment in education: a further update. *Education economics 12*(2), 111–134.

Qian, N. (2009). Quantity-quality and the one child policy: The only-child disadvantage in school enrollment in rural china. *National Bureau of Economic Research*.

Rasul, I. (2008). Household bargaining over fertility: Theory and evidence from malaysia. *Journal of Development Economics 86*(2), 215–241.

Roberts, W. C. (2011). *Landmines in Cambodia: Past, Present, and Future*. Cambria Press.

Robertson, D. and J. Symons (2003). Do peer groups matter? peer group versus schooling effects on academic attainment. *Economica 70*(277), 31–53.

Rockoff, J. E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. *American Economic Review*, 247–252.

Rosenzweig, M. R. and K. I. Wolpin (1980a). Life-cycle labor supply and fertility: causal inferences from household models. *Journal of Political Economy 88*(2), 328–48.

Rosenzweig, M. R. and K. I. Wolpin (1980b). Testing the quantity-quality fertility model: the use of twins as a natural experiment. *Econometrica: journal of the Econometric Society 48*(1), 227.

Rosenzweig, M. R. and J. Zhang (2009). Do population control policies induce more human capital investment? twins, birth weight and china' s one-child policy. *The Review of Economic Studies 76*(3), 1149–1174.

Roth, M., E. Tym, C. Mountjoy, F. A. Huppert, H. Hendrie, S. Verma, and R. Goddard (1986). Camdex. a standardised instrument for the diagnosis of mental disorder in the

elderly with special reference to the early detection of dementia. *The British Journal of Psychiatry 149*(6), 698–709.

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *The Quarterly Journal of Economics 125*(1), 175–214.

Royce, J. M., R. B. Darlington, and H. W. Murray (1983). Pooled analyses: Findings across studies. *As the twig is bent: Lasting effects of preschool programs*, 411–459.

Rutter, M. (2006). *Genes and behavior: Nature-nurture interplay explained.* Blackwell Publishing.

Rutter, M., J. Tizard, and K. Whitmore (1970). *Education, health and behaviour.* Longman Publishing Group.

Sander, W. (1992). The effect of women's schooling on fertility. *Economics Letters 40*(2), 229–233.

Schuerger, J. M. and A. C. Witt (1989). The temporal stability of individually tested intelligence. *Journal of Clinical Psychology 45*(2), 294–302.

Schultz, T. P. (2007). Population policies, fertility, women's human capital, and child quality. *Handbook of development economics 4*, 3249–3303.

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics 95*(2), 186–200.

Shields, M., S. Wheatley Price, and M. Wooden (2009). Life satisfaction and the economic and social characteristics of neighbourhoods. *Journal of Population Economics 22*(2), 421–443.

Shields, M. A. and S. W. Price (2005). Exploring the economic and social determinants of psychological well-being and perceived social support in england. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 168*(3), 513–537.

Slovic, P. (1987). Perception of risk. *Science 236*(4799), 280–285.

Slovic, P., B. Fischhoff, and S. Lichtenstein (1982). Why study risk perception? *Risk analysis 2*(2), 83–93.

Smith, J. R., J. Brooks-Gunn, P. K. Klebanov, et al. (1997). Consequences of living in poverty for young children's cognitive and verbal ability and early school achievement. *Consequences of growing up poor*, 132–189.

Smith, K. (2003). Individual welfare in the soviet union. *Social Indicators Research 64*, 75–105.

Smith, K. R., G. P. Mineau, G. Garibotti, and R. Kerber (2009). Effects of childhood and middle-adulthood family conditions on later-life mortality: Evidence from the utah population database, 1850–2002. *Social science & medicine 68*(9), 1649–1658.

Soares, R. R. (2005). Mortality reductions, educational attainment, and fertility choice. *American Economic Review*, 580–601.

Solon, G., M. E. Page, and G. J. Duncan (2000). Correlations between neighboring children in their subsequent educational attainment. *Review of Economics and Statistics 82*(3), 383–392.

Southgate, V. (1962). *Group Reading Test*. Test.

Stanca, L. (2012). Suffer the little children: Measuring the effects of parenthood on well-being worldwide. *Journal of Economic Behavior and Organization 81*(3), 742 – 750.

Stewart-Brown, S. and K. Janmohamed (2008). Warwick-edinburgh mental well-being scale. *User guide. Version 1*.

Stoler, A. and D. Meltzer (2013). Mortality and morbidity risks and economic behavior. *Health economics 22*(2), 132–143.

Strauss, J. and D. Thomas (1995). Human resources: Empirical modeling of household and family decisions. *Handbook of development economics 3*, 1883–2023.

Strulik, H. and S. Vollmer (2013). Long-run trends of human aging and longevity. *Journal of Population Economics 26*(4), 1303–1323.

Taylor, B. A., E. Dearing, and K. McCartney (2004). Incomes and outcomes in early childhood. *Journal of Human Resources 39*(4), 980–1007.

Thomas, D. (1990). Intra-household resource allocation: An inferential approach. *Journal of human resources*, 635–664.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. American Psychological Association.

Todd, P. E. and K. I. Wolpin (2003). On the specification and estimation of the production function for cognitive achievement. *The Economic Journal 113*(485), F3–F33.

Todd, P. E. and K. I. Wolpin (2007). The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human capital 1*(1), 91–136.

Van den Berg, G. J., M. Lindeboom, and M. López (2009). Inequality in individual mortality and economic conditions earlier in life. *Social Science & Medicine 69*(9), 1360–1367.

Ware Jr, J. E. and C. D. Sherbourne (1992). The mos 36-ltem short-form health survey (sf-36): I. conceptual framework and item selection. *Medical care 30*(6), 473–483.

Watson, N. and M. Wooden (2012). The hilda survey: a case study in the design and development of a successful household panel survey. *Longitudinal and Life Course Studies 3*(3), 369–381.

Weiling, E. (2003). Do returns on investment for educating children in oaxaca de juárez, mexico, pay off? a qualitative analysis. *Qualitative Studies in Education 16*(6), 817–834.

Weitz, E. D. (2009). *A century of genocide: Utopias of race and nation.* Princeton University Press.

White, M. P. and P. Dolan (2009). Accounting for the richness of daily activities. *Psychological Science 20*(8), 1000–1008.

Wiggins, R. D., G. Netuveli, M. Hyde, P. Higgs, and D. Blane (2008). The evaluation of a self-enumerated scale of quality of life (casp-19) in the context of research on ageing: a combination of exploratory and confirmatory approaches. *Social Indicators Research 89*(1), 61–77.

Winkelmann, L. and R. Winkelmann (1998). Why are the unemployed so unhappy?evidence from panel data. *Economica 65*(257), 1–15.

Wozniak, A. (2010). Are college graduates more responsive to distant labor market opportunities? *Journal of Human Resources 45*(4), 944–970.

Zajonc, R. B. (1976). Family configuration and intelligence: Variations in scholastic aptitude scores parallel trends in family size and the spacing of children. *Science*.