The interaction between health, education and life outcomes from childhood to adulthood

By

Daniel de Araujo Roland

Thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy (PhD) in Economics

School of Economics

University of Kent

Canterbury

Kent

United Kingdom

March 2018

Word Count: 34,482

Se enxerguei mais longe,

foi porque me apoiei

nos ombros dos meus pais

Dedicated to my loving wife, Iraci, and to my giants also known as parents.

Acknowledgments

I am deeply thankful to my supervisors, Dr. Yu Zhu, Dr. Sylvain Barde and Dr. William Collier. Without them, this thesis would not have been completed. Yu was my first supervisor and kindly received me at the School of Economics and guided me through my 1st chapter. When he left to take a Professorship at the University of Dundee he offered me a scholarship to continue my studies there. I greatly appreciated the offer but politely declined. After that, Sylvain superbly stepped in as my main supervisor and offered his guidance through the many hardships of my research, always ready with a word of advice, suggestion or motivation. My work has remarkably improved during his supervision thanks to his wisdom, patience and support. I could not be happier with his help.

I am thankful to the University of Kent, the School of Economics and the research, administrative and tech team as I was provided with the space, equipment and human resources necessary to conduct my research. Thanks to Dr. William Collier who was also my module convenor for two modules. His feedback and guidance helped me gain important experience and skills in the classroom, something I will treasure for the rest of my career. I also thank Professor Jagjit Chadha and Dr. John Peirson for their support in other modules. Special thanks to Professor Miguel Leon-Ledesma who is a superb researcher and friend. In addition, thanks to Dr. Adelina Gschawandtner for her friendly words in many times of need.

I am grateful for the support from the research unit I work in, PSSRU. Their friendly and positive work environment have convinced me that academic research is something I wish to do for the rest of my career. Special thanks to my line managers Dr. Karen Jones and Prof. Julien Forder, truly kind, professional and friendly people who I aspire to become in the future.

I thank all the Brazilian teachers, lecturers and professors that have been through my life as my PhD is a culmination of their knowledge inspired in me. Most importantly, I thank the Brazilian National Council for Scientific and Technological Development (CNPq) for their PhD scholarship.

My friends' immense support have helped me through the hardest times and I am enormously thankful to Alessandro, Teresa, Mahreen, Sevgi, Neha, Marina and Ben who have become a family away from home. I also appreciated the helpful talks and company of Monica, Aydan, Matthew, Denise and many others.

I thank my parents for their unconditional love and support. Their belief in me has always been appreciated and there are not enough words in the world to express how much I owe them. From their life lessons to their financial support in my early life, I would not be where I am if it was not for them. They are, indeed, my giants. Together with my brother, I had the support of a loving family.

Last but not least, I thank my wife Iraci for her support. Our relationship grew strong and the distance and difficulties did not diminish our love for one another or our dreams. She has been my rock and supported me through everything. My utmost thanks to her.

Declaration

An earlier version of Chapter 1 was presented at the University of Kent PhD seminar programme on 26th March 2014, at the Work, Pensions and Labour Economics Study Group (WPEG) Conference at the University of Sheffield on 28th July 2014 and at the *Associación de Economía de la Educación* (AEDE) XVII Meeting at the *Universidad Católica de Murcia*, Spain, on 29th June 2017.

An earlier version of Chapter 2 was presented at the University of Kent PhD seminar programme on 17th June 2015, at the 17th Eurasia Business and Economics Society Conference (EBES) at the Venice International University, Italy, on 16th October 2015, at the 1st International Health Policy Conference (IHPC) at the London School of Economics on 19th February 2017 and at the 13th Workshop on Costs and Assessment in Psychiatry at Ca' Foscari University, Italy, on 26th March 2017. This chapter was also submitted for publication in the journal *Health Economics, Policy and Law*, where it was accepted by two editors initially but rejected by the two reviewers.

An earlier version of Chapter 3 has been accepted for presentation at the *Associación de Economía de la Educación* (AEDE) XVIII Meeting at the *Universidade de Catalunya*, Barcelona – Spain.

I declare that this thesis, or part of it, has never been presented for the award of an academic qualification. The thesis consists of 34,482 words.

Contents

List of tables

List of Figures

Thesis abstract

This thesis is formed of three empirical chapters using data from the United Kingdom. The chapters do not build on one another. Instead, they are self-contained and explore different facets of the interaction between health and education, how they affect each other and how they affect other life outcomes. Education and health are well known to be correlated since the second half of the 20th century with the works from Coleman (1966), Kitagawa and Hauser (1973) and Grossman (1976). Many studies have followed, exploring different aspects of this correlation and the thesis aims to provide further information on two of the hypothesis that explain this correlation. The first states that education affects health as people gain skills and knowledge enabling them to make better decisions regarding their health. The second hypothesis suggests that health can affect educational performance as shown by Glewwe et al. (2001) and Bobonis et al. (2006) among many others. The thesis also focus on how health and education each affects other life outcomes, not just one another. This leads to a greater understanding of the importance of health and education. As the three chapters analyse different aspects of the same topic, some information overlap can be found in each of them, despite each one having different a focus.

The first chapter explores the returns to education from a non-monetary, or non-economic, perspective. Following the UK's higher education tuition fees increase in 2012, the importance of understanding what are the returns to education increased as individuals conduct a cost-benefits analysis before deciding whether or not to pursue higher education. If the costs are increasing, it is important to understand what are the benefits. However, most studies assessing returns to education focus on monetary returns. The impact on health status and health behaviour, for example, is considered a wider return. And this is the focus of this chapter and its main contribution – what are the effects of having a degree on health outcomes and behaviour? And do these effects differ according to the type of degrees? By combining both economic and non-economic returns to education, individuals can truly assess the benefits of pursuing higher education and make a more informed decision, reducing information asymmetry and having an equilibrium that is closer to the socially optimum. In order to achieve this objective this chapter made use of the National Child Development Study (NCDS), a British survey that started in 1958 and is following cohort members as they progress through life. Using information on health status and behaviour as outcome variables from each survey from 1981 to 2008, together with the individuals' higher education condition, the results showed a clear positive impact. Having a degree increased self-reported quality of health and decreased the incidence of malaises and smoking frequency. The analysis of different degrees showed no evidence that the wider benefits from higher education differed across degrees, unlike the results for economic returns.

The second chapter is focused on mental health at an early age and its impact on future life outcomes. Attention Deficit and Hyperactivity Disorder (ADHD) is one of the most prevailing mental illnesses in young people, accounting for half the cases of mental disorders. Mental health has slowly gained attention in the health economics literature as now most developed

countries managed to secure good health standards for children. Therefore, the main contribution from this chapter is providing further knowledge of how one of the most common mental disorders affects individuals throughout the course of their lives by using a number of outcome variables ranging from labour market outcomes to physical health status and behaviour. This chapter used data from the British Cohort Study (BCS70), a survey that started in 1970. It is the third longitudinal study in the UK and contains a rich socioeconomic questionnaire, including information that allows for the identification of children potentially diagnosed with ADHD according to the definitions of the 4th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV). The effects of ADHD can be seen early on in educational achievements as individuals with ADHD are less likely to have a higher degree or an equivalent vocational qualification, and the effects can extend to later life outcomes such as a greater likelihood of unemployment, employment at part-time jobs, lower probability of being in a managerial position and lower income.

The third chapter in this thesis aimed at evaluating the effects of health shocks in educational outcomes at an early age. There is robust evidence that health conditions affect academic performance, especially at an early age. However, most of the evidence comes from developing countries where the variance of health status among children is much greater than in developed countries. There are a few exceptions such as Ding et al. (2009), but the unbalance is clear. The purpose of this work is, therefore, to use one of the newest information available in the UK to fill the gap in knowledge. The Millennium Cohort Study (MCS) is the first longitudinal study of the new millennium. It started in 2000-2001 with the purpose to continue UK’s long established tradition in collecting information to help guide public policy. The results from the chapter show that the period of life in which children are affected by a transitory health shock is important to determine how much their performance in tests is affected. Children who reported a longstanding illness in the twelve months leading up to their eleventh birthday were mildly affected in comparison to healthy children between ages seven and eleven. When comparing the same children at the age of fourteen, when both groups were healthy, there was no evidence of any differences in performance. However, when comparing children with a longstanding illness in the twelve months leading up to age fourteen with children who were healthy between ages eleven and fourteen, there was a significant negative effect, suggesting that longstanding illnesses affect children differently according to the period of their lives.

Chapter 1

Health, education and life outcomes – a review of literature

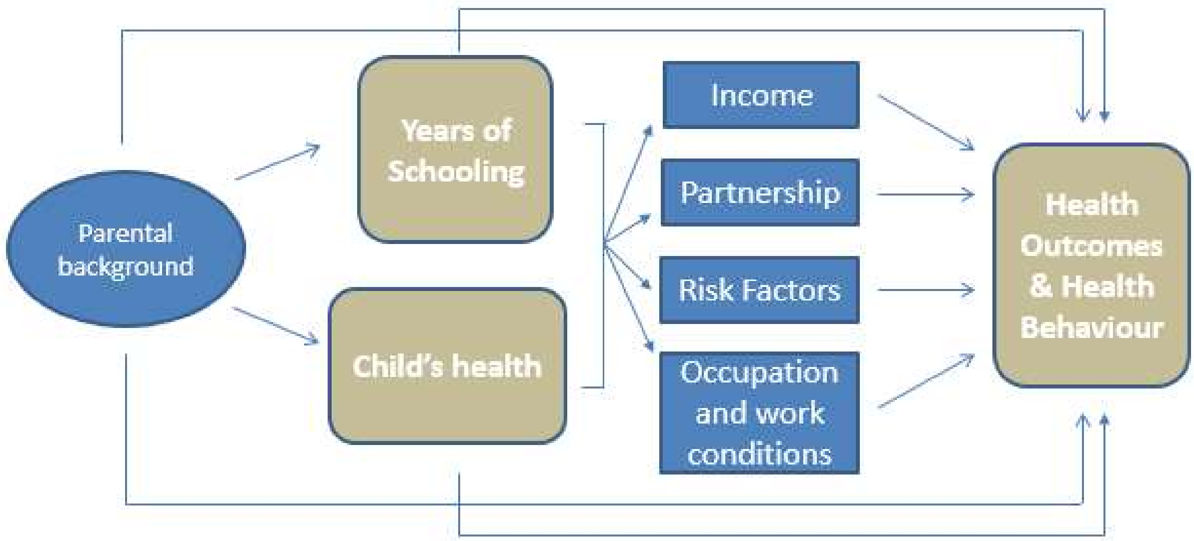
1.1 Introduction

The purpose of this chapter is to help the reader understand the relationship between health and education, how they interact with each other and how they affect life outcomes. The following chapters contain different research questions but are all connected to a common thread which will be explained in detail here. This chapter is divided into sections to help the reader to easily identify the required information for each empirical chapter.

1.2 The channels between health, education and life outcomes.

The three empirical chapters in this thesis analyse different aspects of the same topic. It is important, however, to understand the channels through which health, education and life outcomes interact with each other, not only within an individual but across generations as well. Figure 1.1 shows a simplified flowchart of the interactions and how complicated disentangling all these effects can be.

Figure 1.1: Interaction between health, education and life outcomes.



Parents are the first influence on an individual's health and education. Parents' wealth, income, social class, education, health and health behaviours all affect their children's education and health. Both, in turn, affect the individual's life outcomes, which ultimately lead to health outcomes and behaviour. However, years of schooling and early health status also directly affect health outcomes and behaviour as does parental background. The following sections present detailed literature on these channels.

1.3 Parental characteristics and children's health

Currie (2009) published a review of studies addressing the intergenerational transmission of economic status from parents to their children's health and education. Using a British longitudinal study, the National Child Development Study (NCDS) from 1958, Currie and Hyson (1999) showed that fathers occupying the most prestigious occupations had 5% of their children born with low weight but that figure rose to 6.4% among fathers who were in the lowest prestige occupations or had the information missing in the dataset. In the state of California, in the USA, 6% of children born in high-income areas had low birthweight compared to 7% of the children born in low-income areas. Low birthweight is associated with a number of negative life outcomes. This was first suggested by Barker et al. (1989) when he coined the term "fetal origins hypothesis" which has been widely cited since then.[1] He discovered that the incidence of heart disease in England was geographically correlated with infant mortality rates from 70 years prior. The hypothesis suggests that fetal nutrient deprivation leads to physiological developmental deficiencies, which ultimately leads to medical disorders in adult life.

In the medical literature, Hack et al (2002) found that low birth-weight children were less likely to graduate from high school and more likely to have lower IQ, subnormal height and neurosensory impairments. Men, but not women, were less likely to enrol in postsecondary study. In economics literature, Black, Devereux and Salvanes (2007) argued that the correlation may be reflecting other characteristics such as low income and genetic characteristic and therefore it is difficult to disentangle the effects. They used administrative data from Norway linked to birth records in order to use twin fixed effects and explore the impact of low birth

[1] Studies such as Vagero and Leon (1994), Doblhammer (2004), Royer (2009), Banerjee et al. (2010), Nelson (2010) and Almond & Currie (2011), to name a few. The fetal origins hypothesis argues that conditions in the uterus can shape the future outcomes of children. For instance, nutrient deprived fetuses are more likely to become obese as adults as if somehow their traumatic experience in the uterus designs them to store more fat in case of future starvation periods.

weight on short and long run outcomes. After taking into account potential pitfalls, they still found that not only low birth weight leads to reduced height and IQ at age 18, it also affected education and earnings later in life. The work from Figlio et al. (2014) presented new evidence of the impact of low birthweight by analysing the effect on cognitive development. Using singletons, twin and sibling fixed effects models, results indicate that neonatal health impacts cognitive development and this effect is consistent across children from different family socio-economic groups and is invariant to different measures of school quality.

Case, Lubotsky and Paxson (2002) explored the income gradient in health status. By focusing on children, the authors removed the potential problem of endogeneity originated from reverse causality that originates from health outcomes affecting income since it is highly unlikely that the datasets used from the USA contain children that contribute to household income. They presented evidence that the intergenerational transmission may work through the parents' long run average income effect on their children's health. Their results indicated that low income has an effect not only on children's health in the short-run but also in the long-run as they enter adulthood with poorer general health and more serious chronic conditions. Children from poorer background are also more likely to miss days of school, which together with poor health, can compromise their future earnings ability. The authors also explored the effect of parents' health on their children. They found that although parental health status is correlated with children health status, there is no significant difference between biological and adopted children. The mother's health is more strongly associated with the children's health in comparison with father's health. This may indicate that a mother with poor health is a less able caregiver. It could also indicate that women with poor health bear less healthy children, but considering the results from adopted and biological children sample, the authors caution against the latter conclusion.

Parent's education is another important input for children's outcomes. Currie and Moretti (2003) tried to explore the link between mother's education and birth outcomes by using college availability in their seventeenth year as an instrument for maternal education. Their results showed that mother's education have positive effects on birth weight and gestational age. This may happen because of different pathways as there is also a reduction in smoking by mothers and increased likelihood of being married and usage of prenatal care. Chou et al. (2010) used data from Taiwan to explore the effect of parent's schooling on infant outcomes. Increases in parents' schooling lowers the probability of low birth weight, neonatal or postneonatal infant deaths. The evidence presented corroborate the findings from Grossman

(2006) that showed parent's schooling, most importantly mother's schooling, to be a strong predictor of child health.

1.4 Parental characteristics and children's schooling

The first attempt to understand the determinants of education happened when James Coleman produced the so-called "Coleman Report" (1966). His goal was to document the availability of equal educational opportunities between different ethnic and socio-economic groups as commissioned by the Civil Rights Act 1964. Apart from having a clear picture of the inequality of opportunity between different social groups, his report was a starting point to understand what variables could explain educational outputs and to have a better understanding of what could be done to improve schooling in the USA. Gathering socioeconomic data from regional and national surveys, Coleman and his team produced a wealth of information and found that most of the variation in test scores could be explained by the student's socio-economic background. Coleman said: "when these factors are statically controlled, however, it appears that differences between schools account for only a small fraction of differences in pupil achievement" (Coleman 1966, pp. 21-22). In other words, parents' education and their attention towards their children's educational performance was one of the best determinants of children's schooling.

Many studies have attempted to isolate an exogenous shock to parental education as a way to determine a causal relationship from parents' schooling to children's education and earnings. Compulsory school changes is a common shock used for this purpose. Oreopoulos, Page and Stevens (2006) used data from the Census Bureau in the USA containing information on cohorts from the 1960's, 1970's and 1980's censuses and changes in mandatory schooling laws by year and state to determine exogenous changes to schooling. They suggested that a one-year increase in schooling of either parents reduces the likelihood of grade repetition between two and four percentage points. The impact is larger than found in OLS estimates. For teenagers still living at home there was also a decreased probability of dropping out of high school the more schooling the parents' had. Dickson, Gregg and Robinson (2016) used a 1972 change in school leaving age in England to explore the causal effect on children's outcomes whose parents had been affected by the reform. Using the Avon Longitudinal Study of Parents and Children (ALSPAC), they estimated that the effect of parental education can be seen at age four and lasts all the way to examinations taken at age sixteen. Children from more educated parents perform over 0.1 standard deviations better. The effect is even larger, over 0.15 standard deviations, for children coming from lower socio-economic background.

Another way to tackle endogeneity is using exogenous variation in schooling costs. Carneiro, Meghir and Parey (2013) used changes in costs during mother's adolescence to evaluate the impact of intergenerational maternal education on children's cognitive achievements, behaviroural problems and other outcomes. Using the British survey, National Longitudinal Survey of Youth 1979 (NLSY79) the authors found that maternal education has a positive effect on cognitive skills and test scores in math and reading at age 7-8 and also 12-14, albeit smaller for the latter group. Mothers that are more educated also have children with fewer behavioural problems and grade repetition.

1.5 The relationship between health and education

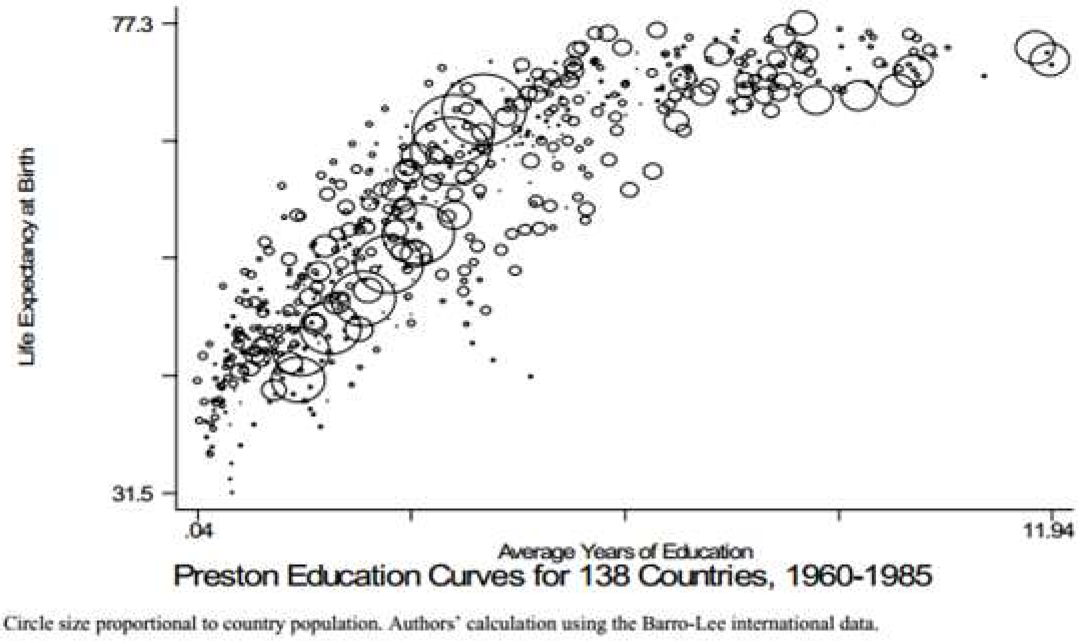
Education has been linked to a number of positive outcomes, both for the individual partaking in education and for the society. The earliest scientific reports of a correlation between health and education originated from small studies comparing cities in the USA. Sydenstricker (1929) and Stockwell (1963) found an inverse relationship between schooling and mortality rates, but the problems with the sample size and methodology caused these and other similar studies to be questioned. However, since the last quarter of the 20th century, researchers have been documenting the relationship between health and education. The seminal epidemiological work from Kitagawa and Hauser (1968, 1973) used data from the 1960 USA census records to show that mortality rates varied according to educational attainment. The more educated people were, the lower the mortality and morbidity rate and the better the self-evaluation of health status.

Shortly after, Grossman (1976) stated that each household has a health production function and that schooling increases the efficiency of the production of health. From that point on, several researchers have found empirical evidence that support this hypothesis such as, Berger and Leigh (1989), Mirowsky and Ross (2003), Currie and Moretti (2003), Lleras-Muney (2005) Cutler and Lleras-Muney (2008). But Grossman was the first economist to develop a structured hypothesis to explain this relationship. He came up with three possible explanations: (i) health may affect education, meaning that better health outcomes and behaviour cause improved educational outcomes measured as years of schooling, performance in test scores or school enrolment. The second hypothesis suggests that (ii) education may affect health, which indicates a possible reversed causality path, in other words there is a causal relationship from schooling to better health outcomes and behaviour. The third and last hypothesis indicates that (iii) health and education are correlated with a third variable, but there is no causality between the former two. Each hypothesis has received attention from researchers since then.

The hypothesis that there is a third variable correlated with both health and education is relevant as explained previously. Differences in a third variable, such as rates of time preference and other taste variables could be the reason why education and schooling are positively correlated. According to this theory, investments in education would have no spillover effect on health and vice-versa. This theory was tested by Fuchs (1982) in an exploratory study with 500 men and women in the United States. Fuchs showed that the correlation between education and health could be explained by the individual's time preference. But he explained that he could not rule out the possibility that education could lower time discount rates which would lead individuals to invest more in health. Grossman (1976) argued that parental characteristics such as schooling, family income and socioeconomic status is largely responsible for shaping the childhood environment. This, in turn, can affect children's outcomes as seen in the previous sections and therefore will not be explained here.

Regardless of which theory is correct, and in fact more than one theory may be correct, the positive correlation between health and education is well documented and it is very clear to see it as shown by Cutler and Lleras-Muney (2008) on figure 1.2, which shows the relationship between life expectancy at birth and years of education. The figure does not control for other covariates, but even when most socioeconomic variables are added, the positive correlation can still be observed.

Figure 1.2: The relationship between education and life expectancy across countries.



Source: Cutler and Lleras-Muney (2008)

1.6 The relationship between health and education in children

When observing children, perhaps the most relevant hypothesis is that (i) health affects educational outcomes. In a similar fashion to Case, Lubotsky and Paxson (2002), it can be argued that by analysing children's health and later educational outcomes the reverse causality can be ruled out as children have little control over their health choices as parents are usually responsible for their vaccination, diet and visits to the doctor.[2] In other words, potential endogeneity issues caused by reverse causation are not a concern, or at least not as much as when analysing adolescents and adults.

In a similar way to Behrman (1996), Glewwe and Miguel (2008) published a chapter where they explain, in details, the problems usually encountered in studies in this topic. They also reviewed the empirical literature on the impact of health status and health behaviour on educational outcomes in developing countries. Results from several studies indicate that poor nutrition and health status impair educational achievements. These results hold regardless of which developing country the data originates from, whether it is in a cross-section or panel

[2] Although there is legislation in England (Human Rights Act 1998 and Children Act 1989) giving children the right to voice their opinions regarding their health choices, Franklin and Sloper (2005) argue that most of the decisions, if not all, are done by the parents or legal guardians.

format and with different identification strategies. Different datasets and different methodologies showed that malnutrition and poor health status affects negatively school enrolment, attainment and test scores.

Glewwe and Jacoby (1995) used cross-sectional data in Ghana and evaluated that the impact of poor health, as measured by height-to-age, on school enrolment at the correct age and school attainment was negative and significant. Height-to-age ratios is a common measure of health used in some studies. It is a current measure of health that reflect past inputs towards children's health. If a child is malnourished, this has a negative effect on their height. Alderman et al. (2001) also used height-to-age to determine the same negative effect except they used panel data from Pakistan that allowed them to control for unobserved effects. Glewwe, Jacoby and King (2001) also used panel data, this time from the Philippines, and found a negative effect of malnutrition on children's test scores at school. Anecdotally, they suggest that an investment of one dollar in childhood nutrition program could yield at least three dollars worth in returns in academic achievements. Following the same idea that malnourished children may have their school performance hindered, Alderman, Hoddinott and Kinsey (2006) used data from rural Zimbabwe to estimate the effect of pre-school malnutrition on human capital formation. Their identification strategy included the use of maternal fixed effects and instrumental variables. There was evidence that improved height-for-age was associated with schooling achievement in the form of grades of schooling completed.

The spill-over effect that improvements in health may have in education has gained attention of researchers and policy makers alike. Bobonis, Miguel and Puri-Sharma (2006) analysed the effect of a deworming program in India. By using a randomized selection process in which 200 preschools with children two to six years old were gradually phased into the program, the authors discovered that not only the intervention improved children's health by reducing iron anaemia but it also increased their preschool-participation rates and reduced preschool absenteeism by one-fifth. Despite that, a review done by McEwan (2015) listed 77 randomized experiments similar to the one described here, i.e. school-based interventions in developing countries, and found that deworming treatments had mean effect sizes on learning close to zero. However, the author acknowledges that there is little information on cost-effectiveness of treatments, meaning a program with relatively small impact can actually be more cost-effective than another one with a larger impact. The author also discusses the apparent contradictory finding that although there is a positive and significant effect on school enrolment and attainment, there is little evidence that this affects actual learning. This may be in line with Hanushek and Woessmann (2008) where they argue that improved school attainment in developing countries has not led to the expected gain in productivity and economic development and perhaps other channels may be important such as cognitive development.

There is also evidence that non-communicable diseases[3] and poor health behaviour lead to worse educational outcomes. Zhao, Konish and Glewwe (2012) used an instrumental variable, a common strategy to deal with endogeneity, in order to evaluate the impact of youth's smoking in their educational achievements. After implementing a two-step estimation strategy with counts of registered alcohol vendors and food price index as instruments, the authors estimated that smoking one cigarette a day can lower test scores in mathematics up to 0.08 standard deviations. However, there was no significant effect on Chinese test scores or school attainment measured by total years of schooling.

Ding et al. (2009) used students' genetic markers in the United States as instrumental variables to estimate the negative effect of Attention Deficit Hyperactivity Disorder (ADHD), depression and obesity on student's test scores. Their findings also support the hypothesis that better health status leads to improved performance on test scores. But there is less variability in children's health condition in developed countries. Health problems such as anemia and lead poisoning are relative rare in comparison with developing countries. Despite that, other conditions are still common such as dental caries and ear infections and they may lead to a negative impact in education. Currie (2009) reports a significant difference between high and low income families. For children from zero to three years old, 11 percent who are in families with income over 50,000 pounds have a chronic condition. That figure more than doubles, at 23 percent, for families with income less than 10,000 a year. Those figures also include mental health conditions but asthma is the leading chronic condition among children. Data from the Netherlands (Costa-Font and Gil, 2005) suggests an incidence of chronic conditions in children in yet another developed country where 16.8% of children aged 11-13 years old had chronic health problems.

[3] In the medical literature, Fernando et al. (2003), Vitor-Silva et al. (2009) and Vorasan et al. (2015) have studied the impact of malaria infections on school performance. Using data from Sri Lanka, Brazil and Thailand-Myanmar border, all researchers found a negative impact on test scores. The studies were not able to separate causality from correlation as the sample sizes were small (N=571 in the largest study) and no robust identification strategy was implemented, but they show some evidence of a relationship between health and education.

1.7 The relationship between health and education in adults

When considering adults, the hypothesis that educational attainment affects health gains strength. Llera-Muney (2005) used synthetic cohorts of U.S. censuses from 1960, 1970 and 1980 along with changes in compulsory education laws as instrumental variables for education. Since this instrument is highly unlikely to be correlated with unobserved determinants of education and health, such as time preference and tastes, the estimates seem to be more accurate. She studied the effects of education on adult mortality and suggested that OLS and IV estimates are not statistically different, but whilst OLS estimates show that an additional year of schooling yields a 1.3 percentage point lower probability of dying within the next 10 years, IV estimates are much larger: 3.6 percentage points lower probability for each additional year.

