Economics of Higher Education in the UK

by

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DECLARATION

This work has not previously been accepted in substance for any degree and is not concurrently submitted in candidature for any degree.

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Abstract

The thesis examines both pecuniary and non-pecuniary benefits to higher education in the UK and empirically tests the model of demand for higher education. The leading theme in this research is the interest in the microeconomic aspect of higher education at empirical level. It sets out to investigate the expectations of individuals in terms of what they can gain from education. It considers various aspects of higher education, including casual effect on pecuniary and non pecuniary returns and demand of higher education participation. This thesis is based on 1958 British National Child Development Survey in the UK. It is composed by three empirical chapters, each on corresponding to a self-contained paper, applying different methodologies and making a unique contribution of these overall objectives. The first empirical chapter focus on the returns to education justified by the importance accorded as an explanation of wage differentials. The second empirical chapter deals with the returns to higher education on health. The third empirical chapter explores the relationship between higher education decision and expected wage income and personal and family characteristics. The main powerful findings of this thesis are: First, the economic return of education rises with the greater disparity of the educational groups as age increases. Females attending higher education usually enjoy higher returns than males, and the gap constantly increases over the years. Second, attending higher education may be an effective way to improve population health and reduce the likelihood of health damaging behaviours. Third, the hypothesis that individuals' higher education decision only depends on their expectation on future wage income is highly rejected.

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Chapter 1: Introduction

Education as a way of increasing human capital is considered to be a basic factor in the growth process of the aggregate economy. It confers benefits on individuals, enterprises, and societies. There are economic benefits and accrue in the form of wage earnings, productivity, or economic growth and social benefits in terms of longer life expectancy, less criminal behaviour, stronger social cohesion or greater political participation. It contributes directly to the growth of economy by improving the skill needs of the modern workplace, productive capacities, faster rate of innovation, and the creation of social capital for an individual. It is widely realized that an increasingly complex society and rapid technical change requires highly educated workforce. Education is also seen almost as a universal cure to some of the severe economic problems such as unemployment and poverty.

In a broad sense, individual's motives for education are associated with human capital theory. Much of this work stems from the study of Becker (1964) that introduced the concept of treating investment in education as a capital investment. The hard core of the human capital theory is a human capital investment undertaken by an individual on his/her own behalf (Blaug, 1976). Individuals make the decision not only for the sake of present enjoyments, but also in expectation of future pecuniary and non-pecuniary returns, the crux of the matter is precisely on whether individual possesses a forward looking view for the justification of present actions. In this context, individuals consider themselves as assets and expect that receiving higher education will help them to produce extra value so that eventually there will be benefits.

Meanwhile, education also provides a variety of benefits to individuals. Most of the benefits of education that directly improve well-being are likely to be reflected in higher income. The estimation of the pecuniary return to education has perhaps been one of the predominant areas of analysis in applied human capital economics for over 50 years since the birth of the human capital theory (Schultz, 1961). Yet the economic benefits that education bestows are not limited to higher expected pecuniary return. They can also give rise to a wide range of non- pecuniary benefits that could also consist in direct additions to welfare possibilities in terms of better health, longer life expectancy, less criminal behaviour, stronger social cohesion or greater political participation.

In case of the UK, there have been many attempts to reform the education system and make it more productive. It aims to increase educational opportunities irrespective of financial means or socio-economic background, and to raise the overall educational level in the population (Kerckhoff and Trott 1993). During last 70 years, education and employment opportunities have changed dramatically. Between 1951 and 1991 the United Kingdom witnessed a significant decline in manual jobs, while employment in clerical occupations has increased, and work in professional and managerial professions has tripled (Gallie 2000). Following the introduction of new technologies and the disappearance of manual jobs, increasing numbers of young people are expected to participate in further education beyond compulsory schooling age (Bynner and Parsons 2002; Furlong and Cartmel 1997), and during the last two decades a growing number of young people have participated in higher education, once the preserve of a privileged minority (Blossfeld and Shavit 1993; Bynner 2005; McVicar and Rice 2001).

Measurements of return to education ought to be the area where one might expect agreement. However, despite a developed theoretical foundation, empirical work on the return to education has been the focus of considerable debate in the economics literature, since it reveals a wide range of estimates. A dominant feature of the literature that estimates the relationship between education and corresponding returns is to make the implicit assumption that education is exogenous, and this has been the focus of recent research efforts. In practice, estimates of this return vary significantly, depending on the data sets used, the assumptions made and the estimation techniques. In terms of broad methodologies, the focus on the issue of endogeneity often requires identifying assumptions that cannot be empirically tested or are somewhat fragile in estimation. Furthermore, attempts at estimating a single rate of return may not be very informative if returns to education differ by education level, or differ by genders.

The leading theme in my research is the interest in the microeconomic aspect of education at empirical level. It sets out to investigate the expectations of individuals in terms of what they can gain from education. In fact, this PhD thesis considers various aspects of education, especially higher education, including casual effect on pecuniary and non pecuniary returns and determinations of higher education participation. This thesis is based on British National Child Development Survey (NCDS), a continuing panel survey of cohorts born between the week of 3 and 9 of March 1958 in the UK. It is composed by three empirical chapters, each on corresponding to a self-contained paper, applying different methodologies and making a unique contribution of these overall objectives. The first empirical chapter (chapter two) focus on the returns to education justified by the importance accorded as an explanation of wage differentials. The second empirical chapter (chapter three) deals with the returns to higher education on health. The third empirical chapter (chapter four) explores the relationship between higher education decision and expected wage income and personal and family characteristics.

In more detail, chapter two examines the impact of different educational attainment on the earnings of individuals in the medium and long term. In calculating the pecuniary return on education, this chapter considers as benefits only the incremental earnings realized by the individual. Individuals with higher levels of education tend to have a higher income level. The average earnings of individuals are strongly and positively related to both education attainment and the level of their qualifications. However, it is difficult to ascertain how much this empirical association between wages and education attainments is due to the causal effect of obtaining a higher education (HE) qualification and how much is due to unobserved factors, such as an individual's abilities and family background, which influence both wages and education decisions. The propensity score matching method (PSM) approach is therefore applied to tackle the selection bias problem, which involves ‘matching’ these individuals according to observed characteristics and then comparing the outcomes between individual with different educational attainments. It is reported in general, HE has a substantial impact on earning at different age levels. The return rises with the greater disparity of the educational groups.One of the main contributions of this chapter is to compare the differences of the return on earnings by gender from age 33 to 50. The wage differentials by genders are higher at various levels of HE attainment than it was with non HE attainment individuals. HE normally has a greater impact on earnings for females rather than males, and gender gap remains significantly constant in a long term.

Chapter three applies same data sweeps used in Chapter two to investigate whether there are any non monetary returns to educational investment. This uses information from ages 33 to 50 to examine whether gaining a HE qualification at age 23 has any effect on health and health related behaviours. Exploiting the panel dimension of the data in this way again allows specifying a PSM approach that eliminates any unobservable time-invariant characteristics that may differ between individuals and affect either education itself or health outcomes investigated. The result shows the non pecuniary benefits to HE attainments on health are substantial, implying that attending the HE may be a relatively effective way to improve population health.

Higher educated men and women are more likely to have better health, more likely to maintain healthy weight, more likely to be non-smokers and to control on drinking alcohol. Nevertheless HE is not significant to help reducing the likelihood of depression.

Chapter four attempts to build a micro model of HE participation incorporating factors for expected return to HE and other personal ability and family socio-economic variables based on framework of education decision making behavior of individual agents. It makes a full use of data obtained from Chapter two and expected wage income estimated by PSM. In contrast to conventional testing and estimation approaches, the main contribution is to adopt the Indirect Inference method to first evaluate the role of factors on participating in higher education, and re-estimate the proposed structural model coefficients. The finding shows individual's family characteristics and personal cognitive ability and academic performance before HE study has an influence on the likelihood of HE participation. There effects are considered as mediated or indirect effects add to the direct effect of wage return on HE decision.

Chapter 2: Estimating the effect of higher education on earnings by Propensity Score Matching Method

2.1 Introduction

Many economists have estimated the returns to education since Mincer (1974). In particular, the concept of private returns of a higher education (HE) is drawn from human capital theory (Becker, 1993), which assumes that an individual's earnings are a function of labour productivity derived from individual investments in education or training. However, estimation of the returns to education across individuals is often complicated by potential endogeneity and self-selection bias problems driven by observable factors (e.g. family background, school quality, personal ability) as well as unobservable factors (e.g. cognitive and noncognitive skills). Over decades in practice, a large number of researchers have used several methods to try to identify the causal impact of education on earnings. There is a vast and comprehensive literature in this area (such as Blundell and Dias, 2000; Card, 2001; and, Heckman, Lochner and Todd, 2006). Given that a twins or sibling study method is usually limited by small sample size and potential endogeneity bias of schooling differences, extensive literature uses a statistical technique called *Proxying and Matching* approach to control for observed factors while comparing the earnings of people with different levels of education by using ordinary least squares (OLS) regression. In addition, Heckman's two stage correction method and instrumental variable (IV) methods are also widely used procedures for estimating the effect of selection bias on unobservable. This chapter sheds light on an alternative ‘counterfactual’ approach to attempt to generate accurate causal estimates by balancing the pre-characteristics between the treatment and the control group, which removes bias due to observable factors. Great attention has been paid to this method of matching. Specifically, the PSM has been used in a large amount of the literature in very diverse fields of study, whereas the implication to return to education has been widely applied since the influential study by Dehejia and Wahba (1999).

The objective of this thesis consists of analysing the effects of private financial returns to HE by examining the impact of HE qualifications on the earnings of individuals living in Britain using the PSM method. Most previous studies report that individuals with HE receive higher wages and earnings than less educated ones while HE usually has a greater impact on females than males. However, these studies have focused overwhelmingly on return to HE among young people rather than older workers, and few studies have focused on whether the incremental return gap has varied or whether the gap has always been substantial over lifetime.

There are two main contributions of the present study. Firstly, I will estimate the impact of HE on education of both males and females across at the ages of 33, 42 and 50. In particular, I will investigate whether the return gap between genders still exists when the cohort is older. Another contribution is to compare the changes of the returns of HE on the earnings and the impact of HE on gender differences in the medium and long term by concentrating on a cohort who were continuously full-time employed during the period from 1991 to 2008. In this case, I will investigate if education has not only an intercept but also a slope effect on earnings. I am also interested to know whether educational attainment has a greater role in affecting the female labour market participating rate when the cohorts are in their late thirties. The subsequent analysis conducted in this chapter is based on data from 1958 National Child Development Survey (NCDS) British Cohort Study. The balance property will be examined in detail after the estimation, while robustness against 'hidden bias' arising from the existence of unobserved variables will also be addressed by the *Rosenbaum bounds* approach. In addition, the result outcome is mainly based on the estimation from nearest neighbour matching (NN) estimator; nonetheless, in order to check robustness and sensitivity of the result to which the choice of matching algorithm is not driving the results, I also perform an alternative Kernel matching estimator.

The rest of this paper is structured as follows. Section 3 describes the main features of the NCDS data and it gives some descriptive analysis of the numbers of men and women entering and completing a HE degree. Section 4 presents the causal inference problem, the methodological approach of the PSM, matching algorithm, and statistical properties of matching estimators. Section 5 illustrates the details of the results on estimated returns and comparisons of the returns on the earnings of individuals by gender at the different ages. In Section 6, I will highlight the main findings and draw some conclusions.

2.1.1 UK education system and route to HE

The UK's education system has been subject to much change and reform since the World War II. It has expanded dramatically and widened access to all parts of the system, from primary school right through to HE level. In the drive to raise standards, the UK education system has been on the forefront of the movement to introduce market forces into education. With parental choice and better school accountability, the UK has strived to improve the productivity and efficiency of its schools.

In early years, the vast majority of students leave school at 14, which is the compulsory school leaving age at that time, although school fees for elementary students were abolished since 1918. In response to the need after the war for a more educated work force, the school leaving age was raised, in 1947 to age 15 and eventually in 1973 to the age of 16. During the 1960s and 1970s, UK secondary schools underwent a period of radical change, in a further attempt to widen access. Students of differing abilities were sent to different types of school, receiving different types of education. Students with higher ability and better academic performance (normally students who passed the age 11 entry exam) were sent to state sponsored academically orientated schools (grammar schools). These students were considerably more likely to go on for participating HE. Other students attended Secondary Modern schools undertaking a range of vocationally orientated subjects, eventually leaving the educational system at the age of 15 (or 16 after 1973). During the 1960s, there was a growing number of students are selected in favour of mixed ability and academic performance, and went to so called comprehensive school. This in turn sparked off an ideological battle that was to rage for the next 20 years or more, between those who favoured the old selective grammar school system and those who wanted comprehensive schooling. Nowadays, most students in secondary school are taught in comprehensive school. However, comprehensive school would still stream their students and allocate them to classes according to their ability[1].

Since the 1950s, secondary school students who were academically inclined took Ordinary Level (O-levels) at age 16 and Advanced Level (A-levels) at age 18 examinations. Obtaining at least one A-level was an essential requirement to enter higher education. Less academic students could take the Certificate of Secondary Education (CSE) at 16 before they left school. In 1980s (after 1988), the O level and CSE exams were combined in the GCSE (General Certificate of Secondary Education) and still taken at age 16. Therefore, it marked a turning point in the measured achievement of 16 year olds in the UK. The fact that all students at 16 now take the same examination in each subject means that they no longer have to decide whether to go for the lower level CSE option or the more difficult O-level examination. This may encourage those who are academically on the borderline between CSE and O level to aim for a higher level of attainment.

Furthermore, what is more unique to the UK is the extent to which an individual

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[1] It presents a detailed classification of educational qualifications for UK education system in Appendix B.

[2] NCDS is an ongoing survey of all individuals born in Britain in the week 3rd-9th March 1958.

participanting HE is strongly related to parental education and social class. It is difficult to make international comparisons because data on the relationship between family background and educational achievement across different countries is remarkably sparse. Hansen and Vignoles (2005) report that currently in the UK 48% of young people from professional, managerial and skilled non-manual backgrounds enter university, whilst only 18% from a skilled manual or unskilled background do so. This gap in participation between rich and poor has been present for a long time

2.2 Literature review

Return to HE is categorised as pecuniary and non-pecuniary as well as private and social to individuals. An individual's earnings can be seen as the pecuniary or financial and private returns. Non-pecuniary private returns include health effect, motivational attributes, continued learning at home, etc. There is a growing literature that uses a variety of approaches and data sources to estimate the private financial return to HE in the UK. In most cases, the average earnings of individuals are strongly and positively related to education attainment and the levels of qualifications. Individuals with higher levels of education gain a higher income level. In addition, there is a consistent feature among these empirical studies: the gender wage differentials either in different degree, class, or subjects.

2.2.1 Current time return to HE

Blundell *et al.* (2000) is one of the most influential studies to examine the impacts on the earnings of individuals who take a university degree level or other form of HE qualification from the NCDS.[2] The paper finds that there are many individuals in the NCDS who have not passed A-levels but who follow a different route into non-degree HE qualifications, such as nursing and teacher training. It tries to distinguish between academic and vocational qualifications, and argues that individuals with non-degree HE qualifications do not represent the return to qualifications for those who have been successful at school. Therefore, it only looks at the effects of HE on wages by comparing a group of British university or college graduates, with a group who obtained their secondary school qualification with one or more A-level that would have permitted them admission to HE but who did not proceed into HE. In other words, the sample of estimated returns is only restricted to those who have performed well at secondary school.[3] It reports an estimated return to a degree over A-level of around 17% for men and 37% for women using *Proxying and Matching* approach and applying OLS estimation under the assumption of *selection on observables*,[4] which imposes homogeneous returns to all qualifications. It also produces some interesting findings. First of all, there are significant and substantial raw wage premia for typical graduates and a large difference in the returns between men and women. However, the gender earnings gap is lower between men and women at levels of HE attainment than

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[2] NCDS is an ongoing survey of all individuals born in Britain in the week 3rd-9th March 1958.

[3] It results to the reduction of sample size from 18,562 to 3,264

[4] It also is referred to conditional independence or unconfoundness assumption that would be explained in detail in following section. Heckman *et al.* (1997, 1998) suggested this estimator is a simplified version of the fully non-parametric propensity score-matching estimators.

it was with just A-levels. Secondly, the returns to HE were different for men and women. They also found that men starting HE but not completing yields a negative return that is 9% lower than those who did not even start HE. However, both men and women had positive returns to HE compared with those who achieved only A-levels. Finally, for men who started their first HE course at the age of 21 or older, they seemed to have an average return of 7% to 8% less than those who started before the age of 21.

A diametrically different approach is taken by Blundell *et al.* (2005), again using NCDS data, who applied four different approaches to examine the impact of HE on individual earnings, both for single treatment and multiple treatments, with and without heterogeneous returns. It compares OLS and matching methods, which are all under the assumption of *selection on observables* and instrument variable (IV), and the control function method, which is under the assumption of *selection on unobservables*. However, instead of trimming the sample only on academic qualifications, it focuses on an individual's highest qualification and uses a broader sample that includes academic qualifications and vocational qualifications at an equivalent level. For instance, individuals initially with O-levels but who have completed professional qualifications can be included as the HE group. On the other hand, in order to avoid the endogeneity problem between employment selection variables with wages, it only pays attention to male participants. In contrast to Blundell *et al*. (2000), Blundell *et al.* (2005) adjusts control variables in equation specifications by excluding, for example, employer characteristics.[5] Since the gender groups and sample selection among these two studies are not identical, the empirical result of comparison is unclear and limited. It is considered that the main contribution of Blundell *et al.* (2005) is more in terms of an empirical and methodological comparison of different approaches for estimating the return to education. This study reports a return to HE (ATT) over anything less for males varies significantly from 27% to 40%, depending on the estimation method and control variable included. Both OLS and matching estimated results are very sensitive to the numbers of inclusion of control variables. Generally, adding a control significantly reduces the returns. The result from matching is slightly lower than that from OLS. The difference arises because the OLS is constrained to estimate the homogeneous return from HE. The ATT is unbiased under the OLS only if the treatment effect is homogeneous across individuals among different characteristics However, it estimates for an observably heterogeneous return when applying PSM. Furthermore, Blundell *et al.* (2005) proves that when allowing interactions between the control variables and the treatment indicator, such as adding later personal ability and late family background in regression, OLS estimates of the ATT are almost identical to the matching ones. Secondly, the estimated sample for matching is restricted in the common support area; hence, the sample size is different from that of in OLS. Therefore, it trims the sample size only to comparable individuals among treated and non-treated groups.

[5] A comparison of the two specifications will be explained in detail in Section 3

Massimiliano *et al.* (2005) showed that the OLS estimates in the common support are very similar to the ATT computed using PSM. However, Blundell and Dias (2000) also indicate the drawback of matching. On the one hand, it does not succeed in finding a non-treated observation with similar propensity score for all the participants. On the other hand, it is important to obtain the relevant information to distinguish potential participants from others and, therefore, it heavily relies on rich data requirements in order to guarantee that the s*election on observation* assumption is verified. In other words, matching conditions on observables is only as good as the conditioning variables. On average, compared to leaving school at 16 without any qualifications, an average incremental return to O-levels is 18%, to A-levels is 24%, and to HE is 48%, respectively, at each educational stage.

2.2.2 More evidence from cross-sectional data and cohort data

Dearden (1999) applies OLS to estimate a 17% wage premium to a degree for men and 32% for women based on NCDS cohort data. Dearden *et al.* (2000) also uses three different datasets to examine the return to individual's highest qualification.[6] They apply the metho d of general OLS under the assumption of *selection on observable*, which can be viewed as a form of regression-based linear matching. Their result suggests that males/females with an additional 10% / 21% return to degree compared to O-level and GCSE equivalent for NCDS data and an additional 21% / 28% return for Labour Force Survey (LFS) data, respectively. Walker and Zhu (2002)

[6] Three dataset are: the National Child Development Study sweep 3 (1991), the British data from the International Adult Literacy Survey in 1995, and the Labour Force Survey in 1998

consider the economic benefits of HE by different subjects using the data from LFS, and find that men with an undergraduate degree achieved an earnings premium of about 15% over individuals who only have A-levels. The corresponding estimate for women was 19%. Men in possession of a mathematics degree achieved a 25.7% earnings premium over those with A-levels as their highest qualification, while women achieved a 38.6% earnings premium. In contrast, the premium for men in possession of undergraduate degrees in the arts was 4% less relative to those individuals with A-levels, while women achieved a 17% premium. Irrespective of the subject of study, the financial benefit of completing a degree is much greater for women than for men, but this may be due to the relatively low earnings of non-graduate women.

Walker and Zhu (2003) estimate the wage premium associated with different levels of education from UK LFS data. Under the assumption that the returns to education for individuals are the same, they find that the effects of an additional year of schooling increase wages by about 9%. O'Leary and Sloane (2005) used a standard OLS human capital model to estimate the returns to different degrees, in a variety of disciplines, by gender and controlled the variations in student quality across disciplines in Britain using LFS. The returns of degrees are considerably higher for women than men. With a higher degree provides an hourly earnings boost of 113.76% then without a higher degree for men, whereas for women it is 131.52%. The paper notices the benefit of a university education on hourly wages is more apparent for women than it is for men. The return from an undergraduate degree is 20.23%, a Master's degree is 29.15%, and a PhD degree is 31.40% for men. In comparison with men, the return from an undergraduate degree for women is 35.49%, a Master's degree is 54%, and a PhD degree is 60.02%. It also argues that there is a considerable heterogeneity in the returns of undertaking a degree because of the different disciplines, and the motivation and performance of the students, which even differs by gender (detailed results are shown in Table 2.1).

The Ramsey and Analytical Services Group of the Department for Employment and Learning (2008) estimated the average rate of return of a university degree across the UK by using a robust sample of 40,296 graduates, who left UK universities in 2004-2005, and combined this with the employment and salary information obtained six months after graduation. They find that there is a relatively large and significant variation in graduate earnings according to the degree classification awarded, particularly for males. Figure 2.1 shows that on average, 21% of graduates from the elite Russell Group of universities enjoy better earnings than others. The average earnings for females are lower than that for males. Figure 2.2 shows a positive correlation between the level of achievement and earnings, such that, the starting salary for those holding a First is on average 18% higher than people holding a Third and the differential is greater for males (26.8%) than females (10.5%).

More recently, Conlon and Patrignani (2011) report that the marginal earnings return associated with an undergraduate degree stands at around 27.4% overall compared to possession of two or more A-Levels. Walker and Zhu (2011) estimate the impact of HE qualifications on the earnings of graduates in the UK by using the LFS data to consider the effects of the subject studied, class of first degree, and the impact of postgraduate qualifications. They provide estimates of the college premium, use regression estimates across the distribution of wages, and comparisons of rates of return to HE investments by subject and gender under alternative tuition fees. This shows the differences on average hourly wages of different HE qualifications by gender. Males with first degrees only earn 20% more than those with two or more A-levels, for females it is 31%. Males with a Master's degree can earn 12% more than those with a first degree, females earn 17% more. Males with PhDs earn 4% more than Master's, for females earn 7% more. Males with a PGCE earn 6% less than those with a first degree, but for females it is 7% more. However, there is an ability bias argument that suggests that their estimates may be an upper bound to the true effect. Another weakness is that they are not able to control for institutional differences because the data does not identify the HE institution that granted the qualifications obtained. They also point out that in the UK the quality of the student entrants varies by institution.

Other researchers have also accessed international evidence. For example, Psacharopoulos and Patrinos (2004) at the World Bank report estimated returns to education across various countries (also see Montenegro and Patrinos, 2012). Caponi and Plesca (2009) accessed the wage differentials between community college and university in Canada. Pfeiffer and Pohlmeier (2012) estimated the returns of an additional year of education in Germany. Moreover, there some recent studies have analysed developing economies, such as China (Kang and Peng, 2012), India

(Agrawal, 2011), or BRIC Countries (Carnoy *et al.*, 2013).

2.2.3 Returns to HE over time

There is little literature on the extent of focusing on the impact of education on lifetime (15 years or more) incremental returns by distinguishing between HE attainment and anything less based on UK evidence. Most of the studies that have been published, without explicitly modelling, usually only compute the average gross graduate premium associated with qualification. PricewaterhouseCoopers (2005 and 2007) undertook recent analysis to consider the lifetime earnings associated with the average degree holder compared to an individual in possession of two or more A-levels. This analysis assessed the lifetime earnings associated with different degree level subjects and qualification levels, such as postgraduate degrees, diplomas and certificates. The results show that the gross additional lifetime earnings for degree graduates are approximately £160,000 in present value terms. Moreover, Conlon and Patrignani (2011) report the mean gross lifetime premium for graduate stands at around £125,000.

(i) Evidence from cross-section data

McIntosh (2004) exploits LFS data from 1996 to 2002 to find how returns to both academic and vocational qualifications have been changing in the cross-section over time for males and females. Surprisingly, there appears to have been virtually little change in the estimated returns to most of qualifications over the time. For instance for academic qualification, with respect to HE, the estimated return to first degree level for men/women is 22.1% / 23.4% in 1996 and 25.3% / 23.5% in 2002, respectively. With respect to obtaining two or more A-levels, the estimated return for men is even decreasing: from 16.9% in 1993, 15.7% in 1996, to 15.4% in 2002; and for women from 14.9%, 13.5%, to 14.4%, respectively. For qualifications lower than obtaining one A-level, both genders appear to have a decreased incremental return. Remarkably, the returns to low GCSEs (grades D-F) have declined to zero for both gender by 2001 indicating that low level GCSEs appear to confer no market value. Similar studies have also been done by Dearden et al. (2002), and O'Leary and Sloane (2011).

The drawback of using cross-sectional data such as LFS is that it does not differentiate between age and cohort effect. The only systematic data in McIntosh's (2004) study is earnings recorded some six years after graduation but the response rate is poor and early wages are not a good guide to lifecycle effects; therefore, the results may suffer from various sources of bias. For instance, the return to a degree is most likely to be higher for those in their thirties than for those in their twenties. Migali and Walker (2011) separately identify lifecycle and cohort effects using LFS and reject the usual separability assumption. Therefore, to assess the robustness to omitted variable bias of the above findings, other studies turn to use the cohort data.

(ii) Evidence from cohort data

Galindo-Rueda and Vignoles (2003) compare the estimated return to a first degree in 1991 by individuals aged 33 using NCDS cohort data to the estimated the return to a first degree in 2000 by individuals aged using the 1970 British birth cohort (BCS70) data. For males, it shows the *incremental* premia between a first degree or equivalent level to A-level slightly decreased across the two cohorts and time, reported at 17.5% in 1991 and 15% in 2000. Comparing A-levels with O-levels, the premia increases from 6.5% in 1991 to 10.3 in 2000. The premia for males achieving O-levels compared to only obtaining CES remains are stable at around 7%. A dramatic fall in the returns at the lowest of the educational scale is also noted. The incremental return for CES certificate over non-qualification in 2000 is almost at zero. Massimiliano *et al.* (2005) also tried to replicate the NCDS cohort analysis of Blundell *et al.* (2000) on BCS70 data. By using the identical specification and subset sample selection, they report an estimated wage return to a first degree over those who attained at least an A-level education to be 15% for men and 23% for women in the BCS70 cohorts, which is similar to 17% and 37%, respectively, from NCDS. Furthermore, they alter the specification, which is similar to the one used in Blundell *et al.* (2005) for the 1970 cohort, and leads to an estimated return to a first degree of 14% for men and 18% for women in 2000, the return to a degree for females appears to fall considerably across the two cohorts. However, it argues that the three-year age gap between the two cohorts might be problematic in the cross-cohort comparison since it might possibly conflate age effect and cohort effect. It also noted that the existing evidence on the magnitude of returns to HE that changed over time is mainly due to the ongoing changes in the policies of the UK government, and the estimation samples are based upon different cohorts. To that extent, few researchers only focus on cohort data sample over time and access in the presence of growing returns to education over the lifetime.

2.3 Methodology

2.3.1 The evaluation problem

Identifying the casual impact is challenging, especially if the variable is not manipulable by the researchers and cannot be randomly assigned. Economists have been interested in estimating the return to education in terms of higher pay as a result of attending university. However, attending university is not randomly assigned. There are various important unobserved factors, including the alternatives available to individuals, such as their personal ability, family background, time preferences, the tuition fee, and reputation of university options. Suppose that university graduates earn £20 per hour and others earn £12 on average. One can argue that HE in university has no real effect on an individual's productivity and earnings, and that those who obtained good A-level results and entered college have enough productivity to earn £20 per hour on average. Therefore, even in the absence of higher education, they would earn the same amount if they could prove their productivity to employers. In this case, for those people who have lower personal ability or who obtained relatively low A-level results would not be able to improve their productivity and this might not affect their earnings. Bonjour *et al.* (2003) summarise two relationships between education and earnings: a) the relation that higher educated people earn a higher wage is causal; and, b) the relation that people with higher ability or more favourable family background are more productive and receive a higher wage is spurious.

2.3.2 Causal inference

This section aims to illustrate the casual inference identification problem in more theoretical terms. In econometrics evaluation studies, it is suggested that observational studies use a randomised trial to obtain an objective causal inference. However, data often does not come from randomised trials but from non-randomised observations.

Suppose an experimental design where the assignment to the case of a binary treatment is determined by a purely random mechanism:

$D \perp X_{all}$ (2.1)

where $D = \{0, 1\}$ is the indicator of exposure to treatment and X_{all} is the multidimensional vector of all observable and unobservable pre-treatment characteristics (covariates). In addition,

$D \perp Y(0), Y(1)$ (2.2)

The potential outcomes are then defined as $Y(D)$. This guarantees that D is independent with both observable and unobservable, and the potential outcomes will be statistically independent of the treatment status. With randomised assignment, all of the characteristics of the individuals are equally distributed between treated and untreated groups, which implies:

$$E(Y(0)|D = 1) = E(Y(0)|D = 0) \qquad (2.3)$$

The causal effect for an individual unit i can be defined as the difference between the potential outcome in case of treatment and non-treatment:

$$\tau_i = Y_i(1) - Y_i(0) \qquad (2.4)$$

where $i = 1,2 \ldots N$ and N denotes the total population. The evaluation problem arises because only one of the potential outcomes is observed for each individual i. The unobserved outcome is called a *counterfactual* outcome. Thus, the true causal effect of a treatment T on individuals not subjected to the treatment can never be identified. The impossibility of observing both treatment and control outcomes for each individual is often referred to as the "fundamental problem of causal inference" (Rubin, 1978, Holland, 1986).

Hence, estimating the individual treatment effect τ_i is not possible without making generally untestable assumptions and one has to concentrate on average treatment effects at the population. The average treatment effect (ATE) is defined as:

$$\tau_{ATE} = E\left[Y(1) - Y(0)\right]. \qquad (2.5)$$

Heckman (1997) argued that ATE might not be of relevance to policymakers because it includes the effect on persons for whom the programme was never participated. One also concentrates on ATEs at a sub-population. The parameter of interest in most evaluation studies is then considered as the average treatment effect on treated (ATT), it is then defined as:

$$\tau_{ATT} = E[Y(1) | D=1] - E[Y(0) | D=1]. \qquad (2.6)$$

which measures the impact of the program on those individuals who intended the program. The problem is that $E(Y(0)|D = 1)$ is a hypothetical outcome because it is not observable and it depends on *counterfactual* outcomes. Under condition of equation (3), it then allows us to estimate the ATT by using:

$$E(Y(1)|D = 1) - E(Y(0)|D = 0) \qquad (2.7)$$

In the absence of an experimental design or observational studies, using the mean outcome of untreated individuals $E[Y(0)| D=0]$ is not recommended because it is likely that the covariates which determine the treatment decision also determine the outcome variable of interest. Thus, the differences in means between treated and untreated units would differ, even in the absence of treatment leading to a *self-selection bias*. For ATT this can be noted as:

$$E[Y(1)| D=1] - E[Y(0)| D=0] = \tau_{ATT} + E[Y(0)| D=1] - E[Y(0)| D=0]. \qquad (2.8)$$

$E(Y(0)|D = 1) - E(Y(0)|D = 0)$ is defined as the *self-selection bias*. Likewise, another parameter of interest is the average treatment effect on the non-treated (ATNT), which is defined as

$$\tau_{ATNT} = E[Y(1)| D=0] - E[Y(0)| D=0]. \qquad (2.9)$$

The additional challenge when estimating ATE is that both counterfactual outcomes $E[Y(1)| D=0]$ and $E[Y(0)| D=1]$ have to be constructed.

2.3.3 The heterogeneous model

Let us turn to the empirical heterogeneous model where returns are allowed to be heterogeneous across individuals. Suppose each individual receives only one treatment, the observed outcome of individual i can be written as

$$y_i = y_i(0) + \big(y_i(1) - y_i(0)\big) * E_i \qquad (2.10)$$

where y_i denotes the log hourly wage of individual i, E_i that denotes highest academic educational attainment completed. The potential outcomes can also be specified between observables and unobservables:

$$y_i(1) = \theta_{1i}X_i + u_{1i}\ ,\ u_{1i} = \alpha_i + b_{1i} + \varepsilon_i$$

$$y_i(0) = \theta_{0i}X_i + u_{0i}\ ,\ u_{0i} = \alpha_i + b_{0i} + \varepsilon_i \qquad (2.11)$$

where u_{1i} and u_{0i} are unobservable components of log wages; α_i measures some unobservable individual trait; b_{1i} and b_{0i} measure the individual-specific unobserved marginal return to education. X_i presents the observable characteristics and maintains exogeneity assumptions throughout. Natural candidates for X_i that are not affected by treatments E_i are time-constant factors, as well as pre-treatment characteristics.

Substituting (2.11) into (2.10), one can get:

$$y_i = \theta_{0i}X_i + u_{0i} + (\theta_{1i}X_i + u_{1i} - \theta_{0i}X_i + u_{0i}) * E_i$$

$$= \theta_{0i}X_i + \alpha_i + \varepsilon_i + (\theta_{1i}X_i - \theta_{0i}X_i) * E_i + (u_{1i} - u_{0i}) * E_i$$

$$= \alpha_i + \theta_{0i}X_i + b_1X_i * E_i + b_{1i}E_i + \varepsilon_i$$

Define $\beta_i = b_1X_i + b_i$,

$$y_i = \alpha_i + \theta_{0i}X_i + \beta_iE_i + \varepsilon_i \qquad (2.12)$$

β_i is then the return to education coefficient and it is allowed to be heterogeneous across individuals. b_1X_i stands for the return for individuals with characteristics Xi and captures observable heterogeneity in returns. The parameter of interest for treatment effect will be $b_1X_i + b_i$. For example, $\beta_{ATT} = E(b_1X_i + b_i|E_i = 1)$

2.3.4 The least square and endogeneity bias

The traditional OLS estimated return to education is potentially susceptible to problems of endogeneity bias that is caused by unobserved characteristics. Suppose that the earning function can be summarised as:

$$lnw_i = \beta X_i + \gamma D_i + \varepsilon_i \qquad (2.13)$$

in which w_i is the wage, βX is a linear function of the observed individual's variables X, and D is the education qualification variable. The parameter of interest is the coefficient γ, which measure the return (lnw) to education (D). In the case of $E(\varepsilon|X, D) = 0$, OLS is an unbiased and inconsistent estimator. However, many researchers argue that the estimated return to education is likely to be upward biased because omitted innate ability and family background is positively correlated with educational attainment. Card (1999), Bonjour *et al.* (2003), and Blundell *et al*. (2003) conclude several reasons why the error term ε is correlated with both X and D, as follows:

(1) *Ability bias*. There might be an unobserved earnings capacity term α, so that the error term consists of two components: $\varepsilon = u + \alpha$ with $E(\alpha|X, D) \neq 0$

and $E(u|X, D) = 0$. One cannot interpret γ as the causal effect of education on wages. Studies concentrate on the issue of 'ability bias' (α) which would unambiguously upward bias the estimated return because individuals with higher ability can both acquire more education and earn higher wages (e.g. Ashenfelter and Kreuger, 1995).

(2) *Return bias*. This happens when returns to different qualifications may be heterogeneous across individuals. In this case, γ itself would be correlated with education D. Massimiliano *et al.* (2005) explain that the return bias is due to the individuals self-select into the different educational qualifications according to their idiosyncratic returns, which only depend on characteristics that are observable to individuals. Therefore, in the homogeneous returns model, the return bias does not exist.

(3) *Measurement error bias.* The measurement error includes wrong self-reported survey measures in education qualification variable D. However, since D normally is a dummy or category variable, measurement error will be non-classical.

Over many years, a large number of economists have attempted to solve the problem of endogeneity. One common approach is to use twins' data to eliminate differences in innate ability, and this provides an unbiased estimator of the return to education (e.g. Bonjour *et al.*, 2003). Nevertheless, the twins methodology has been argued to be problematic. While still applying the least square estimation method, Blundell *et al.* (2000) tackle endogeneity bias by using a *Proxying and Matching* approach, which attempts to control the possible biases. Such regression would include the individual characteristic *X* factors, which might affect both the educational qualification and wages. This approach assumes that HE decisions are made on the basis of observed and included characteristics whereas unobserved characteristics are proxied by the included observed variables in order to ensure that the estimated returns are consistent. They exploit the fact that the data, such as the NCDS, are rich in information on typically unobserved characteristics, for instance: family background, personal ability and past educational variables. Researchers can include these variables as regressors in their log-wage equations in order to address the issue of ability bias. Dearden *et al.* (2000) explain the reason why estimated return based on NCDS has a lower value over that on LFS in their result is because it is less subject to an early age ability bias because the omitted ability and family background at an early age controls are included in the NCDS equations.

With regard to measurement error, Dearden *et al.* (2000) further argue that it may exist in the measurement error,[7] which would tend to down bias coefficients towards zero. If the measurement error is corrected, then the estimated returns to academic qualifications rise by around 10% for men and 12%-20% for women. They conclude that measurement error bias and omitted ability bias largely cancel out in the estimation of returns. McIntosh (2004) agrees with this result in his research, which is based on Dearden et al.'s (2000) work. Meanwhile, Blundell et al. (2004) argue that there is no substantive classical measurement error bias in schooling because NCDS's education measures are fairly accurate. They state that individuals in the NCDS are

[7] They use the qualification measures in the 1991 questionnaire as instruments for the detailed education questions in the 1981 and 1991 surveys, and assume that the measurement errors in the two questions are uncorrelated.

followed since birth and throughout their schooling period, with exams files being collected from schools and interviews being carried out very close to the dates of completion of education. They find no evidence of remaining selection bias given the information available in that data, under the *selection on observables* assumption.

In this study I will focus the matching method, which is one of the alternative solutions that deals with the endogeneity problem. Blundell et al. (2003) concludes that the properties of least squares bias depends on the richness of other control variables that may be entered to capture the omitted factors. However, the matching method would try to control directly and flexibly all of the variables at the root of selection bias.[8] I will describe these procedures in more detail in the sections that follow.

2.3.5 Matching and PSM

PSM is a semi-parametric estimator that has origins in experimental work from the first half of the twentieth century.[9] It was developed by Rosenbaum and Rubin (1983) and applied in statistics and medical literature in both theoretical and empirical works (Heckman *et al.*, 1997; and, Dehejia and Wahba, 1999). In the last 10 years, it has become more widely used by researchers in evaluating labour market policies (Lechner, 2002; Ichino and Nannicini, 2006; Lechner and Wunsch, 2009a; and,

[8] Main methods that are used in the literature to correct for selection bias are the matching estimator, which is based on selection on observables, and the instrument variable, control function or Heckman correction estimator, which are based on the selection of the unobservables.

[9] By necessity, applications use a parametric structure to calculate the propensity score and a non-parametric structure to apply matching method.

Sianesi, 2001 and 2004), assessing the effect of college quality (Berg Dale and Krueger, 2002, 2014; Black and Smith, 2004; Lindahl and Regnér, 2009; and, de Luna and Lundin, 2014), and the return to education (Card, 2001; Blundell *et al.* 2003; Sianesi, 2005; and, Battistin and Sianesi, 2011).

In the non-experimental designs, I have to account for differences between treated and untreated groups in order to estimate the impact of the program properly. The idea of PSM methodology is to attempt, in a non-experimental context, to replicate the setup of a randomised experiment. This refers to pair treatment and control units with similar values on the propensity score, and possibly other covariates, as well as the discarding of all unmatched units (Rubin, 2001).

The matching approach is non-parametric approach that provides one possible solution to the problem of selection bias that has been applied in many social-economics studies. Matching estimators try to resemble an experiment by trying to pair in a group of non-treated units that are as similar as possible to each treatment group in terms of all relevant observed covariates X. As discussed above, the true parameter τ_{ATT} is only identified if equation (2.3) holds. However, equation (2.3) is only valid under two precise assumptions if one applies matching. The first necessary assumption is that the untreated units must be statistically equivalent to the treated units if observable differences in characteristics can be controlled between the treated and non-treated units. This identifying assumption for matching is known as the Conditional Independence Assumption (CIA):

$$D \perp Y(1), Y(0) \mid X \qquad (2.14)$$

The assumption is also referred to as *selection on observables* in other program evaluation literature. The assumption implies that selection is solely based on observable pre-treatment characteristics and that all variables that influence treatment and potential outcomes are all observed by the researcher (Caliendo and Kopeinig, 2008). Secondly, for the matching procedure to have empirical content, the second necessary assumption is that:

$$0 < p(D = 1|X) < 1 \qquad (2.15)$$

The common support assumption implies that probability of receiving treatment for each X lies between 0 and 1 to avoid comparing non-comparable individual units. Therefore, individual units with the same X values have a positive probability of being both treated and untreated units (Heckman, LaLonde, and Smith, 1999; and, Caliendo and Kopeinig, 2008) to ensure that each treated unit can be matched with an untreated unit. In other words, the common support condition requires that at each level of X, the probability of observing untreated unit is positive. When (2.14) and (2.15) are valid, the treatment assignment is said to be strongly ignorable (Rosenbaum and Rubin, 1983).

The drawback of general matching is that, apart from the difference in treatment status, all of the other differences between treated and non-treated units are needed to capture their observable attributes, whereas finding exact matches could be not feasible if the dimension of the X vector is large. One possible way to reduce this 'curse of dimensionality' problem is to use Mahalanobis metric to combine all the matching variables into a scalar measuring the distance between any two observations

(Stuart and Rubin, 2007).

Alternatively, Rosenbaum and Rubin (1983) suggest that this distance can also be measured by balancing score *b(X)* based on Cochran's (1968) extension, which is a function of the relevant observed covariates X such that $D \perp X \,|b(X)$. The propensity score is a balancing score, which is defined as the estimated conditional probability of receiving a treatment given observed covariates X:

$$p(X) = p(D = 1|X) \qquad (2.16)$$

By definition, the probability for a treated given observed covariates X is a possible balancing score.

Ensuring that the PSM estimators identify and consistently estimate the treatment effects of interest leads to the following assumption (Becker and Ichino, 2002, Caliendo and Kopeinig, 2008):

1. Balancing of pre-treatment variables given the propensity score:

$$D \perp X \mid p(X) \qquad (2.17)$$

2. Unconfoundedness[10] or CIA given the propensity score:

$$D \perp Y1, Y0 \mid p(X) \qquad (2.18)$$

3. Common Support or overlap condition:

$$0 < p(D = 1|p(X)) < 1 \qquad (2.19)$$

If the balancing assumption is satisfied, then observations with the same propensity score must have the same distribution of observable characteristics independent of treatment status (Becker and Ichino, 2002). In other words, if all of the relevant

[10] Rosenbaum and Rubin (1983) defined the assumption as Uuncofoundedness or ignorable treatment assignment. They also show that under the strongly ignorable assumption, or if (2.14) and (2.15) hold, assumption (18) is also valid if propensity score is used rather than the vector of *X*.

differences between the control group and treatment group that affect the outcomes can be captured by the observed covariates, then matching on the propensity score can yield a consistent estimate of the treatment impact. The common support assumption for PSM can be enforced by adding a common support constraint, which will be discussed in the following section. Imposing the common support condition in the estimation of the propensity score may improve the quality of the matches used to estimate the ATT (Becker and Ichino, 2002).

Compared to other standard parametric estimators (e.g. OLS or IV regression), a significant advantage of matching or PSM approach is that it doesn't require the assumption of constant additive treatment effects across individuals. Instead, heterogeneous treatment effects are permitted, and can be retrieved via sub-group analysis, whereas standard parametric approaches assume homogeneous treatment effects across the sample analysed. This involves selecting the sub-group of interest and re-matching within that group and makes PSM a flexible tool for studying programme effects on groups of particular interest. PSM estimates of treatment effects are confined to counterfactuals in the area of common support and therefore do not rely on extrapolations beyond this region (Peel and Makepeace, 2012). In particular, PSM has diagnostic methods of screening data prior to parametric estimation so as to reveal the joint degree of overlap of covariates or PS.

PSM has two clear disadvantages relative to experimental techniques. The first and most obvious criticism that may be directed to the matching approach is the fact that its identifying CIA is in general a very strong one. In the case of random assignment, it is confident that the treated and control units are similar on both observable and unobservable characteristics. However, PSM only takes account of selection on observables assumption only and it estimation depends on how good the covariates used. The plausibility of CIA assumption should always be discussed with account being taken of the informational richness of the available dataset in relation to a detailed understanding of the institutional set-up by which selection into the treatment takes place (Blundell et al 2005).

Second, PSM can only estimate treatment effects where there is support for the treated individuals among control units. However, in the case of social experiments, random assignment ensures that there is common support across the whole sample. If the treatment effect is heterogeneous, restricting to the common support may actually change the parameter being estimated; in other words, it is possible that the estimated effect does not represent the mean treatment effect on the treated. It also makes experimental techniques unambiguously superior to PSM.

To formalise the above discussion, in this paper I will begin by looking at a simple single treatment model, which in the UK context is the return from undertaking some form of HE. This methodological approach assumes that HE decisions are made on the basis of variables that are observable in the data. In our model, the control unit is a heterogeneous group that is made up of those leaving school with no formal HE qualifications and those finishing with one or more A-levels. The treated unit includes individuals who achieved HE qualifications, including a first degree or higher degrees.

2.3.6 Matching estimator and algorithm

Under assumption (18) and (19), by the law of iterated expectation, the PSM estimator for ATT can be written as:

$\tau_{ATT}{}^{PSM} = E[Y(1)|D = 1] - E[Y(0)|D = 0]$

$= E_{p(x)|D=1}\{E[Y(1)|D = 1, p(x) - E[Y(0)|D = 0, p(x)]\}$ (2.20)

The PSM estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants (Caliendo and Kopeinig, 2008). A general class of estimators of equation (20) can also be written as:

$\tau_{ATT}{}^{PSM} = \frac{1}{N^T}\sum_{i\in T} d_i Y_i - \frac{1}{N^C}\sum_{i\in T}(1 - d_i) w_j Y_i$ (2.21)

Where N^T and N^C are the number of treated and untreated observations, d_i is the treatment indicator and w_j is a weight related to a function of the estimated PS.

From equation (2.21), the PSM estimator compares the targeted outcomes of treated units with one or more control units. Certain matching algorithms reduce bias by maximising the statistical similarities between treatment and non-treatment case, while others maximise the number of matches to reduce variance by allowing comparisons between less similar treatments and control individuals (Rosenbaum and Rubin, 1985). Descriptions of the most commonly employed matching algorithms are given below.

(a) Nearest neighbour matching

One of the most straightforward and easiest to implement matching estimators is NN matching (Caliendo and Kopeinig, 2008). In its simplest 1:1 or pairwise matching, it starts from each treated unit's propensity score and tries to find a control unit with the closest or most similar estimated propensity scores to use as a match. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units Y_i^T and the outcome of the matched untreated units Y_j^C is computed.

The outcome of treated unit *i* is matched to a control unit *j* with the closest propensity score: $C(i) = min||p(X_i) - p(X_j)||$. The ATT is then obtained by averaging these differences[11] give by:

$ATT = \frac{1}{N_T}\sum_{i\in T}\{w_{1i} - w_{0j}\}$ (2.22)

This method is usually applied *with replacement*, in the sense that an untreated unit can be a best match for more than one treated unit. Each treated unit can only be used once, but the same control unit may be used more than once if it is the closest match for many different treatment units.

Dehejia and Wahba (1999) suggested that matching *with replacement* is beneficial in terms of bias reduction because high-score treated units will match to low-score comparisons when there a large number of treated units with high scores but a few control units with high scores. When researchers apply matching *without replacement*, they may be forced to match treated units to control units that are significantly different in terms of the propensity score. This increases bias but it could also improve

[11] The derivation of formula and variance formula can be seen in See Becher and Ichino (2002).

the precision of the estimates. A similar argument can also be found in Caliendo and Kopeinig's (2008), who suggested that matching *with replacement* involves a trade-off between bias and variance. Matching with *replacement* keeps a low bias at the cost of larger variance. Another problem of NN matching *without replacement* is that the estimates depend on the order in which the observations are matched. However, the results are also potentially sensitive to the order in which the treatment units are matched (Rosenbaum, 1995). Hence, it should be ensured that ordering is done randomly. Although matching *with replacement* can often yield better matched numbers, if in the case that there are few control units comparable to the treated ones, it is most likely that the ATT estimates will be based on just a small number of control units because the controls units can be used multiple times.

Caliendo and Kopeinig (2008) also suggested that matching by *oversampling* (match with more than one NN) also involves a trade-off between variance and bias. When using *oversampling*, one has to decide on how many matching partners should be chosen for each treated individual and for which weight should be assigned. Matching with one NN minimises bias at the cost of larger variance, whereas matching with additional NNs can increase the bias but decrease the variance.

This method considers those observations whose propensity score belongs to the intersection of the supports of the propensity score of the treated and control units. The quality of the matches may be improved by imposing the region of common support restriction. However, Lechner (2002) argued that matches may be lost at the boundaries of the common support and the sample may be considerably reduced;

hence, imposing the region of common support is not necessarily a better solution.

(b) Calliper and radius matching

NN matching faces the risk of bad matches if the closest neighbour is far away (Caliendo and Kopeinig, 2008). Consequently, calliper matching (Cochran and Rubin, 1973) was developed as a variation of NN matching which attempts to avoid bad matches by imposing a pre-specified tolerance δ on the maximum distance $|P_i - P_j|$ allowed, where P is the PS score in both cases. From the treated units, if none of the control units are within tolerance δ, then they will be excluded. The drawback of calliper matching is that it is difficult to know a *priori* what choice for tolerance δ is reasonable (Caliendo & Kopeinig, 2008).

Dehejia and Wahba (2002) developed radius matching as a variant of calliper matching. The idea of radius matching is to use all of the control units with p_j falling within a radius *r* from p_i that match the treated unit but not only the NN within each calliper. Caliendo and Kopeinig (2008) stated the benefit is that it uses only as many comparison units as are available within the calliper and allows for the use of extra units when good matches are available.

(c) Kernel matching

Kernel matching is a non-parametric matching estimator which uses weighted averages of all individuals in the control group within the common support region to construct the counterfactual outcome. In kernel matching, the outcome of the treated unit i is matched to a weighted average of the outcomes of possibly all control units and the weight is set to:

$$g_{ij} = \frac{K\left(\frac{p_i - p_j}{h}\right)}{\sum K\left(\frac{p_i - p_j}{h}\right)} \qquad (2.23)$$

Where $K(.)$ denotes a non-negative and symmetric kernel function and h denotes the bandwidth. ATT advanced by kernel matching is given by:

$$ATT = \frac{1}{N_T} \sum_{i \in T} \{w_{1i} - \sum_{j \in C(i)} g_{ij} w_{0j}\} \qquad (2.24)$$

The advantage of such approach is the lower variance can be achieved since more information on control group is used. However, the estimated results are often very sensitive to choice of bandwidth. High value of bandwidth parameter yield a smoother estimated density function, a better fit and a lower variance between the estimated and the true underlying density function, it nonetheless also leading to a possible biased estimate.

Asymptotically, all different matching techniques produce the same estimation because in arbitrary large sample, they all compare only the exact matches. However, in finite samples, they differ based on the way they construct $C(i)$ and the way they choose the weights. Therefore, these differences lead to a trade off between the bias and the variance of matching estimators. For example, the NN matching minimizes the bias since it chooses only the closest comparison group and assigns all the weight to it in constructing the counterfactual. By contrast, kernel matching assigns positive weights to several control units. Then it increases the average PS distance between treated unit and the observables used to construct the counterfactual which in turn implies a greater bias.

In most of the literature the researchers have used and presented several matching algorithms to test the robustness of the treatment effect results. When the treated and untreated participants are more similar in pre-treatment characteristics [12], the no-replacement algorithms results in similar estimated treatment effects but with lower standard errors. When the treated and untreated units are significantly different in pre-treatment characteristics, NN matching *with replacement*, calliper matching, or kernel matching are considered to apply. The interest of the parameter in this paper is ATT because the estimated ATT may be very sensitive to the applied matching algorithm when the there are relatively few matches. To check that the choice of matching algorithm is not driving the results, in this paper I will apply two matching estimators: one to one NN *with replacement* and kernel matching

2.3.7 Assessing the matching quality

Based on assumption (14), the balancing tests are the specification tests that will be conducted to check if the matching is able to balance the distribution of the relevant variables in both the treated and untreated group. Most of the balance evaluations in the literature typically focus on the first moment. The idea of these approaches to evaluation is to compare the before and after matching results, and check if the differences still exist. If differences still remain, then either the propensity score should be re-estimated using a different approach or a different matching approach

[12] This is accessed by common support or overlap on the propensity-score distribution in section 5

should be used. Multiple versions of the balancing test are discussed in the following section.[13] Most of the tests may be conducted by applying the *pstest* command in STATA.

(a) Equality of means test (*t*-tests)

This approach checks for balance based on two sample individual *t*-tests for each covariate used to estimate the propensity score. Before matching, large differences are expected in the covariate between the two groups; however, after matching, the covariates should be balanced in both groups and no significant differences should be found. Caliendo and Kopeinig (2008) argued that t-test might be preferred if the evaluator is concerned with the statistical significant of the results. The shortcoming here is that the bias reduction before and after matching is not clearly visible.

(b) Standardised bias

The standardised bias (SB) test will be used to illustrate the reduction in bias that can be attributed to matching on the propensity score. The SB test was introduced by Rosenbaum and Rubin (1985) to compute the distance of marginal distributions of the covariates. The SB formula is given by:

$$SB_{before} = 100\frac{(\bar{X}_1 - \bar{X}_0)}{\sqrt{\frac{V_1(X)+V_0(X)}{2}}} \qquad (2.25)$$

[13] There are also other different balance tests to check for the specification of the propensity score, such as the DW test (Dehejia and Wahba, 1999), regression test (Smith and Todd, 2005), bootstrapped Kolomgorov-Smirnov tests (Sekhon, 2011), and multivariate significance tests (Hansen and Bowers, 2008), etc. Here, I will only examine the tests that can be applied in STATA.

$$SB_{after} = 100 \frac{(\bar{X}_{1M} - \bar{X}_{0M})}{\sqrt{\frac{V_{1M}(X) + V_{0M}(X)}{2}}} \qquad (2.26)$$

Where $\bar{X}_1$ and $\bar{X}_0$ are the means for the unmatched treatment and control group; $\bar{X}_{1M}$ and $\bar{X}_{0M}$ are the values for matched samples; and, $V_1(X)$ and $V_0(X)$ are the corresponding variances. For each covariate *X*, the SB is the difference of the sample means in the treated and control group sub-samples as a percentage of the square root of the average of the sample variances in both groups. Although the SB approach is widely applied in most of the literature, Caliendo and Kopeinig (2008) argued that since a bias reduction below 3% or 5% is seen as sufficient in this literature, there is no clear indication for the success of the matching procedure.

(c) Test of joint equality of means test (Pseudo R^2)

Sianesi (2004) suggested to re-estimate the propensity score on participants and matched non-participants, and then compare the Pseudo R^2 before and after matching. The indicator shows how well the covariates *X* explain the participation probability. A low PseudoR^2 value indicates that there should be no significant differences between the control and treatment groups after matching. One can also use a joint F test for the equality of means in all the covariates between two groups. Based on the F test, the null of joint equality of means in the matched sample is expected to be rejected.

(d) Sensitivity analysis

PSM estimators are based on the CIA assumption that selection is based on the observables characteristics. However, if there are unobserved variables that relate to assignment into treatment and the outcome variable, then a ‘selection on unobservable’ or `hidden bias' may arise. Rosenbaum (2002) and DiPrete and Gangl (2004) suggested the use of the bounding approach, which is one of the most widely employed methods to address this problem. The Rosenbaum bound (RB) method is a sensitivity analysis that can assess the inference of how the treatment effects may be challenged by unobserved heterogeneity. However, it can only determine the strength of the influence of the potential unmeasured variable on the selection process and it cannot indicate if there is unobserved heterogeneity in the data and neither can it estimate the magnitude of the selection bias. Alternatively, Peel and Makepeace (2013) formulate a Heckit (Heckman correction) treatment effect version of the RB model and proposed a statistical test for the CIA of no hidden bias for PSM matched treatment estimates. They argue that the Heckit model can test and control for unobserved bias which may override the RB technique.[14]

The RB is designed so that the participation probability $P(X_i)$ is not only determined by observed factors X_i for each participant i but also by an unobservable component u_i. It follows that:

$P(X_i) = P(D_i = 1|X_i) = f(\beta X_i + \gamma u_i)$ (2.27)

Where $\gamma$is the effect of $u_i$on the participation decision. If there is no hidden bias, then

[14] None of the econometrics software packages are able to apply this method; therefore, I will still use RB to access the sensitivity of unobserved selection bias.

γ will be zero and the $P(X_i)$ will be only determined by βX_i.However, if there is a hidden bias, then the two participants with the same observed covariates X have different chances of receiving treatment. For a matched pair i and j, either $\gamma = 0$ (unobserved variables have no influence on the probability) or $u_i = u_j$ (no differences in unobserved variables), the odds ratio can only be 1 and $\Gamma = e^{\gamma} = \frac{1}{e^{\gamma}} = 1$.[15] Therefore, **Γ** is a measurement of the degree of departure from a situation where the hidden bias is free. The unobserved covariate would increase the odds of selection into treatments I increase the **Γ** value. Rosenbaum (2002) proposes test statistics that derives bounds on the confidence intervals for matched ATT estimates as **Γ** varies and define the critical value of **Γ** at which the ATT is statistically insignificant. When this is conducted in STATA, I will increase the **Γ** value until it appears statistically significant when ATTs are estimated

2.4 Data

2.4.1 1958 NCDS data

The availability of birth cohort data in Britain presents an ideal basis for examining the issues that are involved in estimating the returns to education. The data used in this paper came from the British NCDS, which is a continuing panel survey of all individuals born in Britain between the week of 3 and 9 of March 1958. There are currently eight follow-up surveys available, up to 2008. Information is gathered about

[15] Rosenbaum (2002) defines the odds ratio $=\frac{P(X_i)P(1-X_j)}{P(X_j)P(1-X_i)}$, and be bounded by$[\frac{1}{e^{\gamma}}, e^{\gamma}]$

these cohort members and their immediate families at ages 7, 11, 16, 33, 42 and 50 (shown as in Table 2.2). This data has been used extensively in the analysis of economic, education, family, health and social outcomes.

One of the main advantages of using the NCDS is that it allows us to account for the full information on the cohorts' contemporaneous characteristics, such as early cognitive ability, early parental information, educational attainment and subsequent. For educational attainment, it contains detailed information on the HE qualifications achieved by each individual up to 2000, and can be used to identify the type of qualification obtained and the information from the 1978 school exams file in the NCDS on school qualifications. I updated the main surveys that I use to include the surveys that were undertaken from 1965 to 2008, in which the individuals were aged 50 years.

2.4.2 Attainment in HE and sample analysis

Initial educational attainments are usually considered to have a strong positive impact on wage earnings. There is some mixed evidence with regard to impact of qualification attainments. For example, Dearden *et al.* (2002) states the wage premium for different qualifications did not vary associated with the personal ability of individuals for academic qualifications. Nonetheless, vocational acquisition could be of critical importance for the less able individual, who may still be able to receive their highest return. Jenkins *et al.* (2002) based on NCDS data argues that lifelong learning, such as the acquisition of academic or vocational qualifications, at a later age was not overall found to lead to measurable increases in hourly wages. However, certain evidence demonstrates that the economic benefits from lifelong learning were only found in terms of improving employment outcomes rather than wage outcomes. For example, the acquisition of vocational qualifications in age 42 was most likely associated with a higher probability of re-entering or remaining in the labour market. In this paper, in order to avoid considerable heterogeneity in the value of educational qualifications, the education attainment was defined in terms of the highest academic qualifications obtained by the age of 33 in Sweep 5.

To define educational attainment, I began by considering the returns to HE *versus* no HE, which in the UK context is the return from undertaking some form of university level or equivalent. The NCDS data set contains detailed information on the highest academic qualifications achieved by each individual. Here, I assume that individuals stop having further education in 1991 at the age of 33. To focus on the sequential nature of educational qualifications, I separate the qualifications variable into: individuals who dropped out of school with no qualifications; those who stopped in education after completing O-levels or equivalent; those who stopped after completing A-levels or equivalent; and, those who completed O-levels, A-levels, and HE.

A summary of the statistics is presented in Table 2.3. The overall sample includes 11,405 individuals with different educational qualifications. Among the sub-samples, there are 1,131 individuals who have a HE qualification (including diploma, degree, and higher degree) and 1,369 individuals who obtained at least one A-level but who did not continue into HE. There are 4,336 individuals who completed with good O-levels and 4,491 individuals without any qualifications (including no qualifications, bad O-levels, and CSE GRADES 2-5).

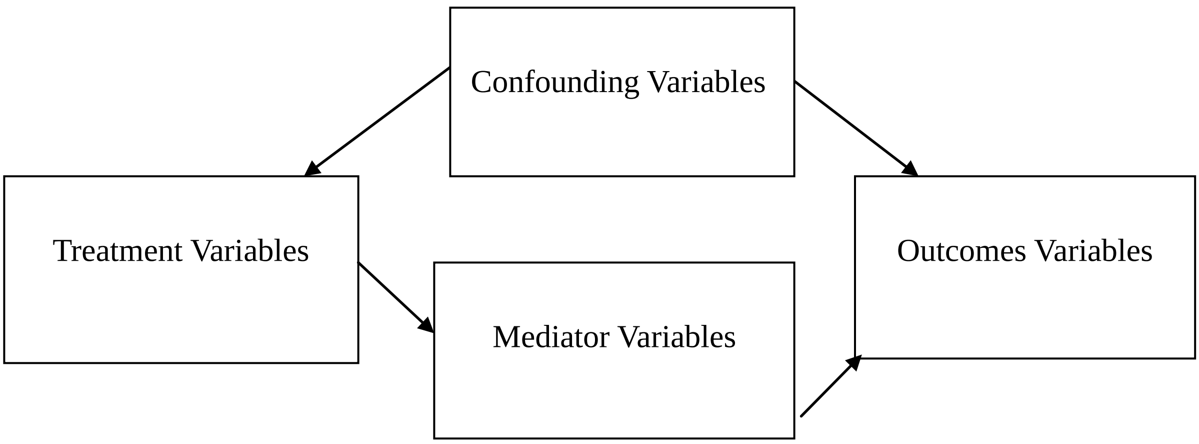
The proportions of an individual's highest academic qualification by age 33 are presented in Table 2.4. From this table it can be seen that about 9.8% of men in the 1958 cohort with A-levels go on to get some kind of HE qualification by the age of 23. The proportion of women obtained HE qualification (10.1%) is somewhat higher than that of men. Nearly 12% of individuals obtained A-levels as their highest qualification, of whom 13.3% are men and 11.7% are women. Most of the individuals stop gaining qualifications at O-levels and below. Over 35% of the men obtained O-levels as their highest academic qualification, and that figure is nearly 41% for woman. The proportion of men with no qualifications is slightly higher than that of women (42% and 33%, respectively). Furthermore, I also focused on the limited number of respondents who have participated in all of the follow-up surveys from 1991 to 2008 (i.e. reported their wage). This is done since one of the important contributions of this paper is to consider the returns by gender and to compare the impacts of education on the earnings to men and women over a lifetime. As shown from Table 3.4, the overall sample reduced by 56% to 5,003 observations. The proportion of each educational group is somewhat similar to the full sample reported in Table 3.3.

Since the highest academic qualifications are disaggregated by various educational groups, I would therefore consider six different matching pair groups[16] thereafter based on groups in Table 2.4.

2.4.3 Variable selection

In terms of choosing the covariates in matching specifications so as to calculate the PS, we first need to classify several variables. There are four types of variables shown in Figure 2.0: treatment variables, outcome variables, confounding variables, and mediators. Confounding variables are those extraneous variables that can explain variations both in treatment and outcomes variables but themselves are not inversely caused by treatments or outcomes. Hence, only confounding variables should be included in the estimation of the propensity score. This is illustrated by the arrows direction in Figure 2.0.

Figure 2.0 Selection of Potential Confounding Variable



As reviewed previously, Blundell *et al.* (2000) include a richer set of controls (F91,

[16] (1) HE vs A-level (2) HE vs O-level (3) HE vs No qualification (4) A-level vs O-level
(5) A-level vs No qualification (6) O-level vs No qualification. The former one is the treated group and the later one is the control group.

specification 3) to control for possible biases when estimating the effect of HE on hourly earnings outcomes.[17] On the other hand, Blundell *et al.* (2005) include most of the variables already included in Blundell *et al.* (2000), apart from employer characteristics. They argue that employers' characteristics may be endogenous in the sense of being choice variables for the individual and were jointly determined with wages, and will also be affected by educational qualifications. Theoretically, all of the control variables need to be attributes that are unaffected by the treatment itself. In other words, variables that are thought to influence both the educational decision of interest and wage outcomes should ideally be included as regressors. Hence, the choice of specification in this paper was dictated to analogy with the one used in the analysis of Blundell et al. (2005):

Box 1 *Covariates used in the Matching Specification*

1. Personal characteristics variables: Region of residence at birth, ethnicity, gender
2. School variables: Type of secondary school.
3. Early personal ability variables: Mathematics score, reading score accessed at age 7 and 11.
4. Family background variables: Father's year of education and father's social class, mother's year of education, mother's employment status number of siblings,

[17] These are: ethnicity, region, standard family background information, family finance status, test score measures at both 7 and 11, school type and parents' years of education, and when the participant was 16' father's social class, mother's employment status and the number of siblings.

parents' interest in participant's education, all at age 16, and family finance status at age 11 and at age 16.

The wages are collected from sweep 5 when participants were at the aged of 33, sweep 6 at the age of 42, and sweep 8 at the age of 50, and are computed on an hourly basis. I only select individuals who are full-time employed. Participants who work as part-time, self-employed, or in full-time education would be eliminated from the sample, I therefore restrict the sample to full-time workers that are defined as working for more than 30 hours per week. Since the survey allows people to choose to report the frequency of their earnings, when the frequency is different from hourly, I then compute wages using the information on the number of weeks worked during the year and the usual number of hours worked in a week. Additionally, in order to minimise *measurement error*, those individual who did not present exam files in the 1978 exam survey will also be dropped out of the sample.

Table 2.6 presents the descriptive statistics for the full sample and it also presents standardised percentage differences, which are defined as the mean difference between treatment and control groups as a percentage of the standard deviation. Reading and mathematics scores are measured by quintile. Father's social class and parents' interest of education are measured by interval. All of the control variables are generated as dummy variables as the regression. In addition, variables with missing values are kept in the data set and also generate as dummy variables that include in the specification.

2.5 Empirical result

In this section, I will report the results of the estimates and corresponding statistical testing. Using the different ages as reference points, the premium that is afforded to graduates with HE relative to non-HE has been estimated. The results that are presented in Tables 2.7 are disaggregated by various educational groups (shown in Table 2.11). Several points should be mentioned in advance. Firstly, the full sample size for both genders is not always equal to the total of the male and female samples because pooling the samples leads to some very different matches to those in the separate samples. Secondly, I did not calculate the bootstrap estimator for NN matching since the bootstrap estimator standard error is invalid for matching. Instead, I apply the *teffects psmatch* command that is newly updated in STATA 13.[18] STATA User's Guide Release 13 (2013) states that *teffects* has one very important advantage over *psmatch2*: it takes into account the fact that propensity scores are estimated rather than known when calculating standard errors.

2.5.1 Propensity score and common support

Concerning the estimation precision, if treated and untreated units are significantly different in pre-treatment characteristics, then it may be necessary to conclude that the result lacks accuracy. As discussed in Section 4, in order to examine the magnitude of the differences between pre-treatment characteristics, I will access the region of

[18] I still use psmatch2 for calculating kernel matching estimator, since *teffects* is only valid for NN or NN with caliper.

common support and propensity score distribution. The common support assumption requires the existence of a substantial overlap region between the propensity scores of treated and control individuals. If the assumption does not hold, then it is impossible to construct a counterfactual to estimate the impact of participate the high education. Several ways to do this are suggested in the literature, where the most straightforward is a visual analysis of the density distribution of the propensity score in both groups (Caliendo and Kopeinig, 2008).

A visual analysis of the density distributions of estimated propensity scores on common support is given in Figure 2.3. Propensity scores for the both full sample and gender sub-groups of age 33 are reported in the first quadrant, the second and third quadrants are for the age 42 and 50, respectively. For each quadrant, the top histogram reports the propensity score distribution for participants with HE attainment, while the bottom histogram represents those with non-HE. The horizontal axis defines the intervals of the estimated propensity score and the height of each bar on the vertical axis indicates the fraction of the relevant sample with scores in the corresponding interval. Problems would arise if the distributions did not overlap. I also imposed the common support using the minima and maxima comparison, which ensures common support by dropping treated observations whose propensity score is higher than the maximum or lower than the minimum propensity score of the untreated units. Table 2.7 reports the number of observations dropped in each group and the propensity score regions after the common support imposition

Figure 2.3 shows that for group 1 both the treated and control individuals span the full range of propensity scores, while the degree of overlap on the estimated propensity score between the treated and untreated individuals is fairly high throughout most of the range of propensity scores. Only a very small fraction of the total sample have dropped out. For group 2, 4 and 6, as seen from the figures, there is a fairly acceptable overlap throughout most of the range of propensity scores, despite a small fraction of the total sample being thrown away. However, a problem arises in group 3 and 5, Figure 2.3 also shows that the PS for most of treated units is approaching 100% whereas that control units are most likely close to 0% and, therefore, both groups rarely overlapped throughout the horizontal axis. Since the treated and control units are almost not used as matches, large numbers of the off-support unit appear to drop out within the range of propensity scores.

2.5.2 Return to HE

The difference between the matching algorithms is insignificant. The estimated ATT from NN matching *with replacement* is very similar to the one from kernel matching, and both methods make use of more information by including more observations when produce matching. However, it is inclusive to say if one is overriding the other. There is, however, a trade-off between the lower variations, on the one hand, and biased estimates, on the other, if many observations are used several times. Although I am not able to conclude that one estimate is more correct than the other, I prefer to present the results obtained using one to one NN *with replacement*.

(i) Evidence at age 33

Table 2.7 shows the impact of HE on individual earnings as compared to the base of obtaining various qualifications at the age of 33. I start by examining the magnitude of returns to HE over A-level attainment. The estimated ATT to a first degree is 16.61% on average when they are aged 33. In particular, having a degree seems to be a bigger advantage to females in the workplace than it is to males. Returns for females with HE are 23.28%% as much as those with at least one A-level. In comparison, male graduates earned just fewer than 13.82% extra. The evidence that the return gaps are more substantial for females than males is consistent with most of the literature reported in Section 2. However, the result from matching is lower than that from the analysis of Blundell *et al.* (2000) (17% for males and 37% for females, respectively) and of Galindo-Rueda and Vignoles (2003) (15% for males), both are based on the NCDS data. This finding is encouraging given the results reported by Blundell *et al.* (2005) and Massimiliano *et al.* (2005), who both find that the PSM estimated ATT coefficient is lower than that computed using OLS. Moreover, in Blundell *et al.* (2000), when controlling late personal ability (F91, specification 4), such as A-level scores and ability tests at age 16 to reduce the heterogeneous return, the returns to first degrees are reduced from 17.1% to 12.2% but are still statistically significant, which is much closer to my findings. Apart from the main differences that are explained in Section 2, the equation specification used in this paper is slightly changed compared with that used in Blundell *et al.* (2000), which excluded variables such as school attendance, employer characteristics. Secondly, my estimated sample is restricted in the common support area; hence, the sample size is different from that of in Blundell *et al.*'s (2000) study (1097 in this study and 1252 in Blundell *et al.* (2002)). This is has forced me to trim the sample to only comparable individuals among treated and non-treated groups. Massimiliano *et al.* (2005) shows that the OLS estimates in the common support region are very similar to that computed using PSM.

Not surprisingly, there is a substantial premium for people with HE over the other qualifications. Among the other sub-samples, when compared with people leaving school with no qualifications, the results show an approximately 12.6% incremental return from individual obtaining O-levels, a 33.3% incremental return from individual obtaining at least one A-levels, and a 49.8% premia for those achieving HE. Similarly, compared with people obtaining O-levels, the average return of a first degree is around 35.2% and people moving from O-levels to A-levels enjoyed a 20.2% return.

In particular, the results also show that, for different comparisons of educational groups, women usually gain more in wages than men, while the return gap between males and females varies among educational groups. For model 3, there is a huge wage gap (almost 20%) between genders, with 39.74% for males and 58.06% for females, respectively. Compared with those who obtained O-levels to those with HE attainment in model 2, the gap of return on wages between genders is about 15% (25.05 % for males, 39.76% for females). For model 5, returns to males are significant lower than those of females, reported as 30.11% and 40.06%, respectively. When individuals move from O-levels to A-levels in model 4, the females (24.58%) enjoy a 10% marginal return than males (15.33%). Moreover, for model 6, the wage gap is not significant (12.99% for males and 12.19% for females).

(ii) Evidence at age 42

In Table 2.7 it summarises the estimated return to HE attainments for men and women at age 42 and 50, separately. I base my analysis on the specification from the previous section and only replace the outcome variable to natural logarithm of hourly wage at age of 42 and 50. There are significant incremental returns to most academic qualifications and these average returns tend to gradually increase somewhat over years in contrast to average return age 33. On average, university graduates enjoy a return of 24.92% (age 42) and of 28.21% (age 50) compared with leaving school with at least one A-level. The return to A-levels over O-levels is 25.92% and the return to HE over O-levels is 44.61% for age 42 and 29.05% and 50.09% for age 50, respectively. With respect to the population of interest relative to a control group of individuals with no qualifications, the estimated ATT to a first degree is 58.59% when they are aged 42, and 65.26% when they are aged 50 on average; while return to one A-level is 40.35% and 45.61% and the return to O-level is 15.86% and 17.14% with respect to different ages.

As might be expected, females with HE attainments usually enjoy higher returns than males. At age 42, male degree graduates have a 17.33% return over people with A-level whereas return for females nearly doubles the figure to 31.10%. From age 33 to 42, the magnitude of the return gap increased to 13% from 9%. A 4% margin for males over 10 years is reported, while the magnitude of increasing is nearly 8% for females. When the caparison group turns to O-level, there is also a significant gap between genders of 11%: with 38.98% for males and 49.64% for females. The wage gap is relatively constant over the years. Furthermore, an increasing return gap (from 20% to 24%) is seen when compared with people with non-qualifications. Males enjoy a return of 50.64% and females have a return of 74.86%.