Arendt (2005) did similar work with data from Denmark in 1958-1975 and 1990-1995 periods. Using compulsory school reforms in former period he evaluated the impact of schooling on self-rated health, body mass index and smoking behaviour. Although the research is subject to some criticism, he found significant effects of schooling on self-rated health with IV estimates being larger than OLS estimates.

Currie and Moretti (2003) studied the effect of maternal higher education on birth outcomes in the United States using information from 1970-2000. They used information availability of colleges in the woman’s county in her 17th birthday as an instrument to control for endogeneity of educational attainment. They found a positive effect of mother’s schooling on child’s birth weight as well as a reduced probability of smoking during pregnancy which can clearly have an effect on a new-born’s health outcomes. The IV estimates again suggest a higher impact than what is shown in OLS estimates.

Sander (1995) also used data from the United States to study the impact of schooling on the odds of quitting smoking. Using parental schooling and region of residence information as instruments for the individual’s own schooling, which was the dependent variable of interest, Sander found a positive effect of schooling on the likelihood to quit smoking. If a man were to have his years of schooling increased from twelve to sixteen years, there would be a 10% increase in the likelihood of quitting smoking.

In the United Kingdom, data also shows a positive relationship between education and health according to qualitative and quantitative studies. Hammond (2004) did a qualitative study with adults living in three rural areas from England and concluded that adult learning had improved psychosocial qualities such as self-esteem, stress and recovery from mental health difficulties. Feinstein (2002), Feinstein & Hammond (2004) and Chevalier & O'Sullivan (2007) did quantitative studies to try to mitigate possible estimation bias and evaluate the causality stemming from education to health outcomes.

In 2002, Feinstein used data from the 1970 British Cohort Study (BCS70) and the NCDS along with Propensity Score Matching (PSM) estimation technique to reduce bias of the estimates. He found that the effects of education on depression appeared to be stronger than the ones on obesity, but there was a clear indication of effects on both health measures. The use of PSM methodology is a strong measure to reduce selection bias, given certain assumptions, but unlikely to eliminate bias altogether. Despite that, the general results seemed robust to different specifications.

Feinstein and Hammond (2004) used another method to deal with selection bias in the NCDS cohort. They argue that individuals partaking in adult learning (vocational or academic) could be systematically different from those who did not. For example, individuals could differ in their levels of ambition. However, if the analysis is done with the *changes* in outcomes instead of *levels* at a single point in time, then this bias could be greatly reduced since the level of ambition can be considered constant over time for the same individual. Selection bias can still remain, especially if there is an unobserved event that causes individuals to change their perceptions and tastes, but the authors argue that this can be dealt with, to a certain extent, with controls for sources of confounding bias. Among the many results, they find that adults taking between three to ten vocational courses between ages 33 and 42 increase their probability of giving up smoking by 7.3%.

Chevalier and O'Sullivan (2007) used changes in compulsory school leaving age in 1947 in the UK as instrument along with data from NCDS to show that mothers with an additional year of education increased birth weight of their children by 75g, a gain equivalent to 2% of average weight. They go on to also briefly analyse economic returns say that this increase could translate into a total benefit of £2,000 per treated child for mothers that were affected by the school compulsory law. As shown before, the OLS estimates seem to give a lower bound to the effect of education on health.

Another study with instruments, done by Siles (2009), used two different changes in compulsory school leaving age in the UK, the first in 1947 and the second in 1973, to evaluate the impact of years of schooling on self-assessment of health and occurrence of illnesses, including whether or not they limited work or activities. The data came from the General Household Survey for England, Scotland and Wales starting in 1971. The results of the two stage least squares showed there is a 4.5 percentage points increase in the probability of being in good health for a one year increase in education and a reduction of long-term illness occurrence and activity-limiting illness by 5.5 percentage points and 4.6 percentage points, respective. As a robustness check, Siles also used a regression discontinuity design using the cohorts just before and just after the changes in legislation. The magnitude of the effects remains similar although are less significant.

1.8 The relationship between ADHD, education and life outcomes

This section focuses on mental health or, more specifically, Attention Deficit & Hyperactivity Disorder (ADHD). Along with depression, ADHD is one of the most common mental disorders. Diagnosed at an early age, up to 50% of individuals affected will continue with the condition well into their adulthood. The diagnosis of ADHD is not consensual but the main diagnostic criteria that is largely accepted by the psychology community is given by the *Diagnostic and Statistical Manual of Mental Disorders,* 4th edition (DSM-IV).[4] The manual describes ADHD as "…a persistent pattern of inattention and/or hyperactivity that is more frequent and severe than is typically observed in individuals at a comparable level of development". The symptoms of this disorder are distributed continuously in the population but the severity and the number of symptoms found will determine a possible diagnosis. Thus, (i) the individual must present six or more symptoms that significantly impair their development; (ii) the symptoms must have been preferably observed before age 7 and (iii) must be present in at least two different settings, most usually at home and at school.

According to Brown (2000), after having interviewed patients with ADHD, he was able to develop a scale of forty items that was based on DSM-IV inattention criteria but moved further and created grouped characteristics. The items were put together into six clusters of ADHD-related impairments in children between 3 and 12 years old and that affected the following executive functions: i) start, organize and prioritize work; ii) shift, focus and sustain attention to tasks; iii) regulate alertness, sustain effort and process speed; iv) manage frustration and modulate emotions; v) utilize working memory and access recall; vi) monitor and self-regulate action. These six executive functions are essential for human capital attainment in a learning environment in which one needs to sit still, pay attention and focus. For example,

[4] The latest edition of this manual is the DSM-5, released in 2013, after 14 years of research. The number of studies using the new manual is still quite limited which is why this study uses DSM-IV instead. The ADHD section in the latest edition went through minor changes, none of which modify the interpretation or assumptions presented here.

problems in starting, organizing and prioritizing work may lead to difficulty in starting and finishing school projects or missing deadlines on assignments. Likewise, inability or difficulty in focusing and sustaining attention to tasks may not only hinder school progress but also lead to poor productivity in the work place as long periods of attention on specific projects and tasks are necessary in this environment. These impairments can lead both to lower human capital attainment and labour productivity.

Some studies have shown that these symptoms can be alleviated and special education can help children cope with their condition. For instance, Fiore, Becker and Nero (1993) reviewed 137 empirical studies to find that some techniques such as use of more colour, eliminating distracting details and providing further help can improve school outcomes. Stage and Quiroz (1997) analysed 99 experiments that aimed to decrease disruptive behaviour in the classrooms and found that psychotherapy and classroom management techniques yielded similar positive results in reduction of disruptive behaviour. A study conducted by the U.S. National Institute of Mental Health (MTA Cooperative Group, 1999) compared four different types of treatment: i) behavioural therapy; ii) medication; iii) medication and therapy; and iv) standard community care along with medication with lower dosage than recommended. The study claimed that "the four groups showed sizable reductions in symptoms over time, with significant differences in degrees of change" (p.1). Unfortunately, the effectiveness of medication is not clear yet. A study by Currie, Stabile and Jones (2014) using data from Canada showed that expanding medication in a community setting in Quebec did not improve the performance of children with ADHD, whilst at the same time there was an increase in the probability that a child would suffer from depression and there was a decreased post-secondary educational attainment amongst girls. Another study, by Dalsgaard, Nielsen and Simonsen (2014), showed that the use of medication in patients with ADHD have fewer hospital visits and are less likely to be charged with a crime, but the authors caution that patients with less severe ADHD may not present similar benefits of such treatments.

Other studies focus more on the negative effects of ADHD in different outcomes. The most usual outcomes analysed are related to education. Currie and Stabile (2006) used nationally representative data from the U.S. and Canada to discover that ADHD had large negative effects on test scores and schooling attainment. Fletcher and Wolfe (2008) did a follow-up analysis on the previous study using data from the U.S. only and found further negative outcomes. Their findings corroborated the short-term effects found by Currie and Stabile (2006) that showed that individuals with ADHD have higher grade repetition and are more likely to receive special education services and they extended the findings showing subjects had lower grade point averages, increased likelihood of suspension and expulsion and fewer years of schooling. Mannuzza and Klein (2000) reviewed three clinic studies done in the U.S. with follow-ups and found that negative effects are initially found in academic and social functioning during childhood. Children with ADHD have worse performance in exams, have fewer friends and have lower skills in psychosocial adjustment. When observed in their mid-twenties, the subjects have fewer years of schooling, have lower-ranking occupations and they are more likely to have substance use disorder. The limitation with these studies is the sample size. Being clinical studies, none of them have more than 115 subjects with ADHD in their sample and the subjects were exclusively white males. The controls were selected in a way that excluded any kind of behavioural problem in the individuals which may overstate the effects of ADHD. Not only that, other cofounding factors could explain the difference in performance, such as poverty or parental socioeconomic information.

Apart from educational outcomes, some other life outcomes were explored as well. A study by Barkley et al. (1993) associated the prevalence of ADHD with higher risk of car accidents and bodily injuries due to car crashes but the sample consisted of 35 patients and 36 control subjects which limit the external validity of the study. Fletcher and Wolfe (2008) used data from the National Longitudinal Study of Adolescent Health (U.S.) and found that subjects with attention deficit or hyperactivity disorders were more likely to be involved in criminal activities than other individuals. In another study, Fletcher (2014) used the same dataset to evaluate the impact on labour market outcomes. He found out that subjects had between 10 and 14 percentage points reduction in the probability of being employed, income is reduced by a third and there was a 15 percentage points increase in social assistance.

In the United Kingdom, Farmer (1993, 1995) used data from a British longitudinal study that began in 1958 and followed individuals throughout their lives in subsequent surveys, the National Child Development Study (NCDS). She studied the effect of children with "externalizing" behavioural problems on educational and labour market outcomes. The results indicated that men had lower school-leaving age, lower educational qualifications at the moment of labour force entry and lower social class employment at age 23. However, the study had a very general approach to behavioural disorder and did not focus on ADHD and only two controls were used which limits the claim for causality as there could be confounding factors involved.

The studies shown helped understand different pieces of a complicated puzzle with different methods. Clinical studies have shown correlations in cross-sectional data but were focused on a small geographic area and in a particular ethnicity. Longitudinal studies provided researchers with more controls and better estimation methods available but, again, were limited to North America or focused on outcomes in a particular point in the individuals' lives.

Brassett-Grundy and Butler (2004) used the British Cohort Study (BCS70) to do a more comprehensive study. Similar to the NCDS, the BCS70 is a longitudinal study that started in 1970 and follows the lives of the cohort members collecting their socioeconomic information as they age. The authors used the survey's questionnaire to identify individuals with ADHD symptoms in 1980 (age 10) and with a sample of 10,405 individuals, of which 721 were identified as having ADHD, they found a broad range of negative effects at age 32 from educational outcomes, labour market outcomes and other social outcomes. The effects were stronger for men than for women and were robust after controlling for socioeconomic information.

Chapter 2

Higher education and the impact on health outcomes and behaviour: does the degree choice matter?

Daniel Roland

Abstract:
Given increases in higher education tuition fees in the United Kingdom in 2012, understanding the returns to education has gained importance. This paper focuses on the evaluation of the wider returns to education, more specifically the impact of education on health outcomes and behaviour considering different choices of higher degrees. It is well known that both monetary and non-monetary returns to education differ according to years of schooling, but recently there has been a renewed interest to also evaluate the difference in monetary returns between subject choices. However, little has been done to understand differences in the wider returns as well. By using panel data from the National Child Development Study (NCDS), a longitudinal data from the UK that followed individuals since their birth in 1958, this study tries to understand if there are any differences between health outcomes and health behaviours between individuals with the same educational attainment but with different degree choices. There are clear significant health returns to having a degree and the finding is very robust, but unlike studies that have shown differences in monetary returns, the results in this paper also show that there are no significant differences in the effects of education on health across different degrees.

2.1 Introduction

In recent decades, education has gained a considerable amount of attention from researchers and policy makers. This is a consequence of the increasing awareness that human capital is an important factor that drives economic growth.[5] The main component of human capital is education, thus it is not surprising that a great deal of attention is put into understanding how and why education helps not only the society but also individuals to improve their socioeconomic wellbeing. Understanding what are the returns to education and further investigating the channels through which education helps increase output and wellbeing can help policy makers concentrate resources on policies that best address these channels in order to maximize cost effectiveness of public spending. Given the 2012 changes in the cost of higher education in the United Kingdom, it has become especially important to understand what exactly are the returns to higher education.

Publicly financed education of children in their early years is widely available across the industrialized world and it is compulsory for children and teenagers to receive education. However, as the individuals get older they have a choice to stop or to continue their education. Therefore, further education is ultimately an individual's choice. They choose to invest in education according to their perception of the returns that they would have and the costs to obtaining further education (Becker 1962; Spence 1973). The costs for the individual can be measured in monetary and non-monetary terms. Tuition fees and other education related expenses as well as forgone earnings during the education period are considered as monetary expenses whilst the effort that must be done in order to complete education is considered a non-monetary cost (Becker, Hubbard and Murphy 2010). In other words, individuals simply do a cost-benefit (returns) analysis.

This paper aims to explore the returns to higher education. Specifically, the focus of this paper is to investigate any differences in the type of degree obtained by individuals and its effect on health outcomes and behaviour. In doing so, this study contributes with new results adding to the literature of returns to education by different degrees. These returns can be arranged into four dimensions. The two main dimensions are the *private* returns to education as well as *social* returns and these can be divided into *private/social economic* returns and *private/social non-economic* returns, the latter also often being referred as non-monetary returns or wider returns to education. Each of these dimensions has been subject of different

[5] Nelson and Phelps (1966), Lucas (1988), Barro (1991), Mankiw, Romer and Weil (1992), Romer (2006).

studies and fully evaluating every type of returns to education is necessary in order to assess the total benefits that investments in education can bring to society.

Private returns are benefits from education that are reaped solely by the individual. A clear example is the fact that higher educated people tend to earn more income throughout their lifetime (Carneiro, Heckman and Vytlacil 2011), they are less likely to be unemployed and, if they do happen to be unemployed, they spend less time before finding another job (Mincer 1991). These are purely economic returns. On the other hand, social returns can be considered as spill-over effects. More educated people have improved civic participation as they are more likely to participate in community meetings and take part in the political process by voting and reading newspaper as well as give more support to free speech (Milligan, Moretti and Oreopoulos 2004; Dee 2004). The fact that an individual is healthier due to increased levels of education is a private wider return to education but that also means that there will be less strain on public resources as the individual will require less attention and treatment (Wagstaff 1993). Individuals with higher levels of education are also less likely to commit crimes and be incarcerated (Lochner and Moretti 2004). The existence of both social economic returns such as suggested by Nelson & Phelps (1966) and Lucas (1988), and social wider returns previously mentioned, is the main argument used by people that advocate public financing of post-compulsory education as individuals would not take into account spill-over effects and would thus socially under-consume education, ultimately constituting a market failure.

When considering *wider returns to education*, perhaps the most widely studied return to education is the impact on health. The correlation and causality between education and health has been studied in depth in the past few decades. Individuals with further education tend to present better health behaviour and health outcomes. Wider returns to education include better health behaviour and outcomes such as family planning (Currie and Moretti 2003), quitting smoking (Sander 1995), lower obesity levels and self-assessment of health status considered good (Silles 2009). More years of schooling are correlated with better health outcomes such as lower mortality and morbidity rates, fewer working days lost, engagement in vigorous exercises, lower BMI and less incidence of depression (Feinstein 2002). Post-compulsory education degrees have also yielded positive effects on health outcomes as well. However, the mechanism through which education affects health is still subject to debate and several researchers have tried to disentangle the connection between education and health. But, while trying to do so, researchers have overlooked the exact impact that post-compulsory education can have on health. For instance, individuals with the same number of years of schooling but who chose different degrees may have very different health behaviour and health outcomes due to that choice. Walker and Zhu (2011) have analysed differences in economic returns between degrees in the UK with data from Labour Force Survey. They show that women's earnings benefit from higher education regardless of the choice of degree while men benefit greatly from Law, Economics and Management degrees in comparison with other courses. Despite contributing to the literature, the study did not address the effects of different degrees on health, which is the main contribution of this paper.

One of the theories that try to explain the connection between those two variables states that people with higher rates of time preference are more likely to invest both in education and in health (Fuchs 1982, Becker and Murphy 1988). In other words, people with higher rates of time preference are more willing to invest time and effort in activities that have positive results at a later moment in life. Activities such as spending additional years being educated and making an effort to have a healthy lifestyle may be costly and the results are not easily seen or noticed until after a certain amount of time. In this scenario, there is clearly a positive correlation between education and health but no apparent causation between the variables. If education does in fact play a role in helping individuals achieve better health outcomes, one would expect that the choice of the degree would yield different positive health outcomes as the curriculum varies significantly across degrees. On the other hand, a lack of differences between individuals with degrees in different subjects could mean that there is a core set of skills and knowledge imbued during higher education and that is shared across all degrees. The focus of analysis is on individuals who had degrees in fields related to Science, Technology, Engineering and Mathematics (STEM), Health, Law, Economics and Management.

This research uses a British longitudinal survey, the National Child Development Study (NCDS), a survey that started in 1958 with nearly 17,500 new-borns and attempted to track the same individuals over eight waves across time, thus creating a longitudinal study with an extensive amount of socioeconomic information. The 8th wave, in 2008, had 9,790 individuals participating.

The results found are in accordance with most of the literature from this topic. The findings suggest a clear impact of higher education qualification on health, especially on self-assessment of health and incidence of disabilities, inadequate Body Mass Index and smoking. The results are robust to different model specifications. However, when comparing differences in wider returns across different subjects, no significant results were found and the hypothesis that the effect on health is the same across degrees cannot be rejected.

The remainder of this paper is structured in the following way. Section two presents the methodology used for the analysis. This is followed by section three in which the data used in this research is presented along with descriptive statistics of the variables used in the study, including a subsection describing the ADHD sample. Section four presents the results with several different specifications as well as discusses what they mean. The last section contains the conclusion. For a detailed theoretical framework and literature review please refer to chapter 1.

2.2 Methodology

The dependent variables used in this research are all binary, so it is possible to estimate the effect of education on health by using a linear probability model such as:

$$H_{it} = \alpha + \beta_{1t} degree_{it} + \boldsymbol{\vartheta X}_{it} + \beta_{2t} H_{it-} + u_i + \varepsilon_{it} \qquad (1)$$

In which the health variable H_{it} is a function of a constant, plus a binary variable indicating whether or not an individual has a degree or has a degree related to a particular field of knowledge, plus a set of control variables $\boldsymbol{X}$, a lagged health variable, an unobserved time invariant individual effect u and finally a zero-mean error ε uncorrelated with the regressors.

However, one of the problems with the linear probability model is that it may yield probabilities that are lower than zero or higher than one, which are meaningless. Thus, the estimations were done with the following model:

$$\Pr(y = 1|\boldsymbol{x}) = G(\boldsymbol{x\beta}) \qquad (2)$$

The probability of treatment, once controlled by the regressors $\boldsymbol{x}$, is equal to the function G which takes on values strictly between zero and one, depends on the values of controls $\boldsymbol{x}$ and coefficients $\boldsymbol{\beta}$, and is non-linear. The most common suggestions in the literature for describing this function are the probit and logit functions. This study uses the probit function, given by:

$$G(\boldsymbol{x\beta}) = \boldsymbol{\gamma}(\boldsymbol{x\beta}) \equiv \int_{-\infty}^{\boldsymbol{x\beta}} \gamma(v)dv \qquad (3)$$

with,

$$\gamma(v) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{v^2}{2}\right) \qquad (4)$$

Where The standard normal density is given by $\gamma(v)$.

Data from NCDS was used to calculate (2) according to different sets of controls and explanatory variables of interest. The first set of regressions was done with no controls followed by *model 2* in which controls for region of birth[6] as well as a dummy for males were added. *Model 3* included the individual's current region and socioeconomic information from the parents': their weekly income, marital status in 1958, whether or not they went into post-compulsory education and their social class. *Model 4* included additional socioeconomic information from the individuals' household: marital status in each survey (from 1981 to 2008), whether or not they had a child and their household weekly labour income.

2.3 Data

In order to estimate the effects of education on health this study used data from the second oldest birth cohort study in the United Kingdom, *The National Child Development Study* (NCDS), which is a longitudinal survey that started in 1958. All babies that were born in England, Scotland and Wales in a given week in March 1958 participated in this survey, a total of 17,415 new-borns. The survey at the time was called Perinatal Mortality Survey (PMS). Since then, nine additional waves where done and there is funding for an additional wave, planned to occur in 2018. Table 2.1 displays information for each year of wave, age and number of individuals interviewed for the NCDS. The 8th and last wave used in this study had 9,790 individuals. In the first three follow-up surveys there were efforts to include immigrants that were born in the same week as the original cohort and that were permanently established in Britain. No further attempts were made after wave 3, so the immigrants are under-represented from wave 4 onwards. There were 380 immigrants added on the first follow-up, 651 on the second follow-up and 929 on the third follow-up survey, wave 3.

Table 2.1 – National Child Development Study.

Wave	Year	Age (years)	Target Sample	Individuals interviewed
0	1958	Birth	17,638	17,415
1	1965	7	17,370	15,425
2	1969	11	16,880	15,337
3	1974	16	16,929	14,654
4	1981	23	16,713	12,537
5	1991	33	16,389	11,469
6	2000	42	16,194	11,419
7	2004	46	16,072	9,534
8	2008	50	16,014	9,790

[6] The United Kingdom was divided into ten regions: Scotland, North (England), Northwest, Yorkshire and Humber, East of England, East Midlands, West Midlands, Southeast, Southwest,

Apart from sample loss caused by individuals that permanently leave the UK, by individuals that cannot be located due to changes to new addresses within the UK and also non-response to efforts of tracking them, refusal to participate in the survey also contributed to sample loss, however small it was. On wave 4 in 1981 the refusal rate was 7.1%, the following wave at age 33 had 11.1% refusal rate and 13.2% of people tracked for the survey refused to participate.[7] The Table A.1 in the appendix shows the attrition throughout the years for individuals that informed their level of schooling in 1981. In 2008, 75.22% of the individuals with degree in 1981 and 70.53% of the individuals with no degree were still in the sample.

As members of the NCDS cohort aged, the surveys had different objectives and the information collected was different as well. The original focus when the PMS took place was to address social and obstetric factors that were linked with stillbirth and neonatal deaths since at the time these rates were concerning and were expected to fall. The data was collected from doctors and midwives that filled out medical records as well as parents who provided socioeconomic information. As the survey took on a longitudinal style study, family background, cognitive and behavioural development and educational achievement were the main focus in early years (ages 7, 11 and 16) and the data was collected through house visits in which the parents provided information along with educational and medical assessments. Teachers also provided information from schools and the study participants themselves completed ability tests. As the individuals moved on to adulthood and are now in late middle age, information such as vocational education and training, employment and health outcomes became the focus of the survey and the information was collected from the cohort members through structured interviews and questionnaires. The individuals started answering the surveys by themselves at age 23, on wave 4 in 1981.

The NCDS is not exactly a panel. The same questions were not asked in every single wave, mainly because the focus of the study changed throughout time. However, a set of core questions were repeated throughout waves 4 to 8, which made it possible to create a panel with the information from the study with the necessary variables for the estimation model. Table 2.2 presents the health related information collected in 1981, 1991, 2000, 2004 and 2008 and that were used as dependent variables. It also contains a brief explanation of how derived variables were created and how some questions were asked in the questionnaires with the exact same words throughout the survey waves.

[7] Centre for Longitudinal Studies – NCDS and BCS70 Technical Report

Table 2.2 – Description of dependent variables used.

Variable	Description
Excellent Health	Binary variable; Indicates individual considers own health to be excellent (options are excellent, good, fair or poor).
Disabilities/Illnesses	Binary variable; Individual has a long standing illness or disability.
Inadequate BMI[a] (underweight; overweight)	Binary variable; Individual's Body Mass Index is below 18.5 (underweight) or above 25 (overweight or obese).
Smoker	Binary variable; Indicates individual smokes at least once a day.
Hazardous drinking	Binary variable; Men consume over 21 units of alcohol per week; women consume over 14 units of alcohol per week.
Backache	Binary variable; "Do you often have backaches?"
Tired	Binary variable; "Do you feel tired most of the time?"
Sad	Binary variable; "Do you often feel miserable or depressed?"
Worried	Binary variable; "Do you often get worried about things?"
Rage	Binary variable; "Do you often get in a violent rage?"
Scared	Binary variable; "Do you often suddenly become scared for no reason?"
Upset	Binary variable; "Are you easily upset or irritated?"
Jittery	Binary variable; "Are you constantly keyed up and jittery?"
Nervous	Binary variable; "Does every little thing get on your nerves and wear you out?"
Heart race	Binary variable; "Does your heart often race like mad?"

Table 2.3 presents the description of explanatory variables used in this study. All are binary variables with the exception of the natural logarithm of parent's income measured in 1958 and the natural logarithm of household's labour income measured in 1981 (wave 4) and sequentially until 2008 (wave 8). The income was deflated using the Retail Price Index (RPI).[8] The information about parents' education and social class was derived from information contained in the 1958 initial PMS, parent's income was collected in the initial survey and the three follow-up waves and all remaining variables were collected from waves 4 (1981) to wave 8 (2008).

[8] The RPI tables are provided by the Office for National Statistics, United Kingdom.

Table 2.3 – Description of explanatory variables used.

Variable	Description
Degree	Binary variable; indicates individual has a first degree. For other specifications, it indicates having a degree from a subject in particular.
Parents post-compulsory education	Binary variable; indicates both parents went on to further education after schooling leaving age.
Parental social class	Binary variable; indicates parents' social class is considered "White Collar"
Parental income (log)	Natural log of parent's weekly income in 1958.
Employed	Binary variable; indicates individual is (self)employed
Male	Binary variable; indicates individual is male
Married	Binary variable; indicates individual is married
Has children	Binary variable; indicates individual has children
Household labour income (log)	Natural log of household's labour income

Due to attrition and non-response, not every individual informed their highest academic degree in every wave. On top of that, the survey's questionnaires asked what was the individual's highest academic achievement since the last wave, not in their lifetime. In order to create an independent variable of interest with the largest number of observations possible, information that was collected in previous waves were kept in the sample in following surveys despite the fact that in any particular survey that information might be missing. In other words, as long as it was known that the individual had a degree, this information was recorded regardless of whether the individual provided this information in following waves or not. This explains why, on Table 2.4, the number of observations is increasing despite the fact that the achieved sample has been reduced over the years.

Table 2.4 – Number of observations for graduates and non-graduates.

	Wave 4 1981	Wave 5 1991	Wave 6 2000	Wave 7 2004	Wave 8 2008
Graduates	1,235	1,448	2,021	2,156	2,497
Non-graduates	2,457	3,489	4,346	9,046	9,616
Total	3,692	4,937	6,367	11,202	12,113

Table 2.5 shows the descriptive statistics of the panel sample with six observations through time (1958, 1981, 1991, 2000, 2004 and 2008). Considering that it is a panel setting with more than 9,000 individuals followed in six different moments in time, it is not surprising the lowest number of observations for a variable is over 38,000. It is possible to see that there

was an increase in higher education attainment between generations. Close to 10% of the subject's parents had pursued further education after school leaving age while more than 24% of the 1958 cohort went on into having a higher degree at some point in their lives.

Table 2.5 – Descriptive statistics of dependent and independent variables.

Variable	Mean	Standard Deviation	Observations
Degree	0.2442	0.4296	38311
Excellent Health	0.3256	0.4686	51235
Backache	0. 2131	0.4095	41716
Tired	0.2417	0.4281	41714
Sad	0.1637	0.3700	41683
Worried	0.4132	0.4924	41733
Rage	0.0454	0.2082	41730
Scared	0.0735	0.2610	41733
Upset	0.2137	0.4099	41735
Jittery	0.0527	0.2234	41729
Nervous	0.0429	0.2026	41721
Heart race	0.0736	0.2611	41718
Disabilities/Illnesses	0.2453	0.4303	51280
Inadequate BMI	0.4081	0.4915	38870
Smoker	0.0349	0.4722	47371
Hazardous drinking	0.2677	0.4427	42532
Married parents	0.8737	0.3322	74440
Parents post-compulsory education	0.1021	0.3028	71670
Parental social class	0.1941	0.3955	72065
Parental income(log)	5.4617	0.7029	38730
Male	0.4948	0.4999	51429
Married	0.6349	0.4814	51073
Has children	0.3886	0.4874	51082
Household labour income(log)	6.1376	2.1707	36078

Similar descriptive statistics are available on the appendix (Table A.2) for the subsample of individuals from the 1958 cohort that informed the subject of their degrees in the year 2000, wave 6, where a total of 829 individuals informed their degree choices.