Nonetheless, the result is dramatically changed at age 42 when I focus on the lower quartile educational groups (model 4, 5 and 6). Comparing individuals A-levels over with individuals who attainted no qualifications, males (42.71%) enjoy a 6% marginal return than females (38.14%). When individuals move from O-levels to A-levels, returns to males are slightly lower than that to females with a 2% margin, reported as 24.79 % and 26.48%, respectively. When comparing O-levels versus no qualifications, the wage gap is not significantly changed over 10 years (16.25% for males and 15.32% for females).

(iii) Evidence at age 50

At age 50 the largest premia appears when comparing people with HE degrees and A-levels. Male degree graduates have a 22.44% return over people with A-level whereas return for females doubles the figure to 35.35%, indicating a significant 13% gap between genders. The magnitude of gap from age 42 to 50 is almost identical to that from age 33 to 42. When an individual moves from O-levels to HE degree, the return gap between genders is around 11% between genders: 47.51% for males and

57.95% for females, respectively. In general, it appears to be continuously decreasing in model 2 (14% at age 33, 12% at age 42 and 11% at age 50). When comparing individuals with non-qualifications versus first degree graduates, the result shows a return gap of 21% between genders (59.01% for males and 80.14% for females).

Among non-HE comparisons, the return gap for individual with O-levels versus A-levels is not significant at age 50: reported as 1%. Comparing individuals with non-qualifications versus A-levels, males enjoy a return of 42.71% while females enjoy a return of 38.14%, which indicates the gap (4%) narrowed in contrast to that reported for age 42. Finally, comparing individuals with non-qualifications versus O-levels, the returns are 17.14% and 16.98%, respectively.

(iv) Analysis

From the previous analysis, the findings from the separate matching equations based on ages suggest that a rise in wage is associated not only with the unit of education but also, apparently, with ages. The results reveal that females appear to experience a marginally higher return to HE than males. Even more striking is that return gaps between genders increase as age increases over 30 years. This is in the line with the findings of Makepeace *et al.* (2004), which only focuses on cohorts aged between 33 and 42 in the 1990s. They explain that the widening gap occurred because as the 1958 cohort grew older in the 1990s they experienced growing levels of unequal treatment. In addition, although females with HE obtained a higher pay premia than males, pay discrimination still exits. For example, women with a first degree only earn 82% of the wages of men with first degrees.

The increase in the gender wage gap among HE attainments seems to reflect a tendency for lower educated women to gain lower wage growth than men, particularly in their late thirties. For example, in the non-HE comparison groups, by looking at the A-levels and no qualifications comparison group between the ages of 33 and 42, the result shows strong evidence of a visible downward trend in the return gaps for women over men: a statistically significant drop in nearly 20 % points (from 15% to -5%); by looking at A-levels and O-levels comparison group, the drop is also calculated as 8%. A similar pattern is repeated from age 42 to 50, although the gap narrows compared at age 42 (8% and 1%, respectively). The profile of a return gap between genders for the bottom comparison group (O-levels versus no qualifications) is also investigated, which is relatively flat over years and the differences are statistically insignificant between males and females.

It must be borne in mind when I compare the differences of earning returns at different ages that individuals who attended the interview at the age of 33 may not have attended the other two interviews at ages 42 and 50. The details of the new interviewees came into the dataset at different ages. In other words, the results of ATT for different age groups were taken by different samples but not from the same group of people. Errors may exist when I compare the changes of returns in a longer term over the lifetime, as well as by gender. Ascertaining the potential longer term returns to HE for individuals, who will be most affected by the labour market changes that have taken place, is important from a policy perspective. The robustness of the results needs to be carefully considered. Results are even more important when establishing within the lifetime of a single cohort. I will then focus on the subset of participants who take part in the three follow-up surveys.

Moreover, it is also noted that the standard errors arising from model 3 and 5 are dramatically large in three cases. The results also need to be carefully considered, because the pre-treatment characteristics of two comparison groups are radically different. As seen above, a large amount of treated and control units are dropped out of the common support region since combinations of characteristics cannot be matched between two comparison groups, and it is therefore not possible to construct a counterfactual to generate an accurately estimation. I will continue to this issue in the following testing section.

2.5.3 Balance test

Diagnosing the quality of the matches obtained from a matching method is of primary importance. I apply the tests in STATA based on *pstest* syntax written and updated by Leuven and Sianesi (2012), which examines the application of matching algorithms, including: the two sample t-tests and the SB test to the individual covariate, and pseudo R^2 and likelihood ratio test to the joint equality of covariates

For example, I will first discuss the results of the balance test for each individual covariate dummy of the full sample at age 33 for group 1,[19] as illustrated in Table 2.12. Column 2 and 3 shows the P-value of two sample t statistics for the difference in the means of all variables before and after the NN matching. Column 4 and 5 presents the standardised difference bias between treated and control individuals before and after the matching. The result in column 5 indicates the reduction in SB that occurs after the matching.

Before the matching, the numbers of covariates are imbalanced due to a relative low P-value below 0.05, indicating that there are statistically significant differences between covariate means with HE and with A-levels individuals. Most of these imbalanced variables are shown as personal ability dummies, such as math score. Others are shown as fairly well balanced based on obtaining a larger P-value. As seen from the table, column 3 demonstrates the improvement in balance relative to column 2, and the differences between these covariates are not statistically significant when the P-value is less than 0.05. Therefore, it is found that the null hypothesis is rejected, which states that the matching is well balanced and most of the differences in covariate means between the two groups in the matched sample have been eliminated. Alternatively, the absolute value of SB result turns out the overall bias before matching lies between 0.7% and 41.5%. When the variation in the two groups is taken into consideration, the personal ability of the single dummies are mostly biased, normally around 20%. Once again, the after matching results clearly indicate that it is able to approach a state of balance in the treated and the matched comparison groups.

[19] I do not list all of the results for age 33 42 and 50 due to space considerations; however, I will conclude whether or not each group passes the balance test.

For most of the variables, the bias is generally decreased around 50% after matching. However, the null is only not rejected if all of the covariates are well balanced after matching. As long as any one variable is imbalanced, the balance property will be rejected.

To test the joint equality of covariates, I also calculated the pseudo-$R2$ and the likelihood Ratio (LR) before and after matching (I do not present the whole table due to space consideration). Theoretically, after the matching, there should be no systematic differences in the distribution of covariates between treated and control groups, the pseudo R^2 should be lower, and the LR ratio is therefore statistically insignificant at a 5% critical level.

Table 2.8 summarises the balance test results after matching for both genders at different ages and all types of balance tests keep the null at the 5% level. P (pass the test) or F (failed to pass) in the table is based upon the different test results in detail disaggregated and is presented in the appendix. Of the six groups examined in three tests, it appears that all of the significant covariate differences disappear after matching in group 1 (for both genders) for all ages since none of the three tests suggested that the balancing property fails. Nevertheless, for all ages in comparison group 3 and 5, it failed to pass all three tests when using NN matching estimator because it detects large numbers of imbalances that are not eliminated by the matching algorithm.

For ages 33 and 42 in group 2 and 6, even though the balancing property still holds based on the results of pseudo R^2 and LR test, the rejection frequencies of the after matching test are still higher among the individual covariates in the two sample t-tests. This consequently results in a failure in passing the t-test. Although the females at age 50 in comparison group 2 hold the balance property when using NN matching, the overall performance is still far from being acceptable. It should also be noted that kernel matching performs than better NN matching based on the test result. This is more satisfactory in group 2 for both genders and in group 4 for females. Again, apart from group 3 in all ages, kernel matching yields a better balance based on the LR test.

To sum up, it seems that the t-test and SB reject the null much too often whereas the LR test is fairly conservative for both genders. It appears that the *t*-test and SB test are too rigid since as long as I specified any one of full covariates, the null is still found to be rejected. Even if it would have succeeded to move the imbalance, an approach such as dropping covariates to obtain balance will result in a departure from the original CIA condition.

2.5.4 Sensitivity analysis

Table 2.9 shows the RB test results. Column 2 presents the Γ value. Under the assumption of no hidden bias caused by unobserved variables ($\Gamma = 1$), ATT is significant (P-value = 0). Assuming that the omitted covariates may result in larger differences existing in odds ratio between HE and non-HE groups, the Γ will then increase and the test statistic from column 3 to 8 for unobserved selection bias consequently largely increases. The bold cells in the table indicate that a statistically insignificant ATT appears as Γ increases. If P-value becomes greater than 0.05

as $\Gamma = 1.25$, the individuals between two groups with the same covariates differ in their odds of participation by a factor of 25%.

Among different ages, in group 1 and 2 for both genders, the ATT is statistically significant at 5% level even if I increase Γ up to 100% points ($\Gamma = 2$). This means that the three matching estimates seem to be robust to an unobserved selection bias in a relatively high degree. For the rest of the groups, three matching estimators perform relatively differently. For the NN matching estimator, it is prudent that the results for males in group 4 and for females in group 6 are fairly sensitive to an unobserved selection bias. In most cases, it takes a relatively low value of unobserved selection (Γ increases 25% to 1.25) to change a statistically significant ATT into a statistical insignificance. On the other hand, males in group 6 and females in group 4 are not largely affected by the unobserved bias, while the ATT are relatively significant as Γ changes. It would take much higher values of Γ, of up to 75%, to change an insignificant effect into a significant effect. However, among these groups, the result proves that a vast majority of the kernel matching ATT estimates are statistically significant for both genders as Γ changes. In most cases for both genders, the estimated treatment effect is significant at a 5% level until Γ increases up to 100 % points. It is not surprising that matching estimators in group 5 gives the worst scenarios, which shows that the ATT effect is completely insignificant, even when Γ equals to one. The lower bond P values are all insignificant for different value of Γ, which suggests that the ATT estimates are most likely downwardly biased.

2.5.5 Return of HE over lifetime

To investigate the impact of education on earnings over a lifetime, from the original full sample I will consider the subset of full-time employed individuals observed in all three follow-up surveys until the age of 50. These participants can be thought of as having been employed continuously over nearly 20 years. The previous analysis suggests that models 3 and 5 are badly performed in terms of balance property and sensitivity assessment, and the estimation precision is also under criticism. Therefore, I will exclude these two models for accessing the lifetime return in this section. The result presented in Table 2.10 is relatively similar to that concluded in Section 2.5.2. This suggests that the theory that there has been an increase in earnings over time for individuals who attained a HE qualification is highly robust.

The magnitude of increase for lifetime returns at different age levels and current time return at certain age vary across time. Return to males with HE against A-levels is slightly higher than the result from the current time return whereas returns to female are lower than that from current time analysis. Although it is not significant enough, there is still a gender effect. Comparing outcomes from age 33 and 42 would suggest that the gender premium for females has increased by 1 %, while comparing outcomes from age 42 and 50 would suggest that the average return has even decreased by 0.6 %.

Incremental returns between females with HE and without HE are not relatively large compared to that reported in Section 2.5.2. The reason why females without HE are lower paid is probably due to the numbers of females who re-enter into labour market in their late thirties or early forties. Females without HE attainment are more likely to suffer from an interruption to employment for maternity and motherhood in their thirties.[20] When they return to the labour market, they can hardly be paid relatively a fair and high due to their lack of working experience and they have fewer opportunities for promotion. However, if females who did not work as full employment from age 33 to 50 are excluded from the sample, then one can eliminate this impact and thus the gender gap narrows. Therefore, improvements in females' human capital seem to be a factor in reducing the pay differentials between genders over time.

The results for models 2, 3 and 4 shown in Table 2.10 are fairly consistent with the previous findings. Model 4 is likely to reflect a tendency for males with A-levels to experience more wage growth, increasing from 19.29% at age 33 (3rd column) to 28.62% at age 42 (5th column), and to 34.64% (7th column) at age 50, while females seem to obtain fewer pay rises and promotions, only increasing from 23.87% (4th column) at age 33 to 28.62% (6th column) at age 42 and to 33.86 % (8th column) at age 50. For model 6, the gender gap is also insignificant and returns for both genders are gradually increasing among ages.

[20] *"The careers of low-educated women were limited by being married, having children who were under the age of 16, or suffering from chronic diseases. Their family duties reduced their labour market participation and likelihood of working full-time."* Cited from: MRC National Survey of Health and Development, 1970 British Cohort Study, 1958 National Child Development Study

2.6 Summarising remarks, policy implications and conclusions

This chapter looks at the effect that HE has on wages by comparing a group of British men and women born in March 1958 and who undertook some form of HE prior to 1991. In order to tackle the issue of exogeneity of educational attainment, instead of applying OLS as used in most of the literature, I will use the PSM method for the estimation of the causal effects of education on earnings on current time and over the lifecycle for both genders. The PSM attempts to replicate a randomised experiment as closely as possible by obtaining treated and control groups with similar covariate distributions to minimise the selection bias in observational studies. As a researcher attempting to use PSM, one of the main issues that needs to be considered is that the sufficient pre-treatment covariates need to be include so that the *CIA* is fulfilled. The NCDS 1958 British birth cohort study contains extensive and commonly administered ability tests at early ages, as well as accurately measured family background and school type variables, which are all ideal for methods relying on the assumption of *CIA*.

A number of important implications are derived from the preceding analysis. In general, HE has a substantial impact on earnings at different age levels. The return rises with the greater disparity of the educational groups. For example, the results showed that the estimated average returns to obtaining HE over A-levels are around 16% for age 33, 24% for age 42 and 28% for age 50. For examination of the causal impact of other disaggregated qualifications, this finding is somewhat in line with the findings of Blundell *et al.* (2005). It reports an average incremental return for males to O-levels of around 18%, to A-levels of 24%, and to HE of 48%, compared to leaving school without qualifications at age 33. My result is qualitatively lower than previous findings, reported as 14 %, 20%, and 40%, respectively. The difference probably arises because the education attainment observed in their study is the actual highest qualification and vocational equivalent achieved. However, in this study, I will only select the individual's highest academic qualification in the sample.

I have also attempted to investigate various subsidiary issues concerning the impact of HE on both genders and produced some findings. In particular, I find that the gender gap was higher at various levels of HE attainment than it was with non-HE attainment individuals, such as A-levels. HE normally has a greater impact on earnings for females than males, and the gender gap remains significantly constant throughout the period considered from 1991 to 2008; whereas, for non-HE groups, the gender gap is relatively insignificant.

Another key contribution is that the application has also highlighted the importance of estimating return within the lifetime of a single cohort. In terms of educational outcomes, incremental returns to all HE qualifications have gradually increased over the years. This confirms that HE has not only a significant and robust educational effect but it also has a cohort effect on earnings over the lifecycle. The gender gap still remains but figures are slightly lower than that from current time analysis. This implies that HE attainment in females in their early thirties has the advantage that cohorts have potentially been in the labour market long enough after graduation for their full returns to be measured. Non-HE females are more likely than men to suffer low labour market participation rate, possibly due to maternity duty or taking care of children and other dependants in their late thirties, and this may lead to attempts to renter the workforce in their forties. This 'women returning' effect will cause a gap since the average return for low-educated females will be under-estimated in current time analysis.

In so far as education is treated as a human capital investment rather than a consumption decision. The extent to which education raises earnings is only the private financial return to education, hence information on returns to different degree programmes can make an important contribution to the educational decisions of future students. The result shows the private financial rate of return to HE in the UK is substantially high than that to non-HE. This implies that individuals would still be willing to invest in their own higher education, even if the government continuously cut subsidies and they are hence required to pay a greater cost.

It has shown that UK government invests heavily in higher education, thereby shouldering an enormous burden. A continuing policy concern is whether subsides should be decreased and whether one form of subsidy should be favoured over another for any particular student. This argument was indeed used in the late 1990s to shift some of the burden of the costs of HE on to individuals via the introduction of tuition fees. Starting in 1998, a series of higher education reforms have aimed, first of all to shift a greater proportion of the cost of undergraduate teaching from tax-payers to graduates, secondly to increase competitive pressure in the higher education sector to raise standards and efficiency, and to ensure that the system remains accessible to all qualified students regardless of ability to pay. In fact, according to Chowdry et al. (2012), up to 2012, the estimated total saving to the taxpayer of the reforms was around £760m. While that is a substantial amount of money, this represents just a 12% taxpayer saving on the previous system.

However someone argue for equity justification for subsidies and other arguments are to support maintaining or even increasing government subsidies. One holds that benefits from such economics ‘externalities’ arises due to a large pool of HE graduates to make the possibility of more advanced and efficient production techniques which in turn improves economy and processes innovation.

One of the policy implications can be drawn that a persistent high private financial return to HE allows a certain level of market failure: higher return should encourage more individuals to complete HE and hence compete for jobs. Job competition then would bring down the financial return to HE comparable to other alternative investments. In such case, public subsidies are justified to be called to encourage overcoming the barriers to HE that attributed to market failure and without financial incentives. Psacharopoulos (2007) point out public subsidies for HE can be reduced while investment in higher education would still remain privately advantageous. On the other hand, the subsidies are justified only if such value added externalities exceeds the subsidies expenses. In practice, equity would be only served if students unable to finance the costs were provided access to a student loan[21] that would be repaid out of earnings after study.

In addition to the policy-relevant suggestion, the evidence that relatively lower incremental financial returns to a given type of low qualification (individual with no qualifications or with O-levels) means that individuals do not expect a significant wage return to acquiring them. This might suggest that the academic knowledges and skills acquired from such level of qualification are not tailored to the requirements of firms and the labour market. However, this should not be taken to suggest that the overall rationale for investments in basic and compulsory education should be weakened. There are two reasons for this. First of all, in particular, these qualifications are often viewed as a way to certify existing academic knowledge and skills, rather than as equipping individuals with new skills and hence increased productivity, and it could be a necessary input into further levels of education which may have higher economic returns. Secondly, basic and compulsory education is valued not only for its economic benefits but also for its non-financial benefits including reductions in fertility and mortality, empowerment, better environment, lower crime, democratic participation, etc.

Several limitations have been observed in this study. First, this study can only support the lifetime results for this special group of people who were born in the 1950s, it may not reflect the situation that followed. The climate in which today's school leavers have to make these decisions is dramatically different. For example, the maintenance

[21] Such student loan schemes are discussed in-depth in Barr (2012)

grant provision has been removed. Since the late-1980s, around one in three young people now go into full-time HE in the UK, compared with one in eight in 1979. This means that there are now many more highly-educated workers entering the labour force every year than when the 1958 NCDS cohort went out to work out to work for the first time. Furthermore, UK education policy has experienced a steady shift in the burden of funding HE away from the government towards the students and their families. Since 2006, a regulated maximum university tuition fee has been paid by all full-time UK university students. It is, therefore, important to examine the magnitude of returns to HE and the extent to which they have changed over the generations in order to examine the effect of the government’s policy of HE. Research has recently been applied on cross-sectional data (e.g. O’Leary and Sloane, 2011), but there are still no lifetime results. There are also few cohort data, the most recently available is BCS70. It is of particular interest to address the question of how lifetime returns to HE vary for younger cohort generations. One might wait until BSC70 data has been updated when the cohorts are in their fifties.

Second, neither NN nor the kernel matching estimator match on covariates, such as early ability scores and family background variables, perform well for calculating the ATT in model 3 and 5 due to failures of balance and RB test. Therefore, the estimated results might not be robust, and will be less precise and of limited use. Third, variation in returns by class of degree or subject of degree is not considered in this chapter and a narrow focus on the average return may be inadequate. Further research should also employ the combined use of PSM and difference-in-differences analyses

(Blundell and Costa, 2000) to examine ATT of different subject and class levels of HE attainment on earnings over the long term. In addition, in this chapter I have only considered the private financial returns to HE and have not asked whether other private returns or social returns may exist. The second chapter will be able to contribute towards asking if the cost of education still secures a health benefit.

APPENDIX A: Tables and Figures

Table 2.1 Percentage returns to qualifications for men and women: LFS 1994Q1-2002Q4

	Men		**Women**	
	Markup	**SE**	**Markup**	**SE**
Higher degree	113.76	0.0111	131.52	0.0124
First degree	96.70	0.0090	101.64	0.0096
Degree equivalent	65.20	0.0072	70.30	0.0066
A-level (or equivalent)	30.03	0.0050	25.33	0.0055
O-level (or equivalent)	27.01	0.0063	23.24	0.0047
Other	6.85	0.0048	9.01	0.0039

Notes: all returns are measured relative to no qualifications;
Statistical significance at the 95% confidence level.

Source: O'Leary and Sloane (2005)

Table 2.2 NCDS 1958 British Birth Cohort

Sweep	Year	Age (Years)
0	1958	0
1	1965	7
2	1969	11
3	1974	16
4	1981	23
5	1991	33
6	1999-2000	42
7	2004-2005	47
8	2008-2009	50

Table 2.3 Percentage of Individuals Educational Qualifications

Qualifications	Sample
No Qualifications	2,489 (19.63%)
GSE Grades 2-5	2,003 (15.00%)
Good O-Levels	4,336 (35.82%)
At least one A-Level	1369 (9.12%)
Diploma	159 (4.27%)
Degree or PGCE	936 (13.60%)
Higher Degree	36 (2.55%)
Total	11,405 (100%)

Table 2.4 Percentage of individuals with highest academic qualification (full sample)

	No qualifications	Good O-levels	1 or more a-levels	HE degree	Total Sample
Men	41.90 (2,349)	35.23 (1,975)	13.34 (692)	9.75 (547)	100 (5,606)
Women	32.91 (2,143)	40.71 (2,361)	11.67 (677)	10.08 (584)	100 (5,799)
All	39.38 (4501)	38.02 (4336)	12.00 (1,369)	9.92 (1,131)	100 (11,405)

Table 2.5 Percentage of individuals with highest academic qualification (subset for reporting the wages in age 33, 42 and 50)

	No qualifications	Good O-levels	1 or more a-levels	HE degree	Total Sample
Men	41.90	35.23	13.34	9.75	100
	(2,349)	(1,975)	(692)	(547)	(5,606)
Women	32.91	40.71	11.67	10.08	100
	(2,143)	(2,361)	(677)	(584)	(5,799)
All	39.38	38.02	12.00	9.92	100
	(4501)	(4336)	(1,369)	(1,131)	(11,405)

Table 2.6 Summary statistics

Variable	Mean	Standard deviation	Variable	Mean	Standard deviation
Real log (hourly wage)			**Father's age in 1974**	46.641	6.39
1991	2.063	0.481	**Mother's age in 1974**	43.561	5.70
1999-2000	2.260	0.413	**Mother employed in 1974**	0.657	0.475
2008-2009	2.580	0.437	**Father's social class in 1974**		
			Professional	0.034	0.181
			Intermediate	0.132	0.338
			Skilled Non-manual	0.063	0.244
White	0.987	0.115	Skilled manual	0.298	0.458
Mathematics ability at 7 years			Semi-skilled non-manual	0.010	0.010
5th quintile (highest)	0.194	0.395	Semi-skilled manual	0.087	0.281
4th quintile	0.114	0.318	Unskilled	0.036	0.185
3rd quintile	0.271	0.445	Missing, or unemployed or no father	0.340	0.474
2nd quintile	0.141	0.348	**Number of siblings in 1974**	1.743	1.512
1st quintile (lowest)	0.280	0.449	**Father's interest in education**		
Reading ability at 7 years			Expects too much	0.024	0.153
5th quintile (highest)	0.192	0.394	Very interested	0.262	0.440
4th quintile	0.132	0.339	Some interest	0.249	0.433
3rd quintile	0.263	0.440	**Mother's interest in education**		
2nd quintile	0.209	0.407	Expects too much	0.037	0.188
1st quintile (lowest)	0.204	0.403	Very interested	0.349	0.477
Mathematics ability at 11 years			Some interest	0.346	0.476
5th quintile (highest)	0.194	0.396	**Bad finances in 1969 or 1974**	0.114	0.317
4th quintile	0.202	0.402	**Region in 1974**		
3rd quintile	0.171	0.376	North West	0.116	(0.320)
2nd quintile	0.202	0.401	North	0.075	0.264
1st quintile (lowest)	0.231	0.422	East and West Riding	0.087	0.281
Reading ability at 11 years			North Midlands	0.076	0.265

Variable	**Mean**	**Standard deviation**	**Variable**	**Mean**	**Standard deviation**
5th quintile (highest)	0.159	0.365	East	0.086	0.280
4th quintile	0.191	0.393	London and South East	0.160	0.367
3rd quintile	0.241	0.428	South	0.063	0.243
2nd quintile	0.168	0.374	South West	0.068	0.251
1st quintile (lowest)	0.241	0.428	Midlands	0.101	0.301
Comprehensive school 1974	0.467	0.499	Wales	0.058	0.234
Secondary modern school 1974	0.170	0.376	Scotland	0.111	0.315
Grammar school 1974	0.087	0.281	Other	0.100	0.299
Private school 1974	0.060	0.214	**Father's years of education**	7.904	1.622
Other school 1974	0.017	0.130	**Mother's years of education**	7.916	1.376

Table 2.7 Incremental treatment effects by highest qualification achieved by matching estimates at age 33, 42 and 50

Models		Age 33			Age 42			Age 50		
		full	male	female	full	male	female	full	male	female
1	ATT	0.1661	0.1382	0.2328	0.2392	0.1733	0.3110	0.2821	0.2244	0.3535
	(NN)	(0.0371)	(0.0485)	(0.0605)	(0.0500)	(0.0715)	(0.0863)	(0.0907)	(0.0887)	(0.0925)
	Control	445	233	211	460	208	238	458	203	255
	Treated	652	392	259	636	349	280	621	345	276
	Support	1097	625	470	1096	557	518	1079	548	531
	Total	1109	631	478	1100	560	540	1094	551	543
	ATT	0.1601	0.1298	0.2301	0.2312	0.1731	0.3009	0.2805	0.2197	0.3431
	(Kernel)	(0.0312)	(0.0345)	(0.0601)	(0.0454)	(0.0671)	(0.0764)	(0.0866)	(0.0773)	(0.0906)
2	ATT	0.3520	0.2405	0.3976	0.4461	0.3898	0.4964	0.5009	0.4751	0.5795
	(NN)	(0.0392)	(0.0500)	(0.6401)	(0.0731)	(0.0706)	(0.0812)	(0.0530)	(0.0713)	(0.0843)
	Control	1538	737	754	1623	665	835	1538	737	754
	Treated	617	378	256	625	344	268	617	378	256
	Support	2155	1115	1010	2248	1009	1103	2155	1115	1010
	Total	2239	1202	1037	2299	1096	1203	2239	1202	1037
		0.3213	0.2300	0.3794	0.4221	0.3663	0.4644	0.5000	0.4712	0.5699
		(0.0301)	(0.0354)	(0.04965)	(0.06521)	(0.0621)	(0.0801)	(0.0511)	(0.0700)	(0.0837)
	ATT									
	(Kernel)									
3	ATT	0.4987	0.3974	0.5806	0.5859	0.5064	0.7486	0.6526	0.5901	0.8014
	(NN)	(0.0874)	(0.0848)	(0.0961)	(0.1001)	(0.1394)	(0.0857)	(0.1378)	(0.1201)	(0.1621)
	Control	1006	518	268	1006	502	190	1006	502	190
	Treated	396	214	105	527	261	96	527	261	96
	Support	1402	732	373	1532	763	286	1532	763	286
	Total	1767	1040	727	1765	948	817	1765	948	817
	ATT	0.4356	0.3331	0.5712	0.5542	0.4711	0.7021	0.6337	0.5821	0.7787
	(Kernel)	(0.0739)	(0.0792)	(0.0911)	(0.0933)	(0.0896)	(0.0801)	(0.1170)	(0.1061)	(0.1313)
4	ATT	0.2022	0.1813	0.2458	0.2592	0.2479	0.2648	0.2905	0.2968	0.2884
	(NN)	(0.0366)	(0.0497)	(0.0544)	(0.0463)	(0.0690)	(0.0520)	(0.0248)	(0.0238)	(0.0211)
	Control	1563	801	666	1660	745	915	1660	745	915
	Treated	447	235	202	455	205	250	455	205	250
		2001	1036	868	2115	950	1165	2115	950	1165

		2024	1043	981	2121	954	1167	2121	954	1167
	ATT (Kernel)	0.1904 (0.0345)	0.1881 (0.0513)	0.2433 (0.0543)	0.2435 (0.0494)	0.2247 (0.0569)	0.2438 (0.0544)	0.2871 (0.0241)	0.2934 (0.0207)	0.2868 (0.0198)
5	ATT (NN)	0.3331 (0.1081)	0.2011 (0.1900)	0.3006 (0.1761)	0.4035 (0.0947)	0.4271 (0.1317)	0.3814 (0.0934)	0.4561 (0.0942)	0.4723 (0.1001)	0.4343 (0.0901)
	Control	1000	572	460	1049	597	529	1049	597	529
	Treated	362	193	154	409	186	119	409	186	119
	Support	1362	765	614	1458	782	648	1458	782	648
	Total	1552	881	671	1587	806	781	1587	806	781
	ATT (Kernel)	0.2987 (0.0961)	0.1842 (0.1354)	0.2655 (0.0438)	0.3699 (0.0884)	0.4033 (0.1131)	0.3557 (0.0836)	0.3988 (0.0716)	0.4462 (0.0846)	0.3964 (0.0793)
6	ATT (NN)	0.1261 (0.0568)	0.1299 (0.0704)	0.1219 (0.0718)	0.1586 (0.0587)	0.1625 (0.0717)	0.1532 (0.0768)	0.1714 (0.0597)	0.1845 (0.0645)	0.1698 (0.0541)
	Control	453	259	184	472	244	214	453	259	184
	Treated	1439	742	637	1589	693	766	1439	742	637
	Support	1892	1001	821	2061	937	980	1892	1001	821
	Total	1996	1048	940	2084	974	1100	1996	1048	940
	ATT (Kernel)	0.1387 (0.0669)	0.1318 (0.0814)	0.1323 (0.0728)	0.1575 (0.0764)	0.1489 (0.0679)	0.1530 (0.0705)	0.1881 (0.0693)	0.1996 (0.0734)	0.1783 (0.0616)

Table 2.8 Summary of balance test results after different matching algorithms

Age 33	Models					
	1	2	3	4	5	6
NN match						
T-test	P/P	F/F	F/F	F/F	F/F	F/F
SB	P/P	F/F	F/F	F/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	F/F	P/P
Kernel match						
T-test	P/P	P/P	F/F	P/F	F/F	F/F
SB	P/P	P/P	F/F	P/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	P/P	P/P
Age 42						
	1	2	3	4	5	6
NN match						
T-test	P/P	F/F	F/F	F/F	F/F	F/F
SB	P/P	F/F	F/F	F/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	F/F	P/P
Kernel match						
T-test	P/P	P/P	F/F	P/F	F/F	F/F
SB	P/P	P/P	F/F	P/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	P/P	P/P
Age 50						
NN match						
T-test	P/P	F/F	F/F	F/F	F/F	F/F
SB	P/P	F/P	F/F	F/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	F/F	P/P
Kernel match						
T-test	P/P	P/P	F/F	P/F	F/F	F/F
SB	P/P	P/P	F/F	P/F	F/F	F/F
LR test	P/P	P/P	F/F	P/P	P/P	P/P

Note: The result for Males presents in former and Female in latter

Table 2.9 RBs analysis for different matching algorithm

Models		*NN*		*Kernel*	
	Γ				
Age 33		*Males*	*Females*	*Males*	*Females*
1	*1.0*	0.000	0.000	0.000	0.000
	1.25	*0.001*	0.000	0.000	0.000
	1.5	*0.040*	0.000	*0.033*	0.000
	1.75	*0.390*	*0.001*	*0.108*	0.000
	2.0	*0.794*	*0.016*	*0.431*	0.000
2	*1.0*	0.000	0.000	0.000	0.000
	1.25	0.000	0.000	0.000	0.000
	1.5	0.000	0.000	0.000	0.000
	1.75	*0.001*	*0.002*	0.000	0.000
	2.0	*0.019*	*0.006*	0.000	0.000
3	*1.0*	0.000	0.000	0.000	0.000
	1.25	*0.002*	*0.002*	*0.002*	*0.002*
	1.5	***0.085***	***0.093***	*0.015*	*0.024*
	1.75	***0.461***	***0.513***	***0.156***	***0.198***
	2.0	***0.843***	***0.919***	***0.363***	***0.457***
4	*1.0*	0.000	0.000	0.000	0.000
	1.25	*0.004*	0.000	0.000	0.000
	1.5	***0.078***	0.000	*0.017*	0.000
	1.75	***0.332***	*0.003*	*0.126*	*0.001*
	2.0	***0.661***	*0.024*	*0.377*	*0.016*
5	*1.0*	***0.240***	***0.231***	***0.225***	***0.235***
	1.25	***0.782***	***0.751***	***0.767***	***0.748***
	1.5	***0.977***	***0.970***	***0.974***	***0.986***
	1.75	***0.999***	***1.000***	***0.999***	***1.000***
	2.0	***1.000***	***1.000***	***1.000***	***1.000***
6	*1.0*	0.000	*0.013*	0.000	*0.009*
	1.25	0.000	***0.652***	0.000	***0.228***
	1.5	*0.048*	***0.994***	*0.025*	***0.742***
	1.75	*0.622*	***1.000***	***0.127***	***0.912***
	2.0	*0.969*	***1.000***	***0.543***	***0.998***
Age 42					
1	*1.0*	0.000	0.000	0.000	0.000
	1.25	0.000	0.000	0.000	0.000
	1.5	0.000	0.000	*0.063*	0.000
	1.75	*0.003*	0.000	***0.069***	0.000
	2.0	*0.031*	*0.001*	***0.154***	0.000
2	*1.0*	0.000	0.000	0.000	0.000

	1.25	*0.000*	0.000	*0.000*	*0.000*
	1.5	*0.000*	0.000	*0.000*	*0.000*
	1.75	*0.009*	*0.000*	*0.000*	*0.000*
	2.0	*0.042*	*0.002*	*0.000*	*0.000*
3	*1.0*	*0.000*	*0.000*	*0.000*	*0.000*
	1.25	0.002	*0.002*	*0.002*	*0.002*
	1.5	0.056	***0.105***	*0.037*	*0.048*
	1.75	0.**246**	***0.813***	***0.178***	***0.246***
	2.0	0.**789**	***0.999***	***0.567***	***0.678***
4	1.0	0.000	0.000	0.000	0.000
	1.25	0.004	0.000	0.000	0.000
	1.5	**0.104**	**0.060**	0.017	0.000
	1.75	**0.573**	**0.115**	0.126	0.001
	2.0	**0.979**	**0.545**	0.377	0.016
5	1.0	**0.546**	**0.231**	**0.347**	**0.335**
	1.25	**0.931**	**0.751**	**0.801**	**0.745**
	1.5	**0.999**	**0.970**	**0.974**	**0.986**
	1.75	**1.000**	**1.000**	**1.000**	**1.000**
	2.0	**1.000***	**1.000**	**1.000**	**1.000**
6	1.0	0.000	0.013	*0.000*	*0.009*
	1.25	0.000	**0.458**	*0.000*	***0.423***
	1.5	0.051	**0.685**	*0.000*	***0.742***
	1.75	0.**547**	**0.969**	***0.113***	***0.999***
	2.0	0.**874**	**1.000**	***0.546***	***1.000***
Age 50					
1	*1.0*	0.000	0.000	0.000	0.000
	1.25	*0.000*	0.000	0.000	0.000
	1.5	*0.000*	0.000	*0.000*	*0.000*
	1.75	*0.000*	*0.000*	*0.000*	*0.000*
	2.0	*0.000*	*0.000*	*0.000*	*0.000*
2	*1.0*	0.000	0.000	*0.000*	*0.000*
	1.25	*0.000*	0.000	*0.000*	*0.000*
	1.5	*0.014*	0.000	*0.000*	*0.000*
	1.75	*0.028*	*0.002*	*0.000*	*0.000*
	2.0	*0.096*	*0.016*	*0.000*	*0.000*
3	*1.0*	*0.012*	*0.023*	*0.000*	*0.000*
	1.25	**0.082**	*0.104*	*0.010*	*0.002*
	1.5	**0.585**	***0.993***	***0.079***	***0.114***
	1.75	0.**901**	***1.000***	***0.213***	***0.576***
	2.0	0.**999**	***1.000***	***0.567***	***0.857***
4	1.0	0.000	0.000	0.000	0.000
	1.25	0.000	0.000	0.000	0.000
	1.5	0.002	0.000	0.000	0.000
	1.75	**0.092**	0.023	0.001	0.001

	2.0	**0.561**	0.095	0.012	0.019
5	1.0	**0.240**	**0.231**	**0.225**	**0.235**
	1.25	**0.782**	**0.751**	**0.767**	**0.748**
	1.5	**0.977**	**0.970**	**0.974**	**0.986**
	1.75	**0.999**	**1.000**	**0.999**	**1.000**
	2.0	**1.000**	**1.000**	**1.000**	**1.000**
6	1.0	0.000	0.001	*0.000*	*0.000*
	1.25	0.012	0.015	*0.000*	*0.000*
	1.5	**0.198**	**0.124**	*0.025*	*0.042*
	1.75	**0.856**	**0.644**	***0.456***	***0.912***
	2.0	**0.999**	**1.000**	***0.865***	***0.998***

* Bold number indicator P value > 5%

Table 2.10 Incremental treatment effects by highest qualification achieved by matching estimates (subset)