2.4 Results

As a benchmark for interpretation of the results, the analysis was initially done in a standard way evaluating the effect of having a higher degree or postgraduate degree on health. Studies about education and health show a positive correlation between both variables and this result was expected to be shown in our benchmark analysis. The initial hypothesis was partially correct as seen on Table 2.6, which shows the marginal effects of a probit regression. All the health related variables were significantly affected by education when no socioeconomic controls were added, with the exception of hazardous drinking. Introducing controls for region slightly changed the magnitude of the effects, but not the significance. Adding socioeconomic controls reduced the magnitude and significance of several malaises and once all socioeconomic controls were added, the significant effects could be seen for self-assessment of health, incidence of backache and disabilities/illnesses, inadequate BMI and smoking, but not for malaises.

Table 2.6 – Impact of having a degree on health outcomes and health behaviours.

Variable	No controls	Model 2	Model 3	Model 4
Excellent Health	0.1102***	0.1053***	0.0517***	0.0490***
Backache	-0.0400***	-0.0395***	-0.0427***	-0.0345***
Tired	-0.0299***	-0.0241***	-0.0089	0.0084
Sad	-0.0378***	-0.0352***	-0.0216**	-0.0000
Worried	-0.0545***	-0.0423***	-0.0376*	-0.0071
Rage	-0.0031***	-0.0028***	-0.0015	-0.0000
Scared	-0.0153***	-0.0139***	-0.0055*	-0.0016
Upset	-0.0424***	-0.0380***	-0.0340***	-0.0123
Jittery	-0.0069***	-0.0060***	-0.0023	0.0009
Nervous	-0.0082***	-0.0077***	-0.0049**	-0.0016
Heart race	-0.0180***	-0.0168***	-0.0113***	-0.0052
Disabilities/Illnesses	-0.0802***	-0.0855***	-0.0480***	-0.0544***
Inadequate BMI	-0.1167***	-0.1281***	-0.0895***	-0.0968***
Smoker	-0.0714***	-0.0713***	-0.0580***	-0.0632***
Hazardous drinking	0.0036	-0.0019	-0.0085	-0.0099

Note: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children.

Having a higher degree had no significant effect at all on hazardous drinking, even when no controls were added. This may be explained by the fact that even though heavy drinking has been known for a long time to be bad for health, the parameters set by the National Health Service (NHS) that were used to create this variable were not of general knowledge until recently. This means that the 1958 cohort was not aware of the healthy limits of drinking alcohol.

A separate analysis was done to evaluate differences in gender. Table A.3 (see appendix) shows results separately for males and females. Since the sample is roughly split in half for each estimation, the loss in the level of significance for the coefficients was expected. The pattern of results remains largely unchanged and it is possible to see that the effects seem to be larger for males than for females, with the exception of incidence of backache. One particular result stands out, having a degree for males reduces incidence of inadequate BMI by almost twice as much as it does for females. It is the largest difference in the results for males and females. This deserved further analysis.

The inadequate BMI variable was measured as a binary variable indicating BMI lower than 18.5 or larger than 25. Table 2.7 shows more details about poor levels of BMI. The analysis was done separately with dependent variables that captured levels too low or too high as well as for males and females only. Results indicate that the effect of having a degree is significant in reducing incidence of being overweight but not underweight and the impact is stronger for males than for females. This result might be explained by the fact that being underweight is usually related to mental disorders such as anorexia and bulimia which are hard to treat and have much more to do with life traumas than with education and knowledge, which means having a degree would not make a difference on the probability of being underweight.

Table 2.7 – The impact of a degree on Body Mass Index problems.

Variable	No controls	Model 2	Model 3	Model 4
Under_bmi	0.0009	0.0019*	0.0052	0.0022
Over_bmi	-0.1211***	-0.1401***	-0.0906***	-0.0985***
Men				
Under_bmi	0.0000	0.0000	0.0000	0.0000
Over_bmi	-0.1452***	-0.1433***	-0.1078***	-0.1084***
Women				
Under_bmi	0.0038	0.0039	0.0107	0.0101
Over_bmi	-0.0965***	-0.0947***	-0.0785***	-0.0970***

Note: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children.

Some robustness checks were conducted to test particular hypothesis. One of them aimed to explore the channels through which having a higher education degree impacts the probability of having an inadequate BMI. It can be argued that individuals with lower qualifications may be employed in jobs that require more physical effort which in turn would lead to gain of muscular mass, thus increasing body weight and BMI levels. But when controlling for employment, as seen on table 2.8, the effects have a small reduction in *model 4.1* in comparison with previous results and the hypothesis that the effects are the same cannot be rejected.

Table 2.8 – Impact of having a degree on health outcomes and health behaviours – employment added as control in model 4.

Variable	No controls	Model 2	Model 3	Model 4.1
Excellent Health	0.1102***	0.1053***	0.0517***	0.0453***
Backache	-0.0400***	-0.0395***	-0.0427***	-0.0301***
Tired	-0.0299***	-0.0241***	-0.0089	0.0160
Sad	-0.0378***	-0.0352***	-0.0216**	0.0053
Worried	-0.0545***	-0.0423***	-0.0376*	-0.0049
Rage	-0.0031***	-0.0028***	-0.0015	-0.0002
Scared	-0.0153***	-0.0139***	-0.0055*	-0.0008
Upset	-0.0424***	-0.0380***	-0.0340***	-0.0138
Jittery	-0.0069***	-0.0060***	-0.0023	0.0010
Nervous	-0.0082***	-0.0077***	-0.0049**	-0.0015
Heart race	-0.0180***	-0.0168***	-0.0113***	-0.0049
Disabilities/Illnesses	-0.0802***	-0.0855***	-0.0480***	-0.0443***
Inadequate BMI	-0.1167***	-0.1281***	-0.0895***	-0.0923***
Smoker	-0.0714***	-0.0713***	-0.0580***	-0.0623***
Hazardous drinking	0.0036	-0.0019	-0.0085	-0.0217

Note: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4.1* includes the individual's marital status, household weekly labour income, a dummy for having children and a dummy for employment.

Another hypothesis considers that having a degree does not necessarily have an impact on health, it is actually the university experience that has an impact on health. The interaction with students, the contact with university staff, workshops, talks and lectures would have a greater impact. Spending one or two years in the university to receive a diploma or certificate, according with this hypothesis, would mean that we would observe similar effects of having a degree or having a diploma. Again, this hypothesis does not find support in the data. Results presented on Table A.4 on the appendix do not show any large change in the size or significance of the coefficients for having a degree and these changes cannot be credited to this hypothesis as they still lie within the confidence interval of previous estimates.

These results show that the methodology used presents results similar to the ones found in the literature, indicating an impact that stems from education to health. The contribution of this paper, however, lies on the analysis of wider returns to education according to subject choice. Two main groups of degrees were chosen for analysis. The first group is formed by individuals who had a degree in fields related to Science, Technology, Engineering and Mathematics (STEM) plus Health, forming a STEMH sample. Individuals with degrees from those fields were compared to individuals who had degrees from other fields of knowledge. Both STEM degrees and Health degrees share a syllabus that motivates individuals to use technical skills such as analytical, logical and critical view of facts. Problem solving based on observation of evidence, experimentation and quantitative research as well as developing numeracy and literacy skills are highly valuable in the job market, so despite the degrees may look different, they actually share many things in common. The second group is formed by individuals with degree in Law, Economics and Management (LEM). This group, according to Walker and Zhu (2011), has the highest monetary returns to higher education and it seemed reasonable to test if the same is true for non-monetary returns. The results are presented on Table 2.9. The estimates do not show a clear picture and it is not possible to clearly say that there are different wider returns between STEMH degrees and other subjects since the coefficients are very similar and still within each other's' confidence interval. The few health variables that seem to be significantly affected by a degree from the related field do not display a robustness of either magnitude or significance in nearly all health outcomes and behaviour as controls are added to the estimations.

Table 2.9 – Impact of different types of degrees on health outcomes and health behaviour, baseline is having no degree.

Variable	No Control	Model 2	Model 3	Model 4
Excelent Health				
STEMH	0.0823***	0.0615***	0.0791***	0.0522***
LEM	0.0732***	0.0544***	0.0702***	0.0456***
Other Degree	0.0709***	0.0567***	0.0675***	0.0421***
Backache				
STEMH	-0.0213**	-0.0168*	-0.0199	-0.0154
LEM	-0.0256**	-0.0197**	-0.0231	-0.0192
Other Degree	-0.0209*	-0.0134	-0.0177	-0.0128

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children. STEMH: Degrees in Science, Technology, Engineering, Mathematics and Health. LEM: Degrees in Law, Economics and Management. Other degree: Degree in any other subject.

Table 2.9 (continued) – Impact of different types of degrees on health outcomes and health behaviour, baseline is having no degree.

Variable	No Control	Model 2	Model 3	Model 4
Tired				
STEMH	-0.0161	-0.0079	-0.0009	0.0182
LEM	-0.0165	-0.006	0.0006	0.0195
Other Degree	-0.0139	-0.0052	-0.0002	0.0208
Sad				
STEMH	-0.0283***	-0.0236**	-0.0010	0.0287
LEM	-0.0265***	-0.0211**	-0.0003	0.0209
Other Degree	-0.0274***	-0.0229**	0.0002	0.0318
Worried				
STEMH	-0.0452***	-0.0248	-0.0127	0.0204
LEM	-0.0496***	-0.0283*	-0.0164	0.0157
Other Degree	-0.0438***	-0.0245	-0.0149	0.0162
Rage				
STEMH	-0.0001	-0.0005	0.0006	0.0001
LEM	0.0002	-0.0002	0.0011	0.0010
Other Degree	-0.0003	-0.001o	0.0007	0.0004
Scared				
STEMH	-0.0129***	-0.0121***	-0.0017	0.0025
LEM	-0.0138***	-0.0110**	-0.0008	0.0034
Other Degree	-0.0122***	-0.0115**	-0.0010	0.0029
Upset				
STEMH	-0.0521***	-0.0447***	-0.0221	0.0036
LEM	-0.0514***	-0.0440***	-0.0217	0.0040
Other Degree	-0.0498***	-0.0425***	-0.0199	0.0054
Jitter				
STEMH	-0.0079***	-0.0065***	-0.0047	-0.0013
LEM	-0.0080***	-0.0066***	-0.0048*	-0.0010
Other Degree	-0.0065***	-0.0049**	-0.0035	0.0002
Nervous				
STEMH	-0.0084***	-0.0082***	-0.0063**	-0.0015
LEM	-0.0085***	-0.0086***	-0.0061**	-0.0017
Other Degree	-0.0087***	-0.0085***	-0.0065**	-0.0020
Heart Race				
STEMH	-0.0194***	-0.0185***	-0.0118***	-0.0052
LEM	-0.0176***	-0.0168***	-0.0101**	-0.0039
Other Degree	-0.0184***	-0.0178***	-0.0112***	-0.0041

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children. STEMH: Degrees in Science, Technology, Engineering, Mathematics and Health. LEM: Degrees in Law, Economics and Management. Other degree: Degree in any other subject.

Table 2.9 (continued) – Impact of different types of degrees on health outcomes and health behaviour, baseline is having no degree.

Variable	No Control	Model 2	Model 3	Model 4
Disabilities/Illnesses				
STEMH	-0.0449***	-0.0396***	-0.0055	-0.0108
LEM	-0.0440***	-0.0385***	-0.0046	-0.0096
Other Degree	-0.0441***	-0.0387***	-0.0052	-0.0101
Inadequate BMI				
STEMH	-0.0562***	-0.0668***	-0.0442	-0.0452
LEM	-0.0557***	-0.0674***	-0.0438	-0.0455
Other Degree	-0.0559***	-0.0670***	-0.0439	-0.0450
Smoker				
STEMH	-0.0642***	-0.0645***	-0.0650***	-0.0586***
LEM	-0.0640***	-0.0642***	-0.0649***	-0.0585***
Other Degree	-0.0630***	-0.0631***	-0.0637***	-0.0572***
Hazardous drinking				
STEMH	0.0329**	-0.0055	-0.0163	0.0250
LEM	0.0326**	-0.0050	-0.0161	0.0245
Other Degree	0.0327**	-0.0051	-0.0161	0.0247

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children. STEMH: Degrees in Science, Technology, Engineering, Mathematics and Health. LEM: Degrees in Law, Economics and Management. Other degree: Degree in any other subject.

The results for Law, Economics and Management in Table 1.9 show similar lack of evidence of differences between wider returns of different degrees. Given that the exact same model was able to find differences between individuals with and without higher degrees, there are two possible explanations for the lack of significant effects when evaluating differences between degrees. The first one is that simply there are no differences in wider returns between degrees, unlike the differences in economic returns as seen on Walker and Zhu (2011). The second explanation is that the subsample of individuals who informed their degrees is not representative of the whole 1958 cohort.

To test this second explanation, the same estimations were made, this time comparing individuals that informed their degree choices with individuals that did not have a higher education degree. The idea was to find the similar results to the ones found in the complete sample. The results of these estimations can be seen on Table A.6 in appendix. For this subsample, the only health variables that are affected by having a degree are self-evaluation of health and the incidence of frequent smoking, similar to the results shown in Table 1.9. All other health indicators do not show any evidence of being affected by having a degree. This tells us two things; first, the subsample chosen to evaluate differences in wider returns between degrees is not entirely adequate as it does not replicate the results encountered in the larger sample. Second, even for self-assessment of health and incidence of smoking, in which positive and significant results were found, the results do not show any significance when evaluating differences between degrees. This leads to the conclusion that although the subsample used is not perfect, it does shows signs that there is, in fact, no difference in wider returns between degrees.

2.5 Conclusion and limitations

Education and economic growth have been known to be correlated for a long time. Likewise, we know there is a correlation between education and a number of other positive outcomes. Alongside that, given recent changes in the cost of higher education in the United Kingdom, it has become especially important to understand what exactly are the returns to higher education. This research focuses on the wider returns to education, more specifically, the impact of higher education on health outcomes and behaviour. The main contribution of this paper is that it also explores the differences in wider returns to education according to degree choice.

The analysis was carried on through a probabilistic model with probit estimations using panel data, although logit estimations and even OLS estimations yielded similar results. The data used for this study comes from the National Child Development Study (NCDS), a longitudinal British survey that started in 1958 and that has eight follow-up waves since then made available to the public, the last one publicly available being carried out in 2008. At the beginning, more than 17,000 participated in the survey and more than 9,000 still remain.

To test the validity of the estimation model used in this research, the first analysis was used on the entire 1958 cohort, comparing individuals that had a higher education degree with those who did not. Results showed that there was a significant positive impact of education on health outcomes and behaviour. Individuals with a degree were less likely to have backache, to be a smoker, have inadequate BMI or disabilities and illnesses. They were also 4.9% more likely to self-assess their health as being excellent in comparison with individuals with no degrees. Some robustness checks were done with different model specifications to test different hypothesis but the results remained largely the same and were more pronounced for males.

When evaluating a subsample for differences in wider returns according to individuals with degrees in fields related to Science, Technology, Engineering, Mathematics and Health (STEMH) and Law, Economic and Management (LEM), results did not show any significant difference in health behaviour and status. However, the subsample lacked statistical power and was not a perfect representation of the NCDS cohort. The same analysis between individuals with and without degree was done with the subsample and the impact of education on health was significant only for self-assessment of health and being a smoker.

A few caveats need to be addressed though. Despite having indications that there are no differences in the wider returns to education between different degrees, the results are far from being conclusive. More data, with better quality, needs to be used for the estimations as well as a more refined model that can clearly separate correlation from causality. Specifically, the co-determination of education and income, the latter being used as a control in model 4, can lead to endogeneity. Clearly there is need for further research. Another limitation of this work is that it does not explore the hypothesis that the effect of education on health may vary over time. Individuals with higher education degrees may eventually have poor health but this may take longer than it does for people without a degree. The use of subjective measures of health is also a problem, but this is not something new in the literature and by using several different measures of health this problem is, to some extent, addressed.

Appendix A

Table A.1 – Attrition for individuals that informed their education level in 1981.

Year	Degree	Proportion	Variation*	No Degree	Proportion	Variation*
1981	1235 (100%)	33.45%	-	2457 (100%)	66.55%	-
1991	716 (57.97%)	33.12%	-42.02%	1446 (58.85%)	66.88%	-41.15%
2000	1013 (82.02%)	33.62%	41.48%	2000 (81.40%)	66.38%	38.31%
2004	925 (74.90%)	34.16%	-8.69%	1783 (72.57%)	65.84%	-10.85%
2008	929 (75.22%)	34.90%	0.43%	1733 (70.53%)	65.10%	-2.8%

*$(year_t/year_{t-1}) - 1$

Table A.2 – Descriptive statistics of subsample of individuals with a STEMH degree.

Variable	Mean	Standard Deviation	Observations
Degree in STEMH	0.2768	0.4475	3024
Excellent Health	0.3717	0.4833	2564
Backache	0.1576	0.3645	1891
Tired	0.2258	0.4183	1891
Sad	0.1360	0.3429	1890
Worried	0.3712	0.4833	1891
Rage	0.0323	0.1768	1890
Scared	0.0513	0.2207	1891
Upset	0.1698	0.3755	1891
Jittery	0.0407	0.1977	1891
Nervous	0.0280	0.1651	1891
Heart Race	0.0323	0.1768	1890
Disabilities/Illnesses	0.2595	0.4384	2563
Inadequate BMI	0.4019	0.4904	1575
Smoker	0.1764	0.3812	2455
Hazardous Drinking	0.2876	0.4528	2225
Married parents	0.9060	0.2919	2616
Post-Compulsory education of parents	0.2558	0.4364	2592
Parental Social Class	0.3000	0.4583	2414
Parental Income(log)	3.3747	0.7252	1181
Male	0.5415	0.4984	2565
Married	0.6448	0.4786	2562
Has children	0.3393	0.4736	2561
Household Labour Income(log)	7.3569	2.2589	2108

Table A.3 – Impact of having a degree on health outcomes and health behaviours.

Variable	No Controls		Model 2		Model 3		Model 4	
	M	F	M	F	M	F	M	F
Excellent Health	0.1206***	0.0970***	0.1192***	0.0912***	0.0648***	0.0375**	0.0682***	0.0312
Disabilities/Illnesses	-0.0734***	-0.0884***	-0.0783***	-0.0921***	-0.0510***	-0.0486***	-0.0654***	-0.0475**
Inadequate BMI	-0.1565***	-0.0952***	-0.1549***	-0.0949***	-0.1112***	-0.0597*	-0.1563***	-0.0843**
Smoker	-0.0581***	-0.0555***	-0.0539***	-0.0601***	-0.0572***	-0.0662***	-0.0646***	-0.0624***
Hazardous Drinking	-0.0167	0.0102	-0.0238*	0.0118	-0.0102	-0.0090	-0.0065	-0.0212
Backache	-0.0330***	-0.0445***	-0.0330***	-0.0447***	-0.0301**	-0.0545***	-0.0230	-0.0437***
Tired	-0.0162*	0.0326**	-0.0156*	-0.0297**	-0.0212	0.0185	-0.0145	0.0289
Sad	-0.0235***	-0.0483***	-0.0244***	-0.0456***	-0.0200*	-0.0202	-0.0101	-0.0021
Worried	-0.0443***	-0.0462***	-0.0466***	-0.0338*	-0.051**	-0.0143	-0.0151	-0.0103
Rage	-0.0017*	-0.0028	-0.0016*	-0.0024	-0.0016	0.0018	-0.0001	0.0052
Scared	-0.0043***	-0.0244***	-0.0046***	-0.0228***	-0.0014	-0.0075	-0.0002	-0.0053
Upset	-0.0235***	-0.0533***	-0.0233***	-0.0505***	-0.0278**	-0.0435*	-0.0131	-0.0216
Jittery	-0.0039***	-0.0073***	-0.0038**	-0.0059**	-0.0016	0.0008	-0.0003	0.0029
Nervous	-0.0055***	-0.0090***	-0.0061***	-0.0080***	-0.0088**	-0.0016	-0.0055	0.0005
Heart Race	-0.0111***	-0.0231***	-0.0116***	-0.0215***	-0.0071**	-0.0140**	-0.0021	-0.0094

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children. STEMH: Degrees in Science, Technology, Engineering, Mathematics and Health. LEM: Degrees in Law, Economics and Management. Other degree: Degree in any other subject.

Table A.4 – Impact of having a degree on health outcomes and health behaviours – diploma/certificate variable added as control in model 4.

Variable	No controls	Model 2	Model 3	Model 4
Excellent Health				
Degree	0.1102***	0.0648***	0.0581***	0.0456***
Diploma	-	-	-	0.0852
Backache				
Degree	-0.0400***	-0.0395***	-0.0377***	-0.0305***
Diploma	-	-	-	0.0196
Tired				
Degree	-0.0299***	-0.0241***	-0.0068	0.0122
Diploma	-	-	-	0.0441**
Sad				
Degree	-0.0378***	-0.0352***	-0.0202**	0.0027
Diploma	-	-	-	0.0031
Worried				
Degree	-0.0545***	-0.0423***	-0.0343*	-0.0020
Diploma	-	-	-	0.0125
Rage				
Degree	-0.0031***	-0.0028***	-0.0016	-0.0001
Diploma	-	-	-	-0.0017
Scared				
Degree	-0.0153***	-0.0139***	-0.0054*	-0.0011
Diploma	-	-	-	-0.0012
Upset				
Degree	-0.0424***	-0.0380***	-0.0333***	-0.0128
Diploma	-	-	-	-0.0315**
Jittery				
Degree	-0.0069***	-0.0060***	-0.0022	0.0011
Diploma	-	-	-	-0.0017
Nervous				
Degree	-0.0082***	-0.0077***	-0.0050**	-0.0015
Diploma	-	-	-	-0.0010
Heart Race				
Degree	-0.0180***	-0.0168***	-0.0110***	-0.0046
Diploma	-	-	-	0.0021
Disabilities/Illnesses				
Degree	-0.0802***	-0.0599***	-0.0448***	-0.0535***
Diploma	-	-	-	-0.0124
Inadequate BMI				
Degree	-0.1167***	-0.1281***	-0.0900***	-0.0947***
Diploma	-	-	-	0.0462*
Smoker				
Degree	-0.0714***	-0.0510***	-0.0546***	-0.0587***
Diploma	-	-	-	-0.0003
Hazardous Drinking				
Degree	0.0036	-0.0051	-0.0327**	-0.0179
Diploma	-	-	-	-0.0334*

Notes: Significance level – *** 1%; ** 5%; * 10%. Controls in *Model 2*: region of birth and sex; *Model 3*: adds region of residence and parent's income, marital status, post-compulsory education and social class. *Model 4*: adds individual's marital status, household weekly labour income and a dummy for having children.

Table A.5 – Impact of a LEM degree on health outcomes and health behaviour.

Variable	No controls	Model 2	Model 3	Model 4
Excellent Health	0.0883*	0.0045	-0.0004	-0.2106
Backache	-0.0153	-0.0101	-0.0259	-0.0436
Tired	-0.0215	-0.0016	-0.0113	-0.0281
Sad	-0.0120	-0.0149	-0.0468	-0.0589*
Worried	-0.0237	0.0046	-0.0809	-0.0881
Rage	0.0057	0.0040	-0.0000	-0.0000
Scared	-0.0032	-0.0027	0.0008	-0.0011
Upset	0.0211	0.0273	-0.0558*	-0.0450
Jittery	0.0005	0.0001	-0.0000	-0.0000
Nervous	-0.0002	-0.0003	-0.0000	-0.0000
Heart Race	0.0005	0.0006	0.0005	0.0008
Disabilities/Illnesses	0.0245	0.0064	0.0140	0.0268
Inadequate BMI	0.1447***	0.1262**	0.1340	0.1787
Smoker	-0.0289**	-0.0136	-0.0289	-0.0039
Hazardous Drinking	-0.0086	-0.0512	0.0099	0.0113

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children.

Table A.6 - Impact of having a degree on health outcomes and health behaviours – Results for subject sample[ǂ].

Variable	**No controls**	**Model 2**	**Model 3**	**Model 4**
Excellent Health	0.0793***	0.0607***	0.0764***	0.0496***
Backache	-0.0221**	-0.0180*	-0.0224	-0.0178
Tired	-0.0152	-0.0064	0.0003	0.0202
Sad	-0.0277***	-0.0227**	-0.0006	0.0311
Worried	-0.0470***	-0.0269	-0.0156	0.0190
Rage	-0.0004	-0.0008	0.0010	0.0008
Scared	-0.0131***	-0.0116***	-0.0011	0.0030
Upset	-0.0510***	-0.0438***	-0.0211	0.0045
Jittery	-0.0071***	-0.0056***	-0.0039	-0.0003
Nervous	-0.0086***	-0.0083***	-0.0060**	-0.0016
Heart Race	-0.0181***	-0.0174***	-0.0108***	-0.0042
Disabilities/Illnesses	-0.0444***	-0.0391***	-0.0051	-0.0103
Inadequate BMI	-0.0560***	-0.0671***	-0.0439	-0.0453
Smoker	-0.0636***	-0.0638***	-0.0643***	-0.0580***
Hazardous Drinking	0.0328**	-0.0053	-0.0163	0.0248

Notes: Significance level – *** 1%; ** 5%; * 10%. *Model 2* controls for region of birth and sex. *Model 3* adds controls for region of residence and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 4* includes the individual's marital status, household weekly labour income and a dummy for having children.%. [ǂ] Dependent variable is a dummy equal to one if subject of degree is known and zero if the individual does not have a first degree.

Table A.7 – Coefficients for the impact of degree, income and an interaction between the two.

Variable	Model 4		Model 5		
	Degree	Income	Degree	Income	Degree x Income
Excellent Health	0.0490***	0.0128***	0.0368***	0.0132***	0.0020
Backache	-0.0345***	-0.0039*	-0.0286***	-0.0023	-0.0083
Tired	0.0084	-0.0044	-0.0761	-0.0080	-0.0166
Sad	-0.0000	-0.0202	-0.0399	-0.0217	0.0081
Worried	-0.0071	-0.0229	0.1010	-0.0190	-0.0193
Rage	-0.0000	-0.0008	-0.0103	-0.0014	0.0032
Scared	-0.0016	-0.0012	0.0092	-0.0009	-0.0017
Upset	-0.0123	-0.0211	-0.0896	-0.0248	-0.0177
Jittery	0.0009	-0.0015	-0.0084	-0.0019	0.0024
Nervous	-0.0016	-0.0018	-0.0106	-0.0022*	0.0028
Heart Race	-0.0052	-0.0074	0.0305	-0.0065***	-0.0050
Disabilities/Illnesses	-0.0544***	-0.1458***	-0.1180***	-0.0127***	-0.0104*
Inadequate BMI	-0.0968***	-0.0758***	-0.3368**	-0.0661***	-0.0482
Smoker	-0.0632***	-0.0069***	-0.1100***	-0.0082***	-0.0090
Hazardous Drinking	-0.0099	-0.0314	-0.0996**	-0.0347***	-0.0150*

Note: Significance level – *** 1%; ** 5%; * 10%. Coefficients for marginal effects of panel probit. *Model 4* controls for region of birth, sex, region of residence, individual's marital status, household weekly labour income, a dummy for having children and parental information at the time of birth - income, marital status, post-compulsory education and social class. *Model 5* includes the same control plus an interaction dummy between having a degree and income.

Chapter 3

A Longitudinal View on the Effects of ADHD on life outcomes – Evidence from the UK

Daniel Roland

Abstract:

Attention deficit/hyperactivity disorder (ADHD) accounts for more than half of the mental problems in children and adolescents. Most studies estimate that roughly 10% of children at school age suffer from ADHD and more than half of them continue to have the symptoms all the way to adulthood. The negative impact of ADHD on educational outcomes has been extensively established in the literature but the impact of this condition on later life outcomes has not received similar attention. Therefore, the aim of this paper is to investigate the effect of ADHD on a broader range of life outcomes. The data used in this research comes from the British Cohort Study 1970, a longitudinal survey which contains a wide range of socio-economic information. I show that individuals diagnosed with ADHD in their childhood are less educated and less likely to have vocational qualifications and they present worse labour market outcomes in terms of their occupation and level of income. However, no significant effects of ADHD are found on other social outcomes such as drug use, alcohol abuse and involvement in accidents. If ADHD is treated during childhood this could possibly decrease the negative impact on educational and labour market outcomes. Moreover, individuals with this condition are also more likely to claim welfare benefits, which supports the need to discuss cost-effective treatment at an early age.

3.1 Introduction

The relationship between health and human capital accumulation and life outcomes has been long established.[9] Grossman and Kaestner (1997) established the positive correlation between physical health and human capital accumulation and many studies have followed since then. However, for a long time the majority of the literature on the subject used physical health problems as a measure for health, leaving mental health aside. This left a substantial portion of health problems such as depression, attention deficit and other mental disorders and their impacts on life outcomes unknown. It was not only until recent years that this gap in our knowledge has been partially filled by studies that have focused on both physical and mental health and their impacts on educational outcomes. As developed countries succeeded in improving the physical health of its citizens, attention has slowly turned towards mental health.

Mental health problems affect between one and two in every ten children and adolescents in developed countries.[10] In the United Kingdom, a total of £1.47 billion were spent in mental health care in 2008, a 47% increase from the mid 1990's, according to Knapp (2013). Out of a number of mental health problems affecting children, attention deficit and hyperactivity disorder (ADHD) is the leading cause of mental health disorders, accounting for up to half of child referrals. It is believed that 4-5% of children in the United States have ADHD (Currie and Stabile, 2006), but a study reviewing 135 original studies showed that these figures can go as high as 19% (Polanczyk, 2014).

According to the Diagnostic and Statistical Manual of Mental Disorders 4th ed. (DSM-IV), the diagnosis for this condition is given by the frequency and severity of symptoms found. Individuals that suffer from ADHD have a range of symptoms that have a continuous distribution in the population, but the severity of the symptoms in these individuals ends up causing debilitating conditions which hinders intellectual development. Naturally, it also hinders the acquisition of important skills required to work productively and efficiently.

---

[9] The link between health and human capital accumulation was first suggested by Schultz (1962) in his book *Investment in Human Beings*. Since then, Grossman (1972) developed a model in which health enters as a predictor in an optimizing equation for longevity and in 1976 he described the correlation between health and years of schooling.

[10] The numbers vary between countries. In the United States the prevalence of mental disorders in children and adolescents stands at 13 to 20% as mentioned by Perou (2013) in the report entitled *Mental Health Surveillance Among Children – United States, 2005-2011*. In Canada's province of Ontario it stands at 18% (Offord et al., 1987). In Great Britain the figure is much lower, 9.6% according to the Office for National Statistics (ONS) in the report "*Mental health of children and young people in Great Britain*" survey in 2004. Many factors contribute to the difference in numbers, mainly the definition of ADHD, the criteria used for diagnosis and the sample selection procedure.

Moreover, up to 50% of children and adolescents diagnosed with this disorder carry out the symptoms into adulthood, which means that these individuals are not only hindered at an early age which can lead to poorer life outcomes, they can also be affected throughout their lifetime which further adds to negative life achievements. Unlike some mental conditions like depression, individuals with ADHD can present a clear path of causality stemming from the onset of the disease at an early age moving towards negative life outcomes. As there is strong evidence that ADHD occurrence can largely be explained by genes,[11] this indicates that the condition is truly exogenous to life decisions, removing concerns regarding reversed causality.

The aim of this paper is to explore to what extent individuals with ADHD symptoms are negatively affected by it over the course of their life. The working hypothesis is that being hindered at an early age, when human capital attainment determines a number of future life outcomes, can have a strong impact in people's lives. Having this condition can also directly affect future life outcomes due to its idiosyncratic symptoms. In order understand more and evaluate the negative impact of ADHD, educational outcomes as well as labour market and other social outcomes are analysed. Using a wide range of outcomes instead of focusing on only one or two provides a more complete picture of how this mental disorder can have impacts that can last longer than previously documented.

The original contribution from this paper stems from two sources. First, by looking at longitudinal data it is possible to determine both short term and long-term effects of ADHD throughout a large number of individuals' lives. Although this is not the first paper to use longitudinal data, it is the first to analyse the impact of mental disorders throughout the individual's lives instead of a particular point in time. Second, this research analyses a broad range of outcomes, from educational and vocational qualifications to labour market outcomes and other social behaviours such as hazardous drinking and smoking habits. With this information it is possible to fully explore to what extent ADHD affects people's lives and provide further knowledge which can be used to determine cost-effective treatments at the onset of the disorder to mitigate or eliminate negative effects in the future.

The results show that there are negative effects on educational and vocational qualifications and labour market outcomes as well as an increased probability of claiming

[11] Weis (2013) provides a thorough review on the causes of ADHD, pointing out genes as responsible for up to 80% of the variance in ADHD symptoms (Brookes et al, 2006) and siblings of children that have ADHD are 3 to 5 times more likely to have the disorder when compared to controls according to Asherson and Gurling (2011).

benefits. Individuals that present ADHD symptoms at age 10 are less likely to have higher educational qualifications, to be employed, be on full-time employment and they also have lower earnings. These individuals are less likely to assume positions as managers or supervisors, which indicates difficulty in their career progression. The effects are stronger for women except for obtaining managerial positions, where men are most affected.

This study's contribution stems from the use of longitudinal data with which both short term and long term effects of ADHD can be assessed. Other studies have used longitudinal data, but this is the first to analyse the impact of mental disorders not only in a single point in time but also throughout the individual's lives from early adulthood to middle-age. Moreover, compared to other studies, this research focus on a larger range of outcomes, going from educational to labour market outcomes and other social behaviours.

The remainder of this paper is divided as follows: section two explains the methodology used in this paper and what model is chosen to analyse the impact on life outcomes. Section three provides details about the data being used in this study, including an explanation of the ADHD sample and how it was selected. Section four has the results and discussion, section five concludes the study with its limitations and plans for future research. For more details on the literature on ADHD, how it is diagnosed and what are the known effects so far, please refer to chapter 1.

3.2 Methodology

The BCS70 allows for both cross-sectional and panel analysis. The initial analysis was done with educational/vocational outcomes only. The simple model to be analysed is the following:

$$education_{it} = \alpha + \beta_1 ADHD_{it} + \boldsymbol{\gamma X}_{it} + \boldsymbol{\delta Z}_{i1970} + u_{it} \qquad (1)$$

As the level of education is a categorical ordered variable it is more appropriate to analyse it as such instead of simply having a binary variable for having a degree, for example. It is also more insightful to have the analysis done for each year of the survey, with separate regressions, starting in 1996 when the cohort members could have already obtained higher degrees. Thus, the education outcome has five levels: (0) No qualification; (1) Certificate of Secondary Education (CSE); (2) O Levels; (3) A Levels; (4) First Degree; (5) Higher

Degree[12]. These outcomes are a function of a binary variable *ADHD* indicating the individual has six or more ADHD symptoms or not in 1980. There are two sets of controls: one for a set of socioeconomic background information collected from the cohort member in each sweep, represented by $\boldsymbol{X}$ and another for parental socioeconomic information at the time of birth in 1970 represented by $\boldsymbol{Z}$. The outcome is also a function of a constant α and an error term u which is assumed to have zero mean and is not correlated with the regressors. Equation (1) cannot be estimated with Ordinary Least Squares consistently as it faces the same problems it would in estimating a binary model – heteroscedasticity and predicted probabilities above one or below zero. In order to estimate the equation above the ordered probit model was used. It is usually associated with latent variables that yield observable thresholds that indicate ordered intensity but the gap between them are not necessarily linear.[13] Thus, in a model where ability (y^*) is considered an unobservable latent variable and leaving aside time and individual subscripts, we have:

$$y^* = \boldsymbol{x\beta} + e \qquad (2)$$

And the observed educational/vocational variable, y, is given by:

$y = 0 \; if \; y^* \leq \tau_1$ (No qualifications)
$y = 1 \; if \; \tau_1 \leq y^* \leq \tau_2$ (Certificate of Secondary Education)
$y = 2 \; if \; \tau_2 \leq y^* \leq \tau_3$ (O Levels)
$y = 3 \; if \; \tau_3 \leq y^* \leq \tau_4$ (A Levels)
$y = 4 \; if \; \tau_4 \leq y^* \leq \tau_5$ (First Degree)
$y = 5 \; if \; y^* \geq \tau_5$ (Higher Degree)

, where τ_j represents the threshold parameters.

Once the model was estimated by a maximum likelihood function, marginal effects were calculated as the estimated coefficients only provide the direction of the effect of having ADHD on moving from having no qualifications to having a higher degree, but provide no

[12] Table B.4 in the Appendix has specific descriptive statistics for the educational variable through sweeps between 1996 and 2012.
[13] We can think of Spence's (1973) signalling model in which ability is an unobservable variable but potential employees acquire educational and vocational credentials to signalize their ability.

information on what is the impact on each threshold. This estimation procedure was only used for the educational/vocational variable.

A second estimation procedure was implemented taken into account the availability of information in a panel data setting. The estimation model in the panel setting is given by:

$$Y_{it} = \alpha + \beta_1 ADHD_{i1980} + \boldsymbol{\gamma X}_{it} + \boldsymbol{\delta Z}_{i19} + c_i + u_{it} \qquad (3)$$

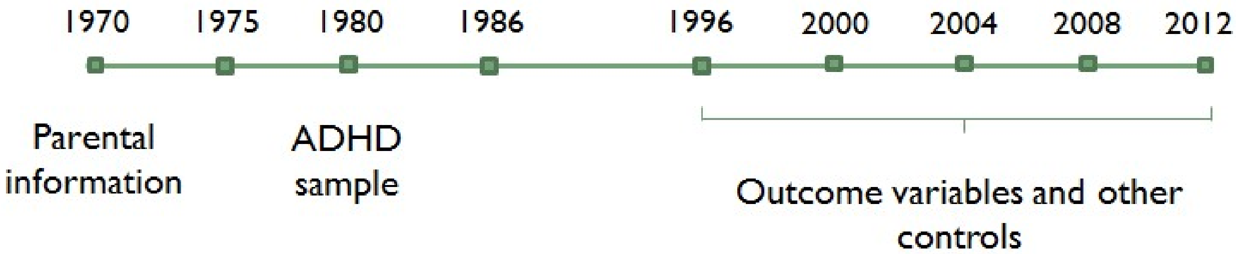
The outcome variable describes one of twelve different life outcomes including labour market, household and social outcomes. Once again the outcomes come from sweeps from 1996 to 2012 with four years gap intervals. Apart from the components of the regression previously discussed for equation (1), the outcomes in equation (3) are also a function of an individual random effect c. For all the regressions a dummy variable for having a degree was added to control for education. The exception, of course, was when the outcome variable was education itself.

3.3 Data

The data for this study came from the *British Cohort Study 1970* (BCS70). The BCS70 started as the British Births Survey (BBS) and it is an ongoing longitudinal study of nearly 17,200 individuals born in the first week of April 1970 in Northern Ireland, Wales, Scotland and England. After the initial survey, the individuals born in Northern Ireland (a total of 626) were dropped from the sample and were not followed anymore.

It is the third oldest birth cohort study in the United Kingdom and it follows a similar structure, meaning the questionnaire being used in the survey changes as the cohort grows older in order to accommodate different interests in different life outcomes throughout several stages of their lives. The initial information obtained in the birth survey in 1970 focused on medical conditions from the babies and socio-economic conditions from parents. It was collected through clinical records and a questionnaire that the midwives completed. In 1980 health visitors interviewed the children's parents to gather socio-economic and health information. The school in which the children were enrolled also provided information through the school health service, the head teacher and the class teacher. In 1996, when the cohort was 26 years old, a follow-up sweep was carried out and started collecting information about labour market outcomes such as employment, type of employment and income as well as health and social behaviour information. There have been eight attempts to trace all the cohort members after the initial survey. At the sweeps at ages 5 and 10 the survey added immigrants that were born in the same week as the initial birth cohort, but since they lacked information from 1970 then they were not used in the regressions. Figure 3.1 provides a time lapse and indications of which sweeps were used to collect the variables for this study and Table B.1 in the appendix has descriptive information about the controls and outcome variables.

Figure 3.1 – Time lapse of the British Cohort Study 1970.



Since 1996 the longitudinal survey has had a new sweep every four years. The sweep used in this study is from 2012 when cohort members were 42 years old. Table 3.1 provides the number of participants for each sweep since the initial one in 1970. Since the start of the survey the number of individuals being interviewed in each sweep is naturally decreasing, except in 2000 when there was more funding and it was possible to target a higher number of cohort members. Out of the original sample in 1970, 57.2% of them were found in 2012 for the eighth and latest available sweep.

Table 3.1 – British Cohort Study 1970.

Sweep	Year	Age	Number of participants	Percentage of original sample
0	1970	0	17198	100%
1	1975	5	13135	76.4%
2	1980	10	14875	86.5%
3	1986	16	11622	67.6%
4	1996	26	9003	52.3%
5	2000	30	11261	65.5%
6	2004	34	9665	56.2%
7	2008	38	8874	51.6%
8	2012	42	9841	57.2%

Source: British Cohort Study 1970.

Some attrition is natural and expected with any longitudinal study, but in panel studies it is also always a concern. In order to illustrate, Table 3.2 shows descriptive statistics of control variables collected in 1970 when the BCS70 started and in the following sweeps from which outcome variables were analysed. As the sample size changed from one sweep to the other, so did the mean of the socioeconomic information collected. The variation is small over the years, being very similar to the values of the initial sample. However, the small differences are significantly different at a 5% level for which can raise concerns regarding estimation bias, a possible limitation of the study. Particularly worrying is the parental social class, where there was an initial increase in the number of cohort members whose parents were "white collar". Nevertheless, after the substantial rise in 1996, the sample did not vary as much and the same pattern is observed for the parents' household weekly income. Table B.2 in the appendix provides further descriptive statistics of the outcome and control variables in the study.

Table 3.2 – Control variable means since 1970.

Sweep	Year	Parents are married§	Parents have post-compulsory education§	Parents' social class§*	Parents' household Income(£/week)
0	1970	0.926	0.098	0.167	113.87
2	1980	0.943	0.094	0.168	113.86
4	1996	0.952	0.115	0.198	119.67
5	2000	0.948	0.103	0.180	116.47
6	2004	0.952	0.110	0.189	117.83
7	2008	0.952	0.115	0.201	119.46
8	2012	0.943	0.109	0.192	117.26

§: These are binary variables, meaning the numbers shown are percentages of the total sample with said characteristic; * Parents' social class indicates whether or not they are "white collar".

3.3.1 The ADHD sample

The BCS70 sweep in 1980 contained a questionnaire filled out by teachers and parents. The questionnaire was designed based on Conners' rating scale (Conners, 1969), a scale that became widely used by teachers in the U.S. to assess behavioural disorders - mostly inattention, hyperactivity and conduct disorder. The questions contained in this rating scale are remarkably accurate in identifying the symptoms for ADHD described in the *Diagnostic and Statistical Manual of Mental Disorders,* 4th edition (DSM-IV). If six or more symptoms are present, if they are observed in at least two different environments and the symptoms have been noticed before age 7 then the diagnosis for ADHD can be done. Using information from the BCS70, the former two criteria are met but not the latter one. Unfortunately the data available before age 7 does not allow for a diagnosis, hence the nearest data point is used, in 1980, when the cohort members are 10 years old.

The final sample of individuals used in the survey has 10779 subjects of which 1486 present six or more symptoms of ADHD and are thus considered as diagnosed. This number corresponds to 13.79% of the total sample. Table 3.3 presents this information and also the variation across sweeps. As mentioned before, attrition is always a concern. If the attrition is caused in a non-random pattern, i.e. if it is correlated with particular life outcomes or being diagnosed with ADHD or any of the explanatory variables, then there is evidence to suggest that the estimations are biased. Table 3.3 also shows attrition in the ADHD sample throughout the years and we can observe that the percentage change across the years is small. The largest change occurs between 1980 and 1996, when the proportion of individuals with ADHD falls 1.61 percentage points. Considering the proportion of individuals with ADHD relative to the total number of cohort members in each sweep, the share remains in small interval between 8.47% and 9.99%.

Table 3.3 – Original ADHD sample 1980 and attrition within the sample over the years.

ADHD	**1980**	**1996**	**2000**	**2004**	**2008**	**2012**
Yes	1486	763	1010	870	788	897
	(13.79%)	(12.18%)	(12.9%)	(12.76%)	(12.52%)	(13.08%)
No	9293	5503	6820	5950	5505	5963
	(86.21%)	(87.82%)	(87.1%)	(87.24%)	(87.48%)	(86.92%)
TOTAL	10779	6266	7830	6820	6293	6860
ADHD sample / BCS Total	9.99%	8.47%	8.97%	9.8%	8.88%	9.11%

Table 3.4 presents the attrition of the BCS70 over the years along with the ADHD sample. They both follow the same pattern, but the loss in the ADHD sample is consistently greater than the loss of individuals in the total BCS70 sample. In order to investigate further, correlation tests were carried out between dropping out of the BCS70 total sample and the ADHD sample and they show that there is a negative correlation, but very small which suggests that there is no systematic relationship in the panel attrition that would indicate the existence of bias.

Table 3.4 – Attrition in the BCS70 survey and the ADHD sample throughout the years

Year	**BCS70(1)**	**(%)(2)**	**ADHD Sample(3)**	**(%)(4)**	**Difference (2)-(4)**	**Corr. (1) and (3)**
1980	14875	100%	10779	100%		
1996	9003	60.52%	6266	58.13%	2.39	-0.055
2000	11261	75.70%	7830	72.64%	3.06	-0.042
2004	9665	64.97%	6820	63.27%	1.70	-0.039
2008	8874	59.66%	6293	58.38%	1.28	-0.043
2012	9841	66.16%	6860	63.64%	2.52	-0.027

A simple way to evaluate if there are any differences between the individuals with ADHD and other individuals that do not present six or more symptoms is to perform a two sample t-test to find out whether or not the samples differ in their outcomes. Table 3.5 shows the overall mean and the mean for the control and ADHD samples respectively as well as the difference between then and whether or not they are significant. The two sample mean t-test shows significant differences in labour market outcomes and health behavior in the form of smoking, but other social behaviours such as consuming illegal drugs or hazardous amounts of alcohol seem to be equally occurring in both ADHD and control samples. This already hints at the results found.

Table 3.5 – Two sample mean t-test for ADHD and control sample.

Outcomes		Sample		
	Mean	ADHD	Control	Difference
Education	2.601	2.286	2.647	-0.0361***
Employed	0.834	0.807	0.838	-0.0314***
Employed FT	0.613	0.588	0.617	-0.0284***
Income (log)	5.567	5.539	5.571	-0.0317***
Manager position	0.495	0.441	0.503	-0.0617***
Benefits	0.165	0.191	0.161	0.0295***
Smoking	0.236	0.261	0.233	0.0283***
Depression	0.142	0.14	0.142	-0.0019
Alcohol	0.290	0.293	0.289	0.0039
Accidents	0.400	0.416	0.394	0.0226
Drugs	0.232	0.234	0.232	0.0023
Lone Parenthood	0.152	0.147	0.153	-0.0064
Life dissatisfaction	0.507	0.508	0.507	0.0004

* Indicates the level of educational/vocational attainment and is on a scale 0-5, starting with “no qualifications”, “CSE”, “O Level”, “A Level”, “First Degree” and “Higher Degree”

3.4 Results and discussion

Most of the studies that explore the effects of ADHD focus on educational outcomes. Following this approach, the first table of results shows the effects on educational/vocational achievement as well. Separate regressions were done for each year of the BCS70 survey from 1996 to 2012 according to equation (2). Table 3.6 shows the results of these regressions. Although there is some variation in the coefficients, they all tell the same story - having ADHD increases the likelihood of obtaining lower level qualifications and reduces the likelihood of obtaining higher level qualifications. In 1996 the probability of not having any qualification for individuals with the disorder was 1.48% higher than an individual without the disorder. For the same year, an individual diagnosed with ADHD in 1980 was 4.77% less likely to obtain a higher degree compared to someone without the disorder.

Table 3.6 – Marginal effects of having ADHD on educational/vocational outcomes.

	1996	2000	2004	2008	2012
No Qualification	0.0148***	0.0053**	0.0138***	0.0155***	0.0225***
	(0.0042)	(0.0021)	(0.0044)	(0.0054)	(0.0059)
CSE	0.0407***	0.0290***	0.0231**	0.0195***	0.0198***
	(0.0101)	(0.0100)	(0.0066)	(0.0062)	(0.0049)
O Level	0.0167***	0.0117***	0.0255***	0.0227***	0.0206***
	(0.0041)	(0.0044)	(0.0067)	(0.0068)	(0.0045)
A Level	-0.0159***	-0.0107***	-0.0059***	-0.0045**	-0.0041***
	(0.0042)	(0.0037)	(0.0021)	(0.0019)	(0.0012)
First Degree	-0.0087***	-0.0092***	-0.0255***	-0.0224***	-0.0253***
	(0.0042)	(0.0037)	(0.0021)	(0.0019)	(0.0012)
Higher Degree	-0.0477***	-0.0261***	-0.0310***	-0.0309***	-0.0335***
	(0.0106)	(0.0083)	(0.0081)	(0.0092)	(0.0067)

*** Significant at 1% level; ** Significant at 5% level. Standard errors in parenthesis. Controls: parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender and test scores at age 10.

An important threshold to observe is the attainment of a first degree qualification which demonstrates post-compulsory education in today's standards.[14] The results show, again, that individuals that suffered from this mental condition were less likely to obtain a first degree. In 1996 and 2000 the effect was close to 1% (0.87% and 0.92% respectively), but from 2004 onward the effect was greater, closer to 2.5% which indicates that although some individuals acquire qualifications later in life, the same does not apply to people with hyperactivity and/or attention deficit and they continue to have lower qualifications throughout their lifetime. This can lead to repercussions in income inequality as higher paying jobs require at least a first degree, which beckons discussion and research about cost-effective treatments to mitigate ADHD effects. The lack of higher qualifications also has an effect on life outcomes, which characterizes an indirect effect of ADHD that works through education. This is addressed in one of the models discussed next.

Table 3.7 shows the results of the regressions from equation (3) in a panel setting. The first three columns of results show the coefficients of the regressions done with Ordinary Least Squares (OLS) estimators, with three different specifications - 1) no controls, 2) a set of socioeconomic variables as controls and 3) the previous set of controls plus a binary variable indicating the individual has obtained a first degree or equivalent vocational qualification. The results are robust and show a clear negative effect on labour market outcomes, income, career

[14] The BCS70 cohort members could leave school at age 16.

progression and increased probability of claiming benefits. There is weak evidence of an increased likelihood of an individual smoking at least one cigarette a day but the effect is sensitive to the choice of model analysed and it disappears once the more appropriate binary outcome model is used. Models (2) and (3) in Table 3.7 show the results of the same regression but in model (3) a binary variable for degree was added. This could test the hypothesis that once the individual has obtained a first degree qualification the effect of having ADHD is mitigated and the negative effects are less pronounced. However, results suggest that, even after controlling for having a degree qualification, individuals with the mental disorder still lagged behind individuals without ADHD diagnosis. This reinforces the evidence that the disorder itself has an effect on multiple life outcomes and it is not mitigated by having higher educational qualifications.

Table 3.7 – Effects of ADHD on life outcomes.

	OLS(1)	OLS(2)	OLS(3)	Probit (2) (dy/dx)	Probit (3) (dy/dx)
Employed	-0.0396***	-0.0339***	-0.0318***	-0.0258***	-0.0246***
Employed FT	-0.0347***	-0.0345***	-0.0339***	-0.0316***	-0.0307***
Income (log)	-0.0374*	-0.0557***	-0.0436**	-	-
Manager	-0.0608***	-0.0473***	-0.0485***	-0.0488***	-0.0494***
Benefits	0.0322***	0.0218***	0.0219***	0.0188***	0.0183***
Smoking	0.0381***	0.0223*	0.0152	0.0114	0.0049
Life dissatisfaction	0.0005	-0.0015	-0.0030	-0.0016	-0.0032
Depression	0.0019	0.0053	0.0051	0.0022	0.0018
Alcohol	0.0033	-0.0102	-0.0113	-0.0105	-0.0113
Accidents	0.0207*	0.0083	0.0063	0.0106	0.0091
Drugs	0.0023	-0.0003	-0.0000	-0.001	-0.0005
Lone Parenthood	-0.0099	-0.0084	-0.0098	-0.0012	-0.0019
Controls	No	Yes	Yes	Yes	Yes
Degree as control	No	No	Yes	No	Yes

Notes: *** Significant at 1% level; ** Significant at 5% level. *Model 1*: no controls; *Model 2*: controls for parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender and test scores at age 10. *Model 3*: adds the individual's marital status, whether they have children and a dummy variable indicating having a degree or equivalent vocational qualification.

The last two columns of Table 3.7 show the marginal effects of probit regression models which are deemed more appropriate since all but one of the outcome variables are binary. They show a lower negative impact for employment and being employed full-time but the negative effect is still present. Individuals with ADHD are roughly 2.5% less likely to be employed compared to individuals without the condition and, given that they are employed, they are 3% less likely to be employed full-time. This effect is captured in the income difference between the two groups, where the first group is clearly negatively affected. Career progression is also affected. Individuals with ADHD are less likely to occupy positions in which they supervise or manage other employees and this also contributes to lower income. Perhaps the inattention that characterizes the disorder does not allow the individual to develop skills necessary to perform well in a job position that requires administrating your own goals as a function of other employees' progress in their own goals. In any case, the results show a clear disadvantage for career progression.

There seems to be no effect of ADHD on other social outcomes which might be a surprise. The literature covered previously suggests comorbidity between ADHD and depression and the results do not show such pattern. Even the difference in mean between the two groups is not statistically significant. Other outcomes, less established to be correlated with ADHD, have shown to not be affected as well. This suggests that although ADHD is a mental disorder that accounts for a great deal of expenditure in mental health issues, the effects are limited to certain life aspects and do not cover a wide range of outcomes that is sometimes commonly hypothesized. In particular, the likelihood of being involved in accidents does not seem to be related to ADHD once controls are added to regressions, which refutes Barkley et al. (1993).[15] These findings do not exclude the need for further research and definitely do not diminish the need for public policies that tackle the negative effects that have been shown.

The DSM-IV establishes the presence of six or more ADHD symptoms as a necessary condition for a diagnosis. The spectrum of symptoms, however, is continuous. From a statistical point of view, it would be interesting to see the effects of different thresholds of symptoms. For robustness checks other ADHD samples were calculated with narrower diagnosis parameters yielding 5.6% and 2.19% of individuals with an ADHD diagnosis. In the appendix Tables B.6 and B.7 present a more strict sample of children possibly diagnosed with ADHD with eight

[15] Vaa (2014) has also refuted the connection between ADHD and road accidents when patients did not present other conditions such as Oppositional Defiant Disorder (ODD) and/or Conduct Disorder (CD).

and ten symptoms, respectively, as a necessary condition for an ADHD diagnosis. The resulting sample is much smaller and lacks adequate statistical power. The results show some evidence that there is in fact an increase in the likelihood of being depressed, involved in accidents and being a smoker besides being less likely to be employed. Although the significance of the coefficients change, the direction of the effects in life outcomes remains the same which adds further evidence of negative effects of ADHD. The children in this sample are the most likely to have had proper treatment for their condition, including medication, therapy and special needs classes, which could explain part of the findings. Descriptive statistics for these samples are found in Tables B.4 and B.5.

Separate analyses were done in order to establish whether or not any gender was more affected by ADHD in the main sample. It is known that prevalence of ADHD is higher in boys than in girls. Numbers appear to be twice as high than girls (Perou et al. 2013). In a similar fashion to the results presented on Table 3.7, the first three columns on Table 3.8 show results of regressions carried out with OLS estimators whilst the last two columns show the same regressions with probit estimator followed by marginal effects of a discrete change. It seems women are more affected by ADHD than men are. Both men and women have worse outcomes for being employed, employed full-time and they have lower income compared to their counterparts without the disorder, but the magnitude of the effect is greater for women, including being more likely to claim benefits. However, men with ADHD fare worse and are more affected. One possible explanation is that women with ADHD seem to have a harder time getting into the labour market compared to women without ADHD but, once they do, they are able to close the gap much better than men are able to. An alternative explanation is that women are not promoted to higher job positions as much as men. In any case, ADHD symptoms for women seem to be less of a problem for pursuing managerial positions, but it is still a problem.

Table 3.8 – Comparison of the effects of ADHD on life outcomes between men and women.