		Age 33		*Age 42*		*Age 50*	
		male	*female*	*male*	*female*	*male*	*female*
1	*ATT*	*0.1473*	*0.2073*	*0.1690*	*0.2387*	*0.2533*	*0.3210*
		(0.0485)	*(0.0660)*	*(0.0652)*	*(0.0660)*	*(0.0715)*	*(0.0863)*
	Control	*184*	*148*				
	Treated	*305*	*191*				
		489	*339*				
2	*ATT*	*0.2186*	*0.3664*	*0.3158*	*0.4359*	*0.4198*	*0.5264*
		(0.0521)	*(0.0714)*	*(0.0787)*	*(0.0745)*	*(0.0706)*	*(0.0812)*
	Control	*584*	*553*				
	Treated	*297*	*180*				
		881	*733*				
4	*ATT*	*0.1929*	*0.2387*	*0.2862*	*0.3154*	*0.3464*	*0.3386*
		(0.0456)	*(0.0669)*	*(0.0700)*	*(0.0669)*	*(0.1394)*	*(0.0857)*
	Control	*608*	*481*				
	Treated	*183*	*134*				
		791	*615*				
6	*ATT*	*0.1466*	*0.1435*	*0.1805*	*0.1720*	*0.2079*	*0.1948*
		(0.0704)	*(0.0718)*	*(0.0917)*	*(0.0819)*	*(0.0690)*	*(0.0520)*
	Control	*165*	*120*				
	Treated	*568*	*409*				
		733	*529*				
		1048	*940*				

Table 2.11 Disaggregated comparison group

Comparison groups	**Educational Attainments**
1	HE vs A-levels
2	HE vs O-levels
3	HE vs No qualifications
4	A-levels vs O-levels
5	A-levels vs No qualifications
6	O-levels vs No qualifications

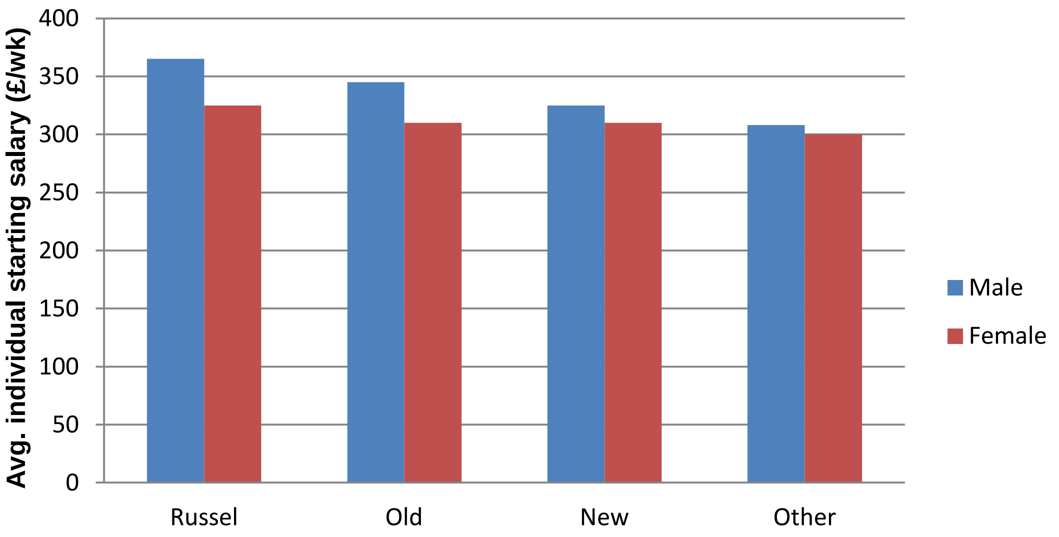
Table 2.12 T-test and SB result for age 33 pooled sample

Variable	*Average P-value of t-test before matching*	*Average P-value of t-test after NN matching*	*% standardised bias before matching*	*% SB after NN matching*	*% reduction of SB*
White	**0.917**	**0.917**	**-0.7**	**0.0**	**100**
female	0.031	0.814	-14.5	-6.0	58.8
Region dummy					
North	0.031	0.709	14.7	4.7	67.9
North Midlands	0.588	0.169	3.7	8.2	-123.5
Midlands	0.725	0.668	-2.4	-4.9	-106.6
School type dummy					
Comprehensive school 1974	0.006	0.691	-18.5	-8.4	54.8
Grammar school 1974	0.001	0.179	21.8	14.0	36.0
Secondary modern school 1974	0.537	0.714	-4.1	-3.7	10.9
Personal ability dummy					
Mathematics ability at 7 years					
1st quintile	0.004	0.153	-19.2	-14.0	26.9
2nd quintile	0.636	0.767	-3.2	-0.9	71.9
Mathematics ability at 11 years					
1st quintile	0.063	0.351	-12.1	-8.8	27.2
2nd quintile	0.000	0.007	-29.6	-23.9	19.0
3rd quintile	0.115	0.731	-10.5	-4.1	61.2
4th quintile	0.018	0.657	-15.8	0.0	100.0
5th quintile	0.000	0.086	41.5	18.6	55.2
Reading ability at 7 years					
1st quintile	0.011	0.194	-16.5	-12.2	26.3
2nd quintile	0.653	0.995	-3.0	-1.6	47.8
Reading ability at 11 years					
1st quintile	0.005	0.086	-18.3	-15.1	17.6
2nd quintile	0.000	0.014	-25.2	-21.1	16.2
3rd quintile	0.000	0.174	-29.4	-15.2	48.3
4th quintile	0.825	0.103	1.5	9.5	-541.8
Social class dummy					
Professional	0.009	0.862	18.0	1.6	90.9
Intermediate	0.161	0.714	9.4	6.3	33.1
Father' interest to education dummy					
Expects too much	0.587	0.984	-3.6	0.0	100

Very interested	0.000	0.059	27.2	15.8	42.0
Mother' interest to education dummy					
Expects too much	0.322	0.898	6.7	1.2	82.5
Very interested	0.000	0.041	24.7	17.0	31.1
Number of siblings in 1974	0.652	0.916	3.1	-0.4	86.4
Mother's years of education	0.013	0.662	-16.7	-6.0	64.0
Father's years of education	0.001	0.651	-22.3	-9.5	57.5
Bad finances in 1969 or 1974	0.485	0.917	-4.6	0.0	100

*

Figure 2.1 Average earnings by gender and HE type



Source: The Ramsey and Analytical Services Group of the Department for Employment and Learning (2008)

Figure 2.2 Average earnings by gender and degree classification

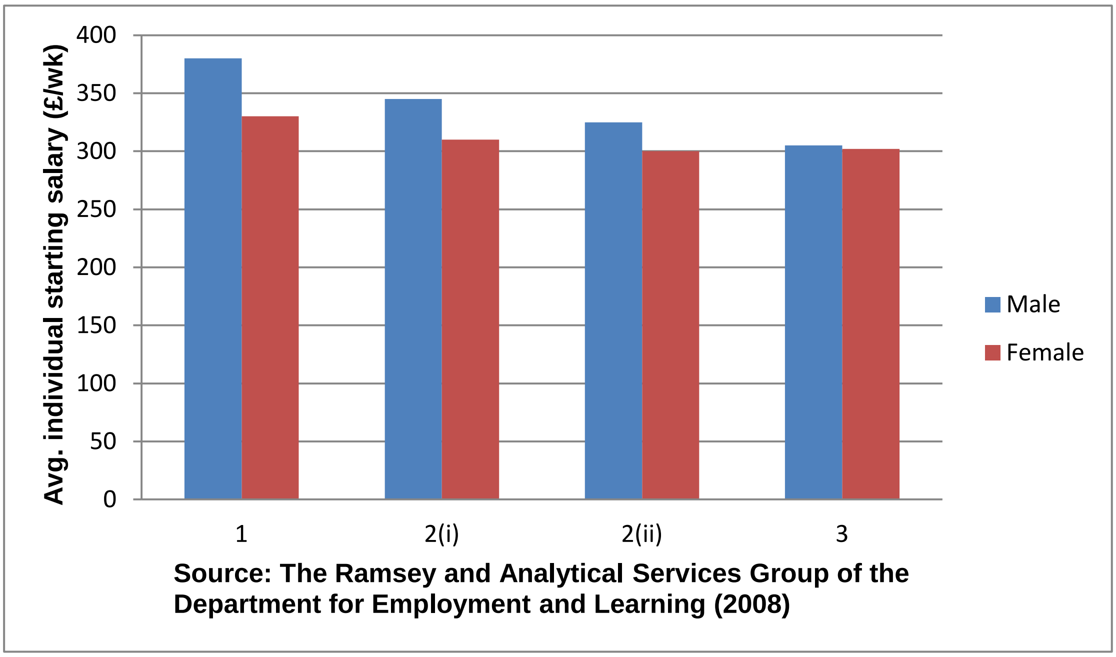
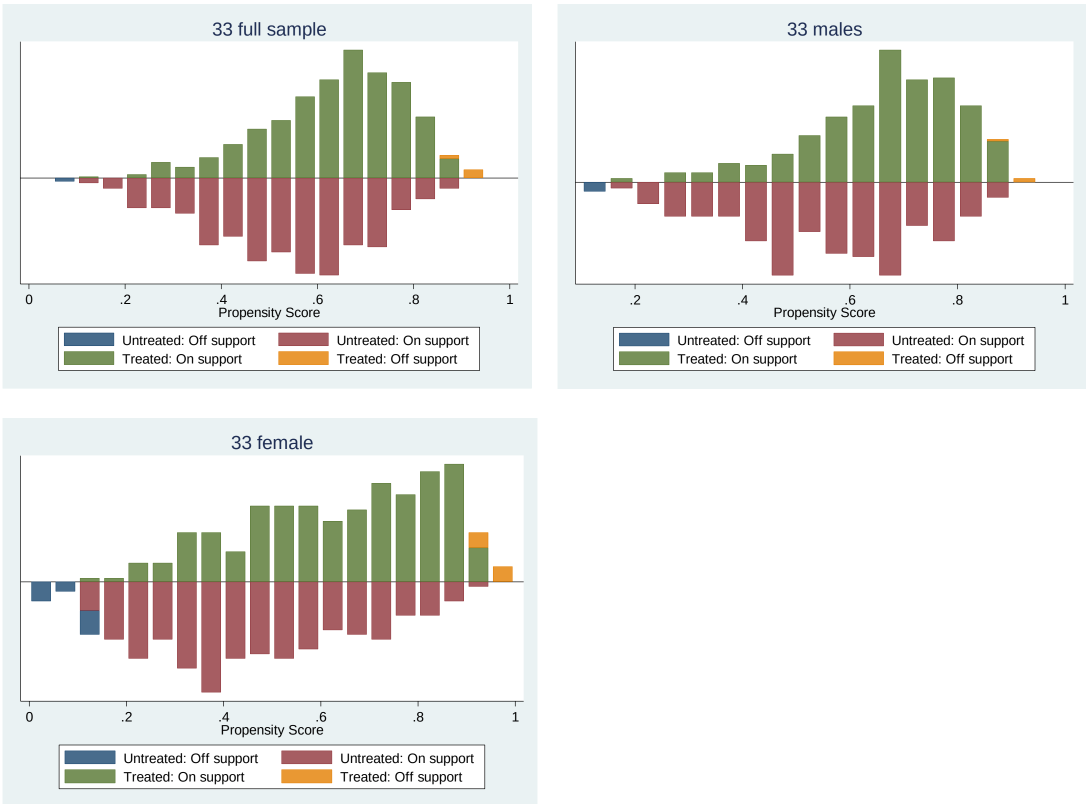
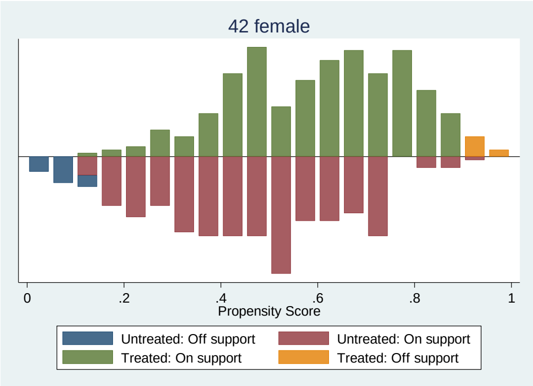


Figure 2.3 Propensity score distributions and common support regions

Model 1

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.6
.8
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Propensity Score
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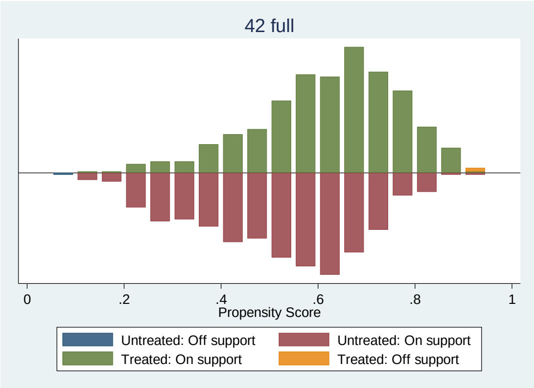
Untreated: On support
Treated: On support
Treated: Off support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Propensity Score
Untreated: Off support
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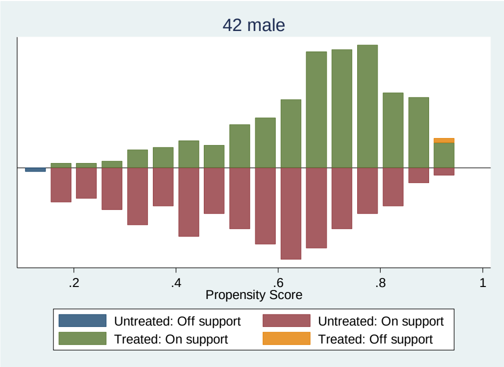
Treated: Off support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.4
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Propensity Score
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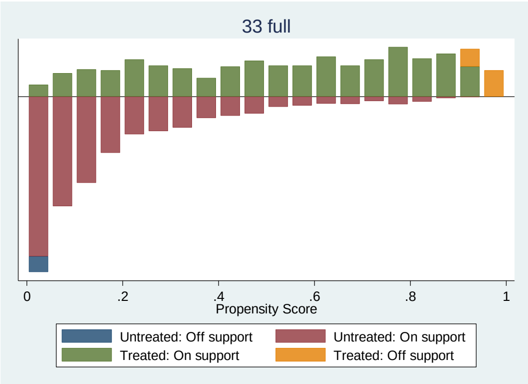
Model 2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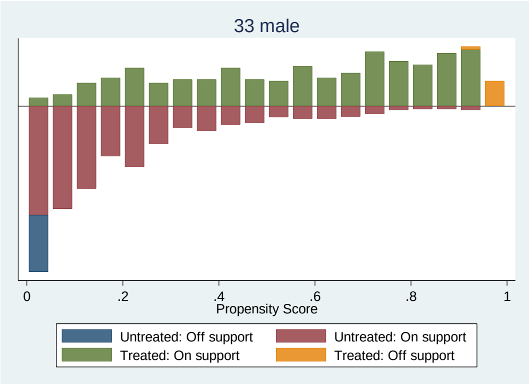
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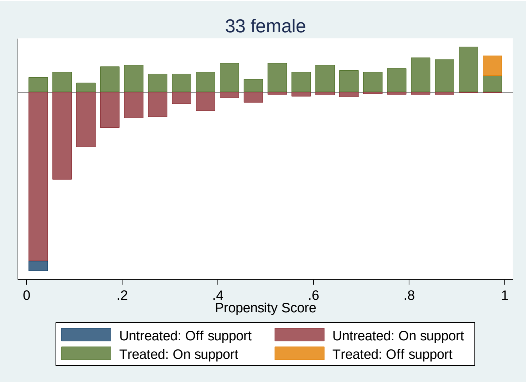
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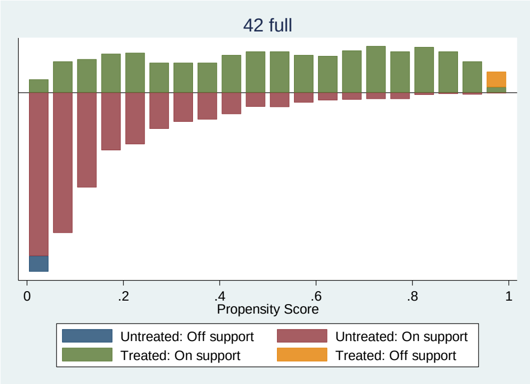
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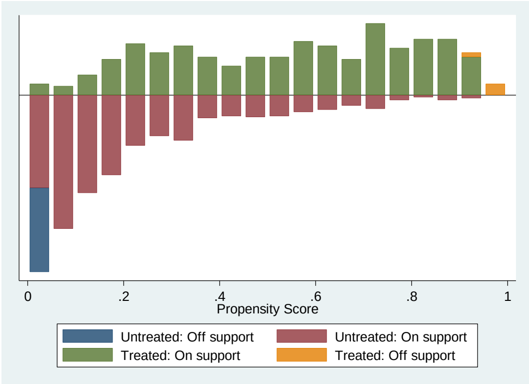
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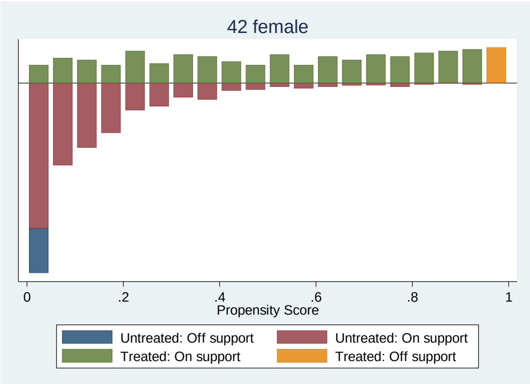
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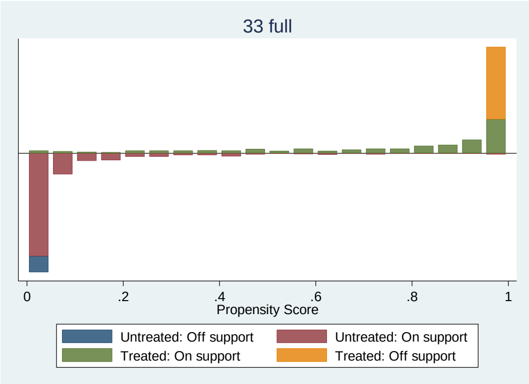
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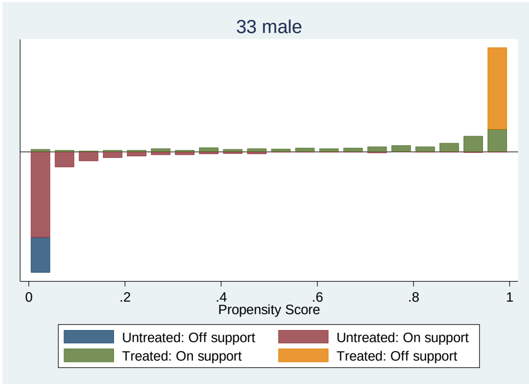
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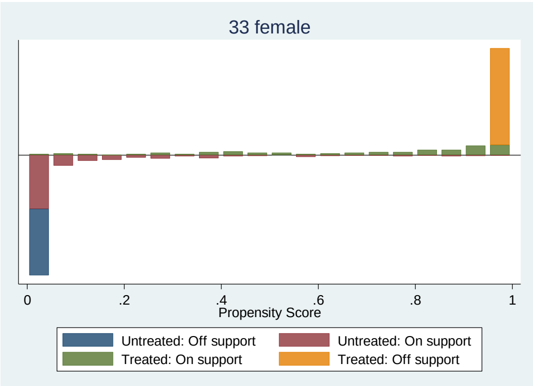
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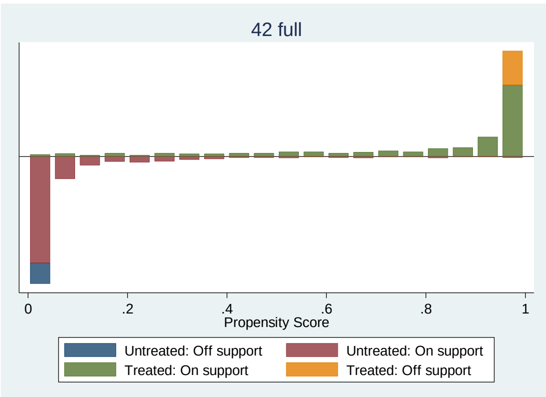
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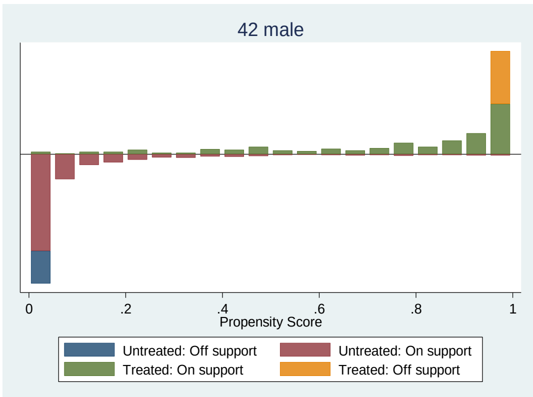
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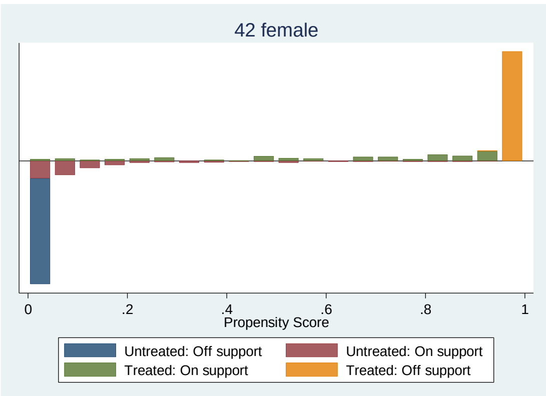
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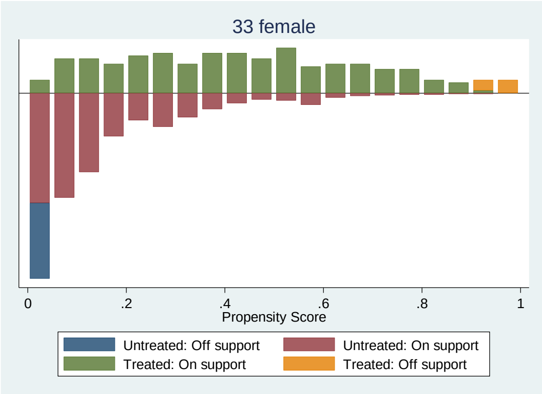
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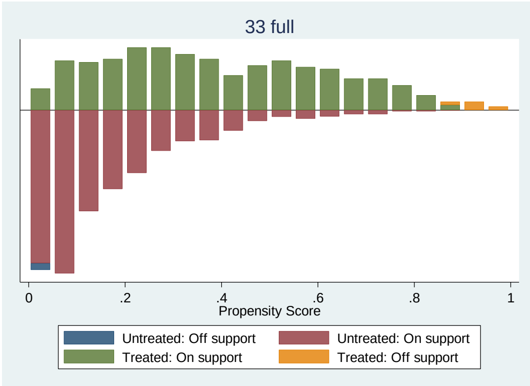
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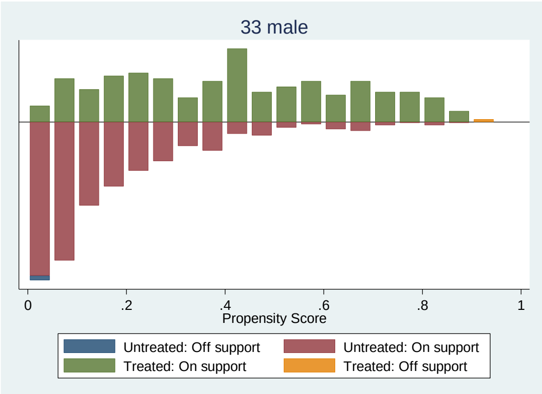
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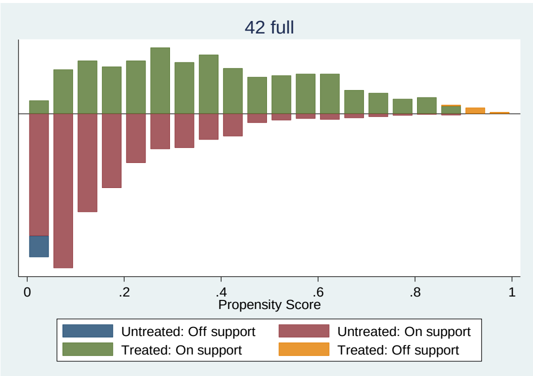
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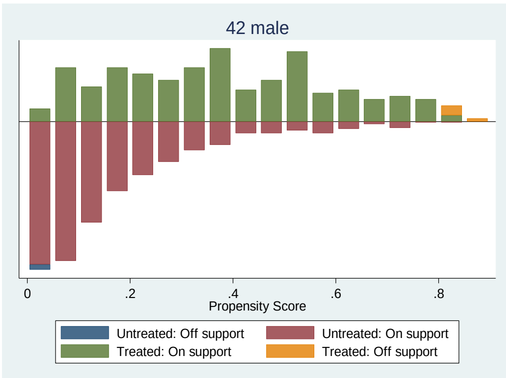
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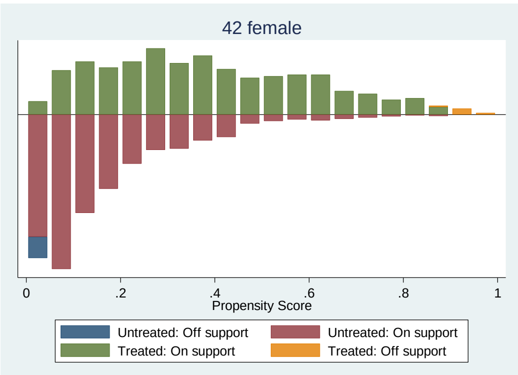
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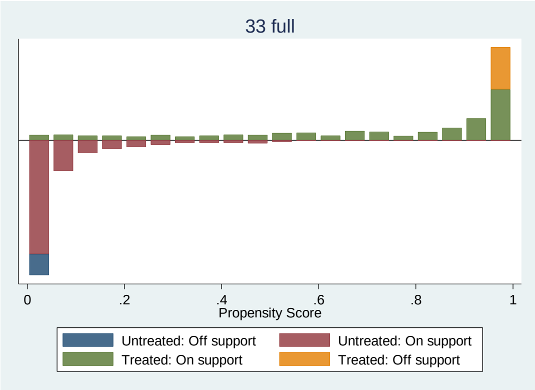
Model 5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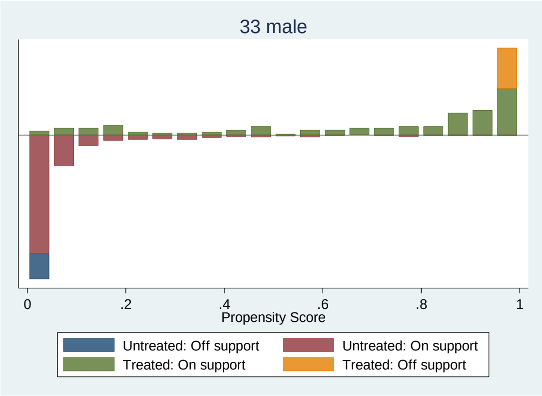
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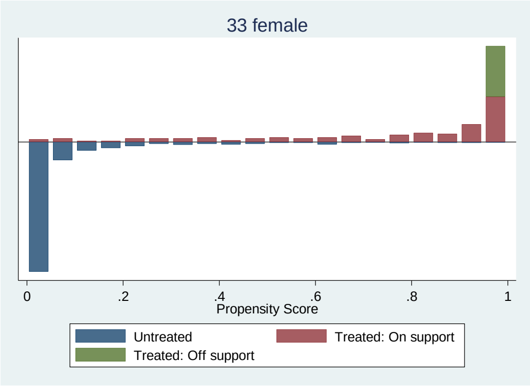
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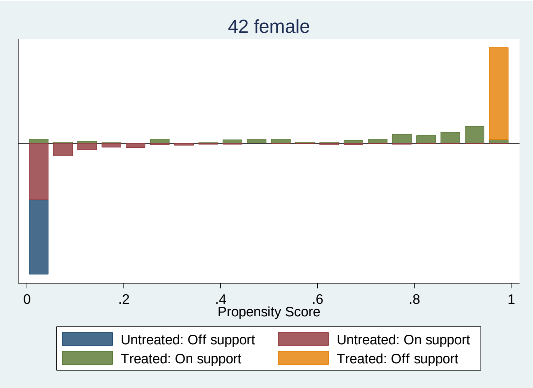
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Propensity Score
Untreated: Off support
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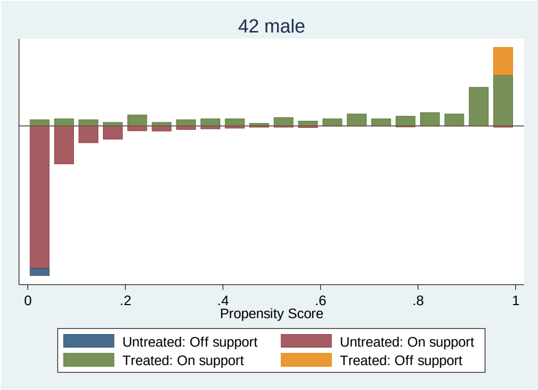
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Propensity Score
Untreated: Off support
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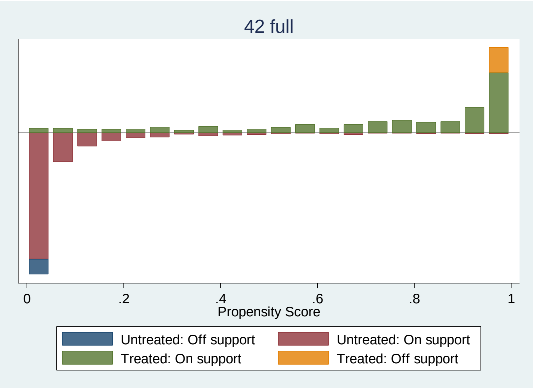
42 full
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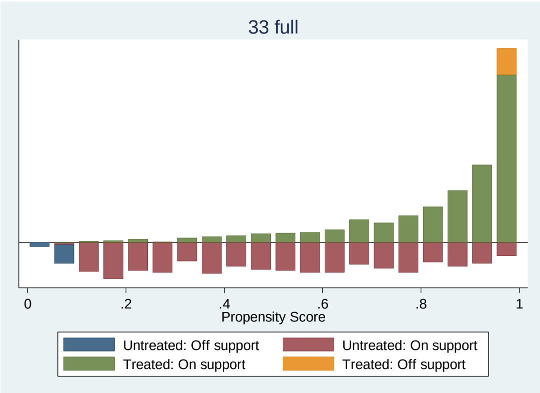
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

Model 6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Propensity Score
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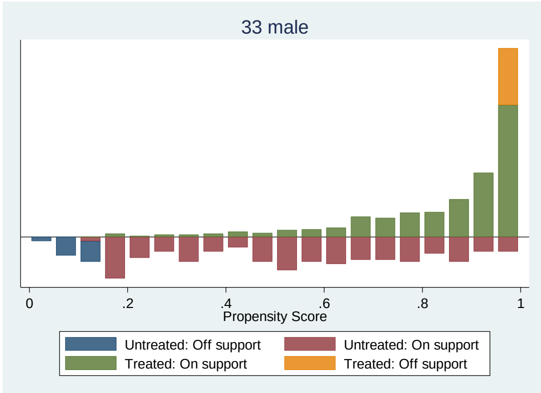
33 male
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Propensity Score
Untreated: Off support
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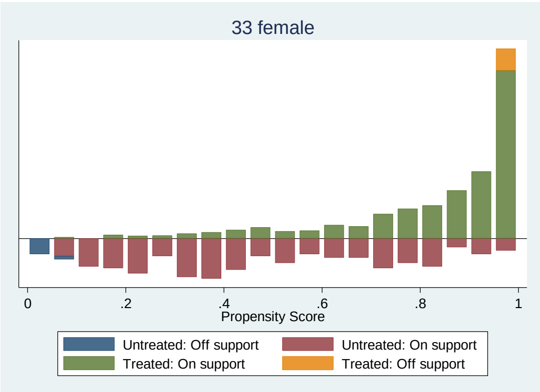
33 female
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Propensity Score
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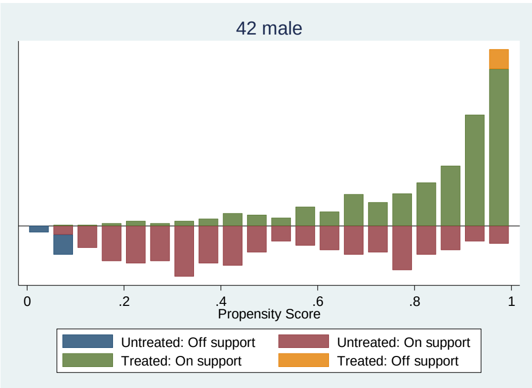
Untreated: On support
Treated: On support
Treated: Off support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Propensity Score
Untreated: Off support
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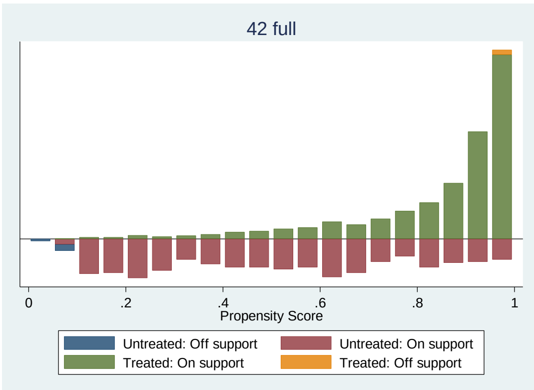
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Propensity Score
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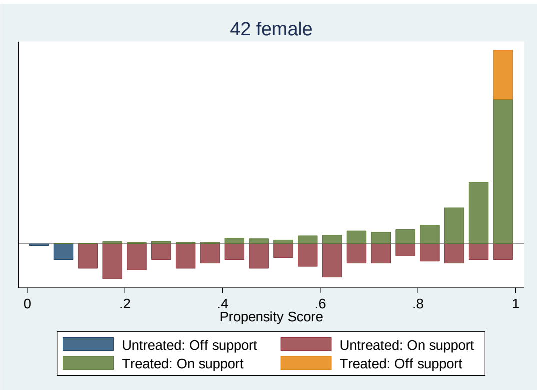
42 female
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Propensity Score
Untreated: Off support
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APPENDIX B: Classification of educational qualifications

B.1. The British educational system

Progression at school beyond the minimum leaving age of 16 years is based on a series of nationally assessed examinations. The wide range of academic and vocational qualifications has been classified into equivalent National Vocational Qualification levels, ranging from level 1 to level 5. Until 1986, students at 16 years of age had to decide whether to apply for the lower level Certificates of Secondary Education (CSE) option or for the more academically demanding Ordinary level (O-level) route (the top grade (grade 1) achieved on a CSE was considered equivalent to O-level grade C).Whereas most CSE students tended to leave school at the minimum age, students who took O-levels were much more likely to stay on in school. (In 1986 CSEs and O-levels were replaced by General Certificates of Secondary Education.) Those staying on in school can then take Advanced levels (A-levels) at the end of secondary school (age 18 years). A-levels are still the primary route into HE.

B.2. No qualifications

The no qualifications group also includes very low level qualifications at National Vocational Qualification level 1 or less, that is: CSE grade 2–5 qualifications, other business qualifications, other qualifications not specified, and Royal Society of Arts level 1 qualifications.

B.3. O-levels or equivalent

The O-levels or equivalent group includes O-levels or CSE grade 1, but also a range of vocational equivalents to these academic school-based qualifications: Royal Society of Arts level 2 and 3; City and Guild operative, craft, intermediate, ordinary or part 1; Joint Industry Board, National Joint Council or other craft or technician certificate.

B.4. A-levels or equivalent

The A-levels or equivalent group includes at least one A-level, but also a range of vocationally equivalent qualifications: City and Guild advanced, final or part 2, or the 3-year or full technological certificate; the insignia award in technology; the Ordinary National Certificate or Ordinary National Diploma, the Scottish National Certificate or Scottish National Diploma, Technician Education Council (TEC) or Business and Technician Education Council (BEC) or the Scottish equivalent SCOTEC and SCOTBEC certificate or diploma.

B.5. High Education

The HE group includes the Higher National Certificate or Diploma, the Scottish Higher National Certificate or Scottish Higher National Diploma, TEC or BEC, or SCOTEC or SCOTBEC Higher or Higher National Certificate or Diploma, professional qualifications, nursing qualifications including National Nursery Examining Board, polytechnic qualifications, university certificates or diplomas, first degrees, postgraduate diplomas, and higher degrees.

Chapter 3: Estimating the non pecuniary benefits of higher education

3.1 Introduction

Although there is a rapidly evolving economic literature studying non-pecuniary returns to education, including health, crime, and marital outcomes (Oreopoulos and Salvanes, 2011), a large body of research is more concerned with returns in terms of health outcomes and health-related behaviours. In particular, educational attainment has been found to have a positive association with various health outcomes: the so called "health education gradient" in decades of research (see Grossman 2006 for extensive surveys). The wider interest stems from the fact if a true causal effect of education on health exists, then the individuals' educational attainments probably represent the most obvious means through which policy makers could affect their health (Braga and Bratti, 2012). Although health education gradient may result in part from reciprocal casual effects between educational attainment and health status, recent research suggests that education does indeed have a causal effect on health (Currie and Moretti 2003; Lleras-Muney 2005; Wolfe and Zuvekas, 1997). Individuals with high levels of education have made an investment in themselves to protect themselves by taking preventative measures to increase the probability of better health; hence, higher educated people tend to have better health than those with lower levels (Saxton, 2000).

The standard OLS or Logit/Probit estimation may only represent simple correlations and face endogeneity (of education) problems, most scholars use instrumental variable (IV) strategies based on regression discontinuity (RD) designs to identify causal effects (Adams, 2002; Arendt, 2005; Clark and Royer, 2010; Glied and Lleras-Muney, 2003; Jürges et al.2009; Meghir et al., 2012; etc). These studies usually only differ in terms of econometric specifications and focus only on single or very few health outcomes and behaviours at a particular age. However, the causal effect of education on the various types of health outcomes has been rarely investigated by using other techniques.

Therefore, the goal of this paper is to construct an estimation of the magnitude of the health returns to higher education (HE). I am not the first to investigate the causal effect of HE on health and health-related behaviours. However, in this paper, I seek to add contributions to the existing literature in three main respects. First, I identify and estimate the treatment effect of HE on health and health-related behaviours by using the Propensity Score Matching (PSM) methodology, which has been intensively discussed in Chapter One. The causal effect of the treatment is usually defined as the change in health outcomes caused by a potential move from untreated to treated status, or *vice versa*. Here, I only focus on assessing the average treatment effects on treated assignment (ATTs); in other words, the premium if individuals have been obtained HE attainment relative to their counterparts (non- HE attainment). It facilitates comprehensive evaluations of employing balance test to check the satisfaction of CIA assumption, a “thick-support” region test (Black and Smith, 2004) to check the estimates robustness, and associated Rosenbaum Bounds (R-bounds) to check the satisfaction of selection on observable assumption.

Second, most existing studies generally consider a restricted number of health outcomes. However, since the National Child Development Survey (NCDS) I used in this study can provide richer data source on health and health-related variables, it is considered to investigate the causal effects on a wider set of health variables. In particular, I consider: (i) general health outcome: self-assessed health; (ii) body weight health outcomes: Body Mass Index (BMI) and threshold of obesity; (iii) health-related damaging behaviours: frequency of smoking and drink alcohol; (iii) mental health outcome: depression based on malaise score. All of these health and health behaviours outcomes together enable me to provide a more general assessment of the effect of education on health. The last innovation is the measurement of an individual’s health outcomes over an extended period of time from age of 33 to 50. By including extensive controls for family background characteristics, personal abilities and health status in childhood and adolescence, I characterise effect commonalities and compare differences between genders up to the age of menopause.

The structure of the rest of this paper is as follows. The following section reviews the background empirical models and related literature, with a special focus on papers seeking to estimate causal effects. Section 3 describes the details of each health and health-related behaviour indicator, and the potential covariates are included in the specification to calculate the Propensity score (PS). Section 4 briefly present the empirical model used. The main results are reported and corresponding test results are discussed in Section 5. Finally, Section 6 highlights the main findings and concludes this paper.

3.2 Literature review

The non-monetary benefits to education were posited in the very earliest work on human capital (Schultz 1961, Becker 1964). From an education perspective, the strength of this relationship suggests that health could be one of the most important sources of non-monetary returns to education (Adams, et al. 2003). Health outcome is an area where there has been a significant body of research literature on the impact of HE in recent years. There is a substantial body of literature examining the well-established yet striking correlation between education and health,[22] but few studies have addressed whether this relationship depends on a causal mechanism since the associations between health and education are not always clear-cut. The available evidence on the causal effect of education on health under controversial and covers a small numbers of countries. Some studies conclude education has a positive effect on health, such as: Adams (2002), Mazumder (2008), and Oreopoulos (2007) for the US; Arendt (2008) for Denmark, Jürges et al. (2011) for Germany; and, Silles (2009) and Oreopoulos (2007) for the UK. On the other hand, some find little or no effects, such as: Clark and Royer (2010), Braakmann (2011), Jürges et al. (2009, 2011) for the UK; Albouy and Lequien (2009) for France; Arendt (2005) for Denmark; Kempter et al.(2011) for German; and, Meghir et al. (2012) for Sweden.

Theoretically, education could improve health through at least the following

[22] As shown in Banks et al. (2006) and Cutler & Lleras-Muney (2007), even at lower levels of education in the UK, these correlations are still strong.

channels[23] that have been proposed in the existing literature:

(a) Raising efficiency in health production, or the *productive efficiency* argument (Grossman, 1972). The main idea is that education directly affects the health production function. Given the same quantity of inputs, more educated individuals produce a higher stock of health than less educated ones. For example, education may impart direct knowledge about health and health behaviours, thereby shifting the health production function.

(b) Changing inputs in health production, or the *allocative efficiency* argument (Grossman, 2005, Rosenzweig and Schultz, 1983). This proposes the idea that education will have no impact on health unless it changes inputs in the health production function. The main mechanism through which education can affect the inputs is by increasing health-related knowledge (e.g. harmful effects of smoking, harmful effects of heavy drink).

(c) Changing time preference (Fuchs, 1982, Becker and Mulligan, 1997), which can be explained that individuals with a high discount rate are likely to be impatient, more likely to invest less in education, and more likely to engage in health-damaging behaviour. Hence, from the this point of view, there could be a negative correlation between education and smoking which stems from an unobserved variable that does not reflect a true causal relationship.

(d) Changing economic factors (e.g. labour market opportunities and income) (Feinstein , 2003, Lochner, 2011) may result in higher levels of income, which encourages individuals to engage in healthy activities and eat more nutritious food. In addition,

[23] Lochner (2011) lists the channels through which education may improve health with other identifications: stress reduction, better decision making or better information gathering, higher likelihood of having health insurance, healthier employment, better neighborhoods and peers and healthier behaviors.

higher labour market opportunities allow individuals to work in less stressful jobs.(Case and Deaton, 2005; Cutler and Lleras-Muney, 2010) and more highly educated people may tend to work in safer environments (Cutler and Lleras-Muney, 2008).

(e) Changing behavioural patterns including diet, smoking, obesity, patterns of alcohol consumption, preventative care and so on (Huisman et al. 2005; Mackenbach et al. 2008).

Among the existing literature, education is reported to have both direct and indirect effects on health. The first two factors (i.e. (a) and (b)) are considered as a direct effect, whereas the others are indirect. These channels provide evidence of the causal effects of an individual's education on a very wide set of health variables investigated in the literature. In what follows, I will summarise these main findings in terms of the health outcome considered.

3. 2.1 General health indicator

Some papers focus on an individual's general health status, which is usually measured through self-reported heath (SRH) measures [24] or biomarker indicators [25]. Lleras-Muney (2005) tests the causality of education effects on mortality in the US using instrumental variables estimation techniques. By using OLS estimation, the author finds that an additional year of schooling lowers the probability of dying in the

[24] It is argued self-reported measures may suffer from a variety of biases. An alternative unbiased measure is to use the objective biomarker indicator. This is because biomarker is a medical indicator allowing characterizing a biological processes as normal or pathological or requiring a pharmacologic intervention.

[25] However, in practice, such information is rarely available. Researchers usually use other health indicator as biomarker indicator, such as BMI, hypertension or chronic conditions.

next 10 years by 1.3 %. By using the IV method, an additional year of schooling is estimated to reduce the probability of dying in the next 10 years by 3.6 %. Lundborg (2008) estimates the health returns to education using data on identical twins in the US for eliminate any unobserved factors that may simultaneously affect education (e.g. family backgrounds) and health (e.g. genetic traits). This study uses both SRH and the number of chronic conditions experienced in an attempt to eliminate any misreporting of health outcomes, and controls for income as a mediating variable. The results suggest there is a causal effect of education on health. Individuals with college levels are found to be positively related to SRH than with high school levels but negatively related to the number of chronic conditions. It seems that education does not always generate benefits, while more education could be associated with negative effects on some aspects of health (e.g. chronic conditions).

In the UK, using compulsory schooling law changes as instruments, Oreopoulos (2006) applies an IV regression approach[26] based on the General Household Surveys (GHS) and identifies a positive and significant effect of education on SRH. This study also reports a negative effect of education (using age left full time education as the measurement) on physical and mental disability in the US. Similarly, Silles (2009) using the same method based on data from Health Surveys of England (HSE) and finds a positive causal effect of education (year of schooling) on SRH, which is much larger than the OLS estimates. The author further indicates that the strong health

[26] In particular, the author adopts the regression discontinuity method involving comparisons at the quarter-of-birth level. A regression discontinuity design can mitigate policy changes concerns by exploiting sharp changes in educational attainment.

gradient is observed for other health measures, such as SRH and smoking behaviour. Using British Household Panel Survey, Contoyannis et al (2004) applied Maximum Simulated Likelihood (MSL) for a multivariate Probit model and find that educational attainment to self-rated health gradient remains significant, even after the inclusion of controls for lifestyles in the estimation and controlling for unobserved heterogeneity. The researchers divide participants into 4 groups (degree, A-level, O-level, no qualification) by their maximum educational attainment.

By contrast, Jürges et al. (2013) assess the causal link of compulsory schooling and health using two nationwide law changes in the minimum school leaving age in the UK as exogenous variation for education. Their result shows there is no causal effect between compulsory schooling and the two biomarkers.[27] The impact of education on SRH is only significantly positive among the older female cohorts, but was negative among younger female cohorts. The effect is insignificant among men across ages. Clark and Royer (2010) study the changes in the duration of compulsory schooling in the UK and find insignificant evidence of health returns in terms of improved health outcomes or changed health behaviours. The health outcomes they used are objective health measures, such as blood pressure, BMI, and levels of inflammatory blood markers.

[27] They are blood fibrinogen and blood C-reactive protein, respectively.

3.2.2 Health-damaging behaviours

The evidence on health-damaging behaviours is also mixed. De Walque (2004) investigates a negative effect of tertiary education on smoking rates in US. He uses retrospective data from the National Health Interviews Surveys from1940 to 2000. On average, the results from the OLS suggest that one additional year of college education reduces smoking prevalence by 4% and increases the probability of smoking cessation by 4%. When controlling for family income, the IV estimates are very close to the OLS estimates, decreasing smoking prevalence by 3.8 % and increasing the probability of smoking cessation by 5 %.

Other studies have come to similar conclusions; for example, Feinstein, et al (2008) find that UK graduates tend to be the healthiest and longest-living members of society. In particular, less educated individuals are 75% more likely to become smokers at age 30. Cutler and Lleras-Muney (2010) report that by controlling for age, gender, and parental background, higher educated individuals in the US and UK[28] are less likely to smoke, less likely to be obese and less likely to be heavy drinkers; on the other hand, they are more likely to drive safely, more likely to live in a safe house, and more likely to use preventative care. In particular, for the UK, individuals with an A-level qualification are 12 % less likely to be smokers than less educated individuals and 4 % less likely to become obese. Jürges et al. (2011) identify the effect of schooling on two main health-damaging behaviour outcomes in Germany: smoking

[28] In the UK case, they use data from Health & Retirement Study (HRS), Survey on Smoking (SOS), and NCDS to collect different health outcomes, and demographic and economic controls.

and obesity. Education is negatively related with smoking for both males and females. However, there is no causal effect of education found on reducing overweight and obesity. Kuntsche et al. (2006) confirms that educational attainment has an influence on drinking behaviour among young people in Holland. Individuals with lower educational attainment are reported to be almost three times more likely to start excessive alcohol consumption than those with a university degree. Le Tien et al. (1998) apply logistic regression analysis and report that years of schooling are negatively related with extreme alcohol use controlling for gender and age. Arendt (2005) using the Danish school reforms of 1958 and 1975 as an instrument for educational effects, and estimates the effects of education on obesity (BMI). The results from their OLS estimation suggest that an additional year of education is associated with a decrease of 0.207 and 0.173 in BMI for both genders, whereas when using IV estimates they found that education has a causal and significant impact on reducing BMI by 0.355 for men but was not significant for women.

In contrast, Lundborg (2008) finds insignificant effects of education on smoking and obesity. The author further attempts to investigate whether overall health is affected through lifestyle, but he cannot establish a causal relationship. Lifestyle factors, such as smoking and overweight, are found to contribute little to the ‘education to health gradient’. In addition, this raises the issue of the mechanisms through which education affects health. For example, it can be argued that smoking behaviour is a health outcome which may be directly influenced by education, but indirectly through peer effects or through occupational choice by way of network effects. In this case, smoking will affect overall health later in life.

3.2.3 Health preventative behaviours

Education to some extent induces individual to have healthy lifestyles. Feinstein and Sabates (2004) propose a probit model based on data from British Household Panel Survey (BHPS) to assess the relationship between education and health, particularly the uptake of health services in UK. The evidence finds that education has a direct effect on preventative health by raising awareness of the importance of undertaking periodic health tests. It favours a mechanism by which education increases the individual's self-efficacy and confidence, while also improving access to health services by increasing the individual's patience and motivation. The impact is still significant and robust after controlling factors such as income, social economic status, and personal life circumstances. The same conclusion is reached by Fletcher and Frisvold (2009), who report spill over effects of increased education on preventative health care choice based on Wisconsin Longitudinal Study in the US. College graduates are associated with approximately 5–15 % increase in the likelihood of using several types of preventative care. However, Clark and Royer (2010) show no evidence that education improves behaviours in terms of dietary regime and regular physical activity in the UK.

3.2.4 Mental health

From the point of view of HE participants, I personally suppose that the positive effect of education may be counteracted somewhat by the increased pressure and stress caused by the expectations that individuals may place on them. A higher occupational grade is associated with greater income, more control over the working life, and with more varied and challenging work, and thus reduced morbidity (Marmot et al., 1991) but also higher levels of stress (Rose, 2001).

Bynner et al. (2002) study a wide range of benefits of HE based on NCDS and BCS. They find that graduates are generally less depressed and present a higher sense of wellbeing than those with lower educational attainment. Feinstein (2003), using data from the NCDS and BCS and matching methods, shows that controlling for childhood abilities, health and family background factors, women from the 1958 cohort with lower secondary education have a 6% lower likelihood of depression than women with no qualifications, while these effects for men are weaker. In general, the results show that differences between individuals with different qualifications are substantially eroded when the selection bias is dealt with using matching methods. Chevalier and Feinstein (2006) rely on NCDS dataset to control for childhood determinants and measures of mental health over the individual's life span to account for possible endogeneity of education. Using PSM, they estimate that individuals with at least O-levels reduce their risk of adult depression by 6 %. This effect is similar for men and women. However, Russell and Shaw (2009) focus on HE students in the UK and point out that a significant proportion of students studying in higher education present social anxiety, of which 10% students are marked to have severe social anxiety. Nonetheless, this study does not identify a casual effect.

I summarise the existing evidence as follows. First, the existing evidence on the causal effect of education on health is inclusive and contains a small numbers of countries. Second, besides methods of standard OLS and probit model, large numbers of studies apply IV regression method with RD design for identification, while the compulsory schooling age reforms are a very common instrument. Third, there are a very limited number of studies investigating the effect on mental health and depression.

3.2.5 Matching related literatures

Studies of effect of education to health status disparities have rarely been found in literatures by adopting PSM or matching related approaches. Only two studies are related to the application of matching mechanism. Rosenbaum (2012) used data from the National Longitudinal Study of Adolescent Health to compare young adults ages 26 to measure the effect of highest degrees on measures of hypertension, obesity, smoking, sleep problems, and depression. The method they applied is the nearest-neighbour mahalanobis matching within propensity score calipers. After matching, they found participants with baccalaureate degrees were 60% less likely to smoke daily, 14% less likely to be obese, and 38% less likely to have been diagnosed with depression.

On the other hand, Conti et al (2010) go beyond the existing literature which typically estimates mean effects to compute distributions of treatment effects and apply the matching method to show how the health returns to education can vary among individuals who are similar with respect to their observed characteristics. Based on a positive correlation between health and schooling conclusion, they then estimate causal effects of education (year of schooling) on adult health and healthy behaviors in a form of matching using the British Cohort Study in 1970. They conclude education has an important causal effect in explaining differences in many health behaviors, (such as smoking and regular exercise) as well as on a number of other outcomes (such as obesity poor health and depression). Besides that, they also show that family background characteristics, and cognitive, non-cognitive, and health endowments developed by early ages, are important determinants of labour market and health disparities at age 30.

3.3 Data

The data used in this paper came from the British NCDS, which is identical to Chapter One. The reason why I have continued to use the NCDS data is because I can utilise the panel feature of the NCDS in order to examine changes in educational attainment, and health indicator and health behaviours between the waves.

3.3.1 HE attainment

Simiar to Chapter One, I classify treatment group (HE) as an invidual's entry to all forms of higher education, including diploma, degree level, and higher degree level, and a control group (non-HE) who obtained one or more A-levels but who did not proceed into HE. I will not present descriptive information on HE attainment here because it has been described in detail in Chapter One.

3.3.2 Dependent variables

Six health-related outcomes are chosen across different ages, including: two indicators of general health status - self-reported health and measured BMI; three indicators of healthy behaviours - alcohol drink frequency, smoking frequency, and obesity; and, one indicator of mental health status - Malaise score.[29] Among these variables, self-assessment of health self-reported health, frequency of drinking alcohol, smoking frequency and Malaise score are directly collected from NCDS. BMI is

[29] Malaise score is calculated from 24 questions on various aspects of well-being and somatic conditions. Since the questions do not directly ask about mental health, the malaise score is likely to be less biased by stigma and misreporting than other more direct measures. In this paper, I use derived score directly from NCDS.

measured based on an individual's height and reported weight. Obesity is categorised by BMI. Since most of the health indicators and health behaviours are ordered and categorical variables, instead of reporting the descriptive statistics I will present the distributions of each indicator (expect for measured BMI and Malaise score).

(a) Self-assessment of health

The first general health indicator is presented as the self-reported health (SRH) made by individuals. It is a subjective indicator of health that individuals assess relative to a representative person of the individual's own age. In NCDS, it measures how they feel about their health by using four categories: excellent, good, fair, and poor. I recode self-reported health so that a higher number corresponds to better SRH (i.e. 1 = poor, 4 = excellent). In Table 3.1 it can be seen that 35% of the participants have excellent health at the age of 33. This falls to 31% at the age of 42, and is less than 20% at 51 years old. Over half of the participants assess themselves to have good health after the age of 33. Only 2% of the respondents reported as having poor health at the age of 33. However, this increases to 3% at the age of 42 and was about 6% for the group of 51 year olds. The women with poor health is greater than men for all age groups. For both men and women, over 50% report themselves as having good health when they are younger, and this rises to over 60% at 51 and above. Figure 3.1 and 3.2 illustrate the distribution of SRH for different age levels by genders. Table 3.2 shows that the self-reported health conditions across different qualifications over lifetime. It can be seen more directly of the differences of health conditions across different qualifications through lifetime. More participants with HE always reported good health conditions than other participants without HE. Better educated people always have better self-reported health conditions. Moreover, at younger age of 33, over 45% of participants with HE reported having an excellent health condition. It declined to 40% at their middle age of 42 and even only about 29% after 50 year-old. However, more participants without HE qualification (e.g:None qualification and GSE) always reported poor health condition compared to those with higher qualifications (e.g: at least 1 A level and HE). For example there is more than 10% of participants with none qualification reported poor health at age of 50, which is 7% higher than that at age of 33. Thus, more people reported poor health when they are getting older. Better educated people still have a large proportion of having a good health compared to others with low qualifications.

However, the SRH seems to suffer various biases. In NCDS, the childhood health indicator relies upon objective medical examinations, while the data in adulthood health is self-reported. It is argued that individuals with disadvantaged socioeconomic characteristics tend to have a more negative view of their health status, and are more likely to report a poorer health condition (Marsh et al. 1999). In this case, I chose data at age 42 as an example and apply a correlation analysis to assess the association between self-reported and chosen variables. This suggests increasing correlations between self-reported health status (Health 42) and a monotonic increase in an individual’s social class, but the correlation coefficients are relatively small. However, self-reported health is highly correlated with long term limiting health and hospital admission, and the correlation in SRH among three periods ranges from 0.46 to 0.55. These high correlations highlight the persistence of SRH over time and suggest that this indicator truly captures some permanent features of an individual's general health status. All of the aforementioned correlation analysis is reported in Table 3.3. Hence, categorical measures of SRH are still considered to be an adequate indicator of general health status and are widely used in many studies.[30]

(b) BMI

Since general biomarkers such as blood C-Reactive protein, blood Fibrinogen, Von Willebrand factor are only available in NCDS Biomedical survey in 2002 (age 42), the second general health indicator is considered to use the BMI, which is usually seen as an objective health measure in the literature. BMI is a useful measure of being overweight and obese, it is an estimate of body fat and is a good gauge of the risk of diseases that are associated with more body fat. The higher the BMI, the higher the risk for certain diseases, such as coronary heart disease, high blood pressure, type 2 diabetes, gallstones, stroke, breathlessness, hypertension, depression, arthritis and cancers.[31]

I use the following formula to calculate the respondents' BMI:

$$BMI = \frac{weight(kg)}{[height(m)]^2} \quad \text{or} \quad BMI = \frac{weight(lb)}{[height(inch)]^2} \times 703$$

[30] For example, van Doorslaer et al. 2000,Manor, Matthews & Power, 2000, Graham & Power (2004), Hertzman & Power (2004), Power & Elliott (2006)

[31] Detailed complications of obesity can be found on the NHS website, available at : http://www.nhs.uk/Conditions/Obesity/Pages/Complications.aspx

The NCDS records the height and weight of the respondents at all sweeps, except for Sweep 7 in 2004. In Sweep 6 (age 42) and Sweeps 8 (age 51), weight and height are self-reported, whereas in Sweep 5 (age 33) they were measured by the interviewers. It is then argued that substantial measurement errors exist in self-reported height and weight (Rothman 2008). For instance, overweighed responders may under report their weight. Several variations based on the BMI have been suggested in order to tackle this measurement error problem in many science studies. For example, Burkhauser and Cawley (2008) use a prediction equation [32] to produce a more accurate BMI to correct classical measurement errors. However, due to the data limitation, I cannot tackle the measurement error in this case. Table 3.4 and Figure 3.3 summarise the descriptive statistics and distributions of BMI. The individual's BMI gradually increases with age. It should be noted that BMI figures are all above 25.5 when individuals become middle-aged. Furthermore, BMI figures are almost normally distributed and do not need to be log-transformed.

The measures of BMI can also be used to construct an indicator of being overweight or obese. According the classification from World Health Organization (WHO), I place measured BMI into four categories, which are: under weight, normal weight, overweight, and obesity (see Table 3.5).[33] It should be noted here that being obese is a health behaviour rather than a general health indicator.

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[32] This require triceps skinfold thickness, waist-to-hip ratio, and bioelectrical impedance analysis to calculate Total Body Fat (TBF) and Percent Body Fat (PBF). Again, these data are only available in the 2002 Biomedical Survey.

[33] WHO classification can be found at: http://www.who.int/mediacentre/factsheets/fs311/en/

Table 3.6 shows the percentages of BMI categories by gender. Among the 33 year olds, about 50% of males have a normal weight and more than 60% of females have a normal weight. Men tend to be more overweight (40%) and obese (10%) than women. Only 24% of women were measured as overweight and 8% were obese. Overall, for the group aged 33, over half of the respondents had a normal weight. However, this changes after 10 years. Among 42 year olds, nearly 46% of men were measured as overweight and 15% were obese. The percentage of people with normal weight falls to 45% compared to 55% at age 33. About 10% of the males w ho had a normal weight at 33 became overweight or even obese at 42. The majority of men at 42 were overweight (46%) but most women (53%) still had a normal weight. At 51 years old, the percentage of men and women with a normal weight falls sharply. Only 27% of men stayed at a normal weight in this category. The percentage of men who are overweight at 51 rises to 46% and obesity rises to 25%, which more than doubled when compared to the age of 33. Overall, about 40% of older people were overweight compared to those with a normal weight at 33. The majority of women kept a normal weight at different age groups. However, men changed from a majority having a normal weight at 33 years old, to the majority becoming overweight and obese after 42 years old. For the 51 year olds, over 70% of men in total were suffering some kind of weight problem. Figure 3.4 exhibits the distribution of obesity by ages while figure 3.5 illustrates the distribution of obesity by educational attainment. At 33 years old, there are over 60% of both participants with and without HE having a normal weight.

However, there is a further 4% more for participants with HE compared to those without HE. The proportion of overweight for participants without HE is about 28% and slightly higher than those with HE (26%). For the obesity category, participant with HE is always less than those without HE over time. It can be seen a similar trend for both age 42 and 50 above. Better educated people are more likely to have a normal weight over life time. However, people without HE are more likely to have overweight and obese problem. As participants getting older, there is about 10% changing to overweight and obese from normal weight.

(c) Frequency of drinking alcohol

Table 3.7 describes the frequency of drinking alcohol by gender at three different age groups. At a younger age, 36% of men and 30% of women drink 2 to 3 days a week. There are about 25% of men drinking on most days, which is 10% higher than women. In the category of "never had an alcoholic drink", there are always more women than men. The total percentage of participants who drink more than "once a week" is about 72% at age of 33, and it goes up to 74% at 42 years old. When the respondents were at 51 or above, it goes down to 71%. Less than 30% have good drinking behaviour. Comparatively, the women drink less than the men. Figure 3.6 presents the distribution of alcohol drink frequency by ages.

(d) Smoking frequency

In Table 3.8, I find that over 45% of participants were non-smokers. At of the age of

33, about 26% of people in total smoke every day, women were slightly more inclined to smoke than men. At 42 the numbers of both men and women who never smoke cigarettes increased by 2%. The percentage of respondents who smoke every day dropped by nearly 4% compared to 26% at age of 33. This continues going down by 2% at 51 years old and above. This means that more smokers turn into non-smokers as they age. The percentage of women who were non-smokers is always greater than men in all age groups. Figure 3.7 and 3.8 illustrate the distribution of smoking frequency by ages and by qualifications, respectively. Better educated people always smoke less than Non-HE group. Thus, participants with HE had a better sense of having a good living style.

(e) The depression indicator

Some research argues that the better educated are substantially less likely to report themselves as suffering from anxiety or depression (Culter and Lleras-Muney 2006). Hence, I use an objective indicator that reflects mental health. The malaise score was designed to identify depression in non-clinical settings and has been found to be a good indicator of depression (Rutter et al., 1970). It is widely used as a broader measure of the mental health and depression (chevalier and Feinstein, 2006). In NCDS, the malaise score is calculated from the *Malaise Inventory* (Rutter et al, 1970), which is a set of 24 self-completion questions combined to measure levels of psychological distress, or depression. The 24 'yes-no' items of the inventory cover emotional disturbance and associated physical symptoms, thus the score ranges from 0 to 24. Figure 3.11 illustrates the distribution of malaise score at different ages. The distribution is very positively skewed, making the mean a less desirable basis for comparison.

According to the classification defined in NCDS, individuals responding 'yes' to eight or more of the 24 items (i.e. malaise score = 8) are considered to be at risk of depression. Hence, I separated the responders into two groups, individuals with and without the risk of depression based up on measured malaise score. As seen from Table 3.8, the gender difference is obvious and women were more likely to feel depressed than men. At 33, only 3.9% of males felt depressed compared to 6.8% of female participants. Individuals at a younger age are comparatively more optimistic and tend to think positively about their current status and future life. However, the percentage of respondents with depression at 42 years old rises to 7.7% for men and 12.4% for women. At age 50, it only falls by about 1% for both males and females, reported as 7.1% and 11.3%, respectively. It can be concluded that middle-aged participants are more likely to feel depressed than other age groups due to the stress from work and family. Figure 3.9 and 3.10 exhibit the distribution of depression by ages and by qualifications respectively. It shows that more participants reported of having depression when they grow older for the Non-HE group. It increased from only 9% at a younger age to 17% at mid-age and nearly 20% at 50 and above. For the HE group, only 7% of participants reported to have depression at age of 33. It starts to rise to 15% at age of 42 but declined to 14% at 50 and above. Hence, better educated people are less likely to be depressed over lifetime. It has an increasing trend at mid-age for the HE group but declining when they grow older.

3.3.3 Potential confounding variables

Now I turn to consider which potential confounders should be included for calculating the PS. Chandola, et al (2006), following Blane (2003) and Feinstein (2002), summarise the links between education and health investigated in the previous literature and highlighted six plausible pathways for which evidence has been consistently found.[34] The first pathway is cognitive ability in childhood. This may

[34] The six pathways include: (a) cognitive ability in childhood; (b) childhood socio-economic circumstances; (c) childhood and adolescent health (d) adult socio-economic circumstances; (e) adult socio-economic circumstances; (f) individual’s sense of controls

confound the association between education and health because it affects both educational attainment and adult health outcomes, and education exerts direct effects on heath by improving cognitive ability. Therefore, cognitive ability may be directly linked to health behaviours and improved decision-making skills.

Second, childhood socioeconomic circumstances may confound the education-health association because it influences educational attainment as well as health. Higher parental social class is strongly associated with greater parental interest in the child's education and, consequently, better educational attainment (Feinstein and Symons, 1999). Lower parental social class in childhood has also been strongly associated with greater morbidity in adulthood (Power and Hertzman, 1997). The association between education and health could therefore arise from the effect of parental social class on educational attainment and adult health. Third, childhood and adolescent health may confound the association between education and health (Grossman, 1976)[35] because it could influence a individual's educational achievement and attainment (Conley and Bennett 2000; Jackson 2009) and later, adulthood health (Jefferis et al., 2002) and mortality (Bengtsson and Lindstrom 2003).

The other pathways are mediators which should not be included in the confounder

[35] Grossman (1976) uses a recursive system of equations to formulate and estimate health-schooling relationships. He found that schooling has a positive effect on health by controlling the past health in his model. His findings indicate that a one-year increase in schooling brings a 3.5 percent increase in health capital when only keeps age constant. The increase in health capital declines to 1.2 percent when all of the relevant variables are held constant; for example age, ability levels, wage rates, background characteristics.

pools. For example, adult health behaviours may mediate the effect of education on health because education might affect a person's receptivity to health education messages which could have a beneficial influence on their health through health promoting behaviours and lifestyles (Fuchs, 1979; Keneckel, 1991). An individual's sense of control over their life may mediate the association between education and health. Education increases the sense of personal control by developing analytic and communication skills (Mirowsky and Ross, 1998). The sense of personal control may also improve health through enhancing healthy behaviours by controlling one's immediate addiction for future long term health benefits (Folkman, 1984), whereas the lack of personal control may be a stressor with consequent adverse physiological consequences (Ross and Wu, 1995).

Therefore, I summarise that an individual's personal ability, family background[36] and childhood health variables are chosen as potential confounders that affect both adulthood health and educational attainment, thus potentially confounding the association between education and health. The NCDS contains rich information on health issues, including the individual's initial health assets, the socioeconomic status during early childhood, and cognitive ability during childhood. Since the descriptive statistic for personal ability and family background variables have been presented in a previous chapter, here I only list the information on childhood health status.

I first measure child health before age 7 (educational entrance) with a measure of the

[36] Also used as covariates in Chapter 2.

infants' low birth weight and maternal behaviour; that is, whether the mother smoked after the fourth month of pregnancy. A widely accepted cut-off as being low birth weight is responders for whom a birth weight of less than 2515g. Secondly, an individual's childhood physical and mental conditions are diagnosed and reported in a medical examination from each Sweep.[37] The medical examination is considered as a relatively unbiased measure since it reflects the condition impeding normal functioning, rather than self-evaluation. I create global measures of childhood general health status by separating physical and mental impairments. There are two reasons to construct this measure. First, it attempts to focus on persistently poor general health. I create variables indicating if there is a diagnosis that the child has had health problems during childhood and adolescence (i.e. ages 7, 11, 14 and 16). An individual with childhood health problems at a single age stage will not necessarily have the same problem across their entire childhood. Second, there are 18 category variables to indicate an abnormal health condition during childhood, which in turn would generate 18 dummies to present such attributes thereafter. However, some dummies may be omitted when calculating the PS.[38]

Instead of using a mental health indicator derived from medical examination, I will use the *Rutter behaviour score*, which is an alternative measure that is widely accepted and used in health economics studies. The *Rutter Behaviour Scores* reported

[37] Physical health conditions include genetic conditions, physical abnormalities (e.g., spinal or limb disfiguration) and systemic abnormalities (e.g., heart, respiratory, blood conditions). Mental health conditions include mental retardation, emotional and behavioural problems.

[38] This happens when there are only a few attributes in such a dummy variable.

in NCDS is an index for assessing a participant's behavioural difficulties in childhood (Rutter, 1967, Rutter et al, 1970).[39] Here, I use the overall score measured based on the responder' mother's report. Figure 3.12 illustrates the distributions of the total Rutter score across three childhood ages. Again, all of the distributions depict a property of positive skewness. Therefore, categorical ratings are re-calculated dividing scores into three levels of severity: "normal" scores of less than the 80th %; "moderate problem" scores between the 80th and 95th %; and, "severe problem" above the 95th %. The missing and incomplete values of health and mental measures are due to non-participation in one particular Sweep, which are also included in a separate category. The descriptive statistics of childhood health indicator are summarised in Table 3.10

3.4 Methodology

To document the basic correlations between education and health, I estimate the following regression:

$$H_{it} = c + \beta_1 E_{it} + \beta_2 X_{1t} + \beta_3 X_{2t} + \varepsilon_{it} \qquad (3.1)$$

where H_{it} is a measure of individual's general health, mental health and health behaviours. E_i stands for whether individual i has done any kind of HE attainment. In this model, E_i only contains two values, which are 0 and 1, and represent individuals with or without HE respectively. X_{1t} is a vector of individual characteristics prior to

[39] The definition is from 'Teaching students quantitative methods using resources from the British Birth Cohorts" Available at : http://www.cls.ioe.ac.uk/shared/get-file.ashx?id=528&itemtype=document

HE decision. In this study, it includes race, region, personal innate ability, type of schooling, family background etc.; X_{2t} is a set of variables presenting childhood and adolescence health characteristics before the HE decision that may potentially depend on E_{it}. c is a constant term and ε is the error term. The coefficient on education β_1 (also referred to as the health education gradient) is the object of interest, and it measures the effect to HE on the particular measure of health status and health-related behaviour.

In this Chapter, I continue to use the PSM method to assess the casual effect of HE on health outcomes. Since PSM approach, and its corresponding matching algorithm and test have been discussed in Chapter 2, section 3, I will not present them again and hence go straight to the results.

3.5 Empirical result

Table 3.11 reports results for the Probit selection models (with HE to 1 in the binary dependent variable) that are used to generate the PS matched estimates. The estimated coefficients exhibit their expected signs. For example, variables such as parental years of education, father's social class with 'professional' are expected to have a positive effect on the treatment variable: HE. On the other hand, financial difficulties are expected to be negatively associated with HE.

I will first report the results for the entire sample, and will then report the results for males and females separately. I estimate the return on health by PSM in order to control the selection bias problem, for example an individual's ability and family background. The treated group includes the individuals who had completed some form of HE attainments. For the control group, the individual's highest education qualification is at least one A-level.

Before commenting on the results of the PSM, I will report a baseline model based on OLS estimates for male, female and pooled samples in Table 3.12. The aim of the baseline model is to assess whether HE is associated with changes in different indicators of adult health and mental outcome, and to find how the health behaviours change overtime with full controls of covariates, and the estimated result is not used for analysing. However, the OLS estimates are not appropriate for the nature of the outcome variables and most likely to be affected by the bias due to the endogeneity of education. Consequently, in the remainder of this section I will report and comment on the PSM estimation while controlling for a rich set of personal and family background, and individual characteristics in childhood and adolescence. The PSM estimates based on two different matching algorithms are presented in Tables 3.13.

In addition, histograms displaying the distributions of PSs for the treated and control groups are displayed in Figure 3.13. They are used to assess whether the overlap assumption was met in this study, and it clearly shows a complete overlap in the distributions of PS. The PS distributions and common support regions are illustrated in Figure 3.13.

3.5.1 General health indicators

I first examine the casual relationship between education and self-reported health outcome. The OLS result from Table 3.11 shows positive effects. The estimated coefficient for the age group of 33 is about 0.064 for pool sample, 0.037 for male, and 0.079 for female participants. In general, the effect for age 42 and 50 are somewhat similar to that of age 33. By gender, education has a greater effect for women rather than men.

However, once I include a full set of covariates, the effect of HE slightly increases in size, while this result is still robust and significant. As shown in Table 3.13 panel A, all of the estimated ATTs are statistically significant at 90% level. The effects on the pooled sample across ages have no significant differences: 0.08 point at age 33, 0.08 point at age 42, and 0.09 at age 50. Furthermore, once I allow for gender heterogeneity, the effect shows a monotonic increase with the increase of ages. Sub-sample analysis by gender further indicates that this result is significant for females where the effect size has a 0.03 margin more than that of the male group at all ages. For males, individuals with HE attainment at age 33 enjoy an extra 0.079 margin on SRH, 0.09 at age 42, and 0.1 at age 50, respectively. Females enjoy an extra 0.04 margin at age 33, 0.045 at age 42, and 0.067 point at age 50. The results seem to stress the importance of taking sex heterogeneity into account since the results from pooled estimates might be misleading, particularly for SRH.

Because the outcome variable SRH is an ordered categorical variable, it may not appropriate to show the percentage change from the estimated ATT results. I therefore compare the fraction of each group with the potential outcomes based on matched samples for both HE and non-HE subjects. This seems to be a relatively straight forward measure of the impact of HE to health status. By doing this, I first tabulate the matched sample size for both treated and control groups, then I calculate the different fraction of each outcome variable based on total matched sample size. The first panel in Table 3.17 indicates the consequent results for SRH. For example, 41.9% males with HE attainments of the total treated sample size are categorised as excellent, whereas that of non-HE males are computed as 32.5% of the total untreated sample. This implies the impact of a HE is to increase the incidence of good health by

30%. On the other hand, when measuring the risk of poor health status, the risk is more than double from 0.9% (with HE) to 2.6% (with non-HE). For females, the fraction of 'excellent' category are relatively close (38.4% and 37.0%), whereas the risk of having poor health status also doubles from 1.3% to 2.8% if females do not obtain a HE attainment. The rest of the results also show substantive evidence to suggest that HE has a significantly positive impact on an individual's general health status in terms of SRH condition over the age. Higher educated participants have better general health conditions and this impact increases as cohorts getting older. The results are somewhat consistent with previous finding by Ross and Wu (1995), and White et al. (1999), which suggest that education has a strong and positive effect on adult self-assessed health.

3.5.2 BMI and obesity

I will next investigate the association between education and BMI and obesity. The baseline estimates shows HE has a strong and negative associate with BMI. This suggests a massive decrease in BMI for obtaining HE attainment. Estimates are almost significant at age 42 and 50, but insignificant at age 33. The size of the association for males is larger than females in absolute values. However, it is striking that in pooled sample, the overall impact increase at age 42 but decreases 8 years later in the absolute value.