		OLS(1)	OLS(2)	OLS(3)	Probit (2) (dy/dx)	Probit (3) (dy/dx)
Employed						
	Men	-0.0298***	-0.0207*	-0.0238*	-0.0129	-0.0135
	Women	-0.0715***	-0.0356**	-0.0368**	-0.0307**	-0.0322**
Employed FT						
	Men	-0.0303*	-0.0262	-0.0272	-0.0164	-0.0167
	Women	-0.0815***	-0.0335**	-0.0334**	-0.0326	-0.0333
Income (log)						
	Men	-0.0363	-0.0083	-0.0233	-	-
	Women	-0.1274***	-0.0702**	-0.0796**	-	-
Manager						
	Men	-0.0589***	-0.0524***	-0.0567***	-0.0533***	-0.0533***
	Women	-0.0466**	-0.0394*	-0.0322	-0.0406*	-0.0406*
Benefits						
	Men	0.0228**	0.0196*	0.0162	0.0146	0.0128
	Women	0.0523***	0.0251**	0.0282**	0.0234**	0.0264**
Controls		No	Yes	Yes	Yes	Yes
Degree as control		No	No	Yes	No	Yes

Notes: *** Significant at 1% level; ** Significant at 5% level. *Model 1*: no controls; *Model 2*: controls for parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender and test scores at age 10. *Model 3*: adds the individual's marital status, whether they have children and a dummy variable indicating having a degree or equivalent vocational qualification.

3.5. Conclusion, limitations and future research

The existent literature and the current study have shown that children that suffer from hyperactivity and/or attention deficit disorder suffer negative impacts on a number of life outcomes, from their educational and vocational achievements to labour market outcomes and welfare benefit claims. These results are robust to different model specifications and different samples in time. The use of a longitudinal survey with panel regression methods and a wide range of outcomes being explored is the original contribution from this chapter.

One of the limitations in this study is that the diagnosis for ADHD was done based on information from the BCS70 1980 survey, when the cohort members were 10 years old. Usually ADHD diagnostic is carried out before age 7 but taking into account the fact that i) medication and treatment were not widely available at the time as it is now-days and ii) up to half the children diagnosed with ADHD still carry the symptoms all the way to adulthood, it is not unreasonable to assume that most of the children that showed six or more ADHD-related symptoms at age 10 already had these same symptoms before age 7.

A second limitation is that we do not control for individuals that have sought treatment for their condition, either during childhood when treatment and information was not so widely available, or later as adults. This could be an important covariate in the estimations but the information is simply not present in the surveys.

Using a different cohort can help shed some light on the impact of ADHD in childhood and adult life outcomes. The National Child Development Study (NCDS) is the second oldest longitudinal study in the UK, it was initiated in 1958 under the name of Perinatal Mortality Survey (PMS). Its design is similar to BCS70. In 1969 the survey collected information on children's behavior as BCS70 did in 1980. Unfortunately the questions on NCDS are only a fraction of what was used in BCS70 and a suitable sample identification of individuals with ADHD is not possible. Future surveys perhaps could shed additional light regarding this issue.[16]

Despite limitations in the study, the results from this research show that individuals with ADHD are less likely to be employed, be employed full-time, they earn less and are less likely to have a job as a supervisor or managers and they are also more likely to claim welfare benefits. The results are stronger for women; they seem to fare worse than men and are more affected by ADHD except for having a job in a managerial position. Other social outcomes seemed to be unaffected, but the extent and magnitude of the negative effects in the labour market and welfare claims are enough evidence to suggest further analysis of cost-benefit treatments to tackle income inequality and inequality of opportunities.

[16] The Millennium Cohort Study is a similar cohort study following the lives of 19,000 children born in the UK in 2000-2001. It has more detailed information about children's health and behaviour and could possibly aid further studies in correcting shortfalls in the current research, once the cohort ages.

Appendix B

Table B.1 – Description of outcome and control variables collected in 1996, 2000, 2004, 2008 and 2012.

Variable	Description
Outcomes	
Education*	Ordered categorical educational/vocational attainment. Scale is given by: (0) No qualification; (1) Certificate of Secondary Education (CSE); (2) O Levels; (3) A Levels; (4) First Degree; (5) Higher Degree.
Employed	Binary variable - Individual is employed.
Employed FT	Binary variable - Individual is employed full-time.
Income (log)	Continuous variable - Log of household weekly labour income.
Manager	Binary variable - Individual is in a managerial or supervision position at work.
Benefits	Binary variable - Individual is receiving benefits.
Smoking	Binary variable – Individual smokes at least a cigarette a day.
Life dissatisfaction	Binary variable - Indicates the individual has ranked his satisfaction in life as 5 or less in a scale 0-10.
Depression	Binary variable - Individual has had depression in the last 12 months.
Alcohol	Binary variable - Individual has drinking problems according to the National Health Service (NHS) definition.
Accidents	Binary variable - The individual has been involved in a car crash, job accident or housework accident.
Drugs	Binary variable - Individual has had problems with illegal drug abuse in the past 12 months.
Lone parenthood	Binary variable - The individual has been a lone parent at some point in life.
Controls	
Parents' marital status	Parents were married in 1970.
Parents' Post-Compulsory	Both parents went on to post-compulsory education.

Parents' Social Class	Parents were considered to be of "white collar" social class in 1970.
Parents' Income (log)	Parents' household weekly labour income in 1970 (in logs).
Male	Individual is male
Marital Status	Individual is married
Labour Income (log)	Individual's household weekly labour income
Degree	Individual has a first degree or higher qualification
Proficiency in Reading	Individual's test score in reading in 1980.
Proficiency in Mathematics	Individual's test score in mathematics in 1980

* This also contains vocational qualifications as the same level according to the National Vocational Qualification (NVQ) levels 1-5.

Table B.2 – Description of control variables from the British Cohort Study 1970 in a panel setting (1970- 2012).

Variable	Observations	Mean	Standard Deviation	Min	Max
Outcomes					
Education	37,971	2.601	1.560	0	5
Employed	42,453	0.826	0.379	0	1
Employed FT	44,816	0.603	0.489	0	1
Income (log)	34,458	5.563	0.780	0	13.369
Manager	32,373	0.494	0.500	0	1
Benefits	39,501	0.169	0.375	0	1
Smoking	48,374	0.243	0.429	0	1
Life dissatisfaction	38,463	0.510	0.500	0	1
Depression	47,413	0.144	0.351	0	1
Alcohol	37,143	0.291	0.454	0	1
Accidents	29,897	0.394	0.489	0	1
Drugs	20,716	0.232	0.491	0	1
Lone parenthood	7,848	0.152	0.359	0	1
Controls					
Parents' marital status	85,895	0.926	0.261	0	1
Parents' Post-Compulsory	85,340	0.098	0.298	0	1
Parents' Social Class	78,060	0.167	0.373	0	1
Parents' Income (log)	62,705	4.735	0.494	0	5.61
Male	48,644	0.475	0.499	0	1
Marital Status	48,301	0.629	0.483	0	1
Children	48,013	0.480	0.500	0	1
Degree*	50,599	0.242	0.428	0	1
Proficiency in Reading	67,690	33.05	16.320	0	100
Proficiency in Mathematics	63,325	43.81	21.260	0	100

* Not used as control for education regressions.

Table B.3 – Qualifications and number of observations in each level from 1996 to 2012.

	1996	%	2000	%	2004	%	2008	%	2012	%
No qualification	487	(5.8%)	427	(3.9%)	841	(6.8%)	1106	(8.8%)	1289	(10.0%)
CSE	1462	(17.4%)	1929	(17.6%)	1649	(13.4%)	1632	(13.0%)	1591	(12.4%)
O Level	3446	(41.0%)	5048	(46.1%)	4673	(38.1%)	4587	(36.5%)	4463	(34.8%)
A Level	894	(10.6%)	1129	(10.3%)	1197	(9.8%)	1163	(9.3%)	1122	(8.8%)
First Degree	374	(4.5%)	692	(6.3%)	2009	(16.4%)	2120	(16.8%)	2344	(18.2%)
Higher Degree	1736	(20.7%)	1738	(15.8%)	1909	(15.5%)	1960	(15.6%)	2036	(15.8%)
TOTAL	8399	(100%)	10963	(100%)	12278	(100%)	12568	(100%)	12845	(100%)

Table B.4 –ADHD sample 1980 and attrition within the sample over the years – sample 2*.

ADHD	1980	1996	2000	2004	2008	2012
Yes	604	290	410	339	304	354
	(5.60%)	(4.63%)	(5.24%)	(4.97%)	(4.83%)	(5.16%)
No	10175	5976	7420	6481	5989	6506
	(94.4%)	(95.37%)	(94.76%)	(95.03%)	(95.17%)	(94.84%)
TOTAL	10779	6266	7830	6820	6293	6860

* Narrower sample with 5.6% of individuals with ADHD.

Table B.5 – ADHD sample 1980 and attrition within the sample over the years – sample 3*.

ADHD	1980	1996	2000	2004	2008	2012
Yes	233	101	153	121	109	124
	(2.16%)	(1.61%)	(1.95%)	(1.77%)	(1.73%)	(1.81%)
No	10546	6165	7677	6699	6184	6736
	(97.84%)	(98.39%)	(98.05%)	(98.23%)	(98.27%)	(98.19%)
TOTAL	10779	6266	7830	6820	6293	6860

* Narrower sample with 2.16% of individuals with ADHD.

Table B.6 – Effects of ADHD on life outcomes using narrower ADHD sample 2[ǂ].

	OLS(1)	OLS(2)	OLS(3)	Probit (2) (dy/dx)	Probit (3) (dy/dx)
Employed	-0.0496***	-0.0242	-0.0279	-0.0207	-0.0241*
Employed FT	-0.0344*	-0.0194	-0.0278	-0.0069	-0.0163
Income (log)	-0.0374*	-0.0358	-0.0736**	-	-
Manager	-0.0456**	-0.0035	0.0052	0.0049	0.0142
Benefits	0.0321***	0.0066	0.0106	0.0046	0.0093
Smoking	0.0699***	0.0324	0.0424*	0.0183	0.0310**
Life dissatisfaction	0.0126	0.0255	0.0322*	0.0292	0.0365*
Depression	0.0185	0.0298**	0.0293**	0.0241**	0.0245**
Alcohol	0.0273*	-0.0094	-0.0069	-0.0078	-0.0059
Accidents	0.0790***	0.0530**	0.0584**	0.0573**	0.0629**
Drugs	0.0053	-0.0091	-0.0088	-0.0122	-0.0128
Lone Parenthood	0.0252	0.0414	0.0439*	0.0276	0.0308
Controls	No	Yes	Yes	Yes	Yes
Degree as control	No	No	Yes	No	Yes

Notes: *** Significant at 1% level; ** Significant at 5% level. *Model 1*: no controls; *Model 2*: controls for parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender and test scores at age 10. *Model 3*: adds the individual's marital status, whether they have children and a dummy variable indicating having a degree or equivalent vocational qualification.

Table B.7 – Effects of ADHD on life outcomes using narrower ADHD sample 3[‡].

	OLS(1)	OLS(2)	OLS(3)	Probit (2) (dy/dx)	Probit (3) (dy/dx)
Employed	-0.0713***	-0.0790***	-0.0805***	-0.0646***	-0.0667***
Employed FT	-0.0378	-0.0452	-0.0553*	-0.0259	-0.0409
Income (log)	-0.0302	-0.0317	-0.0548	-	-
Manager	-0.0538*	0.0079	0.0039	0.0087	0.0069
Benefits	0.0345*	0.0353	0.0384	0.0429	0.0494
Smoking	0.1191***	0.0576*	0.0793**	0.0538**	0.0672***
Life dissatisfaction	-0.0096	-0.0326	-0.0285	-0.0338	-0.0297
Depression	0.0313	0.0453**	0.0452**	0.0432**	0.0442**
Alcohol	0.0660***	0.0323	0.0377	0.0339	0.0391
Accidents	0.1169***	0.0572*	0.0668**	0.0560*	0.0673**
Drugs	0.0210	0.0186	0.0176	0.0191	0.0173
Lone Parenthood	0.0082	0.0353	0.0384	0.0429	0.0494
Controls	No	Yes	Yes	Yes	Yes
Degree as control	No	No	Yes	No	Yes

Notes: *** Significant at 1% level; ** Significant at 5% level. *Model 1*: no controls; *Model 2*: controls for parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender and test scores at age 10. *Model 3*: adds the individual's marital status, whether they have children and a dummy variable indicating having a degree or equivalent vocational qualification.

Table B.8 – Impact of having ADHD and coefficients for degree and an interaction between the two.

	Model 3		Model 4		
	ADHD	Degree	ADHD	Degree	ADHDxDegree
Employed	-0.0246***	0.0228***	-0.0264***	0.0215***	0.0124
Employed FT	-0.0307**	0.0958***	-0.0287**	0.0971***	-0.0128
Income (log)[a]	-0.0436**	0.0381***	-0.0387**	0.0384***	-0.0278
Manager	-0.0494***	0.0730***	-0.0593***	0.0791***	0.0566
Benefits	0.0183**	-0.1677***	0.0171**	-0.0387***	0.0087
Smoking	0.0049	-0.1677***	0.0059	-0.1670***	-0.0100
Life dissatisfaction	-0.0032	-0.0478***	-0.0005	-0.0459***	-0.0168
Depression	0.0018	-0.0238***	0.0052	-0.0216***	-0.0224
Alcohol	-0.0113	0.0007	-0.0174	-0.0034	0.0393
Accidents	0.0091	-0.0521***	0.0165	-0.0470***	-0.0486
Drugs	-0.0005	0.0293**	0.0027	0.0316**	-0.0201
Lone Parenthood	-0.0019	-0.0378***	-0.0022	-0.0408***	0.0055

Coefficients for marginal effects of panel probit. [a] Regressions done with OLS.
*** Significant at 1% level; ** Significant at 5% level.
Model 3 controls: parental marital status at the moment of birth, their education, social class and household income, mother's region of birth and cohort member's gender, test scores at age 10, marital status, higher education dummy and whether or not they have children.
Model 4: Same as the above plus an interaction dummy between ADHD and having a degree.

Chapter 4

Transitory health shocks and educational performance: is there a lasting effect?

Daniel Roland

Abstract:

Health and education have been known to be correlated for decades now (Coleman 1966, Grossman 1976). Empirical studies have provided strong evidence that one of the reasons for this correlation is explained by health conditions affecting educational outcomes, especially at an early age (Glewwe, Jacoby and King 2001; Bobonis, Miguel and Puri-Sharma 2006; Ding et al 2009). Since then, health has been studied as an important determinant of educational outcomes. This study explores the effect of transitory health shocks on educational outcomes in the short-run and long-run. By using a British longitudinal study, the Millennium Cohort Study (MCS), along with propensity score methods suggested by Becker & Ichino (2002) and Abadie et al (2004) to deal with potential selection bias on observables, it is shown that the impact of transitory shocks differs according to the age in which the shocks happens and the effects seem to dissipate over time. The results from this study suggest that transitory health shocks have a negative impact that is larger in older individuals relative to younger ones, but the effect dissipates over time. The implications for public policy seem to suggest that in the presence of random transitory health shocks, an eventual return to the mean is expected and current public policies put in place are sufficient to address the issue. Further research, as more data become available, could indicate the channels that lead to differences in the negative effect according to age and whether they have an impact in life outcomes other than education.

4.1 Introduction

Unsurprisingly, education is at the centre of policy discussions in any country in the world with a stable government. Developing countries aim to provide education to all its citizens while developed countries have reached this stage and now focus on improving quality of education. The reason is simple since education is one of the best determinants for many life outcomes (Oreopoulos and Salvanes 2011) and it has been known for some time that the returns can be not only monetary but also non-monetary (Becker 1964). There are many life outcomes affected. From labour market outcomes, such as income and unemployment spells, to household production, partner matching, civic participation and many other outcomes, there is a wealth of evidence indicating the benefits of education.[17] There is also evidence of causal effect of education on health outcomes (Grossman 2015).[18]

Health, another component of human capital (Schultz 1962), is also important. Early life health indicators are good predictors of life problems later on (Hack et al. 2002; Black, Devereux and Salvanes 2007). Healthier individuals are also more likely to live longer (Paffenbarger, Blair and Lee 2001), have better quality of life in their last years before their deaths (Leveille et al. 1999) and have increased productivity (Mattke et al. 2007). Physical health also has an effect on subjective well-being (Helliwell 2003). There is little doubt that health and education are fundamental to an individual's development, their well-being and society's productivity. Education itself is an outcome that can be affected by many variables as initially suggested by the Coleman Report (1966). Alongside parental education and other socio-economic characteristics, health is highly correlated with education (Grossman 1976). It is possible that this correlation originates from a third variable as argued by Fuchs (1982) such as time preference, but even when controlling for time preferences, the effect of education on

[17] See Angrist and Krueger (1991), Card (1999) and Harmon, Oosterbeek & Walker (2003) for effects of education on income and unemployment spells, Grossman (2006) for effects on household production, Becker (1973) and Lafortune (2013) for partner matching and Dee (2004), Wantchekon, Klasnja and Novta (2015) for civic participation.

[18] Becker's (1964) seminal work, *Human Capital*, already proposed that education can have positive effects not only on earnings but also on household production. Grossman (1976, 2006, 2015) later developed the idea that health, alongside education, also plays a role in many life outcomes. Angrist and Krueger (1991) used quarter of birth and school starting age with an instrumental variable approach to determine that schooling had a causal and positive effect on earnings, something that Card (1999) later confirmed in a literature review of studies showing more robust methodologies yielded similar results as naïve OLS estimates. Lafortune (2013) presented evidence that investments in education are made in order to increase an individual's attractiveness in the marriage market in the face of adverse shocks on sex ratio in the market. Dee (2004) found increased voting participation and defence of freedom of speech among individuals with higher schooling and Wantchekon, Klasnja and Novta (2015) showed that the benefits of civic participation lasted not only for individuals with more schooling but also for their descendants.

health remains (Van der Pol 2011). Since the seminal work from Grossman, many studies have tried to assess access a causality path from health to education, but not without problems.

The dynamics between health and education are not clear as impact estimations may suffer from reverse causality, measurement error and omitted variable bias, all leading to endogeneity problems. This renders the estimated coefficients biased and, depending on the source of bias, there is no way of telling if the estimates provide an upper or lower bound for the real effect. Thus, although the correlation between the two variables is known to be strong, separating correlation from causality claims has been an arduous exercise for many researchers. The use of instrumental variables is present in some studies in the form of exogenous shocks (Alderman et al. 2001; Alderman, Hoddinott and Kinsey 2006) or genetic characteristics (Ding et al. 2009) while others used longitudinal data with siblings within a household to control for fixed effects (Glewwe, Jacoby and King 2001). Currie (2009) has done an extensive review of the literature in which many studies use similar strategies to address spurious or biased correlations but one way or another there are shortfalls in each study. Nevertheless, they all contribute to a better understanding of the relationship between health and education and possibly a causal pathway from the former to the latter.

The aim of this paper is to provide further evidence and explore to what extent adverse health conditions in early life can affect educational outcomes. By using a propensity score matching approach in a longitudinal setting, it is possible to provide a stronger claim of causality that stems from health conditions affecting educational outcomes. With this objective in mind, this study uses the Millennium Cohort Study (MCS), a longitudinal survey that started in the year 2001-2002 with children born across all over the United Kingdom.

This paper brings forth new evidence from a young cohort of individuals in the United Kingdom. Although at first look the relationship between health and education seems to have been well documented enough, there is a degree of heterogeneity in the effects estimated according to the sample and method used. For example, Currie (2009) presented studies that observed different attitude towards children in the USA and in China. Rosenzwig and Zhang (2006) showed that parents have preferences for the stronger child because Chinese parents often rely on their offspring for support in old age. However, Ermisch and Francesconi (2000) show in the USA that investments in children by their parents are mostly compensatory. While some studies prefer to use siblings' information to control for family fixed effects, there may be a bias towards one child or another as suggested by Becker (1991), even among twins.

The results from this paper indicate that the impact of illnesses differs according to the period of life it afflicts the children. The onset of an illness between ages seven and eleven seems to not greatly affect children's performance in tests, or at least not strongly enough to yield statistically significant results. A few years later, by comparing healthy children with ones that had an illness between the ages of eleven and fourteen, there is an observable negative impact associated with illnesses. The impact is even stronger when the sample is limited to children whose illnesses are debilitating. It is too early to tell whether these effects persist in the long-run since there may be coping strategies that allow children to catch up. As further surveys are conducted, more information will be available to investigate such hypothesis. However, by observing children between ages seven and fourteen, the weak impact estimated between ages seven and eleven disappear altogether at age fourteen, suggesting that in the long-run there is a return to the mean by children affected by illnesses.

The rest of the paper is structured as follows: section two explains the econometric problems that are usually found, the motivation for methodology used in this study and how it is implemented. Section three describes the data giving a brief summary of the structure of the MCS and descriptive statistics. Section four presents the results and discussion and finally section five concludes with limitations from this paper and next steps for research. For a more detailed literature review on the topic, please refer to chapter 1.

4.2 Methodology

Trying to distinguish correlation from causation can be troublesome in many fields of economics research. This section will explain the common problems that researchers face when trying to estimate the causal effect of health on educational outcomes and present the estimation method used in this study.

As shown in the literature review section, controlling for parental characteristics and birthweight is essential to isolate the effect of children's health on their educational outcomes. However, other variables may also affect test scores and other measures of school success for children. Starting with a naïve model, we could try to estimate the following equation with OLS:

$$TS = H + SC + PC \qquad (1)$$

where the coefficients, subscripts and error term have been omitted for clarity. *TS* is the student's test score, *H* stands for their health status, *SC* represents school and teacher characteristic and *PC* is the parental characteristics such as education, socio-economic position and income. It is very unlikely that someone could argue that somehow children's test scores can affect their health in some way. Therefore, we can rule out reverse causality as a source of possible endogeneity. But this specification is missing a vital part of inputs to children's test scores – previous health conditions, parental inputs and innate abilities. Clearly, engodeneity can arrive from unobserved variables missing in the equation.

Following the work of Glewwe and Miguel (2008), consider a modified but still simple model with two periods $t = 1, 2$. The first period ($t = 1$) contains information about initial inputs to a child's development and consequently their educational performance. Health and parental characteristics measured not only in the second period, when tests are taken, but also in the first period, when children's cognitive abilities are already being stimulated. Thus, we have the specification in equation (2).

$$TS_2 = TS_2(H_1, H_2, PC_1, PC_2, \alpha, SC) \qquad (2)$$

Here the test score TS_2 is a function of health in both periods, parental characteristics in both periods, the children's innate ability and school characteristics. In the presence of all relevant variables affecting test scores, a method as simple as OLS regression would provide an unbiased estimate of the impact of health. However, this information is not easily obtained. Rich datasets, such as the MCS, are a good source but innate ability is hard to observe for example. Parental characteristics obtained may not capture parents' preference for health and education which also leads to omitted variable bias.

Several methods, some of them briefly discussed in the literature review, have been developed and used to overcome such estimation problems. The next two sections presents a brief explanation of the methods used in this study from a theoretical and empirical perspective, respectively.

4.2.1 Propensity score matching

Rosenbaum and Rubin (1983) proposed a propensity score to enable appropriate comparisons between treatment and control groups to estimate treatment effects. In the present study, treatment is being considered as the occurrence of a health condition that can potentially affect educational performance. This interpretation holds for the remainder of this section.

Rosenbaum and Rubin argue that the problem with nonrandomized studies is missing data. Consider an unit i in which we observe the effect of a treatment given as response r_{1i}.

Comparing this with the unit's response in the absence of treatment, r_{0i} , would show the treatment effect. However, it is not possible to observe both r_{1i} and r_{0i} at the same time, that is, we observe one or the other but not both, hence the missing data problem. In randomized studies, comparison between responses from the treatment group and control group formed of different units is somewhat simple and straightforward since both control and treatment groups should have similar characteristics on average[19]. But this is not the case with observational nonrandomized data. It is unlikely that the only differences between the two groups is the treatment and, therefore, failure to account for possibly systematic differences can lead to biased estimates of treatment effect.

Using a balanced score, $b(x)$, where x are covariates, can solve the problem given some assumptions. If we consider $z = 1$ for treated and $z = 0$ for control, $b(x)$ is calculated so that the distribution of x is the same for treated and untreated, conditional on $b(x)$. In other words, $x \perp z|b(x)$. Later this condition was named as the *Conditional Independence Assumption* (CIA) which also applies to the outcome y_{zi}, that is $(y_{0i}, y_{1i}) \perp z|b(x)$. A weaker assumption is the *Conditional Mean Independence* (CMI), given by $E(y_z|b(x), z) = E(y_z|b(x))$, which means that independence is restricted only to the mean.

The easiest way to calculate a balancing score would be with x itself. The problem with simply having x as the balancing score is that the more covariates are added the harder it is to find units in treatment and control group that match each other on every single covariate, sometimes a condition referred to as *curse of dimensionality*. Therefore, another balancing score can be used, $e(x)$ such that.

$$e(x) = Pr(z = 1|\, x) \qquad (3)$$

where

$$Pr(z_1, \dots, z_n|\, x_1, \dots, x_n) = \prod_{i=1}^{N} e(x_i)^{z_i} \{1 - e(x_i)\}^{1-z_i}$$

The function $e(x)$ is the probability or propensity of exposure to treatment given the observed covariates. Function $e(x)$ is also known as *propensity score*. Following Bayes' Theorem, the propensity score can be rewritten as:

[19] However, depending on the sensibility of analysis being performed, simply observing the expected treatment effect $E(.)$ is not sufficient if the variance is large as there are other options to consider and the outcomes distribution may become important if the magnitude of treatment effects found is not large. For references in the health economics literature, see Briggs, Claxton and Sculpher (2006).

$$e(x) = Pr(z = 1 \mid x) = \frac{Pr(z=1)Pr(x|z=1)}{Pr(z=1)Pr\ (x|z=1)\ +Pr(z=0)Pr(x|z=0)} \qquad (4)$$

Equation (4) can be estimated based on observed data with a probabilistic model. As shown in Caliendo and Kopeinig (2008), the true effect of treatment on the treated, τ_{ATT}, is given by

$$E[Y(0)|D = 1] = E[Y(0)|D = 0] \qquad (5)$$

where $Y(0)$ represents the outcome in the absence of treatment and D is a binary variable for treatment. This means that the expected observed or potential outcome in the absence of treatment should be the same for treated and control group. If the difference between the expected means is not equal to zero, then the estimates are biased. The use of propensity score matching (PSM) can properly estimate this if the conditional independence assumption holds.

The propensity score function in equation (4) is the coarsest balancing score but Rosenbaum and Rubin (1983) have shown that, if treatment assignment is strongly ignorable conditioned on the balancing score, matching and covariance adjustment on a balancing score can produce unbiased estimates of treatment effects. Once the propensity score has been estimated, the average treatment effect can be calculated according to a number of matching algorithms. The most common algorithms are the *nearest neighbour, radius, kernel and stratification*.[20] It is also important to note that the covariates selected for calculation of the propensity score are also relevant to the chosen outcome.

In comparison with Ordinary Least Square estimations, the PSM is a more robust method as the use of a balancing score can reduce bias depending on the richness of the dataset being used. Different robustness checks can also be performed to test the validity of the conditional independence assumption and the reduction of bias as a consequence. The difference in means of the variables between control and treatment group before and after the calculation of PSM can show how well the matching procedure has eliminated differences between the groups and the visual inspection of the kernel distribution of propensity scores before and after matching can show further evidence of a good fit between groups.

[20] For details on proofs and theorems, see Rosenbaum and Rubin (1983). For the implementation of the propensity score matching (PSM) and further developments on different matching algorithms, see Caliendo and Kopeinig (2008). For empirical analysis of some results in the literature using propensity score matching see Smith and Todd (2001).

4.2.2 Empirical Strategy

This study implemented different approaches to evaluate the impact of longstanding illnesses. There were two outcome variables tested: one for verbal skills and another for quality of decision-making. The tests varied in style and difficulty in each wave, so instead of actual scores, a percentile distribution was calculated based on the children's performance in the test relative to their peers as a way to standardise the results of different tests in each year. As this study uses a cross-sectional propensity score matching to evaluate the average effect on the treated, the outcome variable is calculated as the difference between the percentile rankings of each children from one wave to the other.