When turning to PSM estimation with the inclusion of full controls for covariates, estimated coefficient from PSM has no large difference comparing to OLS result (-0.297 compare to -0.259) at age 33 in the case of pooled samples. It should be noted here that although the PSM results support the OLS results, they are not directly comparable because the latter only provides an estimate of premiums based on whole sample in question while PS estimates are restricted to the area of common support. In terms of gender, participating in HE also appears to have a larger effect on reducing the BMI figure for males (0.356) than females (0.136) at age 33. However, except for males, none of these estimated coefficients is statistically significant at a moderate level. The HE educational reduces BMI figure up to 0.472 at age 42 and 0.617 at age 51 in the case of pooled samples. The decreased effects at age 51 in baseline model are not observed here. As the cohorts grow older, males still get more benefit from being highly educated to control the BMI figures. The figures are reduced by 0.529 at age 42 and 0.856 at age 50, respectively, almost twice as large as that of females.

BMI figure can be used to reflect a relatively objective health status and it is likely to be normal distributed. It used to access the impact of HE on overall health status. Obesity measures is a threshold value that derived from BMI, it is considered to mainly access whether HE can reduce the risk of being obesity. I therefore consider the effects of HE on the threshold of obesity. The estimated effect is still insignificant when the cohorts are aged 33 (a 0.064 margin for males and 0.015 for females). Once cohorts grow to age 42, the marginal effects become -0.123 for males and -0.107 for females, both significant at 95 % confidence level. The magnitude of the effect continues to slightly increase when individuals are aged 50, which accounts for -0.136 (males) and -0.114 (females). This implies that HE attainment have a significant but small restraining effect on obesity growth for individuals from age 42 to 50.

Moreover, being ‘overweight’ and ‘obesity’ in this study is based on an ordered categorical measure; therefore, males are conclude to be nearer ‘overweight’ and ‘obesity’ category than women for all age groups. According to what reported in the second panel in Table 3.17, the portion of ‘under’ and ‘normal’ weight are relatively close when comparing treated and control group for both genders. However, the risk of being obesity is increased by 38% (6.6% to 9.1%) at age 33, 75% at age 42 (8.1% to 14.0%) and 23.4% (15.4% to 19.0%) on average, if males do not obtain HE attainment; on the other hand, if females are only with non-HE qualifications, the risk of being overweight is brought up by 23.9% at age 33, 17.4% at age 42 and 48.2% at age 50.

3.5.3 Health behaviours

Panel B in Table 3.13 shows the results of the effect to HE on drinking alcohol by gender. As seen from this panel, all of these effects on health behaviour are relatively large. However, it is worth noting that these health behaviours only explain some but not all of the differences in general health. For example, in the famous Whitehall study of British civil servants (Marmot 1994), smoking, drinking, and other health behaviours can explain only one-third of the difference in mortality. Third (drinking frequency) and fourth (smoking frequency) panel in Table 3.17 report the fraction of each categorical outcome based on matched sample.

(a) Drinking alcohol

For baseline OLS result, there is a negative effect of HE on alcohol drinking frequency. The absolute values of coefficients increase as age increases. This indicates that individuals with HE attainments lead to a gradual reduction in alcohol consumption frequency from 33 to 50. However, when I split the sample by gender and run separate OLS analysis, one can see that this effect is only significant for females.

The PSM estimates somewhat confirm the result getting from OLS. Compared to the results obtained by using PSM, the OLS approach again underestimates the education effects. By gender, HE also has a larger impact on females than men. The estimated effect for males at age 33 is insignificant whereas it shows a -0.255 margin for females. It indicates higher educated females are likely to drink less alcohol. As the participants grow older, the marginal effect for men dramatically goes up to 0.156 at age 42 and -0.201 at 50, both statistically significant at 90% level. For women, the parameter of interest also has a remarkable increase to 0.416 at age 42 and 0.474 at age 50. Overall, both male and female respondents are likely to drink less as they grow older.

When looking at the fraction changes, for males are not obtaining HE attainment, the fraction of drinking frequency as ‘once a day’ is increased by 15% (from 26.5% to 30.5%) at age 33, 21% at age 42 (from 29.9% to 36.1%) and 23.4% (from 15.4% to 19.0%) on average, if males do not obtain HE attainment; on the other hand, if females are only with non-HE qualifications, the drinking frequency as ‘once a day’ is then increased by 35 % (from 14.6% to 19.8%) at age 33, 15% at age 42 and 5% (25.2% to 26.4%) at age 50. The impact of education seems to be decreasing as the age for females.

(b) Smoking frequency

The OLS results briefly show a positive impact of HE on the incidence of smoking. Individual with HE attainment reduces ranges from 0.07 to 0.15 on average and the effect on smoking steadily decreases in the long term for both genders. The results for PSM estimates are mixed. The parameter of interest that shows the impact of HE on smoking at age 33 is reported about 0.15 for the pooled sample. Meanwhile, higher educated women are nearer to “never smoke” when compared to men. Attending HE can significantly gain a 0.204 for females, as suggested by the estimated coefficients. By contrast, the effects are observed to be insignificant for males. When participants grow older, the impact goes down by 0.05 at age 42 for the pooled sample. On the female sub-sample, the marginal effect only accounts for 0.106, or almost half the figure compared to that when they were 9 years younger. This effect for males is still insignificant. Furthermore, I do not find any significant effects of HE on reducing the frequency of smoking behaviour when the participants enter their fifties, for males or females, although the coefficients appear to be negative.

Turning to the fraction changes of each category, the results shown in fourth panel in Table 3.17 are interesting. At age 33, males with HE are more likely to quit smoking (18.7%) than the ones without HE (15%). Occasional smoking frequency for HE participants (6.0%) is less than that for Non-HE participants (8.2%), whist daily smoking frequency for both groups are almost same (16.2% and 17.2%). For females, daily smoking frequency for HE group (17.0%) is higher than that for non-HE group (17.0%), but the occasional smoking frequency does not have significant differences. Moreover, the quit-smoking fraction of non-HE group (24%) is higher than HE group (21%) is possibly because people in HE group are more likely to be a non smoker.
As the participants getting older, the differences between the two groups become less. It is found that at age 50, the fraction of four categories for both treated and control group are almost same.
Overall, these findings reinforce the findings by a number of previous studies which have found a negative correlation between smoking and education (Feinstein et al., 2008), and between drinking alcohol and education in the case of the UK (Cutler and Lleras-Muney, 2010). More educated young adults tend to hold risk perceptions more closely related to the actual risks of these behaviours. However, the impact of HE is decreasing as the people are getting older. In particular, HE does not effectively affect the smoking behaviour as the results tell.

3.5.4 Depression

The final panel in Table 3.13 shows the impact of education on depression for pooled male and female samples. The baseline results find that HE has a negative relationship with depression. a positive effect of enrolling in HE on BMI, but the education effect is not significant different form zero. These associations vary significantly for individuals of different ages. Based on the OLS estimation, education has a larger impact on depression for females at age 33 than for males. The effect starts increasing to about 0.03 until middle-age, and is 0.04 after 50 and above for females.

However, the result is not robust to the above conclusion once I allow for the inclusion of the full set of covariates in the analyses and apply the PSM estimation. Although all of the estimated coefficients appear to be small and negative, the effect is only significant at 90% level for females at age 33. The descriptive statistics in Section 3.4 suggest a general increase in the malaise score and depression indicator over time for both genders, but it appears that participation in HE does carry some potential effects. Therefore, the PSM results suggest that most of the depression-education gradient in OLS comes from selection rather than causation.

On the other hand, the results shown in last panel in Table 3.17 are slightly different. There are no large differences between the treated and control groups expect for male participates are in their mid ages. The risk of being depression for non-HE group is increased by 72% (from 3.9% to 6.7%) at age 42 and by 48% at age 50 (6.4% to 9.5%), respectively, although the fraction margin is relatively small.

Contrary to previous research (Bynner et al., 2003; Feinstein et al., 2002), my finding does not suggest a significant impact of HE on the reduction in depression. The result of insignificant effect of HE on reducing the likelihood of depression in the UK is new to the literature. This possibly arises because these papers mainly focus on those participants with lower or no qualifications. Lower educated individuals can benefit from education, and they may acquire better labour market opportunities or higher wages in return. As a result, they are more likely to work and have a better lifestyle and will be less likely to suffer from depression. However, the casual effect of HE on depression is ambiguous since there may be contrasting mechanisms. HE attainment may be associated with more control over working standards and thus has a positive effect on mental health and reduces rates of morbidity; on the other hand, higher occupational attainment also leads to higher levels of stress. It is believed that there may be important trade-offs between stress and satisfaction that may lead to a complex and non-linear relationship between educational success and mental health (Hartog and Oosterbeek, 1998).

3.5.5 'Thick-support' robustness test

Making causal claims about effects are considered to satisfy three assumptions: overlap, covariate balance, and conditional independence or unconfoundness (Imbens & Wooldridge, 2009). Hence, to further test the credibility of the estimated results, I conduct a ‘thick region’ test and balance test, and examine the sensitivity of the results due to unobserved heterogeneity by Rosenbaum Bounds (R-bounds), which will be discussed in the following subsections.

To test the robustness of the estimates, I follow Black and Smith (2004) and estimate the ATTs on the region of ‘thick-support’, which is defined as the region with an estimated PS in the interval by $0.33 < \hat{P}(X) < 0.67$. The authors adopted this approach based on two reasons. First, the fact that individuals with high estimated PSs observed at low levels of treatments may actually represent a measurement error in the treatment variable. Second, there may be a residual selection on unobservables which will have a large effect on the bias for values of the PS in the tails of the distribution. In practice, the ‘thick-support’ region is characterised by having a substantial number of observations in both the treatment group and the comparison group, which means that the average frequency with which a comparison observation is used as a match is comparatively low.

The estimated effects for the thick-support region thus refer to samples that, in terms of sheer size, are very different to those on the entire common support. For example, imposing the thick-support condition leads to a drop of roughly one-third of the observations in the pooled samples (i.e. 741 out of 1858). However, as presented in Table 6, the thick-support estimates in the majority of the cases seem fairly robust compared to the estimates based on the entire common support reported in Table 3.14.

Although the estimates generally indicate a slight increase in the HE impact of health and health-related indicators, according Black and Smith (2004), the estimated effects on the thick-support are similar to those on the entire common support, which is an indication of effect homogeneity over different values of the PS.

3.5.6 Balance test for matching quality

According to the conclusion in Chapter One, the t-test and SB of balance are too rigid to reject the null too often. In this thesis, the adequacy of the matching process was evaluated by assessing covariate balance using mean absolute bias and Pseudo-R^2, as advocated Caliendo and Kopeinig (2008).

Table 3.15 presents the covariate balance statistics concerning the joint quality of the matching before and after matching. The overall mean absolute bias before matching lies between 10 to 30 %. The matching generates a reduction in mean bias by approximately six times. After matching, the bias is significantly reduced for the NN and kernel matching estimators, ranging from 2 to 8 %. In particular, Kernel matching provides the better result and shows that all after matching covariates display a mean absolute lower than that from NN matching. On the other hand, Pseudo-R^2 indicates how well the covariates explain the probability of receiving treatment. The reported Pseudo-R^2 before matching is normally around 15 to 30 % whereas after matching it drops to roughly about 3 %. This indicates that there are fewer systematic differences in the distribution of covariates between the treatment and the control groups. These results clearly show that the matching procedure is fairly successful in terms of balancing the distribution of covariates between the two groups.

3.5.7 Sensitivity analysis for unobserved heterogeneity

Although Mantel and Haenszel (1959) test statistics[40] for checking the hidden bias are generally preferred for dichotomous outcomes (Becker and Caliendo, 2007), this procedure has not been adapted to the Stata13 program. Therefore, I still apply sensitivity analysis based on Rosenbaum Bounds (R-bounds) method to test the robustness of the results, as displayed in Table 3.15. The increasing bound parameter Γ would result in a statistically insignificant treatment effect if there is an unobserved heterogeneity. As discussed in Chapter One, starting from $\Gamma = 1$, i.e. there is no hidden bias.

I first assessed the effects on general health indicator in Panel A, and some problems arose. The sensitivity analysis shows that for effect on SRH, through the increase of Γ up to 1.10, the upper bound[41]of the p-value exceeds the 5%-level, and this occurs to all matching algorithms. This indicates that the result is relative vulnerable to unobserved bias, while it only requires a 10% increase in the odds of selection to negate the effect. Similarly, for effects on BMI and obesity, it would also generally take relatively low Γ values of unobserved selection (about 1.15 on average for the

[40] See Caliendo and Kopeinig (2008) for a detailed description for non-parametric Mantel and Haenszel test statistic.

[41] Since the estimated coefficient is positive

former and about 1.10 on average for the latter) to make the treatment effect statistically insignificant. Moreover, when I considered adding economics factors into covariates (log wage), the results were not improved significantly. For example, the P-value exceeds the 5%-level when $\Gamma \approx 1.15$ in the case of SRH. Therefore, the robustness of the effect on general health indicators may be of interest for further investigation.

When turning to health behaviour outcomes in Panel B, the treatment effect would have been insignificant when $\Gamma \approx 1.31$ to 1.45. It is at this value that the treatment effect is no longer statistically significant at 5 %. This suggests that having matched on observed covariates, any unobserved confounding variables would have to increase the likelihood of selection by around 35 %. This is considered a fairly large value. In addition, in common with health behaviour outcomes, any unobserved confounding variable would have to increase the odd ratio by over 50% ($\Gamma \approx 1.50$) to overturn the causal effects on depression, as shown in Panel C. Therefore, apart from the general health indicator, the estimated causal effects appear robust to the unobserved heterogeneity.

3.6 Conclusion and policy implication

This survey adopts a quasi-parametric approach (PSM) to estimate the causal effects of HE attainment on a very wide range of individual's health-related outcomes across different age levels. I have used five waves of a longitudinal survey data for UK gathering a wealth of information on an individual's general health, mental health, and health-related behaviours and I draw the following conclusions from the reviews of the evidence:

(a) In general, the non-pecuniary benefits to HE attainments on health are substantial, implying that attending the HE may be a relatively effective way to improve population health. Educated men and women are more likely to report better health, are less likely to be obesity, more likely to be non-smokers and to have a higher sense of control on drinking alcohol, which in turn is associated with better health.

(b) Some of effects fall continuously with age (such as smoking), while others increase with age (e.g. SRH, BMI, drinking alcohol). Gender has an influence on the effects. HE has a larger effect on BMI and likelihood of being obesity for men, while for women HE has greater effect on SRH and health-damaging behaviours, such as frequency of drinking alcohol and smoking.

(C) Furthermore, I find no significant evidence that HE reduced the likelihood of depression, for males or females.

According to Cutler, Deaton, and Lleras-Muney (2006), education-health gradients arise or increase when there is knowledge and technology available to prevent or treat disease (a similar theory is tested in Link and Phelan (1995), and Glied and Lleras-Muney (2003)), because there is a universal demand for better health and those with more education (or more income, or more power) are likely to use new knowledge and new techniques more rapidly and more effectively. This idea is consistent with the fundamental causes of disease hypothesis (Link and Phelan 1995), which suggests that education gives an individual a wide range of serviceable resources, including money, knowledge, prestige, power and beneficial social conditions, which can be used to one's health advantage. Thus, a higher effect on an individual's health outcomes and health-related behaviours over time may be caused by the benefits of new effective techniques and the individual's confidence in curing disease, which has been built by having more knowledge. I support the view that education has a positive effect on an individual's health outcomes and reduces damaging health behaviours.

The causality is important not only for determining the exact relation between education and health, but also from a policy point of view. Public expenditures would only be effective in improving the health of the population if in fact HE causes health. We control the family background and individual characteristics for estimating the impact of HE. Adding these measures are expected to lowered the effect of education, but it generally remains large and significant in most cases.

There appear to be significant benefits attached to HE that contributes to better health status and less unhealthy behaviour. Nevertheless, these social benefits of HE play only a minor role in policy making. Much of the policy discussion about reducing health disparities across socioeconomic groups has focused on improving health insurance coverage and access to health care. The importance of higher education seems to be underestimated. During the past decades in UK, public expenditures on NHS and health care have increased more than that on HE. On the other hand, the policy maker may try to remedy the negative effects and social costs of a relatively lower educated population by increasing unemployment benefits and by increasing health care budgets to counter the detrimental effects of unhealthy behaviour. Spending on HE could consequently yield savings in health care and unemployment benefits. This makes that the causal relation between education and health has important implications for public policy.

However, even if it accepts positive impact of increasing expenditures on HE, two important questions remain before I can conclude an appropriate policy response. Firstly, as discussed in Chapter 2, it would sorely call for education subsidies to the extent there is a market failure, otherwise Individuals would base their education decisions on the health benefits along with the financial benefits. Secondly, understanding the mechanism by which education affects health is also important for policy maker consideration. Education might matter for health not just because of acquisitions of healthy information and behaviour, but rather because education improves incomes and hence improves health status and behaviours. In that case, it would possibly be less expensive to increase income directly, rather than to subsidise HE.

In my point of view, if it is proved that individual decisions to invest in HE are based only on the financial returns and individuals may be unaware of the health benefits of education when they make their education decisions, possible rationales for HE subsidies can be introduced. In addition, HE subsidies may be considered as the last resort if there is no alternative less expensive method to acquire the skills that ultimately affect health.

The findings of this study should be interpreted in the context of several limitations. Firstly, although I am able to control for many more factors than some of the literature, the estimates of the effect to HE on health may nonetheless not be fully identified. A review of the research literature on education and health has suggested a causal relationship from education to health, while conceding that the direction of causality may be reversed. In this paper, an individual's childhood cognitive ability, regions, secondary school types, parental information, health status in childhood, and adolescence have been taken into account as control variables to reduce the measurement errors. However, the R-bound result shows that the treatment effect on SRH is relatively sensitive to the unobserved heterogeneity. In other words, there may exist other unobservables that were not included in this analysis but which could drive the association between education and health. The economics literature suggests that a 'third variable' determines both education and health, and this drives their correlation. For other outcomes examined in my analysis, the PSM already does a good job of explaining the causal effects.

Another potential limitation of this study was its focus on British data. Country-specific cohort effects may have been observed in this study. For example, the participants were all born in 1958. The educational attainments of this cohort may have uniquely affected the estimated effects on their health outcomes. The association between education and health may differ in other groups of people or in groups that were born in different years, although the mechanisms underlying the association should be similar. However, the results in this paper can only represent this unique group of 1958 cohorts.

Appendix C Tables and Figures

Table 3.1 Distribution of SRH by gender

Age Group	Gender	General Health Condition				Total
		Excellent	**Good**	**Fair**	**Poor**	
Age 33	**Men**	1571	2221	488	71	**4351**
		(36.11)	(51.04)	(11.22)	(1.63)	**(100)**
	Women	1500	2391	545	81	**4517**
		(33.22)	(52.93)	(12.66)	(1.79)	**(100)**
	Total	**3,071**	**4612**	**1033**	**152**	***8868***
		(34.63)	**(52.01)**	**(11.65)**	**(1.71)**	***(100)***
Age 42	**Men**	1365	2260	634	144	***4403***
		(31.00)	(51.33)	(14.40)	(3.27)	***(100)***
	Women	1376	2345	658	164	***4543***
		(30.29)	(51.62)	(14.48)	(3.61)	***(100)***
	Total	**2741**	**4605**	**1292**	**308**	***8946***
		(30.64)	**(51.48)**	**(14.44)**	**(3.44)**	***(100)***
Age 51	**Men**	723	2363	475	198	**3759**
		(19.23)	(62.86)	(12.64)	(5.27)	**(100)**
	Women	768	2422	487	239	**3916**
		(19.61)	(61.85)	(12.44)	(6.10)	**(100)**
	Total	**1491**	**4785**	**962**	**437**	***7675***
		(19.43)	**(62.35)**	**(12.53)**	**(5.69)**	***(100)***

Table 3.2 General Health Indicator by Qualifications

Age Groups	Health Categories	Qualifications					
		None	GSE	O Level	At least 1 A Level	HE	Total
Age 33	Excellent	300	350	1,063	294	715	2,722
		24.81	27.80	36.16	40.11	45.28	
	Good	636	707	1559	378	743	4023
		52.61	56.16	53.03	51.57	47.06	
	Fair	234	171	286	53	113	857
		19.35	13.58	9.73	7.23	7.16	
	Poor	39	31	32	8	8	118
		3.23	2.46	1.09	1.09	0.51	
	Total	1209	1259	2940	733	1579	7720
Age 42	Excellent	362	340	997	298	733	2730
		20.65	25.37	31.15	36.52	40.23	
	Good	871	733	1709	418	873	4604
		49.69	54.70	53.39	51.23	47.91	
	Fair	389	216	417	87	181	1290
		22.19	16.12	13.03	10.66	9.93	
	Poor	131	51	78	13	35	308
		7.47	3.81	2.44	1.59	1.92	
	Total	1753	1340	3201	816	1822	8932
Age 51	Excellent	140	151	492	176	453	1412
		11.48	14.31	18.64	25.62	28.84	
	Good	702	689	1744	430	944	4509
		57.59	65.31	66.06	62.59	60.09	
	Fair	248	151	286	54	128	867
		20.34	14.31	10.83	7.86	8.15	
	Poor	129	64	118	27	46	384
		10.58	6.07	4.47	3.93	2.93	
	Total	1219	1055	2640	687	1571	7172

Table 3.3 Correlation analysis for self-reported health at age 42

	Health 42	Professional	Intermediate	Skilled non-manual	Skilled manual	Semi-skilled non-manual	Semi-skilled manual	Unskilled
Health 42	**1.00**	**0.0292**	**0.0287**	**0.0198**	**-0.0129**	**0.0069**	**-0.0166**	**-0.0129**
Professional	-	1.00	-0.0828	-0.0541	-0.1330	-0.0200	-0.0620	-0.0373
Intermediate	-	-	1.00	-0.1139	-0.2800	-0.0421	-0.1304	-0.0785
Skilled non-manual	-	-	-	1.00	-0.1830	-0.0275	-0.0853	-0.0513
Skilled manual	-	-	-	-	1.00	-0.0677	-0.2096	-0.1261
Semi-skilled non-manual	-	-	-	-	-	1.00	-0.0315	-0.0190
Semi-skilled manual	-	-	-	-	-	-	1.00	-0.0587
Unskilled	-	-	-	-	-	-	-	1.00

	Health 42	long term limiting health	Hospital admission
Health 42	**1.00**	**0.5562**	**0.1172**
Log wage 42	-	1.00	0.1057
Working Hour	-	-	1.00

	Health 33	Health 42	Health 50
Health 33	**1.00**	**0.5042**	**0.4313**
Heatlh 42	-	1.00	**0.5497**
Health 50	-	-	1.00

Table 3.4 Descriptive statistics of BMI by gender over time

		Mean	S.D
Age 33	**Men**	25.39	4.01
	Women	23.68	4.38
Age 42	**Men**	26.28	4.21
	Women	25.27	5.08
Age 50	**Men**	27.52	4.63
	Women	25.50	4.77

Table 3.5 Categories of BMI

Categories	BMI
Under Weight	< 18.5
Normal Weight	18.5-24.9
Overweight	25-29.9
Obesity	BMI of 30 Or Greater

Table 3.6 Distribution of being obesity at age 33, 42, and 51 by gender

Age Group	Gender	BMI				Total
		Under Weight	**Normal Weight**	**Overweight**	**Obesity**	
Age 33	**Men**	90 (2.09)	2,066 (47.91)	1,726 (40.03)	430 (9.97)	**4,312 (100)**
	Women	332 (7.41)	2,745 (61.26)	1,057 (23.59)	347 (7.74)	**4,481 (100)**
	Total	**422 (4.80)**	**4,811 (54.71)**	**2,783 (31.65)**	**777 (8.84)**	***8,793 (100)***
Age 42	**Men**	77 (1.78)	1624 (37.64)	1973 (45.72)	641 (14.86)	***4315 (100)***
	Women	133 (2.96)	2363 (52.65)	1352 (30.12)	640 (14.26)	***4488 (100)***
	Total	**210 (2.39)**	**3987 (45.29)**	**3325 (37.77)**	**1281 (14.55)**	***8803 (100)***
Age 51	**Men**	55 (1.77)	852 (27.40)	1431 (46.01)	772 (24.82)	**3110 (100)**
	Women	175 (5.30)	1477 (44.77)	1082 (32.80)	565 (17.13)	**3299 (100)**
	Total	**230 (3.59)**	**2329 (36.34)**	**2513 (39.21)**	**1337 (20.86)**	***6409 (100)***

Table 3.7 Frequency of Drinking Alcohol by ages

Age Group	Gender	Frequency of Drinking Alcohol							Total
		On most days	2 to 3 days a week	Once a week	2 to 3 times a month	Less often or only on special occasions	Never nowadays	Never had an alcoholic drink	
Age 33	**Men**	1087 (24.72)	1597 (36.31)	793 (18.03)	374 (8.50)	372 (8.46)	143 (3.25)	32 (0.73)	**4398 (100)**
	Women	689 (15.18)	1346 (29.65)	906 (19.96)	543 (11.96)	787 (17.34)	196 (4.32)	72 (1.59)	**4539 (100)**
	Total	**1,776 (19.87)**	**2,943 (32.93)**	**1,699 (19.01)**	**917 (10.26)**	**1,159 (12.97)**	**339 (3.79)**	**104 (1.16)**	***8,937 (100)***
Age 42	**Men**	1040 (28.49)	1330 (36.44)	590 (16.16)	249 (6.82)	278 (7.62)	132 (3.62)	31 (0.85)	***3650 100***
	Women	748 (19.25)	1185 (30.49)	678 (17.45)	400 (10.29)	598 (15.39)	218 (5.61)	59 (1.52)	***3886 100***
	Total	**1,788 (23.73)**	**2,515 (33.37)**	**1,268 (16.83)**	**649 (8.61)**	**876 (11.62)**	**350 (4.64)**	**90 (1.19)**	**7,536 (100)**
Age 51	**Men**	1034 (27.49)	1257 (33.42)	643 (17.10)	255 (6.78)	405 (10.77)	152 (4.04)	15 (0.40)	**3761 (100)**
	Women	734 (18.74)	1157 (29.55)	640 (16.34)	643 (16.42)	764 (19.51)	246 (6.28)	51 (1.30)	**3916 (100)**
	Total	**1,768 (23.03)**	**2,414 (31.44)**	**1,283 (16.71)**	**579 (7.54)**	**1,169 (15.23)**	**398 (5.18)**	**66 (0.86)**	**7,677 (100)**

Table 3.8 Frequency of smoking by gender

Age groups	Gender	Frequency of smoking				Total
		Never smoked cigarettes	Used to smoke but don't at all now	Smoke cigarettes occasionally	Smoke every day	
Age 33	**Men**	1927 (43.82)	1137 (25.85)	206 (4.68)	1128 (25.65)	**4398 (100)**
	Women	2069 (45.58)	1102 (24.28)	186 (4.10)	1182 (26.04)	**4539 (100)**
	Total	**3,996 (44.71)**	**2,239 (25.05)**	**392 (4.39)**	**2,310 (25.85)**	**8,937 (100)**
Age 42	**Men**	1669 (45.71)	1053 (28.84)	160 (4.38)	769 (21.06)	**3651 (100)**
	Women	1859 (47.81)	1006 (25.87)	141 (3.63)	882 (22.69)	**3888 (100)**
	Total	**3,528 (46.80%)**	**2,059 (27.31%)**	**301 (3.99%)**	**1,651 (21.90%)**	**7,539 (100%)**
Age 51	**Men**	1662 (44.19)	1268 (33.71)	116 (3.08)	715 (19.01)	**3761 (100)**
	Women	1877 (47.93)	1124 (28.70)	128 (3.27)	787 (20.10)	**3916 (100)**
	Total	**3,539 (46.10%)**	**2,392 (31.16%)**	**244 (3.18%)**	**1,502 (19.56%)**	**7,677 (100%)**

Table 3.9 Distribution of depression risk by gender

		Risk of depression (Malaise score >=8)	No Risk of depression (Malaise score <8)
Age 33	**Men**	3.9%	96.3%
	Women	6.8%	93.2%
Age 42	**Men**	7.7%	92.3%
	Women	12.4%	87.6%
Age 51	**Men**	9.69%	90.31%
	Women	14.5%	85.5%

Table 3.10 Summary of childhood health indicators

Variable	**Mean (%)**		**Mean(%)**
Birth weight (<2500g)	6.4		
Mother smoking during pregnancy		**Behaviour Score 7**	
Non-smoker	66.4	Normal	60.84
Medium smoker	15.7	Moderate problem	8.64
Heavy smoker	12.3	Severe problem	4.09
Variable smoker	5.6	Missing or Incomplete	26.44
General health at age 7		**Behaviour Score 11**	
Good	78.0	Normal	55.39
Abnormal	6.7	moderate	7.73
Missing Value	15.3	Severe problems	3.76
General health at age 11		Missing or Incomplete	33.13
Good	70.5	**Behaviour Score 16**	
Abnormal	9.4	Normal	48.58
Missing Value	20.1	moderate	9.80
General health at age 11		Severe problems	2.99
Good	69.3	Missing or Incomplete	38.63
Abnormal	10.6		
Missing Value	20.1		

Table 3.11 Probit model for PS estimations

Ethics (non-White)	0.025	**Number of siblings in 1974**	-0.054
Mathematics ability at 7 years		**Father's interest in education**	
5th quintile (highest)	0.194	Over concerned	0.596
4th quintile	-0.014	Very interested	0.181
3rd quintile	-0.156	Some interest	0.055
2nd quintile	-0.354	**Mother's interest in education**	
1st quintile (lowest)	-0.254	Over concerned	0.198
Reading ability at 7 years		Very interested	0.068
5th quintile (highest)	0.045	Some interest	0.007
4th quintile	0.022	**Bad finances in 1969 or 1974**	-0.112
3rd quintile	-0.263	**Region in 1974**	
2nd quintile	-0.209	North West	-0.175
1st quintile (lowest)	-0.204	North	0.198
Mathematics ability at 11 years		East and West	-0.008
5th quintile (highest)	-0.466	East	-0.448
4th quintile	-0.402	London and South East	0.249
3rd quintile	-0.171	South	-0.345
2nd quintile	-0.002	South West	0.037
1st quintile (lowest)	0.231	Midlands	-0.148
Reading ability at 11 years		Wales	omitted
5th quintile (highest)	0.159	Scotland	-0.560
4th quintile	0.068		
3rd quintile	-0.110		
2nd quintile	-0.298	**Father's years of education**	0.275
1st quintile (lowest)	-0.505	**Mother's years of education**	0.387
Comprehensive school 1974	0.193		
Secondary modern school 1974	0.112	**Birth weight (<2500g)**	0.086
Grammar school 1974	0.387	**Mother Smoking**	

		During Pregnancy	
Private school 1974	0.560	Non smoker	0.002
Other school 1974	-0.017	Medium smoker	0.041
Father's social class in 1974		Heavy smoker	0.012
Professional	0.474	Variable smoker	0.058
Intermediate	0.234	**General health at age 7**	
Skilled Non-manual	0.182	Good	0.100
Skilled manual	-0.063	Abnormal	0.090
Semi-skilled non-manual	0.008	Missing Value	0.121
Semi-skilled manual	-0.025	**General health at age 11**	
Unskilled	-0.287	Good	0.045
Missing, or unemployed or no father	Omitted	Abnormal	0.025
		Missing Value	0.097
Behaviour Score 7		**General health at age 11**	
Normal	0.015	Good	0.067
Moderate problem	-0.012	Abnormal	0.045
Severe problem	-0.045	Missing Value	0.089
Missing or Incomplete	0.025	**Behaviour Score 16**	
Behaviour Score 11		Normal	0.045
Normal	0.044	moderate	-0.001
moderate	0.065	Severe problems	-0.094
Severe problems	-0.058	Missing or Incomplete	0.056
Missing or Incomplete	0.045		

Table 3.12 Returns to HE on Health and Health related conditions, OLS results

	Full	Male	Female
Panel A			
	Self-Reported Health		
Age 33	0.0639**	0.0365	0.0786
	(0.142)	(0.105)	(0.134)
Age 42	0.0653	0.0521	0.0832
	(0.034)	(0.053)	(0.045)
Age 50	0.0671	0.0590	0. 0856
	(0.054)	(0.083)	(0.072)
	BMI		
Age 33	-0.2591	-0.3424	0.1023
	(0.165)	(0.229)	(0.108)
Age 42	-0.5462**	-0.5497**	-0.4820**
	(0.181)	(0.24)	(0.147)
Age 50	-0.3304	-0.4671*	-0.6318**
	(0.206)	(0.279)	(0.273)
	Obesity		
	Full	Male	Female
Age 33	-0.032	-0.071*	-0.041
	(0.028)	(0.040)	(0.044)
Age 42	-0.075**	-0.108**	-0.087**
	(0.029)	(0.039)	(0.433)
Age 50	-0.065*	-0.116**	-0.079*
	(0.035)	(0.047)	(0.049)
Panel B			
	Drinking Frequency		
Age 33	Full	Male	Female
	-0.1779**	-0.0317	-0.2864**
	(0.069)	(0.096)	(0.099)
Age 42	-0.2321**	-0.1384	-0.2615**
	(0.076)	(0.104)	(0.111)
Age 50	0.2631***	0.1298	0.3615***
	(0.034)	(0.106)	(0.113)
	Smoking Frequency		
Age 33	Full	Male	Female
	-0.141**	-0.134**	-0.150**

	(0.041)	(0.050)	(0.057)
Age 42	-0.101**	-0.093*	-0.129**
	(0.042)	(0.058)	(0.058)
Age 50	-0.098**	-0.073*	-0.116**
	(0.039)	(0.041)	(0.053)

Panel C			
	Depression		
Age 33	Full	Male	Female
	0.097**	0.080**	0.113**
	(0.034)	(0.052)	(0.044)
Age 42	0.082**	0.078**	0.120**
	(0.050)	(0.045)	(0.097)
Age 50	0.104**	0.094**	0.123**
	(0.084)	(0.072)	(0.094)

Note ***Significant at the 1% level; **significant at the 5% level; *significant at 10% level

Table 3.13 Returns to HE on Health and Health related conditions, PSM results

	PSM (Nearest Neighbour)			PSM (Kernel)		
Panel A						
			Self reported health			
Age 33	Full	Male	Female	Full	Male	Female
	0.081*	0.078*	0.118**	0.078*	0.0704*	0.111**
	(0.049)	(0.070)	(0.075)	(0.034)	(0.054)	(0.067)
Age 42	0.085*	0.090**	0.135**	0.081*	0.090**	0.131**
	(0.051)	(0.057)	(0.074)	(0.045)	(0.050)	(0.071)
Age 50	0.091*	0.102*	0.167**	0.090*	0.100*	0.165**
	(0.070)	(0.075)	(0.076)	(0.072)	(0.064)	(0.069)
			BMI			
Age 33	Full	Male	Female	Full	Male	Female
	-0.297	-0.355*	-0.136	-0.301	-0.360*	-0.138
	(0.192)	(0.152)	(0.362)	(0.114)	(0.140)	(0.245)
Age 42	-0.472**	-0.529**	0.377**	-0.475**	-0.528**	0.376**
	(0. 031)	(0.040)	(0.035)	(0. 15)	(0.40)	(0.30)

Age 50	-0.617**	-0.859**	-0. 481*	-0.601**	-0.821**	-0. 424*
	(0.242)	(0.364)	(0.127)	(0.211)	(0.301)	(0.114)
			Obesity			
Age 33	Full	Male	Female	Full	Male	Female
	-0.026	-0.064	-0.015	-0.024	-0.060	-0.015
	(0.032)	(0.076)	(0.060)	(0.029)	(0.070	(0.060)
Age 42	-0.110**	-0.123**	-0.107**	-0.101**	-0.119**	-0.100**
	(0.052)	(0.051)	(0.046)	(0.050)	(0.049)	(0.042)
Age 50	-0.124**	-0.136**	-0.114**	-0.118**	-0.130**	-0.109**
	(0.064)	(0.059)	(0.045)	(0.061)	(0.048)	(0.039)

Panel B

			Alcohol Drinking Frequency			
Age 33	Full	Male	Female	Full	Male	Female
	-0.231**	-0.073	-0.255**	-0.214**	0.067	-0.245**
	(0.034)	(0.053)	(0.045)	(0.031)	(0.050)	(0.038)
Age 42	-0.301**	-0.156*	-0.416	-0.294**	-0.148*	-0.409*
	(0.041)	(0.024)	(0.044)	(0.034)	(0.014)	(0.039)
Age 50	-0.358**	-0.201*	-0.474**	-0.345**	-0.194*	-0.456**
	(0.034)	(0.025)	(0. 048)	(0.028)	(0.025)	(0.040)

			Smoke Frequency			
Age 33	Full	Male	Female	Full	Male	Female
	-0.145**	-0.082	-0.204**	-0.141**	-0.080	-0.200**
	(0.072)	(0.070)	(0.101)	(0.072)	(0.070)	(0.101)
Age 42	-0.093**	-0.053	-0.106**	-0.088**	-0.048	-0.101**
	(0.048)	(0.109)	(0.051)	(0.048)	(0.109)	(0.051)
Age 50	-0.074	-0.046	-0.097	-0.071	-0.039	-0.089
	(0.034)	(0.057)	(0.064)	(0.034)	(0.057)	(0.064)

Panel C

			Depression			
Age 33	Full	Male	Female	Full	Male	Female
	-0.007	-0.001	-0.026*	-0.006	-0.001	-0.021*
	(0.009)	(0.010)	(0.013)	(0.009)	(0.010)	(0.013)
Age 42	-0.011	-0.006	-0.073	-0.010	-0.006	-0.070
	(0.049)	(0.026)	(0.093)	(0.049)	(0.026)	(0.093)
Age 50	-0.018	-0.012	-0.107	-0.015	-0.010	-0.102
	(0.064)	(0.053)	(0.105)	(0.064)	(0.053)	(0.105)