There are four estimations in this study with the methods described above. First, only information from children between ages 7 and 11 was used. Children who were reported to be healthy at age 7 and remained healthy at age 11 were considered as the control group. Children who were healthy at age 7 but were reported to have a longstanding illness that lasted for 12 months or more were considered as the treatment group.[21] Second, the same rationale was used but looking at the difference between ages 11 and 14. These two estimations show the impact of illnesses on children's performance in the short-run. The third estimation narrows down the treatment to children that not only had an illness at age 14 but also reported limitations to every-day activities due to it. The fourth and last estimation looks at the long-run impact. The control group is formed of children who were healthy at age 7, 11 and 14. The treatment group is composed of children who were healthy at age 7, had a longstanding illness at age 11 (the same treatment group as in the first estimation) and were healthy again at age 14. This way, it was easier to isolate the long-run effect as the only observed difference between treatment and control group is their health status at age 11. The propensity score matching for this last estimation was calculated based on characteristics prior to age 11, the same way it was done in the first procedure.

4.3 Data

The Millenium Cohort Study (MCS) was the fourth longitudinal survey in the United Kingdom and the first in the 21st century. It started with around 19,000 children in the first

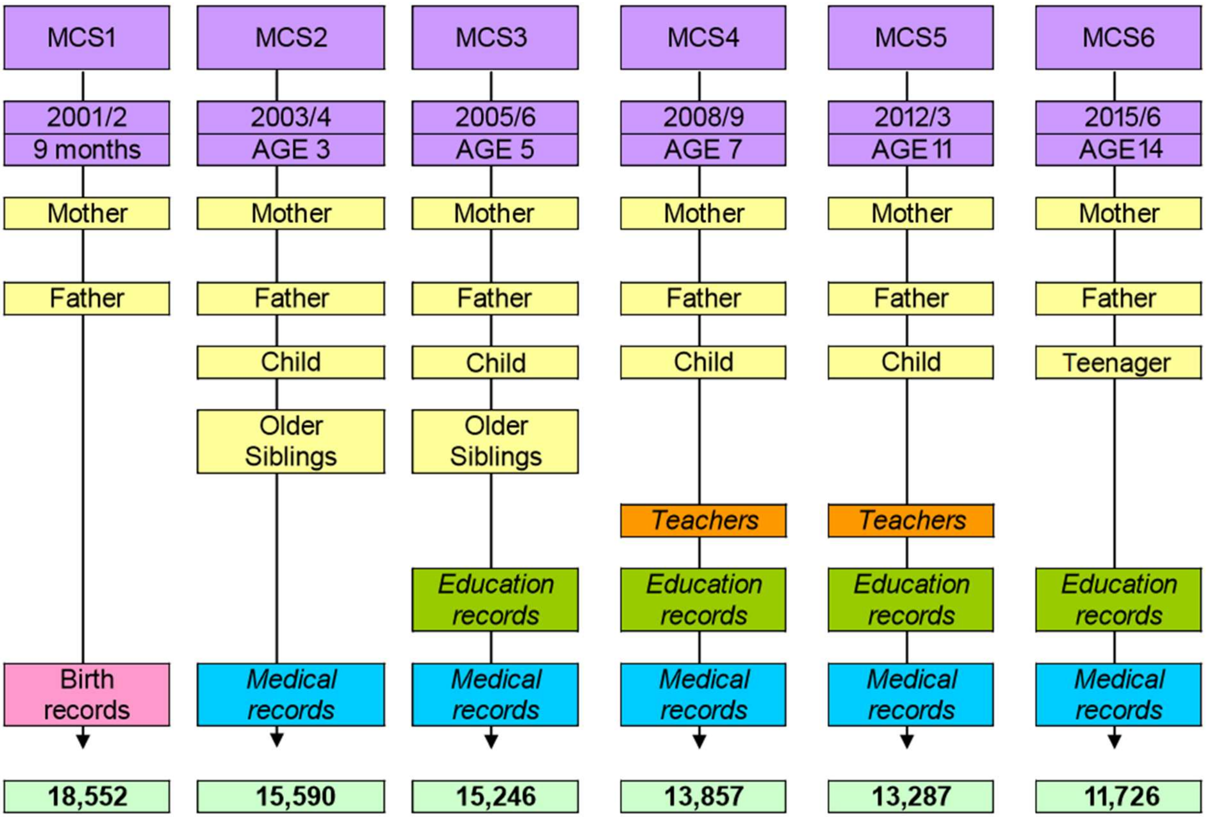
[21] In wave 4, when children were age 7, the 12 months period was simply stated as "a period of time" in the questionnaire.

survey with some more added in the second, for a total of 19,519.[22] The selected children were born between September 2000 and 31st August 2001 in England and Wales, and between 23rd November 2000 and January 2002 in Scotland and Northern Ireland. Selection was based on Child Benefit claimants and to mitigate self-selection problems families were provided with an opt-out option rather than opt-in. The survey lasted between June 2001 and September 2002. Unlike previous cohort studies, where children selected for the study were all born in the same week, the MCS allows for analysis of season effects. It also has a different stratification in order to over-represent key areas, namely all the four UK countries, economically disadvantaged areas and areas in England with higher minority ethnic populations in 1991. Since the first survey carried out in 2001-2002, there have been five follow-ups, the latest one in 2015, and there is a planned one for 2018. Figure 4.1, adapted from Hansen (2012), shows the survey code, the period of data collection, the age of cohort members, the type of information collected and the number of individuals in each wave.[23]

In 2001-2002, when the survey started, there were 18,522 cohort members and the latest wave, in 2015-2016, has 11,726 individuals surveyed at the age of 14. This means nearly a third (63.31%) of the original cohort members are still present in the longitudinal study. The type of information collected has changed over the years in each survey, but parental and medical information have been present since the start. The type of information collected from the cohort member has changed as well, moving from basic questions to more complex ones, as the child moves from infancy to adolescence.

[22] For more information, see Hansen (2012) for a complete description of the survey.
[23] Every survey has a sample target and an actual productive response rate. The number of individuals reported is the number of productive individuals in each wave.

Figure 4.1: Millennium Cohort Study (MCS) structure.

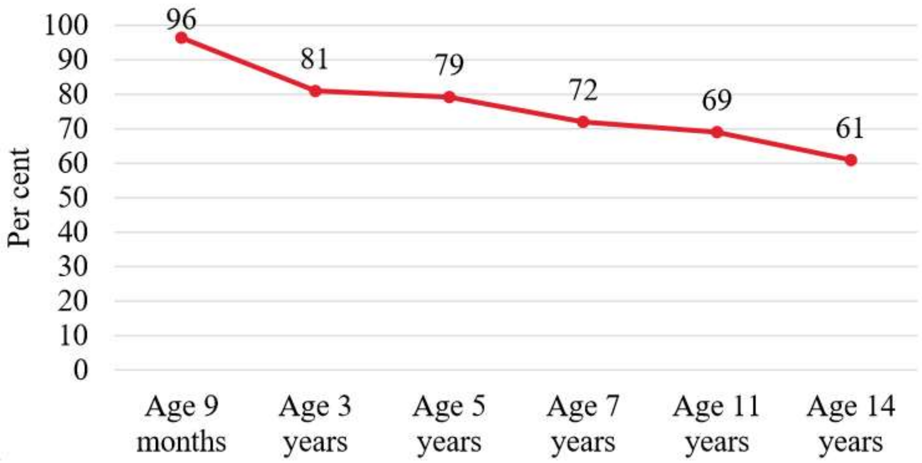


Source: Author's own work based on Hansen (2012).

Attrition in longitudinal surveys is common and the MCS is no different. Figure 4.2 (Fitzsimons 2017) shows the proportion of productive cases in each MCS wave until 2015/6.[24] There is a natural decrease in the number of productive cases but the sample remains large with 61% of the target sample in the last sweep being achieved, with nearly 12,000 individuals surveyed successfully. Table C.1 in the appendix shows the two-sample t-test for the initial cohort members present in the first wave and the ones that provided all information throughout the years all the way to when they were age 14. There are significant differences between the two groups for all variables but one. In order to avoid any risk of attrition bias, robustness checks should be performed such as Heckman's selection model.

[24] Number of productive cases as a proportion of target sample.

Figure 4.2 - Proportion of individuals§ in each MCS wave.



§ Ratio of achieved productive cases over the total targeted sample.
Source: MCS Sixth Survey User Guide (Fitzsimons 2017).

4.3.1 Descriptive Statistics

Information from the control and dependent variables chosen in this study have been summarised on Table 4.1.[25] Observations with missing information were dropped from the sample. The total number of remaining observations is 4516 and the information spans across five waves of surveys starting at MCS1 (2001/2) and ending at MCS6 (2015/6). The parental background dimension was captured by the parents' interview at the time of birth describing their marital status, household composition, i.e. whether father lived in the household and the number of child's siblings, work status, mother's health status along with information from the child including ethnicity, birth weight, health condition and school test scores. Three fourths of the couples were married at the time of birth, nearly all fathers were living in the household and 59.4% of the couples were both working. The standardised verbal score show a decrease in the mean between ages eleven and fourteen, going from 67.64 to 38.99. It may appear that there was a drop in verbal skills, however each test is done according to the child's capacity at a given age and the drop in the mean score may indicate a harder test. The differences between variables at different age periods are shown in the bottom of the table. Between ages seven and eleven, 6.7% of children were sick at age eleven but healthy at age seven. Close to 10% of children were healthy at age eleven and sick at age fourteen. These two groups form the treatment group in each regression.

The two outcome measures, also shown in Table 4.1, are based on the ranking of the verbal and quality of decision-making scores. The children were ranked into percentiles

[25] Table C.1 describes the definition of each variable on Table 4.1.

according to their performance in each test, from zero to a hundred. This lead to the calculations of the outcome measures: (i) the difference in the ranking of verbal scores and (ii) the difference in the ranking of quality of decision-making scores. The sharpest negative change in verbal score ranking was a drop by 96 percentage points and the largest gain for quality of decision-making was a 69 percentage points increase.

Table 4.1 – Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Observations = 4516				
Control variables				
Parents are married[§]	0.7508	0.4326	0	1
Father lives in the household[§]	0.9818	0.1335	0	1
Number of siblings	0.8745	0.9654	0	9
Both parents work[§]	0.5945	0.4910	0	1
Income band[1]	3.8833	1.1375	1	6
Education/Qualification[2]	2.8736	1.3317	0	5
White	0.9104	0.2857	0	1
Male	0.4750	0.4994	0	1
Birth weight (kilograms)	3.4143	0.5702	0.6	5.87
Nº of health problems[§] (Mother)	1.6684	1.7410	0	30
School readiness score	31.4233	15.0180	0	100
Mother's level of health[ǂ] (1=poor; 5=excellent)	4.3882	0.8137	1	5
Word test score (Age 7)	52.8371	20.1005	0	100
Maths score (Age 7)	47.7156	22.1027	0	100
Level of health (Child at age 7)	4.5330	0.7293	1	5
Treatment				
Longstanding Illness is present (Age 7)	0.1752	0.3801	0	1
Longstanding Illness is present (Age 11)	0.1178	0.3223	0	1
Longstanding Illness is present (Age 14)	0.1521	0.3591	0	1

[§] At the moment of birth. [ǂ] When children were 5 years old. [ξ] Based on the difference between the ranking in the mathematics test at age 7 and decision-making quality at age 11.

[1] Household income per annum was grouped into 6 bands, (1) £0 to £3099, (2) £3100 to £10399, (3) £10400 to £20799, (4) £20800 to £31199, (5) £31200 to £51999 and (6) £52000 or more.

[2] At the start of the MCS, the National Vocational Qualification (NVQ) framework was used to rank work qualifications instead of the current Regulated Qualifications Framework (RQF). In the MCS, both vocational and academic qualifications were put together in five levels. The first lower three levels are equivalent to RQF, level 4 NVQ was equivalent to levels 4-6 RQF and level 5 NVQ was equivalent to 7-8 RQF.

Table 4.1 (continued) – Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Observations = 4516				
Dependent variables				
Verbal score (Age 11)	67.6439	15.1963	0	100
Verbal score (Age 14)	38.9856	13.8910	0	100
Quality of Decision Making (Age 11)	81.6870	16.7850	0	100
Quality of Decision Making (Age 14)	86.6107	15.9511	0	100
Differences (Age 11 – Age 7, N=3725)				
Longstanding Illness is present	0.0668	0.2498	0	1
Verbal Score (ranking)	-2.8656	35.7038	-97	95
Mathematical reasoning (ranking)[ξ]	-2.5521	36.0224	-98	83
Differences (Age 14 – Age 11, N=3984)				
Longstanding Illness is present	0.1009	0.3012	0	1
Verbal score (ranking)	-3.3161	34.2786	-96	91
Quality of Decision Making (ranking)	-5.0828	28.4235	-82	69
Differences (Age 14 – Age 11, N=3776)				
Longstanding Illness is debilitating	0.0514	0.2208	0	1
Verbal score (ranking)	-3.2728	34.3047	-96	85
Quality of Decision Making (ranking)	-4.6887	28.3135	-90	69

[ξ] Based on the difference between the ranking in the mathematics test at age 7 and decision-making quality at age 11.

The two-sample differences in means test of variables between the control and treatment group for children at age eleven are shown in Table 4.2. From the selected control variables in the study, nearly none of them have statistically different means. This is an early indication of the reasonably random nature of long standing illnesses . However, some small differences are statistically significant. Children with an illness seemed to have a lower subjective quality of health at age seven and their mothers were more likely to have poorer health as well. There is also indication that children with an illness at age 11 performed worse in their test scores and had dropped in ranking relative to other, healthy, children. These differences, however, are not significant.

Table 4.2 – Two-sample mean t-test for treated and control groups (Age 11 – 7).

	Mean		
Variable	Treated (N=249)	Control (N=3476)	Difference
Parents are married	0.7631	0.7534	0.0096
Father lives in the household	0.9880	0.9822	0.0058
Number of siblings	0.7912	0.8818	-0.0906
Both parents work	0.6225	0.5964	0.0261
Income band	3.9157	3.9007	0.0149
Education/Qualification	2.9708	2.9763	-0.0055
Cohort Member is white	0.9317	0.9065	0.0252
Male	0.5020	0.4663	0.0357
Birth weight	3.4586	3.4173	0.0413
Number of health problems (Mother)	1.8112	1.5990	0.2123*
School readiness score	32.5529	31.5109	1.0421
General level of health (Mother)	4.2290	4.5132	-0.2843***
Word test score (Age 7)	51.6778	53.5082	-1.8304
Maths score (Age 7)	47.4495	48.4783	-1.0288
General level of health (Age 7)	4.4900	4.6749	-0.1850***
Verbal score (Age 11)	66.1754	67.8328	-1.6574
Quality of Decision Making (Age 11)	79.0562	81.9730	-2.9167
Differences in ranking (Age 11-7)			
Verbal score	-4.5706	-2.3816	-2.1890
Mathematical reasoning	-5.8212	-2.2998	-3.5114

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

As opposed to the group of children that were healthy at age seven and had an illness at age eleven in comparison to the control group in the same period, the children who were healthy at age eleven and had an illness at age fourteen seem to differ more than their control group, as shown in Table 4.3. Nearly half the variables show some statistical difference, albeit small. The treatment group in this case appeared more likely to have more siblings, be female, have mothers with more number of health problems, worse scores for school readiness and have worse general level of health at age seven. The scores for verbal and quality of decision making indicate that there are no statistically significant differences between treatment and control group at age eleven, but at age fourteen the two groups differ as the group of children with an illness performed worse, on average, in both exams. At the bottom of the table, the two-sample mean t-test for the two outcome variables show a highly significant difference between the two groups, indicating a negative correlation between illness and test scores. This can be seen more clearly in the results section. The two-sample mean t-test for treated and control groups for debilitating illnesses between ages eleven and fourteen is in the appendix (Table C.3).

Table 4.3 – Two-sample mean t-test for treated and control groups (Age 14 – 11).

Variable	Mean		
	Treated (N=402)	Control (N=3582)	Difference
Parents are married	0.7264	0.7527	-0.0263
Father lives in the household	0.9851	0.9813	0.0038
Number of siblings	0.9751	0.8710	0.1041**
Both parents work	0.5896	0.5944	-0.0048
Income band	3.9055	3.8894	0.0160
Education/Qualification	2.8035	2.8649	-0.0614
Cohort Member is white	0.9104	0.9065	0.0040
Male	0.4154	0.4754	-0.0600**
Birth weight	3.3982	3.4143	-0.0161
Number of health problems (Mother)	1.8035	1.6145	0.1890**
School readiness score	30.2380	31.5863	-1.3483*
General level of health (Mother)	4.2438	4.4665	-0.2227***
Word test score (Age 7)	51.3405	53.4245	-2.0840**
Maths score (Age 7)	46.5174	48.2904	-1.7730
General level of health (Child at age 7)	4.4030	4.6145	-0.2115***
Verbal score (Age 11)	67.2181	67.8932	-0.6751
Quality of Decision Making (Age 11)	80.8060	81.9693	-1.1633
Verbal score (Age 14)	37.0728	39.2001	-2.1275***
Quality of Decision Making (Age 14)	78.1357	87.5618	-9.4262***
Differences in ranking (age 14-11)			
Verbal score	-7.9324	-2.7980	-5.1344***
Quality of Decision Making	-14.0095	-4.0810	-9.9285***

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The kernel distribution of propensity scores before and after selecting the control group can highlight the differences in treatment and control group and evaluate the quality of the fit between them before the calculation of the average treatment effect. The better the fit, the better the estimates. Figures 4.3 through 4.5 show similar pictures. All the plotted graphs used an *epanechnikov* kernel function.[26] Before matching, both treated and untreated groups had similar modes but different means as the untreated group seemed to be clustered at a lower propensity

[26] The Gaussian function has convenient mathematical properties but it is not the default option in the Stata package. Nonetheless, as a robustness check, the normal kernel function was also used and the plotted graphs were virtually the same.

score value and the treated group had a slightly heavier right-tail. After matching, the selected control group kernel distribution fits almost perfectly with the treated one in the three figures.

Figure 4.3 – Kernel distribution of propensity scores by treatment (Age 11 – 7).

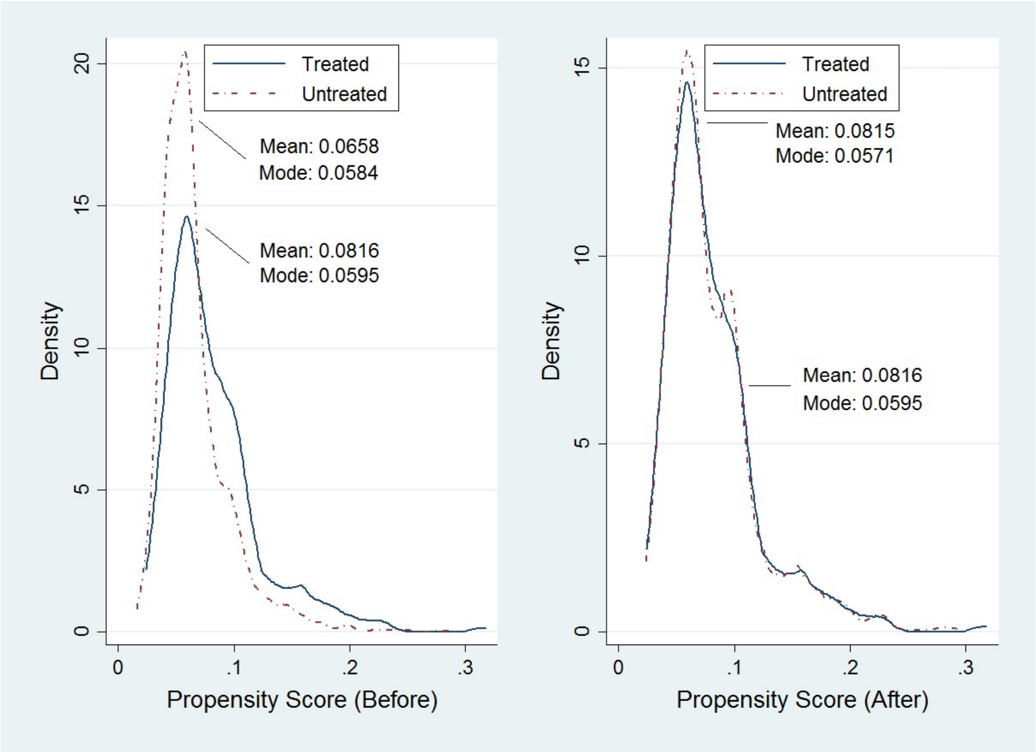


Figure 4.4 – Kernel distribution of propensity scores by treatment (Age 14 – 11).

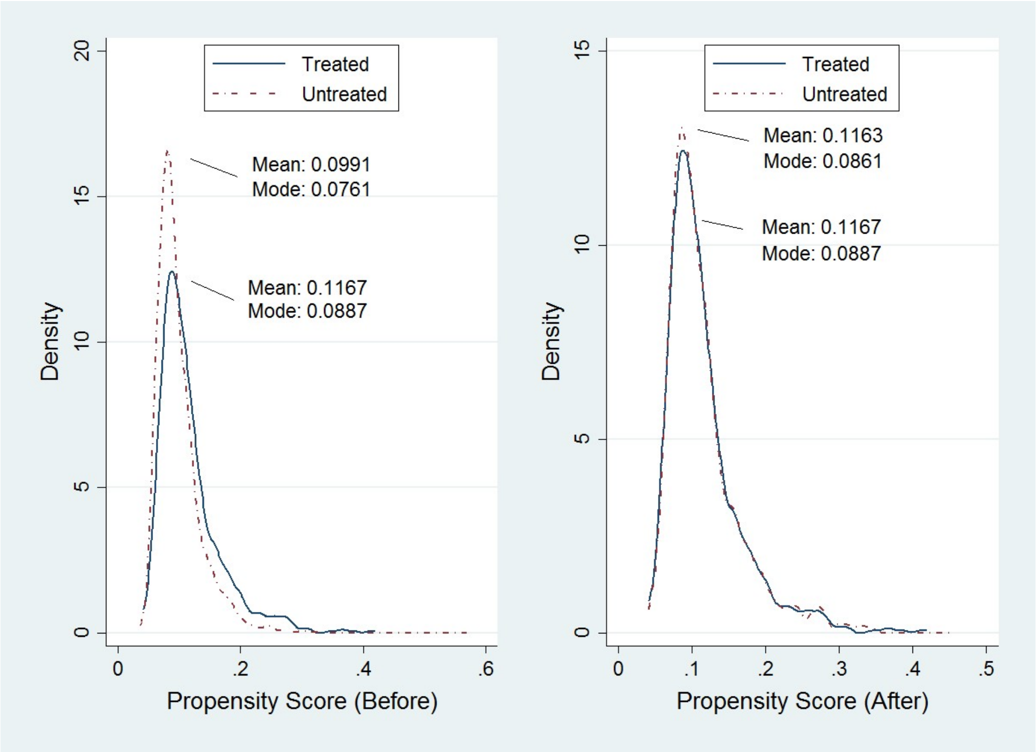
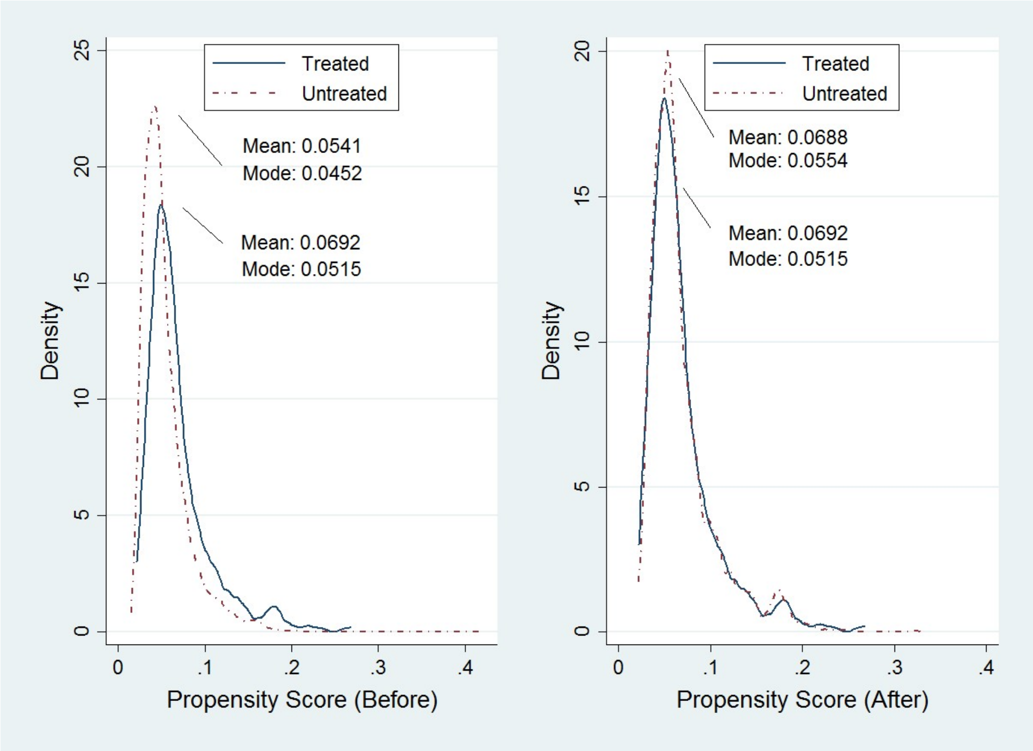


Figure 4.5 – Kernel distribution of propensity score, age 11-14, for debilitating illnesses.



A closer look in the differences in means after matching helps identifying any remaining difference between treatment and control group. Table 4.4 shows the differences in means after calculating the propensity score and selecting the control group, or untreated group, to be used in the estimations of the average treatment effect. The differences between groups before matching were small and after matching seemed to disappear. None of the variables seems to have differences in means that are statistically significant.

Table 4.4 – Differences in control variables after matching, age 11-7.

	Mean		t-test	
Variable	Treated	Untreated	t	p>|t|
Parents are married	0.7631	0.7759	-0.34	0.734
Father lives in the household	0.9880	0.9912	-0.35	0.725
Number of siblings	0.7912	0.8001	-0.11	0.913
Both parents work	0.6225	0.6329	-0.24	0.810
Income band	3.9157	3.9582	-0.41	0.679
Education/Qualification	3.0763	3.0787	-0.02	0.983
Cohort member is white	0.9317	0.9398	-0.36	0.715
Male	0.5020	0.5068	-0.11	0.915
Birth weight	3.4586	3.4477	0.23	0.820
Number of health problems (Mother)	1.8112	1.8321	-0.11	0.914
School readiness score	32.5530	32.3380	0.16	0.877
General level of health (mother)	4.2289	4.2361	-0.09	0.925

As previously stated, children with illnesses at age fourteen were more likely to have more siblings, be female, have mothers with a greater number of health problems, worse scores for school readiness and have worse general level of health at age seven. From the t-test shown in Table 4.5, it is evident that the selection of the control group was successful as the two groups had no statistically significant difference and therefore were comparable. The same can be said from the t-test for the subsample of children whose illnesses limited their activities (Table C.4 in the appendix).

Table 4.5 – Differences in control variables after matching, age 14-11.

	Mean		t-test	
Variable	Treated	Untreated	t	p>|t|
Parents are married	0.7264	0.7358	-0.30	0.763
Father lives in the household	0.9851	0.9871	-0.24	0.810
Number of siblings	0.9751	0.9716	0.05	0.962
Both parents work	0.5896	0.5906	-0.03	0.977
Income band	3.9055	3.9318	-0.32	0.748
Education/Qualification	2.8035	2.8478	-0.45	0.652
Cohort member is white	0.9104	0.9114	-0.05	0.961
Male	0.4154	0.4174	-0.06	0.954
Birth weight	3.3982	3.4156	-0.42	0.676
Number of health problems (Mother)	1.8035	1.7891	0.10	0.918
School readiness score	30.238	29.837	0.38	0.703
General level of health (Mother)	4.2438	4.2577	-0.22	0.822
Word test score (Age 7)	51.3405	51.6065	-0.20	0.839
Maths score (Age 7)	46.5174	46.7674	-0.25	0.803
General level of health (Child at age 7)	4.4030	4.4030	0.01	0.998

Visual analysis of the histogram for both outcome variables, (i) the difference in verbal skills test and (ii) the difference in maths/decision-making skills between the years, shows the frequency distribution. Figures 4.6 and 4.7 show the distribution for the frequency of differences in percentile rank between ages seven and eleven for verbal and mathematical/ decision-making skills, respectively. Both graphs in each figure have a normal distribution plotted against the diagram for comparison. They also show the distribution for the group of healthy children on the left and on the right there is the distribution of children with illnesses in the 12 months before the last survey indicated. For verbal score, there is a peak frequency close to zero in the untreated group and the remainder of the frequency fits the normal distribution somewhat closely. The treated group has a heavier left tail in comparison with the untreated group.