Note **significant at the 5% level; *significant at 10% level

Table 3.14 Returns to HE on Health and Health related conditions, PSM results

(the thick support region)

	PSM (Nearest Neighbour)			PSM (Kernel)		
	Full	Male	Female	Full	Male	Female
Panel A						
			Self reported health			
Age 33	0.097*	0.082*	0.132**	0.091*	0.079*	0.125**
Age 42	0.106*	0.115**	0.153**	0.101*	0.109**	0.151**
Age 50	0.111*	0.125*	0.199**	0.107*	0.120*	0.185**
			BMI			
Age 33	-0.356*	-0.400**	-0.213	-0.323*	-0.390**	-0.203
Age 42	-0.511**	-0.598**	0.412**	-0.505**	-0.590**	0.400**
Age 50	-0.679**	-0.899**	-0. 513**	-0.661**	-0.873**	-0. 507*
			Obesity			
Age 33	-0.036	-0.098	-0.026	-0.035	-0.097	-0.0234
Age 42	-0.156**	-0.175**	-0.154**	-0.149**	-0.169**	-0.150**
Age 50	-0.187**	-0.201**	-0.181**	-0.180**	-0.197**	-0.173**
Panel B						
			Alcohol Drinking Frequency			
Age 33	-0.270**	-0.113	-0.295**	-0.250**	0.107	-0.282**

Age 42	-0.352**	-0.200*	-0.470	-0.343**	-0.194*	-0.459
Age 50	-0.358**	-0.201*	-0.474**	-0.345**	-0.194*	-0.456**
			Smoke Frequency			
Age 33	-0.198**	-0.145	-0.281**	-0.189**	-0.143	-0.265**
Age 42	-0.135**	-0.083	-0.139**	-0.128**	-0.078	-0.135**
Age 50	-0.114	-0.069	-0.121	-0.110	-0.063	-0.116

Panel C						
			Depression			
Age 33	Full	Male	Female	Full	Male	Female
	-0.012	-0.003	-0.036	-0.010	-0.003	-0.034
Age 42	-0.017	-0.011	-0.082	-0.016	-0.010	-0.080
Age 50	-0.022	-0.017	-0.110	-0.015	-0.015	-0.106

Note **significant at the 5% level; *significant at 10% level

Table 3.15 Joint quality of matching indicators

	PSM (Nearest Neighbour)			PSM (Kernel)		
Panel A						
			Self reported health			
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	13.82	12.44	18.55			
Pseudo R^2	0.11	0.10	0.19			
After match						
Age 33						
Mean absolute bias	4.84	4.56	6.27	3.75	3.96	5.15
Pseudo R^2	0.02	0.02	0.03	0.01	0.01	0.03
Age 42						
Mean absolute bias	3.65	4.74	5.96	3.57	4.29	5.57
Pseudo R^2	0.01	0.02	0.03	0.01	0.02	0.03
Age 50						
Mean absolute bias	3.22	3.45	3.25	2.45	2.84	2.67
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01
			BMI			
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	26.12	27.45	30.12			
Pseudo R^2	0.31	0.29	0.34			
After match						
Age 33						
Mean absolute bias	7.84	6.56	6.27	5.49	5.79	5.87
Pseudo R^2	0.05	0.04	0.04	0.03	0.03	0.03
Age 42						
Mean absolute bias	6.29	7.14	7.45	6.22	6.80	6.45
Pseudo R^2	0.03	0.04	0.04	0.02	0.02	0.02
Age 50						
Mean absolute	7.46	8.01	7.12	6.45	5.78	5.49

bias						
Pseudo R^2	0.05	0.05	0.04	0.03	0.03	0.02
			Obesity			
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	10.13	9.46	9.65			
Pseudo R^2	0.07	0.07	0.06			
After match						
Age 33						
Mean absolute bias	2.13	2.07	2.04	1.98	1.54	1.45
Pseudo R^2	0.005	0.005	0.005	0.00	0.00	0.00
Age 42						
Mean absolute bias	3.45	3.78	2.98	2.82	2.62	2.97
Pseudo R^2	0.01	0.01	0.01	0.005	0.005	0.005
Age 50						
Mean absolute bias	3.79	4.02	4.14	3.76	3.67	3.46
Pseudo R^2	0.01	0.02	0.02	0.01	0.01	0.01
Panel B						
			Alcohol Drinking	**Frequency**		
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	12.41	11.16	11.97			
Pseudo R^2	0.12	0.11	0.12			
After match						
Age 33						
Mean absolute bias	4.84	4.56	6.27	3.75	3.96	5.15
Pseudo R^2	0.02	0.02	0.03	0.01	0.01	0.03
Age 42						
Mean absolute bias	4.87	4.13	4.41	3.13	2.45	3.01
Pseudo R^2	0.02	0.02	0.02	0.01	0.01	0.01
Age 50						
Mean absolute bias	3.79	4.02	4.14	3.76	3.67	3.46
Pseudo R^2	0.01	0.02	0.02	0.01	0.01	0.01

	Smoke Frequency					
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	14.17	13.64	13.75			
Pseudo R^2	0.12	0.11	0.12			
After match						
Age 33						
Mean absolute bias	8.41	8.45	8.17	6.13	6.47	6.97
Pseudo R^2	0.05	0.06	0.05	0.01	0.01	0.03
Age 42						
Mean absolute bias	7.16	7.57	7.13	7.01	6.13	6.48
Pseudo R^2	0.04	0.04	0.04	0.04	0.03	0.03
Age 50						
Mean absolute bias	3.79	4.02	4.14	3.76	3.67	3.46
Pseudo R^2	0.01	0.02	0.02	0.01	0.01	0.01

Panel C						
			Depression			
Before match						
	Full	Male	Female	Full	Male	Female
Mean absolute bias	12.16	11.71	12.23			
Pseudo R^2	0.11	0.10	0.11			
After match						
Age 33						
Mean absolute bias	6.18	5.39	6.40	5.56	4.79	5.57
Pseudo R^2	0.03	0.03	0.03	0.03	0.02	0.03
Age 42						
Mean absolute bias	7.16	7.57	7.13	7.01	6.13	6.48
Pseudo R^2	0.04	0.04	0.04	0.04	0.03	0.03
Age 50						
Mean absolute bias	7.64	7.24	7.61	7.12	6.97	7.00
Pseudo R^2	0.04	0.03	0.04	0.03	0.03	0.03

Table 3.16 Rosenbaum Bounds for PSM estimation on different health outcomes.

	PSM (Nearest Neighbour)			PSM (Kernel)		
Panel A						
			Self reported health			
	Full	Male	Female	Full	Male	Female
Age33						
Γ cut-off	1.08	1.09	1.10	1.12	1.10	1.12
P value	6.0%	5.6%	6.0%	5.5%	5.4%	5.7%
Age 42						
Γ cut-off	1.06	1.05	1.06	1.11	1.08	1.09
P value	5.6%	5.5%	5.4%	5.5%	5.2%	5.4%
Age 50						
Γ cut-off	1.07	1.07	1.08	1.11	1.10	1.11
P value	6.2%	5.4%	5.2%	5.6%	5.7%	5.6%
			BMI			
Age33						
Γ cut-off	1.14	1.16	1.13	1.16	1.16	1.16
P value	6.2%	6.4%	5.8%	5.4%	5.2%	5.1%
Age 42						
Γ cut-off	1.12	1.13	1.12	1.11	1.08	1.09
P value	5.5%	5.4%	5.8%	5.1%	5.3%	5.4%
Age 50						
Γ cut-off	1.07	1.07	1.08	1.11	1.10	1.11
P value	5.2%	5.4%	5.4%	5.2%	5.7%	5.4%
			Obesity			
Age33						
Γ cut-off	1.09	1.08	1.09	1.13	1.15	1.14
P value	8.2%	7.2%	8.4%	6.7%	5.8%	5.4%
Age 42						
Γ cut-off	1.12	1.13	1.12	1.11	1.08	1.09
P value	8.7%	9.2%	7.5%	6.2%	5.7%	5.9%
Age 50						
Γ cut-off	1.07	1.07	1.08	1.11	1.10	1.11
P value	7.5%	6.5%	5.8%	5.9%	5.4%	5.7%
When adding log wage in covariates						
			Self reported health			
Age33						
Γ cut-off	1.15	1.16	1.14	1.16	1.17	1.16
P value	12.0%	11.6%	12.0%	11.5%	12.4%	10.7%
Age 42						

Γ cut-off	1.06	1.07	1.07	1.15	1.12	1.10
P value	9.6%	10.2%	11.1%	9.5%	11.2%	12.4%
Age 50						
Γ cut-off	1.13	1.15	1.12	1.11	1.10	1.11
P value	11.2%	12.4%	10.2%	10.2%	9.7%	11.3%
			BMI			
Age33						
Γ cut-off	1.24	1.20	1.23	1.25	1.26	1.25
P value	6.2%	6.4%	5.8%	5.4%	5.2%	5.1%
Age 42						
Γ cut-off	1.19	1.20	1.22	1.21	1.22	1.21
P value	5.5%	5.4%	5.8%	5.1%	5.3%	5.4%
Age 50						
Γ cut-off	1.17	1.18	1.17	1.20	1.21	1.24
P value	5.2%	5.4%	5.4%	5.2%	5.7%	5.4%
			Obesity			
Age33						
Γ cut-off	1.13	1.12	1.11	1.15	1.17	1.18
P value	8.2%	7.2%	8.4%	6.7%	5.8%	5.4%
Age 42						
Γ cut-off	1.13	1.13	1.12	1.12	1.11	1.12
P value	5.1%	6.3%	504%	5.2%	5.2%	5.3%
Age 50						
Γ cut-off	1.12	1.11	1.13	1.15	1.16	1.12
P value	5.2%	5.1%	5.2%	5.5%	5.8%	5.9%
Panel B						
			Alcohol Drinking Frequency			
Age33						
Γ cut-off	1.42	1.41	1.40	1.43	1.45	1.41
P value	6.2%	5.2%	5.4%	5.7%	5.8%	5.4%
Age 42						
Γ cut-off	1.40	1.43	1.42	1.44	1.45	1.44
P value	5.2%	5.6%	5.5%	5.2%	5.2%	5.8%
Age 50						
Γ cut-off	1.40	1.37	1.38	1.45	1.42	1.41
P value	5.5%	5.7%	5.8%	5.4%	5.8%	5.5%
				Smoke Frequency		
Age33						
Γ cut-off	1.32	1.31	1.37	1.38	137	1.39
P value	5.2%	5.2%	5.4%	5.7%	5.8%	5.4%
Age 42						
Γ cut-off	1.35	1.34	1.32	1.38	1.37	1.38

P value	5.1%	5.2%	5.4%	5.2%	5.2%	5.1%
Age 50						
Γ cut-off	1.35	1.35	1.35	1.40	1.40	1.41
P value	5.1%	5.1%	5.2%	5.4%	5.3%	5.2%

Panel C						
			Depression			
Age33						
Γ cut-off	1.54	1.57	1.58	1.62	1.64	1.61
P value	5.2%	5.2%	5.4%	5.1%	5.3%	5.4%
Age 42						
Γ cut-off	1.61	1.59	1.54	1.65	1.67	1.68
P value	5.1%	5.2%	5.4%	5.2%	5.2%	5.1%
Age 50						
Γ cut-off	1.55	1.58	1.61	1.65	1.66	1.68
P value	5.1%	5.1%	5.2%	5.4%	5.3%	5.2%

Table 3.17 Fraction of each outcome variable based on total matched sample size

	Male		Female	
	HE	Non HE	HE	Non HE
Self Reported Health				
Age 33				
Excellent	257 (41.9%)	77 (32.5%)	229 (38.4%)	107 (37.0%)
Good	321 (52.4%)	122 (51.4%)	323 (54.2%)	147 (50.9%)
Fair	29 (4.8%)	32 (13.5%)	36 (6.1%)	27 (9.3%)
Poor	6 (0.9%)	6 (2.6%)	8 (1.3%)	8 (2.8%)
	613	237	596	289
Age 42				
Excellent	228 (44.3%)	63 (32.1%)	182 (35.8%)	78 (32.9%)
Good	241 (46.8%)	99 (50.5%)	241 (47.4%)	110 (46.4%)
Fair	37 (7.2%)	25 (12.7%)	63 (12.4%)	29 (12.2%)
Poor	8 (1.7%)	9 (4.7%)	22 (4.4%)	10 (8.5%)
	515	196	508	237
Age 50				
Excellent	135 (26.9%)	37 (18.4%)	97 (20.3%)	40 (17.3%)
Good	205 (40.7%)	83 (41.3%)	208 (43.5%)	91 (38.8%)
Fair	125 (24.8%)	60 (30.0%)	132 (27.6%)	64 (27.3%)
Poor	39 (7.6%)	21 (10.3%)	41 (8.6%)	39 (16.6%)
	504	201	478	234
Obesity				
Age 33				
under	15 (2.9%)	5 (2.3%)	37 (6.9%)	15 (5.4%)
normal	248 (48.2%)	106 (48.4%)	371 (70.1%)	187 (67.8%)
over	223 (43.3%)	88 (40.2%)	82 (15.5%)	53 (19.2%)
obesity	29 (6.6%)	20 (9.1%)	39 (7.4%)	21 (7.6%)
	515	219	529	276
42				
under	11 (2.1%)	4 (1.7%)	30 (5.7%)	12 (4.3%)
normal	204 (40.2%)	98 (43.0%)	333 (63.5%)	166 (60.3%)
over	251(49.5%)	94 (41.2%)	102 (19.5%)	63 (22.9%)
obesity	41 (8.1%)	32 (14.0%)	59 (11.3%)	34 (12.4%)
	507	228	524	275
50				
under	4 (0.9%)	2 (1.0%)	8 (1.7%)	4 (2.2%)
normal	172 (38.6%)	50 (27.2%)	291 (62.6%)	130 (56.5%)
over	212 (47.4%)	97 (52.7%)	89 (19.1%)	65 (28.3%)
obesity	59 (15.4%)	35 (19.0%)	62 (13.3%)	31 (13.4%)
	447	184	465	230
Drinking Frequency				

Age 33				
Once a day	143 (26.5%)	105 (30.5%)	65 (14.6%)	85 (19.8%)
2 to 3 days a week	253 (46.9%)	173 (50.3%)	207 (46.5%)	199 (41.7%)
Once a week	57 (10.6%)	28 (8.1%)	72 (16.2%)	65 (15.2%)
2 to 3 times a month	46 (8.5%)	16 (4.7%)	51 (11.5%)	17 (4.0%)
Less often or only on special occasions	30 (5.6%)	16 (4.7%)	30 (6.7%)	45 (10.5%)
Never nowadays	7 (1.3%)	3 (0.9%)	15 (3.3%)	9 (2.9%)
Never had an alcoholic drink	3 (0.5%)	3 (0.9%)	5 (1.1%)	9 (2.9%)
	539	344	445	429
Age 42				
Once a day	141 (29.9%)	104 (36.1%)	104 (24.6%)	110 (28.3%)
2 to 3 days a week	203 (43.0%)	126 (43.8%)	162 (38.3%)	147 (37.8%)
Once a week	67 (14.2%)	31 (10.8%)	70 (16.5%)	60 (15.4%)
2 to 3 times a month	22 (4.7)	19 (6.6%)	27 (6.4%)	25 (6.4%)
Less often or only on special occasions	34 (7.2%)	6 (2.1%)	37 (8.7%)	25 (6.4%)
Never nowadays	3 (0.6%)	1 (0.3%)	18 (4.3%)	17 (4.4%)
Never had an alcoholic drink	2(0.4%)	1 (0.3%)	5 (1.2%)	5 (1.3%)
	472	288	423	389
Age 50				
Once a day	181 (39.2%)	133 (43.8%)	106 (25.2%)	99 (26.4%)
2 to 3 days a week	147 (31.8%)	91 (30.0%)	145 (34.4%)	137 (32.4%)
Once a week	62 (13.4%)	34 (11.1%)	64 (15.2%)	53 (12.6%)
2 to 3 times a month	17 (3.7%)	13 (4.3%)	52 (12.4%)	25 (6.0%)
Less often or only on special occasions	52 (11.3%)	28 (9.2%)	40 (9.5%)	45 (10.7%)
Never nowadays	2 (0.4%)	1 (0.3%)	13 (3.1%)	12 (2.8%)
Never had an alcoholic drink	1 (0.2%)	0 (0.0%)	1 (0.2%)	4 (0.9%)
	462	304	421	422
Smoking Frequency				
Age 33				
Never smoke	359 (60.0%)	139 (59.6%)	355 (60.2%)	155 (54.8%)
Used to smoke	112 (18.7%)	35 (15.0%)	124 (21.0%)	68 (24.0%)
Smoke occasionally	36 (6.0%)	19 (8.2%)	20 (3.4%)	12 (4.3%)
Smoke everyday	97 (16.2%)	40 (17.2%)	91 (15.4%)	48 (17.0%)
	598	233	590	283
Age 42				
Never smoke	310 (60.0%)	116 (58.6%)	310 (59.8%)	128 (54.2%)
Used to smoke	104 (20.1%)	40 (20.2%)	110 (21.2%)	60 (25.4%)
Smoke occasionally	42 (8.1%)	17 (8.6%)	39 (7.5%)	21 (8.9%)

Smoke everyday	61 (11.8%)	25 (12.6%)	59 (11.4%)	28 (11.9%)
	517	198	518	236
Age 50				
Never smoke	313 (61.2%)	110 (59.3%)	296 (59.3%)	130 (54.6%)
Used to smoke	118 (23.1%)	48 (23.5%)	151 (29.3%)	64 (33.6%)
Smoke occasionally	35 (6.9%)	16 (7.8%)	13 (2.6%)	6 (2.5%)
Smoke everyday	45 (8.8%)	19 (9.3%)	44 (8.8%)	22 (9.2%)
	511	204	499	238
Depression				
Age 33				
No	711 (98.9%)	311 (98.8%)	725 (96.7%)	376 (95.5)
Yes	8 (1.1%)	4 (1.2%)	25 (3.3%)	18 (4.5%)
	719	315	750	394
Age 42				
No	697 (96.1%)	294 (93.3%)	709 (91%)	354 (89.8%)
Yes	28 (3.9%)	21 (6.7%)	69 (9%)	40 (10.2)
	719	315	778	394
Age 50				
No	631 (93.6%)	248 (89.5%)	588 (86.1%)	285 (84.5%)
Yes	43 (6.4%)	29 (9.5%)	95 (13.9%)	52 (15.4%)
	674	227	683	337

Figure 3.1 SRH for Men by different ages

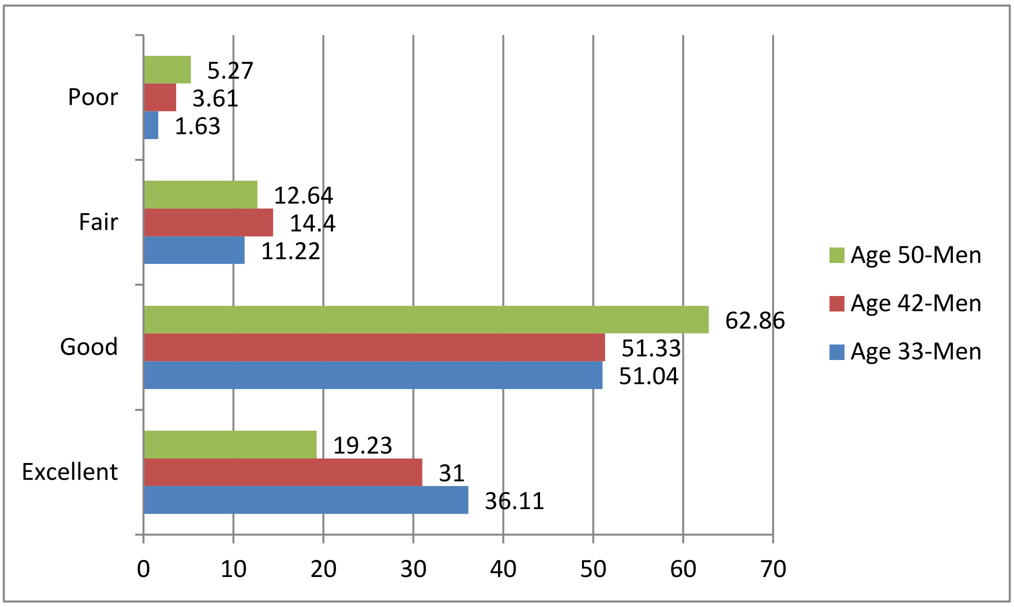


Figure 3.2 SRH for Women by different ages

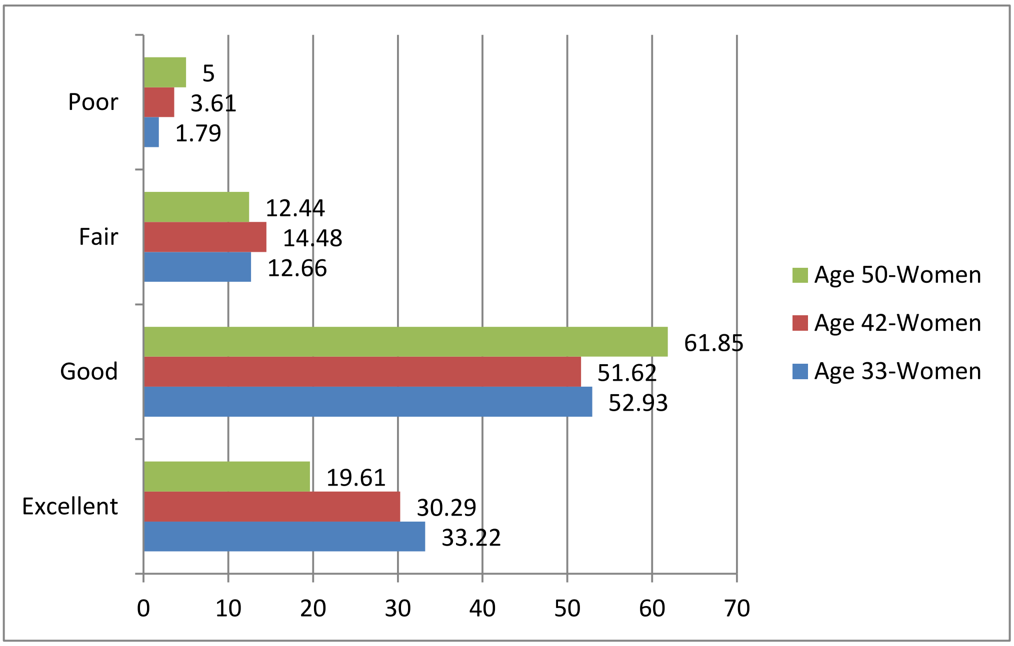


Figure 3.3 BMI distribution across different ages

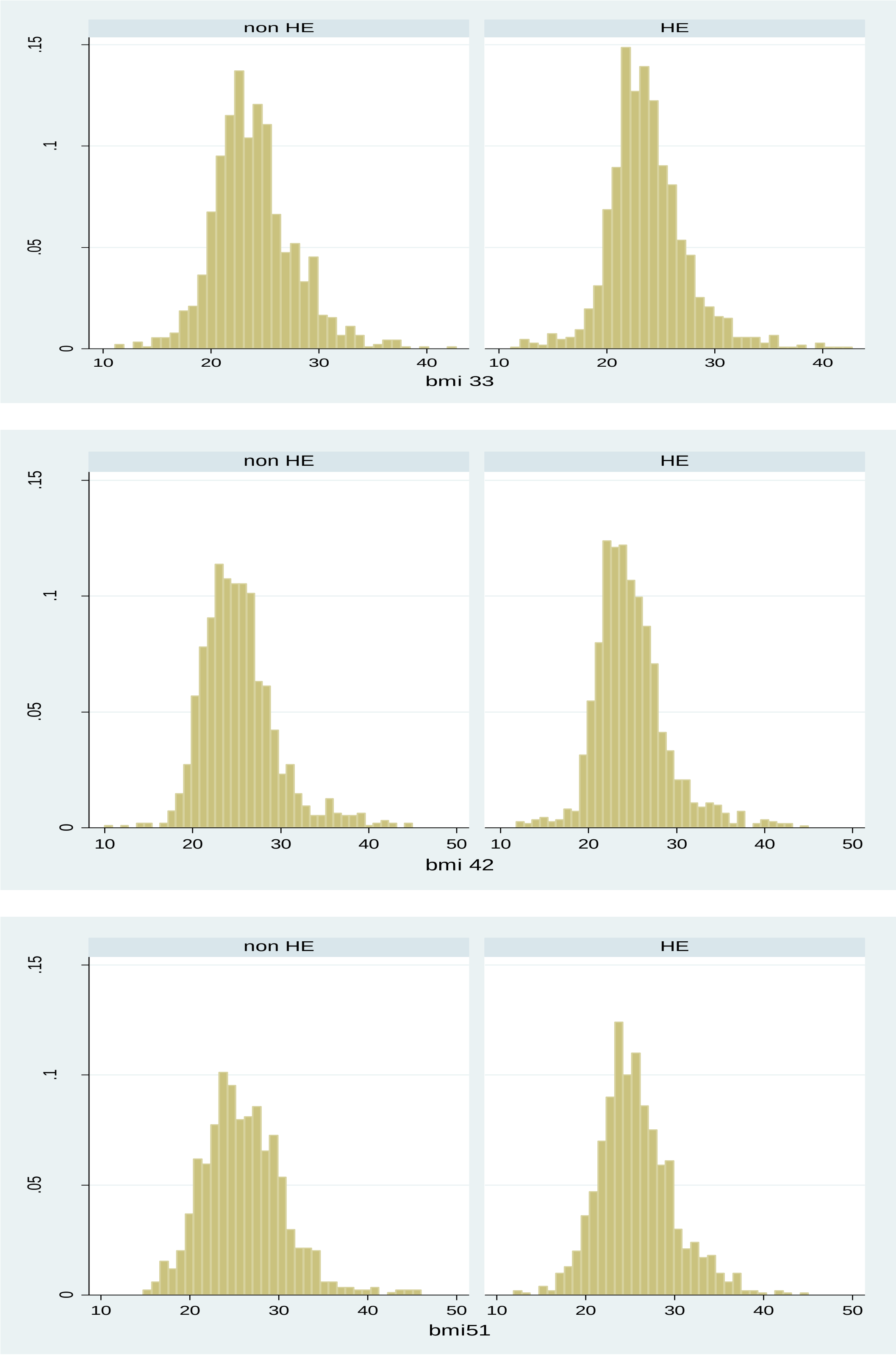


Figure 3.4 Comparisons of obesity by age (include men and women)