Figure 4.6 – Histogram for untreated and treated groups' difference in verbal ranking – Age 11 – 14.

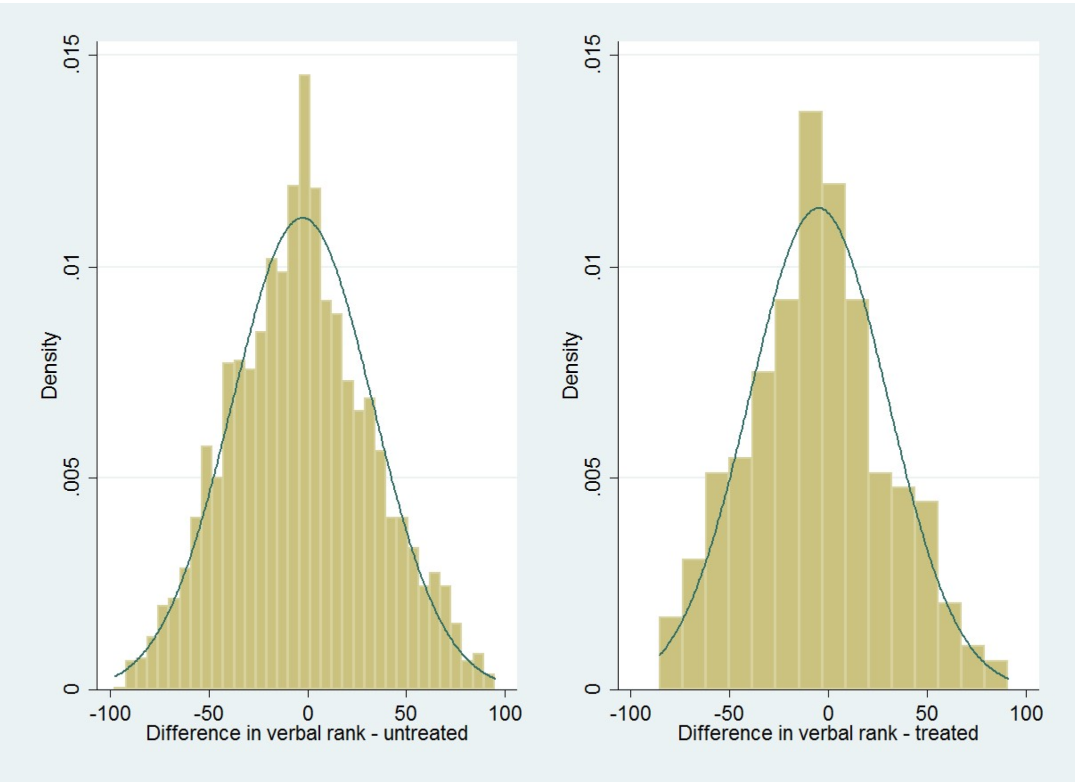
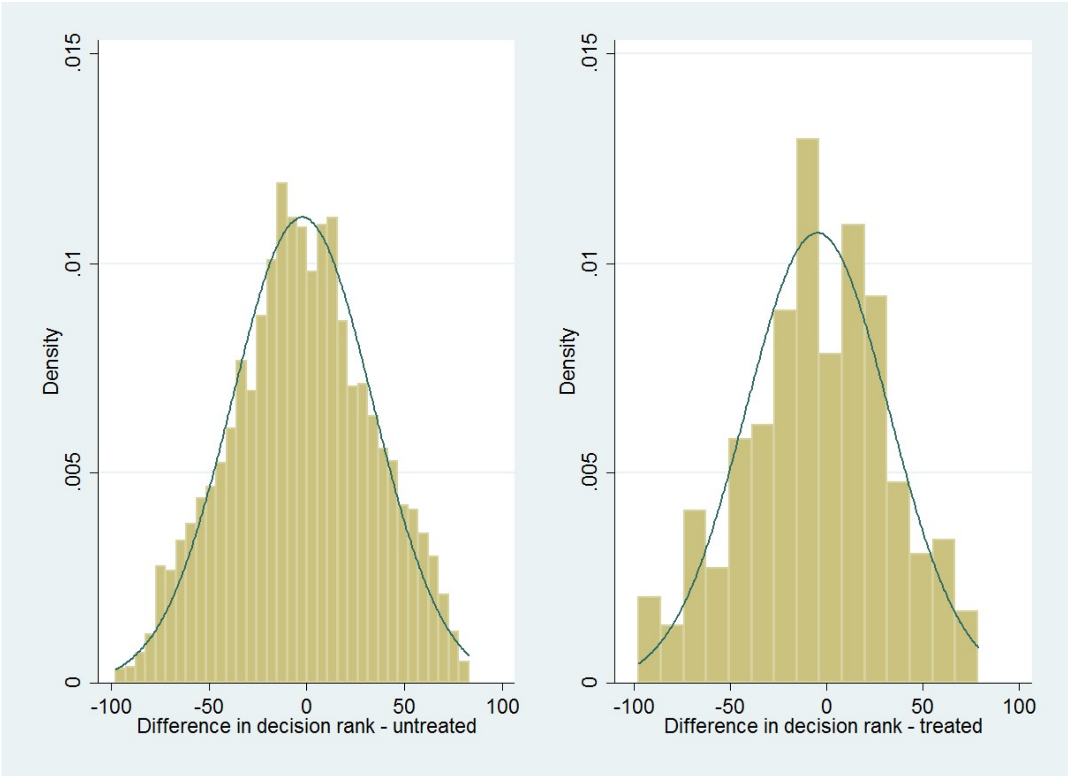


Figure 4.7 shows the histogram for maths/decision-making difference in ranking. The distribution for the untreated group, on the left, is close to the normal distribution but seems to be flatter in the mean. On the right hand side, the distribution is more balanced than in the

histogram for verbal skills, but the histogram also shows a flatter, even a gap in the middle, almost suggesting a bimodal distribution.

Figure 4.7 – Histogram for untreated and treated groups' difference in maths/decision-making ranking – Age 11 – 14.



Figures 4.8 and 4.9 show the differences between ages eleven and fourteen. As the figures above, they present untreated and treated groups on the left and right, respectively. They also have a normal distribution plotted in the graph for comparison with the histogram. Figure 4.8 seems to follow a normal distribution, with the untreated group displaying an indented shape at some points. Figure 4.9, displaying the frequency of the difference in decision-making ranking, shows a similar picture, except for the group of children with illness, on the right, having a heavier right-hand tail but higher frequency on close to the left-side of the mean. The four figures of histogram are helpful to understand the distribution of frequencies but tell us very little about the variable's means, available at the bottom of Tables 4.2 and 4.3.

Figure 4.8 – Histogram for untreated and treated groups' difference in verbal ranking – Age 11 – 14.

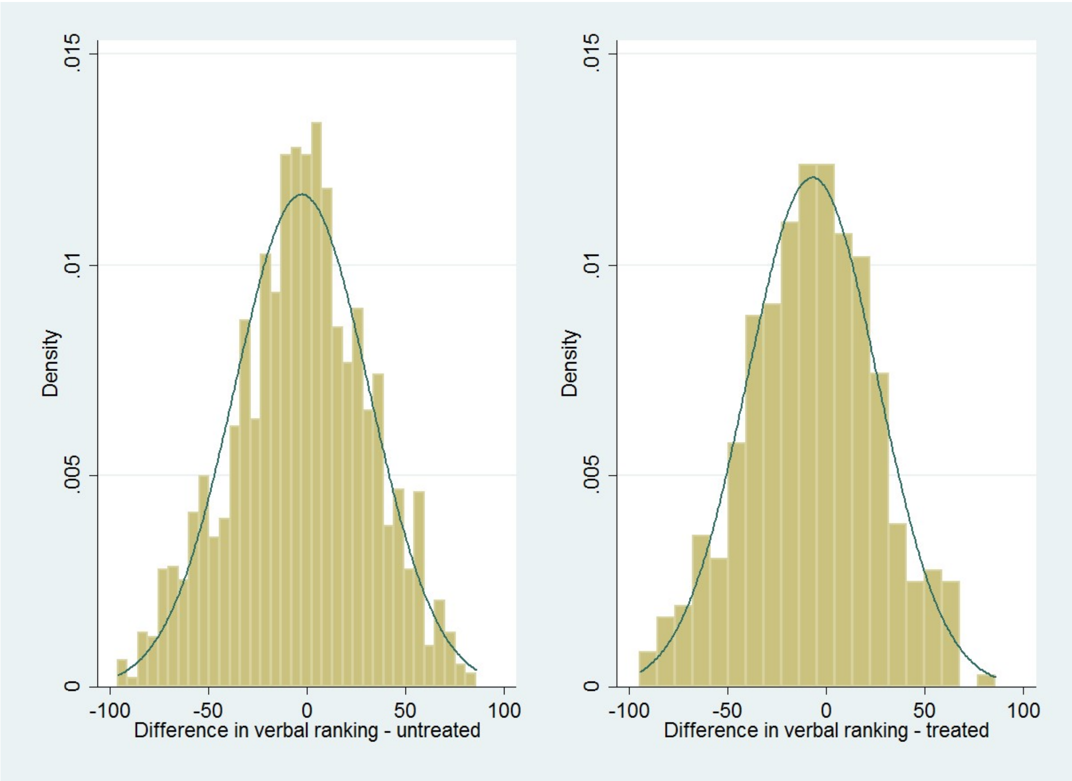
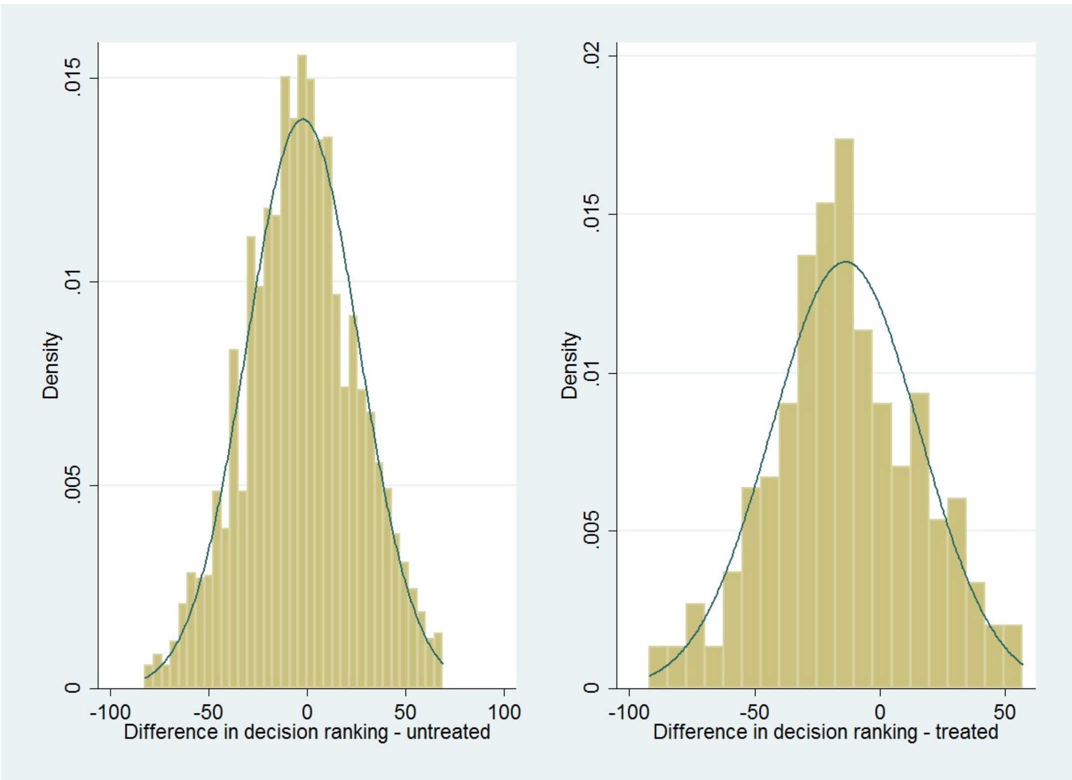


Figure 4.9 – Histogram for untreated and treated groups' difference in decision-making ranking – Age 11 – 14.



4.4 Results

Several different matching algorithms were chosen to determine how consistent the results were. Each algorithm can be modified slightly for this purpose. The *nearest neighbours* selects a number of observations in the control group that have the closest propensity score value of a treated observation and the number of neighbours selected can be modified. *Radius* algorithm, as the name says, uses a radius around the value of the propensity score of treated observation. Any propensity score of an observation in the control group that falls within this window is used for estimations, the rest are discarded. The *kernel* algorithm uses weighted averages of the observations in the control group and bandwidths of variation. The larger the bandwidth in the algorithm, the smaller the variation but the estimation bias can increase, leading to a trade-off. It can be calculated with a Gaussian or Epanechnikov function. Finally, the *stratification* algorithm divides the treated and untreated into sub-groups that have the same average propensity score. All of these options have been explored to test the robustness of results. The reported estimations from Tables 4.6 through 4.8 are based on routines in STATA econometric software.[27] To further test the robustness of the results, different sub-sets of covariates were used to calculate the propensity score and estimate the effects. There was little variation in the magnitude of the results and they pointed in the same direction as the findings presented in this section.

The first set of results presented on Table 4.6 refer to the impact of an illness in the 12 months prior to the early age of eleven. There is no statistically significant impact of illness on differences in percentile ranking for either verbal skills or mathematical/reasoning skills. However, a pattern does seem to emerge as the estimations lack statistical power but are all negative. This could potentially indicate that there is a negative impact of illness, however it is not strong enough to yield significant results. The estimations vary between a fall in 1.6 to 2.5 percentage points (pp) in the verbal ranking and between 1.6 to 2.4 pp in the mathematical/reasoning ranking. These results are surprisingly similar to naïve OLS estimations which show a negative impact, but not significant, of 2.1 pp in the verbal ranking and 2.0 in the mathematical/reasoning ranking.

[27] Based on all algorithms used the common support option, meaning that only the observations included in the common support between treatment and control groups were used. The reported *Nearest Neighbours* algorithm used four neighbours according to the *nnmatch* routine by Abadie et al. (2004). For robustness, *attnd* routine by Becker and Ichino (2002) was also used. The *radius* algorithm used a 0.0001 window. The *kernel* algorithm used a Gaussian function, therefore the bandwidth was not taken into account. In addition, for the Epanechnikov function, the bandwidth was the default, 0.06. The *stratification* algorithm used the number of blocks given by the propensity score estimation which varied from four to six blocks.

Table 4.6 – The impact of illnesses on tests between ages 7 and 11.

	Nearest Neighbours	p-value	Radius	p-value	Kernel	p-value	Stratification	p-value
verbal	-1.5572	0.552	-2.007	0.519	-2.474	0.284	-2.532	0.273
math	-2.4249	0.358	-1.621	0.547	-2.387	0.291	-2.227	0.365
Control	*1235*		*1388*		*3429*		*3429*	
Treatment	*249*		*225*		*249*		*249*	

There could be a number of explanations for the lack of a clear negative association between having illnesses and performance in tests. Parents could potentially provide assistance to children with illnesses, mitigating the negative impact. By either spending time with the child engaging in learning activities or by arranging a tutor as a way to overcome the difficulties caused by the illness, the sick child would be able to perform better despite their condition. Another explanation is that transitory negative shocks early in the child's education are well absorbed by children. The results from the same cohort a few years later brings additional clues to interpret these findings.

Table 4.7 shows the results for older children, between the ages of eleven and fourteen. There is a stark contrast with previous results as the impact is quite clear in this case. Children with illnesses in the 12 months before turning age fourteen had, on average, a fall between 4 and 5 positions in the percentile rank of the verbal tests in comparison with healthy children. Naïve OLS estimations show a negative impact as well, a fall on average of 4.9 positions in the percentile ranking, significant at 5% level. The impact on decision-making was twice as large, suggesting a fall between 8 and 10 positions in the percentile rank. All the results are significant at 5% or 1% level, this includes an OLS estimation of an average drop by 9 positions in the ranking, significant at 1%. Considering that illnesses at an early age do not seem to significantly affect performance in tests, the findings on Table 4.7 suggest that the period of life in which the child suffers from a sickness seems to matter. At later stages, education becomes more complex. Although it builds on knowledge previously acquired, it becomes harder to overcome difficulties without support, or perhaps even with support.

Table 4.7 – The impact of illnesses on tests between ages 11 and 14.

	Nearest Neighbours	p>|z|	Radius	p>|z|	Kernel	p>|z|	Stratification	p>|z|
verbal	-4.810	0.015	-5.233	0.009	-5.150	0.010	-4.940	0.012
decision	-9.405	0.002	-8.445	0.006	-9.992	0.001	-10.166	0.000
Control	*1368*		*1731*		*3573*		*3574*	
Treatment	*402*		*355*		*402*		*401*	

The results from table 4.8 show the impact on a sub-sample of children whose illness limited their daily activities. As expected, the effects are larger than in the whole sample and are all significant at 1% level. The negative impact ranges from a fall of 9 positions in the verbal percentile rank to nearly 13 positions in decision-making percentile rank. The analysis could not be carried out in the previous period from age seven to eleven due to the small size of the sub-sample, which prevented the proper estimations of propensity scores. Together with the results of the larger sample, the indications of a significant impact are clear.

Table 4.8 - The impact of debilitating illnesses on tests between ages 11 and 14.

	Nearest Neighbours	p>|z|	Radius	p>|z|	Kernel	p>|z|	Stratification	p>|z|
verbal	-9.804	0.000	-10.447	0.000	-9.382	0.002	-9.427	0.002
decision	-11.389	0.000	-12.468	0.000	-11.924	0.000	-12.616	0.000
Control	*880*		*1245*		*3527*		*3527*	
Treatment	*194*		*174*		*194*		*194*	

The longitudinal design of the MCS and the richness of its data allowed for an analysis of the impact of a transitory health shock. Table 4.9 shows the effects of illness at age eleven in the subsequent tests taken at age fourteen in comparison with healthy children. The short-run impact, shown in Table 4.6, suggested a modest negative impact with no statistical power. The long-run impact, however, seems to be non-existent. The estimated coefficients are nearly all very close to zero and are far from being statistically significant even at the 10% level. It is true that the initial short-run impact was small to begin with, but there is indication that in the long-run the transitory negative health shock is also has a transitory impact on test performance, suggesting a return to the mean.

Table 4.9 – The long-run impact of illnesses from age 7 to 14.

	Nearest Neighbours	p>|z|	Radius	p>|z|	Kernel	p>|z|	Stratification	p>|z|
verbal	-0.223	0.935	-1.345	-0.621	-0.221	0.904	-0.155	0.921
math	-1.411	0.837	0.860	-0.773	-0.773	0.741	-1.177	0.632
Control	*638*		*1050*		*3125*		*3176*	
Treatment	*143*		*127*		*143*		*143*	

Reading the results all together provides a clearer picture of how children, in a developed country such as the United Kingdom, face the negative impact of an illness. The short-run impact of an illness depends on which period of life it affects a child. Illness seems to not have a strong negative effect early on, but as the children grow older, the impact grows stronger and, not surprisingly, it is the strongest for children who point out that they cause limitations to their daily activities. The evidence for long-run impact is less conclusive for two reasons. First, there is data limitation as the MCS cohort is a young one and there are few learning and educational outcomes available, therefore the estimations are bound to a small time period from age seven to fourteen. The initial short-run impact between ages seven and eleven was small to begin with and non-existent in the long-run. As more data becomes available, it will be possible to carry out the same analysis with a group of children that have indeed displayed a strong negative association between having an illness and test performance.

4.5 Conclusion and limitations

This research explored the impact of illnesses on children's performance in tests for verbal skills, mathematical skills and decision-making ability in a developed country context. By using the longitudinal setting of the Millennium Cohort Study (MCS), a British survey that started in 2001-2002, children that were healthy and children that had longstanding illnesses were identified, first between the ages of seven and eleven years old and then between eleven and fourteen years old. This way, the short-run impact at two different periods in the children's lives could be evaluated. The results suggest that the timing of an illness affects children in a different ways. When comparing healthy children with ones that had an illness at age eleven, the estimations consistently showed a negative impact but there was no statistically significant difference between their performances. The estimations were different when looking at children at a later age. The comparison between healthy children at ages eleven through fourteen and the ones with an illness at age fourteen showed a stronger, statistically significant, negative impact on test performance. Results varied from a fall between four and six positions in the percentile rank for verbal skills test and between eight and eleven positions in the rank for quality of decision-making test. Possibly, the reason for such findings is that children at a later stage in education have more difficulty in catching up in a short period of time as the complexity of the subjects increases. Even stronger results were found when limiting the sub-sample to children whose illness were debilitating and limited their daily activities.

The literature on health interventions claims that early childhood interventions are more efficient and cost-effective in comparison with interventions during adolescence or adulthood (Conti, Heckman and Pinto, 2015; Conti and Heckman, 2014). The results from this research suggest that negative health shocks matter more at a later age instead. It may seem contradictory to the established literature, however the findings concern transitory health shocks while early childhood interventions are meant to educate and permanently change parental care of children in disadvantaged households. This, in turn, leads to permanent improvement in health outcomes which bears other positive life outcomes. Therefore, early childhood interventions and transitory health shocks are not necessarily meant to have similar dynamics.

To test the long-run impact of illnesses, the group of children who were healthy at age seven, had an illness at age eleven but were healthy at age fourteen were compared to children who were healthy from age seven to fourteen. The initial findings, from age seven to eleven, showed a small negative impact, not strong enough for statistical significance. The long-run analysis showed even less evidence of any impact, positive or negative. It could be argued that if there was a negative impact in the short-run caused by a transitory health shock, it dissipates in the long-run. This analysis can be extended to children at an older age once more data from the MCS is released.

This study is by no means exhaustive since more research can be done as the survey progresses. The estimation method used, the propensity score matching, is only as good as the quality of information used. Despite using a list of covariates consisting of recognized predictors of health and academic performance as suggested by the literature and also having evidence that the main assumptions for the method were satisfied according to the robustness tests, it is not possible to clearly and undisputedly suggest a causal relationship in the findings without an exogenous variation. However, the contribution of this study can help guide further research.

Appendix C

Table C.1: Two-sample t-test for starting cohort and individuals who provided all information throughout each survey.

	Mean		t-test		Sample
Variable	2001/2002	2001-16	t	p>|t|	Size[1]
Parents are married	0.6852	0.7509	-7.99	0.000	13993
Father lives in the household	0.7366	0.9818	-36.81	0.000	16978
Number of siblings	0.9364	0.8747	3.35	0.001	16978
Both parents work	0.3487	0.5943	-29.44	0.000	16978
Income band	3.1396	3.8833	-37.03	0.000	16941
Education/Qualification	2.1115	2.8736	-30.28	0.000	16939
Cohort member is white	0.8148	0.9103	-15.11	0.000	16934
Male	0.5264	0.4750	5.93	0.000	16978
Birth weight	3.3247	3.4142	-8.79	0.000	16921
Number of health problems (Mother)	1.6479	1.6690	-0.06	0.541	16951

[1] Cohort sample size in 2001/2002. The sample size used in the study (2001-16) was 4516.

Table C.2: Description of the variables used in the study.*

Variable	Description
Parents are married	Binary: Parents were married at the time of birth.
Father lives in the household	Binary: Father lived in the household at the time of birth.
Number of siblings	Number of siblings.
Parents work	Binary: Both parents were working within a year of birth.
Income Band	Household income at the time of birth, separated into 6 bands.
Education/Qualification	Mother's highest academic/vocational qualification at the time of birth.
White	Binary: Cohort Member is white.
Birth weight	Cohort Member's birth weight.
Nº of health problems (Mother)	Mother's number of health problems.
School readiness score	A score on the Bracken Basic Concept Scale designed to assess development and school readiness
Mother's level of health (Mother)	Mother's self-assessed general level of health. 1=poor, 2=fair, 3=good, 4=very good, 5=excellent.
Word test score (Age 7)	English reading assessment by the British Ability Scales.
Maths score (Age 7)	Assessment based on NFER Progress Maths Test.
Level of health (Cohort Member)	Cohort Member's general level of health. 1=poor, 2=fair, 3=good, 4=very good, 5=excellent.
Longstanding Illness is present	Binary: Cohort Member has at least one longstanding illness.
Verbal score	Assessment for verbal reasoning and knowledge by the British Ability Scales.
Quality of Decision Making	Based on a test by CANBT Cambridge Gambling Task*, it indicates the percentage of correct choices made.

* For more detailed information, refer to the Questionnaire's Guide from the Millennium Cohort Study, waves one through six, available at the Centre for Longitudinal Studies (www.cls.ioe.ac.uk).

Table C.3: Two-sample mean t-test for treated and control groups for debilitating illnesses, age 14 – 11.

Variable	Mean		
	Treated	Control	Difference
Parents are married	0.6598	0.7527	-0.9286***
Father lives in the household	0.9742	0.9813	-0.0071
Number of siblings	1.0206	0.871	0.1496**
Both parents work	0.5309	0.5944	-0.0634*
Income band	3.6907	3.8894	-0.1987**
Education/Qualification	2.6856	2.8649	-0.1793*
Cohort Member is white	0.9072	0.9065	0.0007
Male	0.3608	0.4754	-0.1146***
Birth weight	3.3902	3.4143	-0.0241
Number of health problems (Main carer)	1.8608	1.6145	0.2464*
School readiness score	28.1279	31.5863	3.4583***
General level of health (Main carer)	4.2938	4.4665	-0.1727***
Word test score (Age 7)	50.8133	53.4245	-2.6112*
Maths score (Age 7)	45.8147	48.2904	-2.4756
General level of health (Cohort Member)	4.3866	4.6145	-0.2279
Verbal score (Age 11)	66.7268	67.8932	-1.1664
Quality of Decision Making (Age 11)	79.1443	81.9693	-2.8250**
Verbal score (Age 14)	32.0713	39.3721	-7.3008***
Quality of Decision Making (Age 14)	73.1492	87.3398	-14.1906***
Differences in rank			
Verbal score	-12.0403	-2.7980	-9.2423***
Quality of Decision Making	-15.9098	-4.0810	-11.8288***

Table C.4 – Differences in control variables after matching for debilitating illnesses, age 14-11.

	Mean		t-test	
Variable	Treated	Untreated	t	p>|t|
Parents are married	0.6598	0.6567	0.06	0.949
Father lives in the household	0.9742	0.9742	0.01	0.997
Number of siblings	1.0206	1.0464	-0.23	0.815
Both parents work	0.5309	0.5299	0.02	0.984
Income band	3.6907	3.7062	-0.13	0.895
Education/Qualification	2.6856	2.7072	-0.15	0.879
Cohort member is white	0.9072	0.8907	0.54	0.591
Male	0.3608	0.3629	-0.04	0.966
Birth weight	3.3902	3.3814	0.15	0.878
Number of health problems (Mother)	1.8608	1.8155	0.25	0.799
School readiness score	28.1280	28.1001	0.02	0.985
General level of health (Mother)	4.2938	4.2629	0.36	0.721
Word test score (Age 7)	50.813	50.2620	0.26	0.797
Maths score (Age 7)	45.815	46.3690	-0.24	0.809
General level of health (Child at age 7)	4.3866	4.3990	-0.16	0.876

Chapter 5

Conclusion

This thesis explored the relationship between health and education, how they affect each other and how they affect other life outcomes in different periods of peoples' lives. It consists of three self-contained chapters, each of them using longitudinal datasets from the United Kingdom. They separately analysed different aspects of the relationships between health, education and life outcomes.

Chapter 2 looked at the impact that higher education has on health outcomes and behaviour. Its original contribution came from the evaluation of different degrees and their impact in health. Following increases in tuition fees, the cost of pursuing higher education increased and this sparked new interest in understanding what are the returns to education, including narrowing down these returns by each subject. This way, individuals can make an informed decision based on the predicted returns that their chosen subjects have, including not only monetary returns but also wider returns, such as health outcomes and behaviour explored in this chapter. Data from the National Child Development Study (NCDS) was used in this study. Starting in 1958, the survey follows individuals since their birth recording a broad range of information, including academic achievements and health outcomes and behaviour. By using panel methods regressions, the findings of this chapter suggest that individuals with higher education indeed have better health outcomes and behaviour, something already well established in the literature through studies that used other datasets, but most importantly they suggest that the choice of subject for a higher degree does not imply any bonus to health outcomes and behaviour in comparison to any other choice of higher education degree. This result differs from the studies about monetary returns, where there is a difference between subjects. In other words, the choice of the subject of your first degree does matter when it comes to money, but in terms of health outcomes and behaviour, the bonus is the same for every subject.

At the moment, tuition fees in higher education institutions vary according to the type of degree, whether the student is from the UK/EU or international and what is the degree's subject (OFFA 2017). Diplomas and Foundation Courses cost less than full-time Masters degrees, on average, and international students pay up to three times the tuition fees of UK/EU students. However, nearly all universities charge the same fees, £9,250, for UK/EU undergraduate full-time students starting their degrees in 2018/2019, regardless of the subject. Future discussions about at what level should tuition fees be set by universities may focus not only in the costs for universities, but also on the potential benefits to the user, in this case the students. The literature on the topic already has some evidence that the economic returns to a degree differ according to the subject, with Law, Economics and Management (LEM) and Science, Technology, Engineering and Mathematics (STEM) degrees leading the top (Walker and Zhu 2011). This chapter shows that the returns for health outcomes and behaviour are the same. The implication of these results is that should universities consider the different benefits according to each subject in order to calculate tuition fees for full-time undergraduate students, they should focus on the different economic returns only, given an important aspect of the wider returns to a higher education degree, health, being the same for any subject. Of course, there are limitations to this study and it is, to my knowledge, the first to evaluate differences in wider returns according to choice of degrees. Other studies should follow with different datasets and robust identification strategy before any strong policy implication can be drawn. This could be, however, only the first step in the right direction.

The third chapter addresses a different aspect of the relationship between health and education and expands the analysis to other life outcomes. It focuses on the impact of health on life outcomes, specifically at the effect of mental health, as opposed to physical health, on life outcomes. The main contribution from this chapter stems from the use of a longitudinal survey with panel methodology to analyse the impact of Attention Deficit / Hyperactivity Disorder (ADHD) at 10 years old on a wide range of outcomes, from educational and vocational qualifications to labour market outcomes and other social behaviours such as hazardous drinking and smoking habits. Earlier studies focused on cross-sectional data or on too few outcomes. These studies are somewhat recent since, for many years, mental health was set aside and did not have nearly the same importance as physical health in the discussion of public policies. This slowly changed in developed countries as they dealt with physical illnesses more and more efficiently. As a result, mental health is now seen as just as important as physical health, it is even present in public policy debates in mainstream media. The data used in this chapter is from the British Cohort Study 1970 (BCS70). The BCS70, just like the NCDS, is a British longitudinal survey and follows the lives of individuals since their birth, collecting a wealth of information on their health status, educational achievements and other life outcomes. The identification of children potentially diagnosed with ADHD at age 10 followed the guidance of the *Diagnostic and statistical manual of mental disorders*, 4th edition

(DSM-IV) as closely as possible. With the help of panel regression methods, the results show that labour market outcomes are greatly affected by ADHD. Individuals with this mental difficulty earn less, are less likely to be employed, work full-time or in a managerial position and are more likely to be recipients of cash benefits. The effects are stronger for men, except for working in a managerial position.

The policy implications that rise from these findings suggest that, ADHD has the potential to hinder people's professional development, leading to less productivity and earnings. It also has an effect on welfare costs as they are more likely to receive benefits associated with low earnings and unemployment. A closer look, following on the results from this study, could determine the actual cost of the negative effects of ADHD and pave the way for research on cost-effective treatments that would not only provide private benefits for the individuals affected but also wider benefits for the society as more people would be able to fully contribute to the economy.

The fourth chapter revisits the well-known relationship between health and education stemming from health affecting educational performance. The innovative focus and original contribution is the attention to the transitory negative health shocks in different periods of children's lives, whether they differ according to when there is an incidence of a longstanding illness and how permanent the effects are. There are many studies attesting for the positive correlation between health and educational achievements at an early age, with the causality path running from better (worse) health to better (worse) academic performance. But the majority of these studies, or at least the most well-known studies, focus on children in developing countries or disadvantaged areas where the variance of children's health conditions is greater than their counterparts in developed countries. This chapter adds to the smaller number of papers that look at children's health conditions in developed countries. For this purpose, the data used is from the first British longitudinal survey in this millennium, the Millennium Cohort Study (MCS) that started in 2001-2002, following a long tradition of data collection in the United Kingdom. Equipped with data from medical records and parents at the time of birth and early educational tests, this study used the Propensity Score Matching (PSM) method in a variety of model specifications to understand how children were affected by longstanding illnesses occurring, at least, in the 12 months prior to each test. The results indicate two things: (i) first, the period of life in which children are affected by a long-standing illness seems to matter as older children were more affected, negatively, than younger children. And (ii) second, there is weak evidence that the negative effect may be transitory if the negative health shock is also transitory. It is too early to tell if this second finding is robust, but as more data from the MCS becomes available this hypothesis may be tested.

The findings are enlightening as the usual findings on health intervention show that the earlier the intervention, the better the results. By extension, a negative health "intervention" should yield worse effects at an early age rather than the opposite. However, even when these interventions focus on providing treatments to particular diseases to a child, they are planned to result in a permanent change in health knowledge and behaviour from the parents or guardians that will, in turn, positively affect later life outcomes. The results in this chapter, therefore, do not challenge the established literature as they refer to transitory health shocks, not permanent ones. Policy implications are too early to be considered but they suggest that older children would benefit more from additional help, should they face a long-standing illness, in comparison with younger children. However, the implications of the second finding, that the negative effects are transitory, could suggest that children do "bounce" back with the current assistance programs in place and there is no need to further implement such programs. As more data is made available and more research explores this issue, it will be easier to determine which path to take.

Overall, this thesis analysed three separate, but intertwined, topics within the economics of health and education. Each chapter can stand-alone and does not build on the results of others. The policy implications are varied and specific to the results of each chapter but the grand message is that health and education play a very important role in people's lives as they affect different life outcomes many years later. As such, the more we understand about it and the more we disentangle the many different causality paths in this topic, the easier it will be to formulate public policies that correctly address the many issues surrounding it. This thesis is by no means the first step, nor the last, hopefully, but it is a small step in the right direction.

References

Abadie, A. Drukker, D. Herr, J. L. & Imbens, G. W. 2004. Implementing matching estimators for average treatment effects in Stata. *The Stata Journal*. Vol 4(3): 290-311.

Alderman, H. Behrman, J. R. Lavy, V. & Menon, R. 2001. Child Health and School Enrolment: a Longitudinal Analysis. *The Journal of Human Resources*, Vol. 36(1): 185-205.

Alderman, H. Hoddinott, J. & Kinsey, B. 2006. Long Term Consequences of Early Childhood Malnutrition. *Oxford Economics Papers*, Vol. 58(3): 450-474.

Almond, D. & Currie, J. 2011. Killing Me Softly: The Fetal Origins Hypothesis. *Journal of Economic Perspectives*, Vol. 25(3): 153-172.

American Psychiatric Association. 1994. Diagnostic and statistical manual of mental disorders, 4th Edition, Washington DC: *American Psychiatric Association*.

American Psychiatric Association. 2013. Diagnostic and statistical manual of mental disorders, 5th Edition, Washington DC: *American Psychiatric Association*.

Angrist, J. D., & Krueger, A. B. 1991. Does Compulsory Schooling Attendance Affect Schooling and Earnings? *Quarterly Journal of Economics*, Vol. 106(4): 979–1014.

Arendt, J. N. 2005. Does education cause better health? A panel data analysis using school reforms for identification. *Economics of Education Review*, Vol. 24(2). April, pp 149-160.

Asherson, P. & Gurling, H. 2011. Quantitative and Molecular Genetics of ADHD. *Current topics in behavioral neurosciences*. Vol 9: 239-272.

Banerjee, A. Duflo, E. Postel-Vinay, G. & Watts, T. 2010. Long-Run Health Impacts of Income Shocks: Wine and Phylloxera in Nineteenth-Century France. *The Review of Economics and Statistics*, Vol. 92(4): 714-728.

Barker, D. J. P. et alii. 1989. Weight in Infancy and Death from Ischaemic Heart Disease. *The Lancet*, Vol. 334(8663): 577-588.

Barkley, R. et alii. 1993. Driving-related risks and outcomes of attention deficit hyperactivity disorders in adolescents and young adults: a 3 to 5 year follow-up survey. *Pediatrics* Vol. 92: 212-218.

Barro, R. J. 1991. Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*. Vol, 106 (2). May, pp. 407-443.

Becker, G. S. 1962. Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, Vol. 70(5), Part2: Investment in Human Beings (Oct), pp. 9-49.

__________. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. University of Chicago Press for the National Bureau of Economic Research, Chicago.

__________. 1973. A Theory of Marriage: Part I. *Journal of Political Economy*, Vol. 81(4): 813–46.

__________. 1991. *A Treatise on the Family*. Cambridge and London: Harvard University Press.

Becker, G. S., & Murphy, K. M. 1988. A Theory of Rational Addiction. *Journal of Political Economy*, Vol. 96 (4): 675-700.

Becker, G.S., Hubbard, W.H.J. & Murphy, K.M. 2010. Explaining the worldwide boom in higher education of women. *Journal of Human Capital*, Vol. 4(3) (Fall): 203-241.

Becker, S. & Ichino, A. 2002. Estimation of average treatment effects based on propensity scores. *Stata Journal*. Vol 2(4): 358-377.

Behrman, J. 1996. The impact of health and nutrition on education. World Bank Research Observer; Vol. 11(1):25-37.

Berger, M. C. & Leigh, J. P. 1989. Schooling, Self-Selection and Health. *Journal of Human Resources*, Vol. 24(3): 433-455.

Black, S. E. Devereux, P. J. & Salvanes, K. G. 2005. Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. *American Economic Review*, Vol. 95(1): 437-449.

____. 2007. From the cradle to the labor market? The effect of birth weight on adult outcomes. *Quarterly Journal of Economics*, Vol. 122(1): 409-439.

Bobonis, G.J., Miguel, E. & Sharma, C.P. 2006. Iron deficiency anemia and school participation. *Journal of Human Resources*, Vol. 41(4): 692-721.

Brasset-Grundy, A. & Butler, N. 2004. Prevalence and adult outcomes of Attention-Deficit/Hyperactivity Disorder. Evidence from a 30-year prospective longitudinal study. *Bedford Group for Lifecourse & Statistical Studies*. Institute of Education, University of London.

Briggs, A. Claxton, K. & Sculpher, M. 2006. Decision Modelling for Health Economic Evaluation. In: Gray, A. & Briggs, A. (Eds). *Handbooks in Health Economic Evaluation*. Oxford (United Kingdom): Oxford University Press.

Brookes at alii. 2006. The analysis of 51 genes in DSM-IV combined type attention deficit hyperactivity disorder: association signals in DRD4 DAT1 and 16 other genes. *Molecular Psychiatry*, Oct Vol. 11(10): 934-53.

Brown, T. 2000. Attention-Deficit Disorders and Comorbidities in Children, Adolescents and Adults. *American Psychiatric Press,* 1st ed.

Caliendo, M. Kopeinig, S. 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, Vol. 22(1): 31-72.

Card, D. 1999. The causal effect of education on earnings. In: O. Ashenfelter and D. Card, eds. *Handbook of Labor Economics*, vol. 3 (Elsevier, Amsterdam): 1801-1863.

Carneiro, P., Heckman, J.J. & Vytlacil, E.J. 2011. Estimating Marginal Returns to Education, *American Economic Review*, Vol. 101, (Oct): 2754-2781.

Carneiro, P. Meghir, C. & Parey, M. 2013. Maternal Education, Home Environments, and the Development of Children and Adolescents. *Journal of European Economic Association*. Vol. 11(1): 123-160.

Case, A. Lubotsky, D. & Paxson, C. 2002. Economic Status and Health in Childhood: The Origins of the Gradient. *American Economic Review*, Vol. 92(5): 1308-34.

Chevalier, A. & O'Sullivan, V. 2007. Mother's Education and Birth Weight. *IZA Discussion Paper Series*. Paper No. 2640.

Children Act 1989. United Kingdom. Available at:
https://www.legislation.gov.uk/ukpga/1989/41/contents (Accessed 8th March 2018)

Chou, S. Liu, J. Grossman, M. & Joice, T. 2010. Parental Education and Child Health: Evidence from a Natural Experiment in Taiwan. *American Economic Journal: Applied Economics*. Vol. 2(1): 33-61.

Coleman, J. S. 1966. *The Coleman Report: Equality of Educational Opportunity*. Washington: US Government Printing Office.

Conners, C. K. 1969. A teacher rating scale for use in drug studies with children. *American Journal of Psychiatry*. Vol 126, pp. 884-888.

Conti, G. & Heckman, J. J. 2014. The economics of child well-being. In: A. Ben-Arieh et al. (Ed.) *Handbook of Child Well-Being*, pp. 363-401. Dordrecht: Springer.

Conti, G. Heckman, J. J. & Pinto, R. 2015. The effects of two influential early childhood interventions on health and healthy behaviors. *NBER Working Papers* 21454, National Bureau of Economic Research, Inc.

Costa-Font, J. & Gil, J. 2005. Obesity and the incidence of chronic diseases in Spain: A seemingly unrelated probit approach. *Economics & Human Biology*. Vol. 3(2): 188-214.

Currie, J. 2009. Healthy, Wealthy and Wise: Socioeconomic Status, Poor Health in Childhood and Human Capital Development. *Journal of Economic Literature*, Vol. 47(1): 87-122.

Currie, J. & Hyson, R. 1999. Is the Impact of Health Shocks Cushioned by Socioeconomic Status? The Case of Low Birthweight. *American Economic Review*, Vol. 89(2): 245–50.

Currie, J. & Moretti, E. 2003. Mother’s Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings. *The Quarterly Journal of Economics*, Vol. 118(4) (Nov): 1495-1532.

Currie, J. & Stabile, M. 2006. Child mental health and human capital accumulation: The case of ADHD. *Journal of Health Economics*. Vol. 25: 1094-1118.

Currie, J. Stabile, M. & Jones, L. 2014. Do stimulant medications improve educational and behavioral outcomes for children with ADHD? *Journal of Health Economics*. Vol. 37: 58-69.

Cutler, D.M. & Lleras-Muney, A. 2008. Education and health: Evaluating theories and evidence. In: James, S.H. at alii. (Eds), *Making Americans Healthier? Social and Economic Policy as Health Policy*, Russel Sage Foundation, New York.

Cutler, D.M. & Lleras-Muney, A. 2012. Education and Health: Insights from International Comparisons. *NBER Working Paper*, No. 17738.

Dalsgaard, S. Nielsen, H. & Simonsen, M. 2014. Consequences of ADHD Medication Use for Children's Outcomes. *Journal of Health Economics*. Vol. 37: 137-151.

Dee, T.S. 2004. Are there civic returns to education? *Journal of Public Economics*, Vol.88: 1697-1720.

Ding, W., at alii, 2009. The impact of poor health on academic performance: New evidence using genetic markers. *Journal of Health Economics*, Vol. 28: 578–597.

Dickson, M. Gregg, P. & Robinson, H. 2016. Early, Late or Never? When does Parental Education Impact Child Outcomes? *The Economic Journal*, Vol 126 (Oct): 185-231.

Doblhammer, G. 2004. *The Late Life Legacy of Very Early Life*. Heidelberg, Germany and New York, USA: Springer.

Ermisch, J. & Francesconi, M. 2000. Educational Choice, Families, and Young People's Earnings. *Journal of Human Resources*, Vol. 35(1): 143-176.

Farmer, E. 1993. Externalizing behavior in the life course: The transition from school to work. *Journal of Emotional & Behavioral Disorders*. July, Vol.1 (3):179-189.

_________. 1995. Extremity of Externalizing Behavior and Young Adult Outcomes. *Journal of Child Psychology and Psychiatric.* Vol. 36(4): 617-632.

Feinstein, L. 2002. Quantitative Estimates of the Social Benefits of Learning, 2: Health (Depression and Obesity)", Wider benefits of Learning Research Report No. 6, *The Centre for Research on the Wider Benefits of Learning – Institute of Education*.

Feinstein, L. & Hammond, C. 2004. The Contribution of Adult Learning to Health and Social Capital. *Oxford Review of Education*. Vol 30(2). June, pp.199-221.

Figlio, D. Guryan, J. Karbownik, K. & Roth, J. 2014. The Effects of Poor Neonatal Health on Children's Cognitive Development. *American Economic Review*, Vol. 104(12): 3921-3955.

Fiore, T. A. Becker, E. A. & Nero, R. C. 1993. Educational Interventions for Students with Attention Deficit Disorder. *Exceptional Children*. Vol. 60(2) Oct-Nov.

Fitzsimons, E. (Ed). 2017. Millenium Cohort Study Sixth Survey 2015-2016: User Guide. (1st edition, March 2017). London: Centre for Longitudinal Studies, Institute of Education.

Fletcher, J. 2014. The effects of Childhood ADHD on Adult Labor Market Outcomes. *Health Economics*. Vol. 23: 159-181.

Fletcher, J. & Wolfe, B. 2008. Comment: Child mental health and human capital accumulation: The case of ADHD revisited. *Journal of Health Economics*. Vol. 27: 794-800.

___________________. 2009. Long-Term Consequences of Childhood ADHD on criminal activities. *The Journal of Mental Health Policy and Economics*. Vol. 12(3): 119-138.

Franklin, A. & Sloper, P. 2005. Listening and responding? Children's participation in health care within England. *International Journal of Children's Rights*, Vol. 13(1/2): 11- 29.

Fuchs, V.R. 1982. Time preference and health: an exploratory study. In: Fuchs, V.R. (Ed.), *Economic Aspects of Health,* University of Chicago Press, Chicago.

Glewwe, P. & Jacoby, H. G. 1995. An Economic Analysis of Delayed Primary School Enrolment in a Low Income Country: The Role of Early Childhood Nutrition. *Review of Economics and Statistics*, Vol. 77(1): 156-169.

Glewwe, P. Jacoby, H. G. & King, E. M. 2001. Early childhood nutrition and academic achievement: a longitudinal analysis. *Journal of Public Economics*, Vol. 81: 345-368.

Glewwe, P. & Miguel, E. A. 2008. The Impact of Child Health and Nutrition on Education in Less Developed Countries. In: Schultz, T. P.; Strauss, J. A. (Ed.) *Handbook of Development Economics* (4) chapter 56: 3561-3606.

Grossman, M. 1972. On the Concept of Health Capital and the Demand for Health. *The Journal of Political Economy*, Vol. 80, No.2. (Mar-Apr), pp. 223-255.

___________. 1976. The Correlation between Health and Schooling. In NBER Books: *The Household Production and Consumption*, (ed) Nestor, E. T., pp. 147-224.

___________. 2006. Education and Nonmarket Outcomes. Chapter 10, Handbook of the Economics of Education, Vol 1: 577-633.

___________. 2015. The Relationship between Health and Schooling: What’s new? Discussion paper 9369, September 2015. Institute for the Study of Labor (IZA).

Grossman, M. & Kaestner, R. 1997. Effects of Education on Health, Chapter 4 in *The Social Benefits of Education*. Edited by Behrman, J., Stacey, N. *University of Michigan Press*.

Hack et alii. 2002. Outcomes in young adulthood for very-low-birth-weight infants. *The New England Journal of Medicine*, Vol. 346(3): 149-157.

Hammond, C. 2004. Impacts of lifelong learning upon emotional resilience, psychological and mental health: fieldwork evidence. *Oxford Review of Education*. Vol. 30(4). December, pp. 551-568.

Hansen, K. 2012. *Millennium Cohort Study First, Second and Third Surveys: A Guide to the Datasets*. 7th Edition. October 2012. Centre for Longitudinal Studies, Institute of Education, University of London.

Hanushek, E. A. & Woessmann, L. 2008. The Role of Cognitive Skills in Economic Development. *Journal of Economic Literature*, Vol. 46(3): 607-668.

Harmon, C. Oosterbeek, H. & Walker, I. 2003. The returns to education: Microeconomics. *Journal of Economic Surveys*, Vol. 17(2): 116-155.

Heckman, J.J. Humphries, J.E. & Veramendi, G. 2016. Returns to education: the causal effects of education on earnings, health and smoking. Discussion Paper 9957, May 2016. Institute for the Study of Labor (IZA).

Helliwell, J. F. 2003. How's life? Combining individual and national variables to explain subjective well-being. *Economic Modelling*, Vol. 20: 331-360.

Human Rights Act 1998. United Kindom. Available at: https://www.legislation.gov.uk/ukpga/1998/42/contents (Accessed: 8th March 2018).

Kitagawa, E. M. & Hauser, P. M. 1968. Educational Differentials in Mortality by Cause of Death: United States, 1960. *Demography*, Vol. 5(1): 318–53.

____________________________1973. *Differential Mortaility in the United States: A Study in Socioeconomic Epidemiology*. Cambridge, MA: Harvard University Press.

Knapp, M. et alii. 2013. Economic impact of childhood psychiatric disorder on public sector services in Britain: estimates from national survey data. *Journal of Child Psychology and Psychiatry*. Vol. 54(9): 977-85.

Lafortune, J. 2013. Making yourself attractive: Pre-marital investments and the returns to education in the marriage market. *American Economic Journal: Applied Economics*, Vol. 5(2): 151-178.

Leveille, S. G. et alii. 1999. Aging successfully until death in old age: opportunities for increasing active life expectancy. *American Journal of Epidemiology*, Vol. 149(7): 654-664.

Lleras-Muney, A. 2005. The relationship between education and adult mortality in the U.S. *Review of Economic Studies*, Vol. 72 (1): 189-221.

Lochner, L. & Moretti, E. 2004. The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports. *American Economic Review*, Vol. 94 (1): 155-189.

Lucas, R. 1988. On the mechanics of economic development. Journal *of Monetary Economics*, Vol. 22 (1): 3-42.

Mankiw, G., Romer, D. & Weil, D. 1992. The contribution to the empiric growth. *The Quarterly Journal of Economics*, Vol. 107: 407-37.

Mannuzza, S. & Klein, R. 2000. Long-Term Prognosis in Attention-Deficit/Hyperactivity Disorder. *Child & Adolescent Psychiatric Clinics of North America*. 9(3) pp.711-726.

Mattke, S. et alii. 2007. A review of methods to measure health-related productivity loss. *The American Journal of Managed Care*, Vol. 13(4): 211-217.

McEwan, P. J. 2015. Improving Learning in Primary Schools of Developing Countries: A Meta-Analysis of Randomized Experiments. *Review of Educational Research*, Vol. 85(3): 353-394.

Milligan, K., Moretti, E. & Oreopoulos, P. 2004. Does education improve citizenship? Evidence from the United States and the United Kingdom. *Journal of Public Economics*, Vol. 88: 1667-1695.

Mincer, J. 1991. Education and unemployment. *NBER Working Paper*, No. 3838.

Mirowsky, J. & Ross, C.E. 2003. Education, Social Status and health. *New York: Aldine de Gruyter*.

MTA Cooperative Group, 1999. A 14-month randomized clinical trial of treatment strategies for attention-deficit/hyperactivity disorder. *Archives of General Psychiatry* 56, 1073–1086.

Nelson, R. E. 2010. Testing the Fetal Origins Hypothesis in a Developing Country: Evidence from the 1918 Influenza Pandemic. *Health Economics*, Vol. 19: 1181-1192.

Nelson, R. N. & Phelps, E. 1966. Investment in humans, technological diffusion, and economic growth. *American Economic Review: Papers and Proceedings*, Vol. 51 (2): 69-75.

Office for Fair Access (OFFA). 2017. Access agreements for 2018-19: key statistics and analysis. *Office for Fair Access*.

Office for National Statistics (ONS), 2004. Mental health of children and young people in Great Britain. *National Statistics publication*.

Offord, D. et alii. 1987. Ontario child health study. II. Six-month prevalence of disorder and rates of service utilization. *Archives of General Psychiatry* Vol. 44: 832–836.

Oreopoulos, P. & Salvanes, K. G. 2011. Priceless: The Nonpecuniary Benefits of Schooling. *Journal of Economic Perspectives*, Vol. 25(1): 159-84.

Oreopoulos, P. Page, M. E. & Stevens, A. H. 2006. The Intergenerational Effects of Compulsory Schooling. *Journal of Labor Economics*, Vol. 24(4): 729-760.

Paffenbarger, R. S. Blair, S. N. & Lee, I-M. 2001. A history of physical activity, cardiovascular health and longevity: the scientific contributions of Jeremy N Morris. *International Journal of Epidemiology*, Vol. 30: 1184-1192.

Perou, R. at alii. 2013. Mental Health Surveillance Among Children – United States, 2005-2011. *Morbidity and Mortality Weekly Report: Supplements*. May 17, 2013. Vol. 62(2): 1-35.

Plewis, I., Calderwood, L., Hawkes, D. & Nathan,G. 2004. National Child Development Study and 1970 British Cohort Study Technical Report – Chances in the NCDS and BCS70 Populations and Samples over time. *Centre for Longitudinal Studies*, Institute of Education, University of London.

Polanczyk, G. et alii. 2014. ADHD prevalence estimates across three decades: an updated systematic review and meta-regression analysis. *International Journal of Epidemiology*. Vol 43: 434-442.

Romer, D. 2006. *Advanced macroeconomics*. New York, McGraw-Hill, 3 ed.

Rosenbaum, P. R. Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, Vol. 70(1): 41-55.

Rosenzweig, M. R. & Zhang, J. 2006. Do Population Control Policies Induce More Human Capital Investment? Twins, Birthweight, and China's 'One Child' Policy. Harvard University Bureau for Research in Economic Analysis of Development. Working Paper 114.

Royer, H. 2009. Separated at Girth: US Twin Estimates of the Effects of Birth Weight. *American Economic Journal: Applied Economics*, Vol. 1(1): 49-85.

Russell A. et al. 1993. Driving-Related Risks and Outcomes of Attention Deficit Hyperactivity Disorder in Adolescents and Young Adults: A 3- to 5-Year Follow-up Survey. *Pediatrics*, Vol. 92(2): 212-218.

Sander, W. 1995. Schooling and Quitting Smoking. *The Review of Economics and Statistics*, Vol. 77(1) (Feb): 191-199.

Schultz, T. 1962. Investment in Human Beings, Chicago: *University of Chicago Press*.

Siles, M. 2009. The causal effect of education on health: Evidence from the United Kingdom. *Economics of Education Review*, Vol. 28: 122-128.

Smith, J. A. & Todd, P. E. Reconciling Conflicting Evidence on the Performance of Propensity-Score Matching Methods. *American Economic Review*. Vol. 91 (2): 112-118.

Spence, M. 1973. Job Market Signalling. *The Quarterly Journal of Economics*, Vol. 87(3) (Aug): 355-374.

Stage, S. & Quiroz, D. 1997. A meta-analysis of interventions to decrease disruptive classroom behavior in public education settings. *School Psychology Review* Vol. 26(3): 333–368.

Stockwell, E. G. 1963. A Critical Examination of the Relationship between Socioeconomic Status and Mortality. *American Journal of Public Health*, Vol. 53(Jun): 956-964.

Sydenstricker, E. 1929. Economic Status and the Incidence of Illness: Hagerstown Morbidity Studies No. X: Gross and Specific Illness Rates by Age and Cause among Persons Classified According to Family Economic Status. *Public Health Reports* (1896-1970), Vol. 44(30): 1821-1833.

Vaa, T. 2014. ADHD and relative risk of accidents in road traffic: A meta-analysis. *Accident Analysis & Prevention*. 14 January 2014. Vol. 62: 415-425.

Vagero, D. & Leon, D. 1994. Ischaemic Heart Disease and Low Birth Weight: A Test of the Fetal-Origins Hypothesis from the Swedish Twin Registry. *The Lancet*, Vol. 343(8892): 260-263.

Van der Pol, M. 2011. Health, education and time preference. *Health Economics*, Vol. 20: 917-929.

Wagstaff, A. 1993. The Demand for Health: An Empirical Reformulation of the Grossman Model, *Health Economics*, Vol. 2(2) (Jul): 189-198.

Walker, I. & Zhu, Y. 2011, Differences by degree: Evidence of the net financial rates of return to undergraduate study for England and Wales. *Economics of Education Review*, Vol. 30: 1177-1186.

Wantchekon, L. Klasnja, M. & Novta, N. 2015. Education and Human Capital Externalities: Evidence from Colonial Benin. *The Quarterly Journal of Economics*, Vol. 130(2): 703-757.

Weis, R. 2013. Introduction to Abnormal Child and Adolescent Psychology. SAGE publications.

Zhao, M. Konishi, Y. Glewwe, P. 2012. Does smoking affect schooling? Evidence from teenagers in rural China. *Journal of Health Economics*, Vol. 31(4): 584-598.