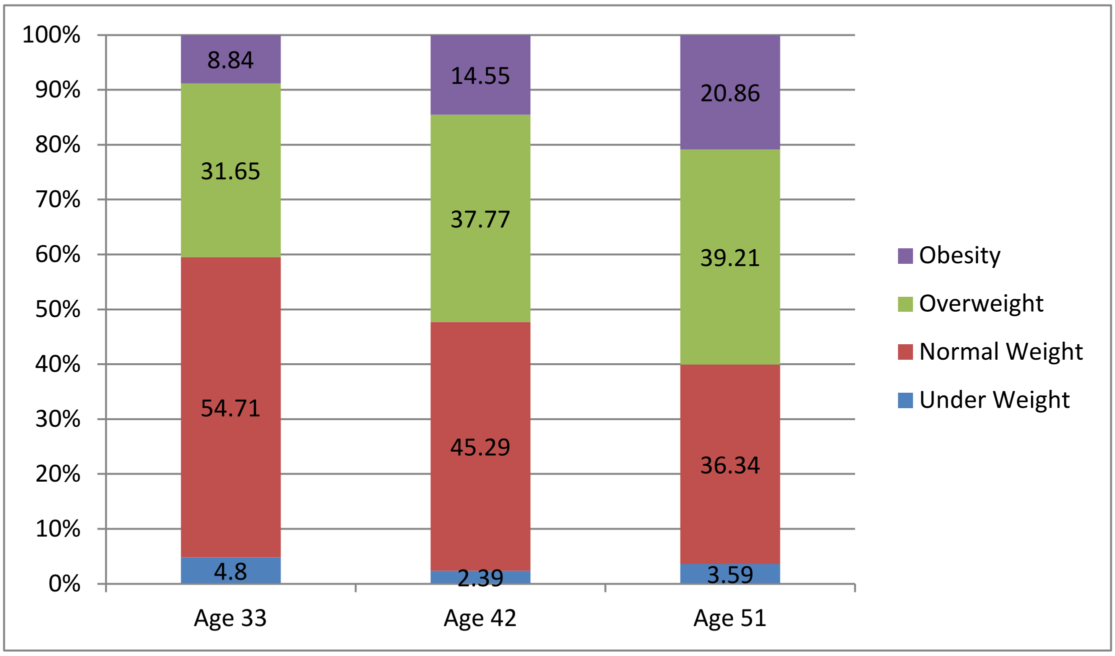


Figure 3.5 Percentages of obesity by qualifications

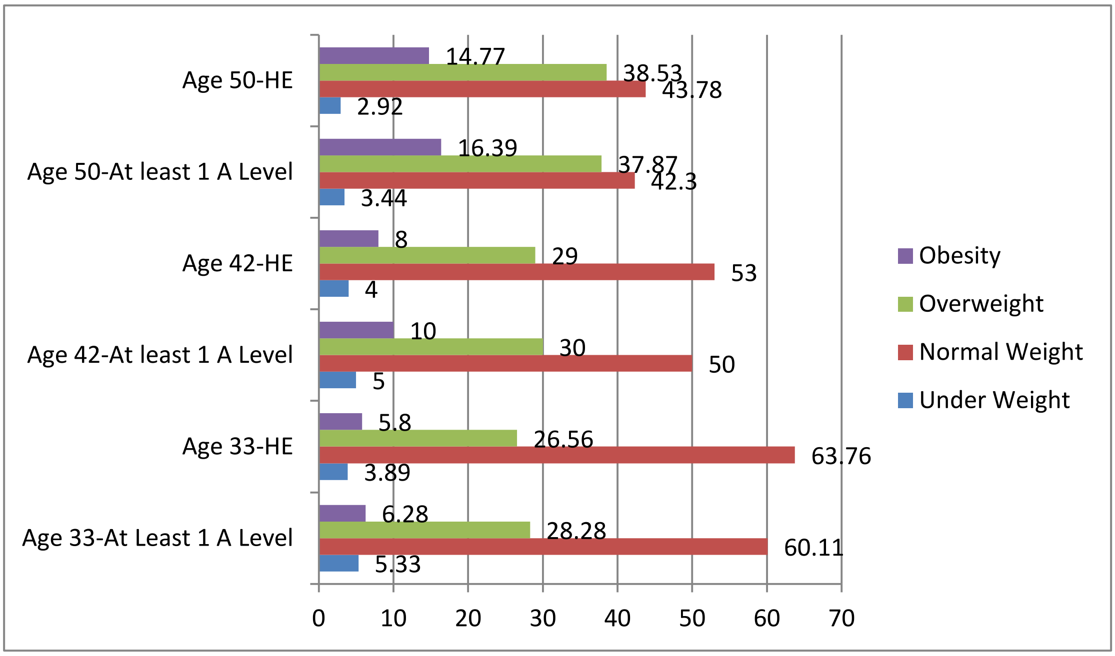


Figure 3.6 Percentages of drinking alcohol by age

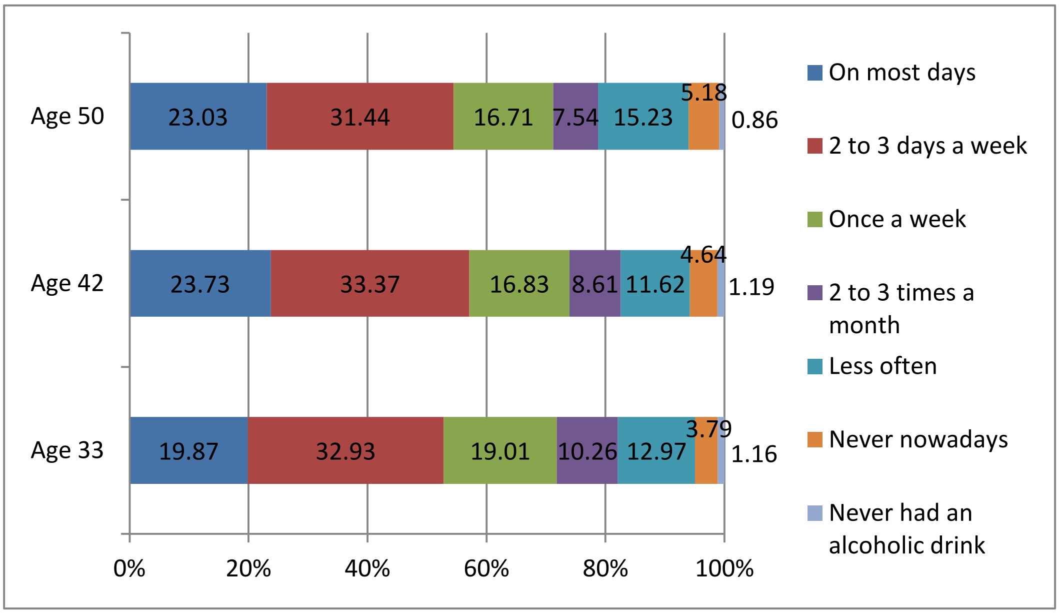


Figure 3.7 Frequency of smoking by age

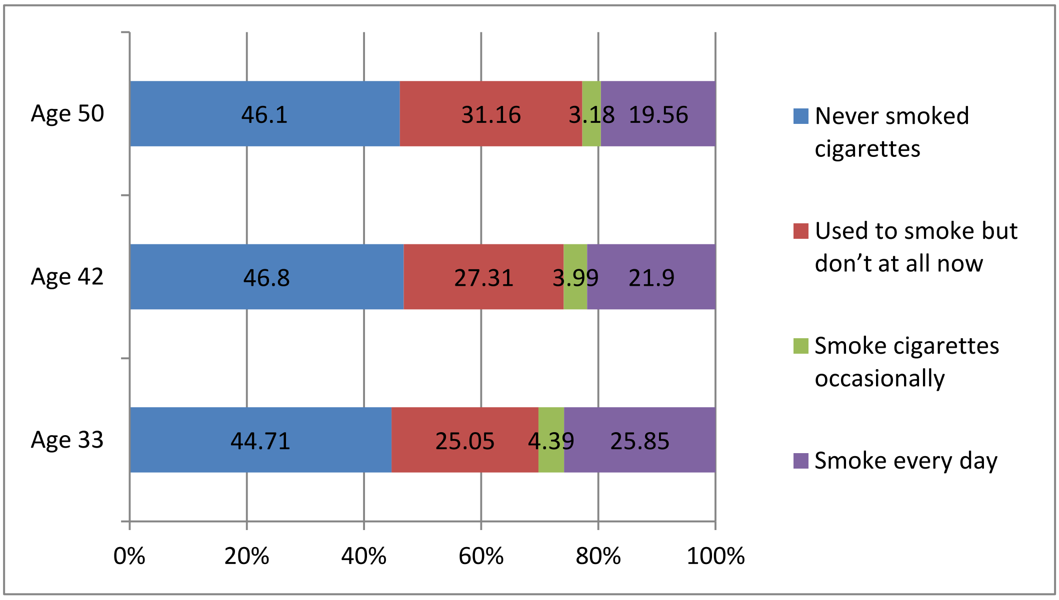


Figure 3.8 Percentages of smoking by qualification

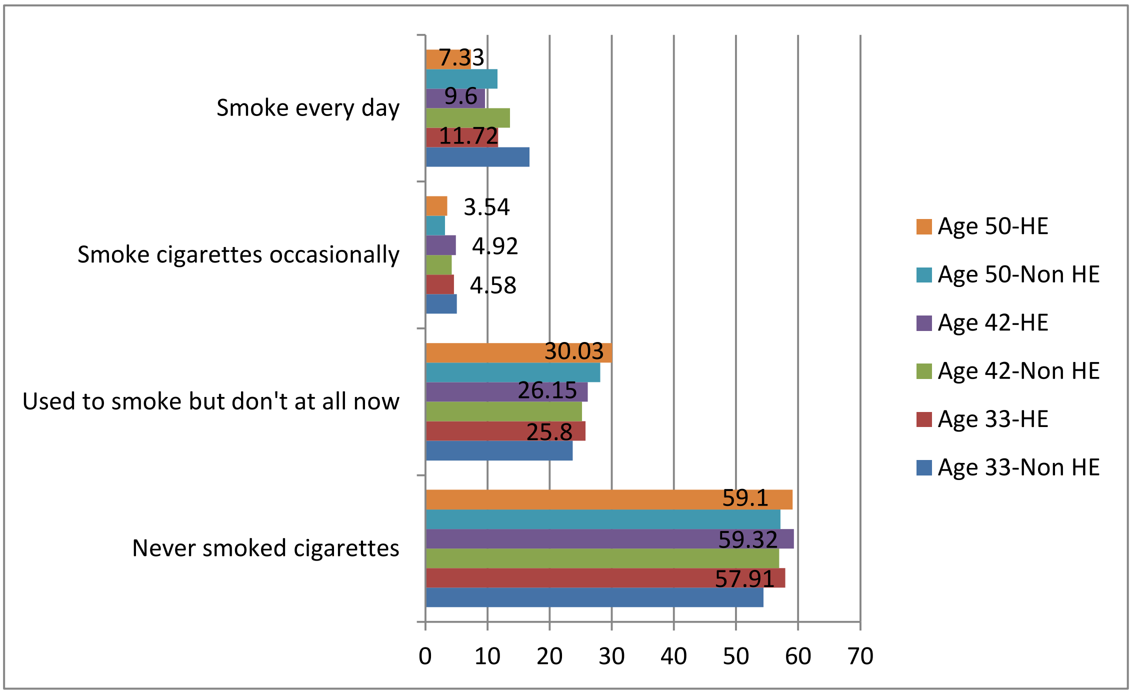


Figure 3.9 Sample of depression by gender

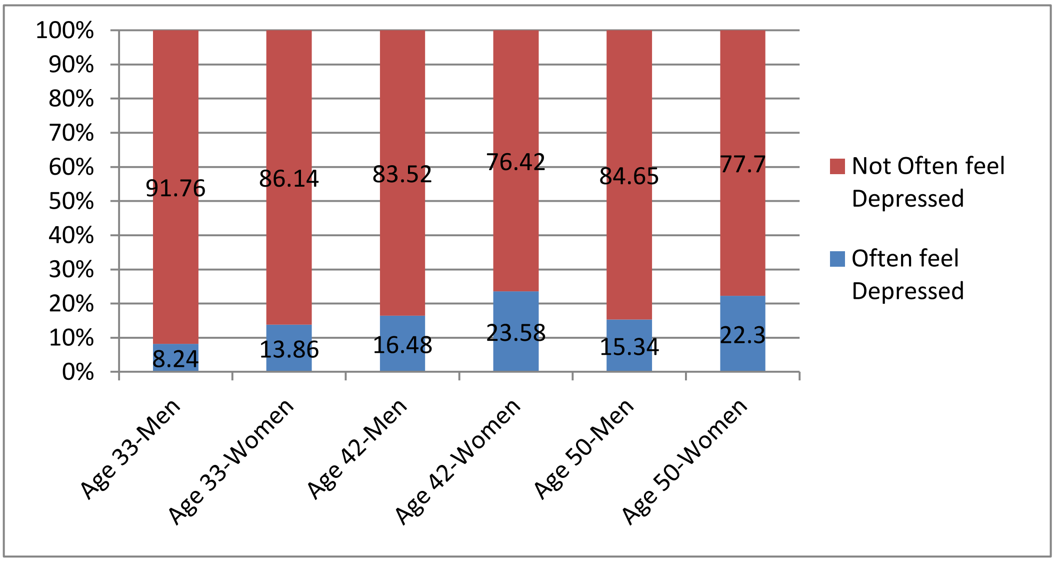


Figure 3.10 Percentages of depression by qualification

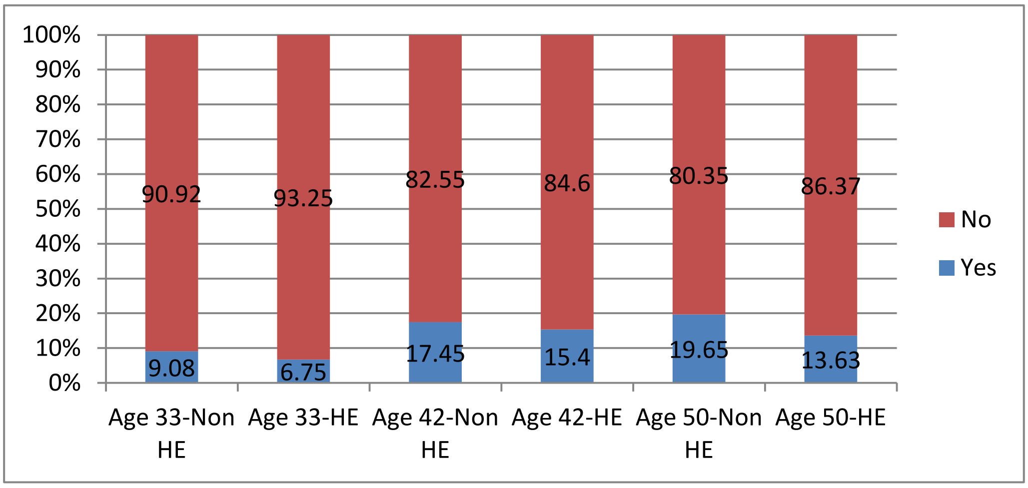
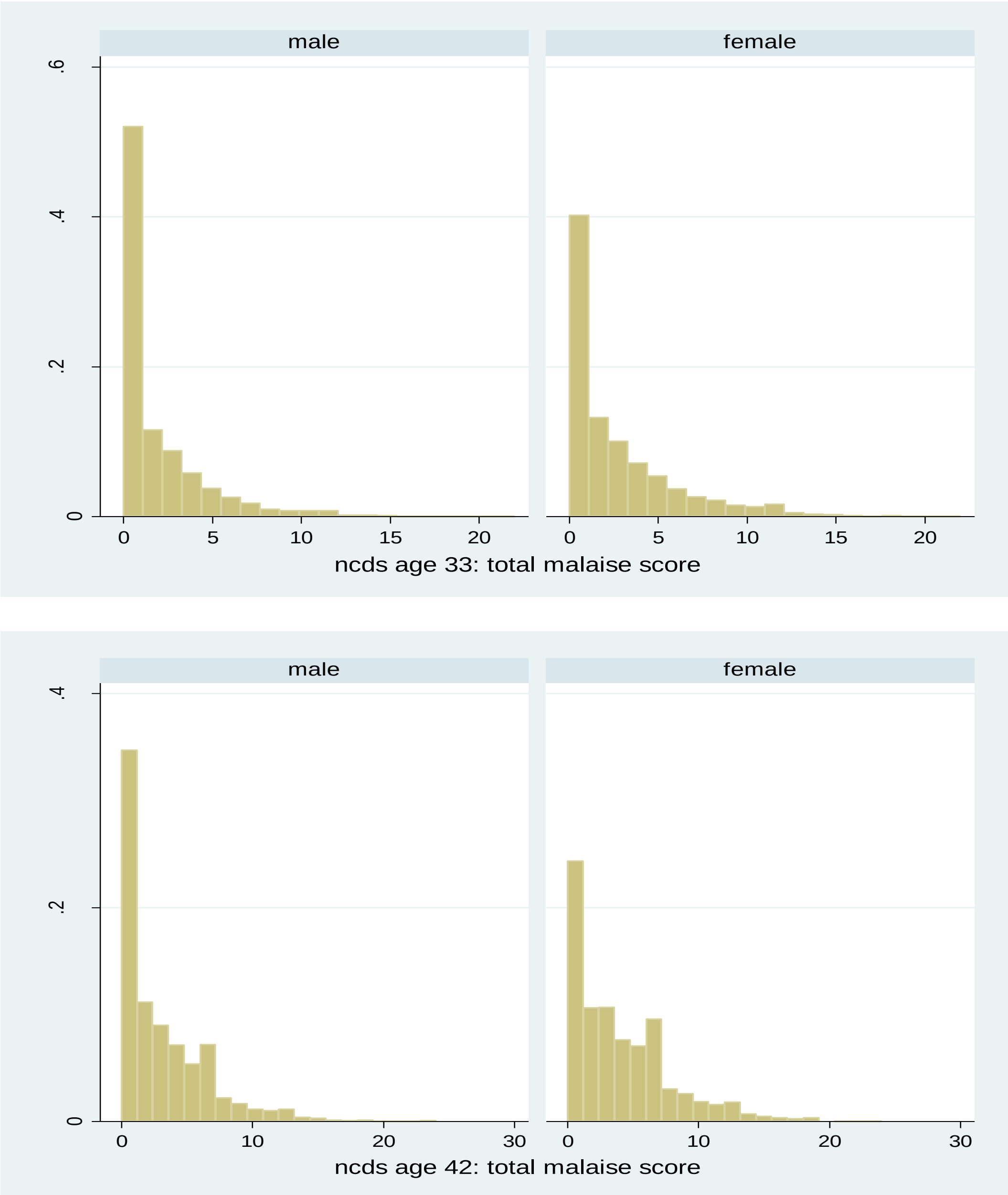


Figure 3.11 Distribution of the malaise score at different ages



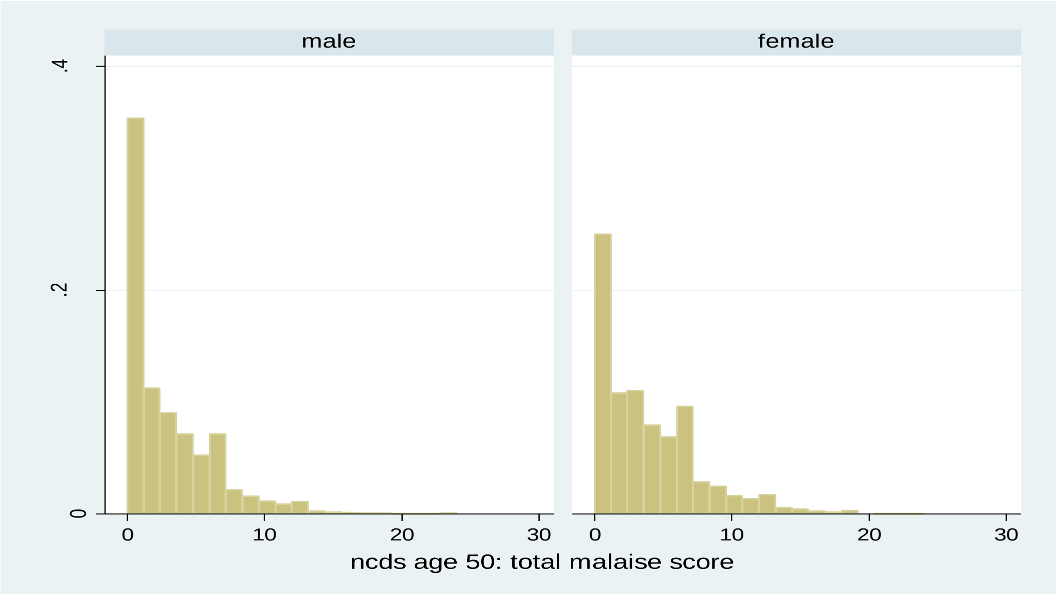
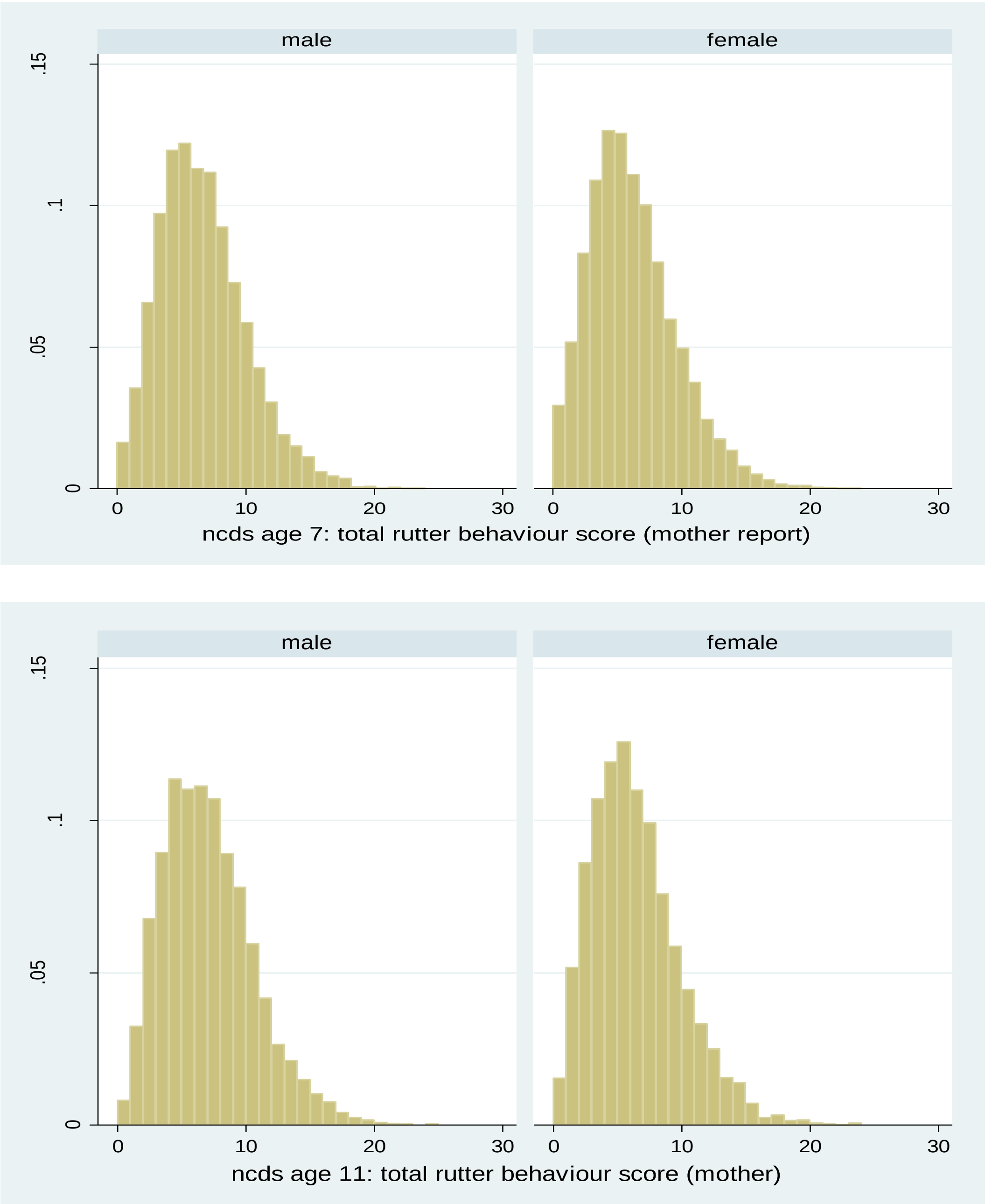

male
female
.4
.2
0
0
10
20
30
0
10
20
30
ncds age 50: total malaise score

Figure 3.12 Total Rutter behaviour score



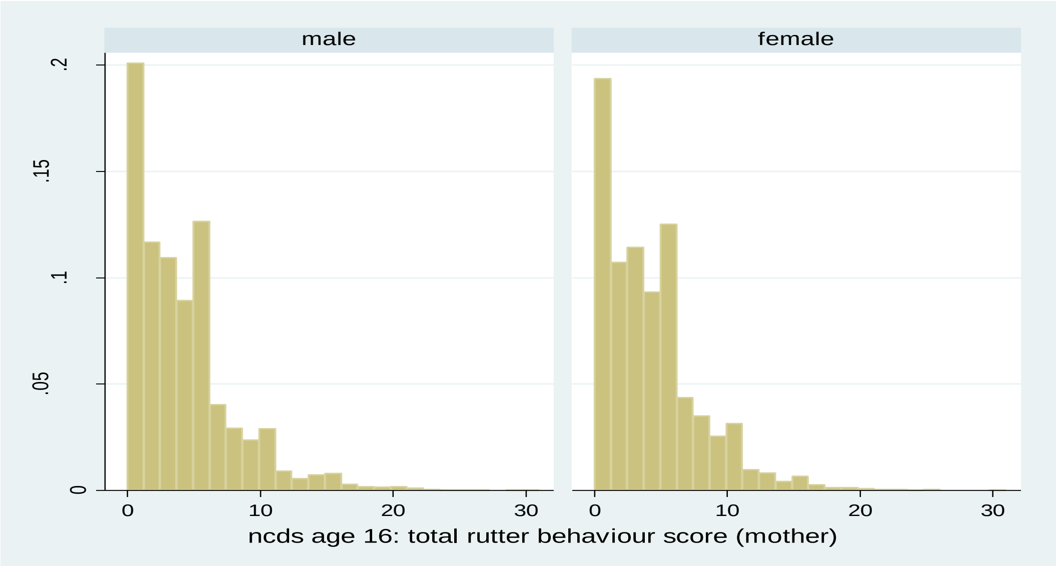
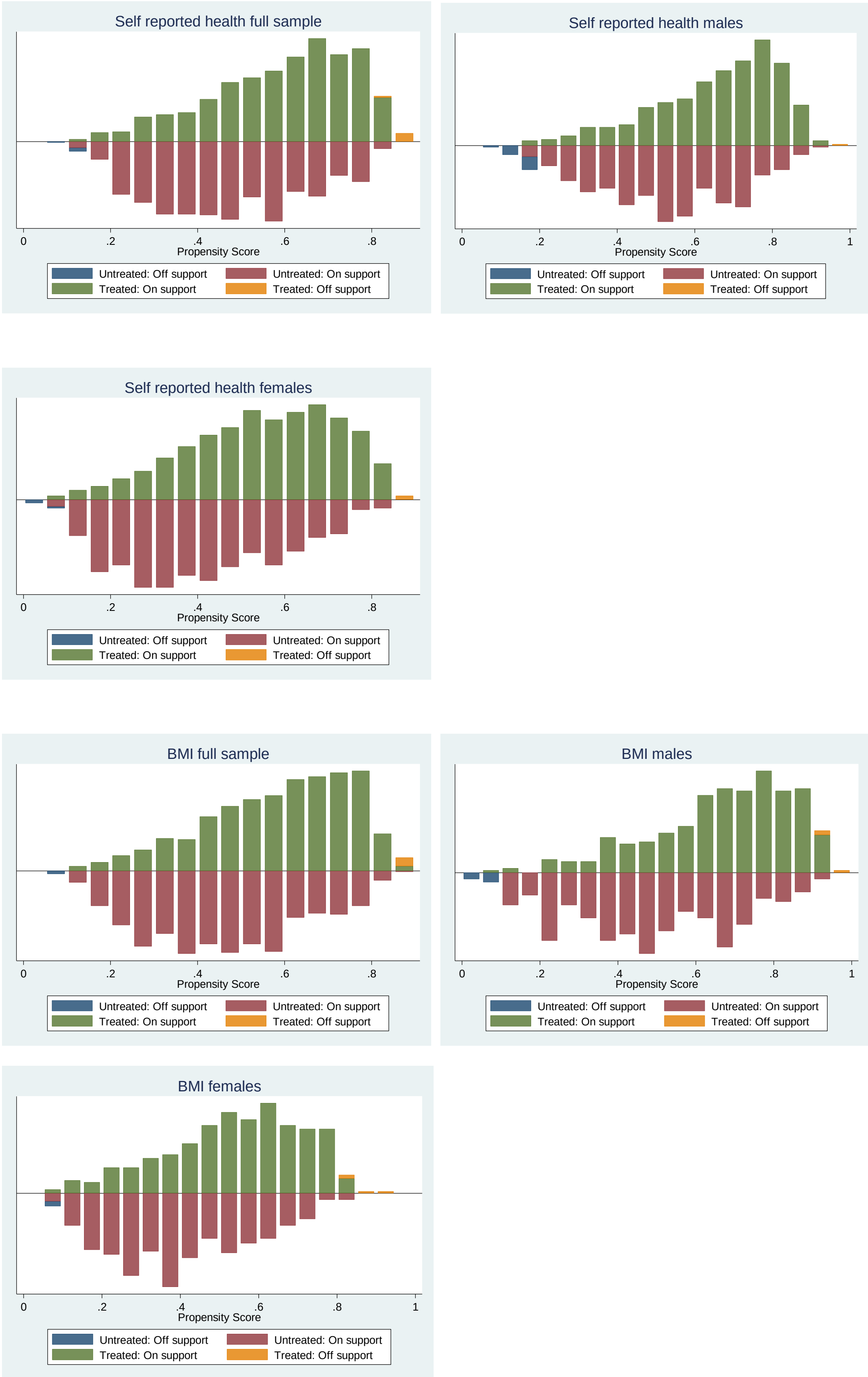
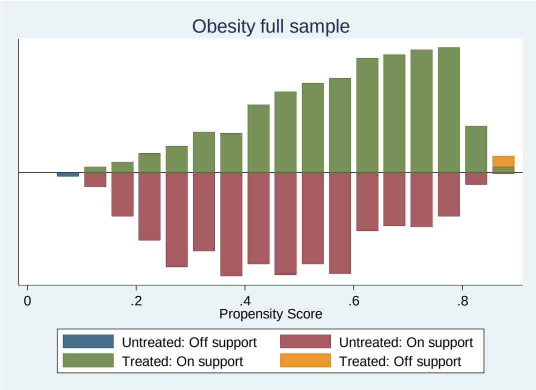
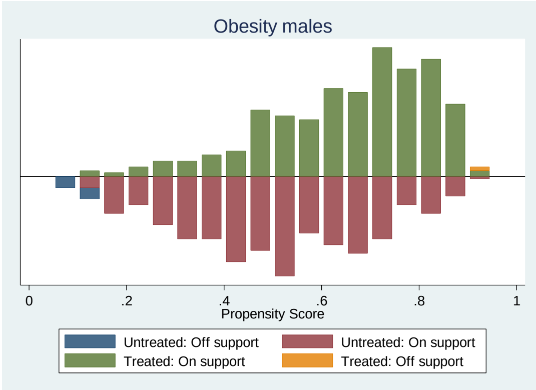

male
female
0
.05
.1
.15
.2
0
10
20
30
0
10
20
30
ncds age 16: total rutter behaviour score (mother)

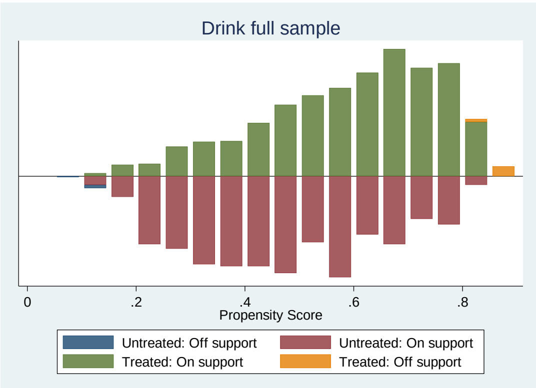
Figure 3.13 Propensity score distributions and common support regions

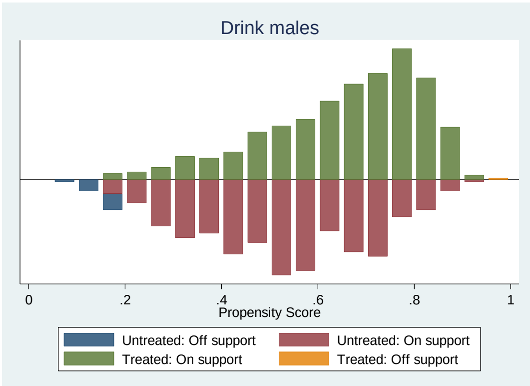


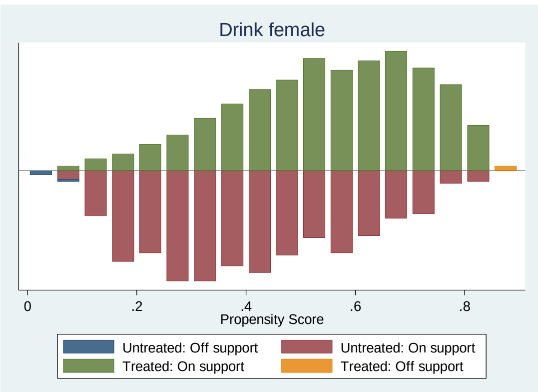

Obesity full sample
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

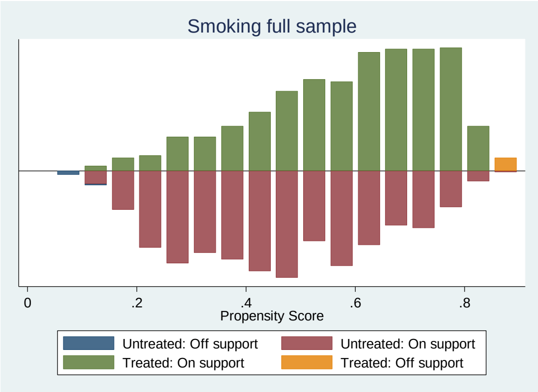

Obesity males
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

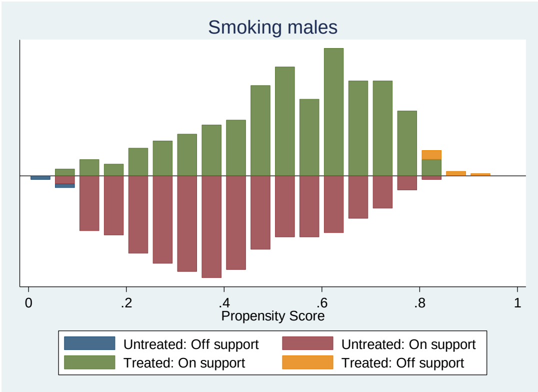

Obesity females
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

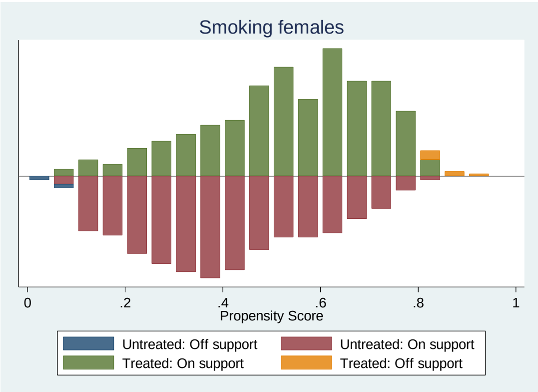

Drink full sample
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

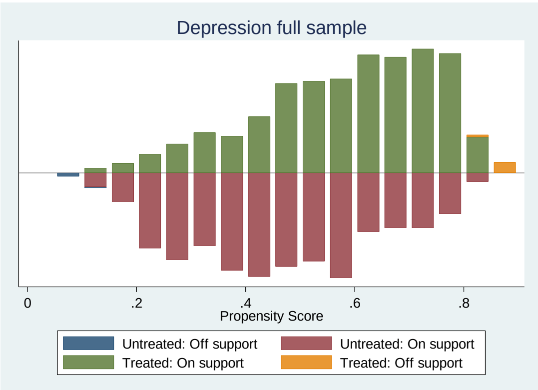

Drink males
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

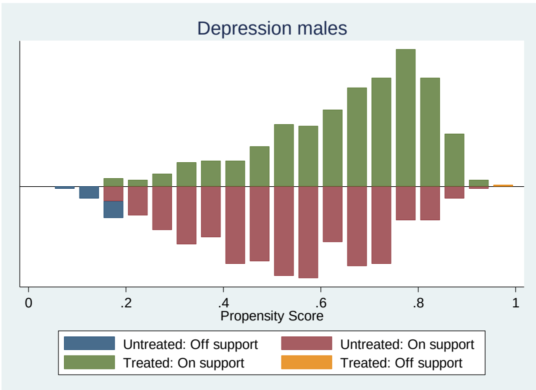

Drink female
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

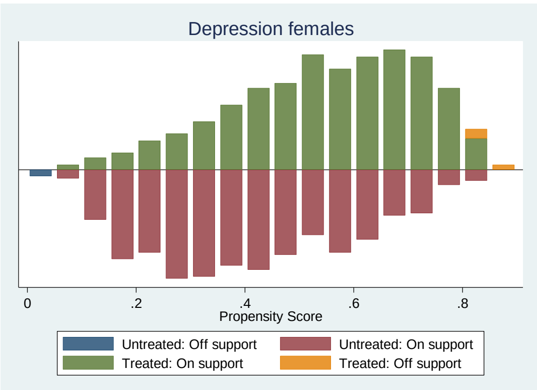

Smoking full sample
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


Smoking males
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


Smoking females
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


Depression full sample
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


Depression males
0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


Depression females
0
.2
.4
.6
.8
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support

Chapter 4: Testing the model of demand for higher education by Indirect Inference method

4.1 Introduction

The quality of the labour force is the key issue in the aim of improving economic growth. One of the main paths is to increase in the educational attainments, especially higher education (HE). As discussed in Chapter two, HE enhances both individual's capacities to work and their opportunities in the labour market. However, questions about access to and the impact of HE have long occupied the attention of labour economists and sociologists. In the rational behavioural model for the choice of attaining HE qualifications common to the economics literature, individuals normally make decisions about whether or not to continue HE is normally on the basis of cost-benefit analyses. The students choose to participate HE if it enables them to earn more lifetime earnings, at least in expectation, or demand for education can also be driven by students' and parents' perception of education as an investment in future income earning capacity. (Becker, 1962; Card, 1995; Mincer, 1974; Willis and Rosen, 1979). In other words, individuals choose HE versus non-HE according to their expected economic returns such that they attain HE only if the economic returns outweigh the costs. However, the mechanism influencing HE attainment may differ by other determinates. Quite a few researchers have asked whether family attributes (e.g. parental educational attainment, family socio-economic) are the causal effects on HE participation (Shavit and Blossfeld, 1993; Lauer, 2003; Dustmann, 2004).

Other researchers have analysed how personality traits can influence educational attainment obtained. (Almlund et al, 2011, Vignoles, 2005). All these authors argue that for individual with advantaged backgrounds, attending HE is an expected outcome. The likelihood of attending HE and earnings prospects are relatively high. In contrast, the earnings prospects for lower educated individuals are bleak, particularly if they come from disadvantaged backgrounds, which in turn result in lower HE participations.

The contribution of this paper is twofold. On the one hand, instead of exploring the direct associations between HE participation and other determinants found in most of the studies, the principal aim of this chapter is to study the role of expected returns to HE itself and of perceived returns to HE - expected returns are endogenously formed by family socio economics characteristics or personal cognitive, as determinants of HE participations. Figure 4.1 describes the hypothesised mediation effect. An individual's family social-economic characteristics and innate ability at early ages contribute to determining expected wage return, which in turn has an influence on the likelihood of HE participation. Such mediated or indirect effects add to the direct effect of wage return on HE decision.

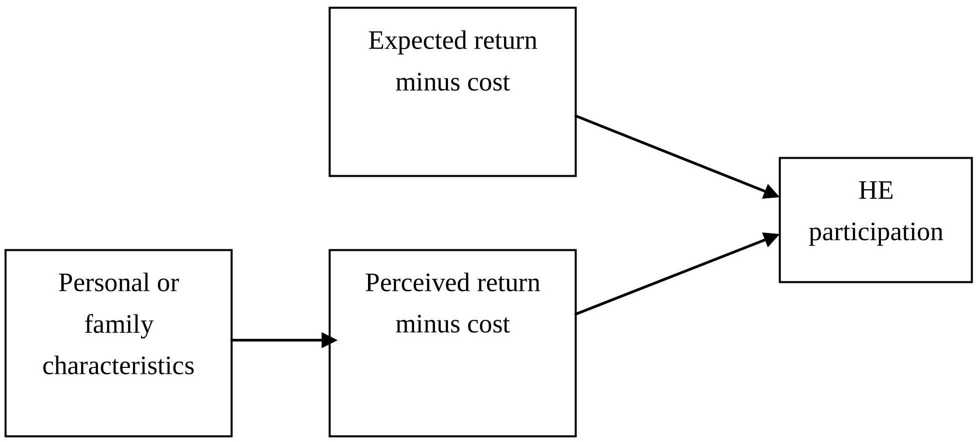
On the other hand, most of the existing microeconomics literatures related to HE decisions use standard Direct Inference estimation[42]. By contrast, I adopt a relatively advanced type of method, Indirect Inference (II, thereafter) (Smith. 1993; Gourieroux, et.al 1993 and Gourieroux and Monfort 1995) that widely used in macroeconomics

[42] This includes OLS, IV, Probit model, Sequential logit response model, Ordered Logit model, etc. discussed in Section 2.

(Le et al, 2011, 2015, Minford et al, 2012). Method based on II usually attempts to test or re-estimate a calibrated or already estimated Macroeconomic model (Le et al, 2011). However, II method is barely applied in microeconomic model and on cross-sectional or panel data. In general, models assessing HE participation is usually based either on a country macro level data or on an individual micro level data. In this chapter I will attempt to investigate the micro level determinants of HE participation by II method based on a longitudinal and cross-sectional data in the UK.

Applying econometric method that widely used in macro-econometrics on microeconomics has several advantages. The primary advantage is its generality. Unlike other estimation methods, the II method calibrates the bias function through simulation/bootstrapping and then does not require an explicit form for the bias function. Therefore, II is applicable in a broad range of model specifications. For example, in microeconomics, II have a promising advantage to least square estimation when applied on Panel data estimation. Panel data model are two dimensional (time series and cross section dimensions) in sample size, applying least square estimation method on demeaned data is inconsistent when supposing the time dimension is short. On the other hand, if observed data are with measurement error or if there is unobserved cross-section dependence, the least square estimates are inconsistent even if both the time and cross-section dimension are large. Komunjer and Ng (2010) prove that II can use the estimates of an auxiliary model that are known to be inconsistent to obtain consistent estimates of the original model. Secondly, in contrast to conventional test and estimates procedure applied in microeconomics, test power of the II (using Wald test) is substantially greater than that of the Direct Inference (LR test) and test the power of II tends to rise as the number of variables increases (Le et al, 2015). Thirdly, Wald test override the LR test is that latter one is based on model's in-sample current forecasting ability rather than its ability to mimic data behaviour such as whether the model's causal structure is also found in the data (Minford et al, 2012). Furthermore, II takes advantage of a simplified auxiliary model that is easier to estimate than a proposed structural model.

Figure 4.1 Direct and Indirect effect to HE participations



The rest of the paper proceeds as follows: Section 2 reviews the relevant literatures. The model and empirical methodology are presented in Section 3. In Section 4 I describe the dataset used and characteristics of the variables chosen. The empirical result of testing and re-estimating are listed in Section 5. Finally, Section 6 concludes and raises some general points on further researches.

4.2 Background and related literature

Following Becker (1962), the current studies use the human capital theory to model the education decision in terms of the expected value of educational investment. They typically conceptualise returns to education as labour-market or earnings returns. Willis and Rosen (1979) are among the earliest and most influential studies that attempt to solve self-selection bias resulted in the estimation of participation equations. The researchers allow the demand for college education depended on expected future earnings, and examine the role of earnings expectations and family background in the schooling decision, particularly in the decision to go to college and equivalent. Using a switching regression, they extend the Roy model to allow for endogenous self-selection into college education, with the difference in expected utility between college education and high school education affecting the likelihood of college education and estimates take accounts for earnings expectations and for heterogeneity in ability levels, in tastes, and in capacity to finance schooling investments. They found evidence for this selection bias because individuals who attended college would have earned less as high school graduates than observably similar persons who stopped schooling after high school, and individuals who did not attend college would have earned less as college graduates than observably similar persons who did attend.

The papers that study educational attainment have recently been becoming broader. One of the branches has recognised the sequential nature of educational decisions. For example, Mare's (1980) model of educational transitions represents one of the major methodological contributions to the literature on family background and educational success. Mare (1980) extends the contribution from Boudon (1973) and suggests to treat educational attainment as a sequence of discrete transitions from lower to higher educational levels and to develop a sequential logit response model to school continuation, restricting the individual sample for each successive transition to those who had completed the prior educational transition. He estimated the effect of family background characteristics on the transition probabilities. A main result in his paper is that the effect of parental characteristics decline as the grade levels increase. Hence, one of the consistent findings from applied research using the Mare model suggests that the effect of family background variables tends to decrease across successive educational transitions (e.g. Merz and Schimmelpfennig, 1998; Couch, 1994; Buechtemann et al., 1993).

Cameron and Heckman (1998) criticised Mare's transition model because it empirically reduces the impact of family background across transitions. They characterise a source of strong attenuation bias on the role of parents' wealth or education in the schooling decision in upper grades. The main argument is that educational decisions should originate from the long-term effects of family characteristics on ability, motivation, and other unobserved characteristics in contrast to short run credit constraints. They propose an alternative choice-theoretic model for educational attainment that can be implemented empirically using an Ordered Choice

Model that deals with the presence of endogeneity of education decision model caused by unobserved individual heterogeneity. Evidences can be found by Cameron and Heckman (2001), Ermisch and Francesconi (2001), Keane and Wolpin (2001), Cameron and Taber (2004), Todd and Wolpin (2006), etc.

4.2.1 Causal effects on Educational attainments: Evidences in UK

Compared to the vast literature within the economics of education that is concerned with returns at different levels of qualifications, empirical research into the decision to educational attainment associated with return to education and other factors is fairly sparse. Empirical studies mainly have assessed the relative contributions of family background, prior educational attainment and attributes of schools. Educational attainment also differs across socio-economic groups, and the existing literature has documented a strong relationship between individual's educational attainment and family background. However, whether both parents' education causally affects their children's own educational attainment is controversial.

In empirical the microeconomic literature for the UK, early studies on observed HE decision of high school graduates, the interest of parameters is usually estimated using Probit model analysis. Rice (1987) develops a Probit model of post-compulsory schooling using data from the 1976 Family Expenditure Survey. The result reveals that family income has an insignificant effect in the decision to continue in post-compulsory education for males, while for females it is significant. However, the socio-economic background of individual has an influence on the probability of undertaking post-compulsory education. Blundell et al. (1997) state that individuals without a 'father figure' at age 16 has little impact on the probability of achieving an A-level or HE, whereas the indicator of bad financial status has a strong negative effect on A-level attainment.

Ermisch and Francesconi (2001), following Cameron and Heckman (1998), try to identify causal effects of family background on educational attainment using data from the British Household Panel Survey (BHPS). They apply an Ordered Logit Model and suggest that family background has causal effects on children educational attainment if, and only if, family background affects the cost of schooling. They report that when family background affects the cost of education, the relation between parents and children education represents a causal effect. In particular, for individuals belonging to the group of "poor parents" both family structure and parental education have a positive causal effect on the children's educational attainment. For example, the parental qualification level increases from less than O-level to above degree qualifications, the probability of their child achieving degree qualifications level increases dramatically from -5% for father and 40% for mother (less than O-level) to 61% for father and 78% for mother (degree qualifications), respectively. Experiencing a single parent family has a significant negative effect on an individual's educational attainment, which accounts for -0.323. Individuals with more brothers and sisters also have lower education attainments (-0.159 and -0.261, respectively). Individuals whose parents are in the bottom quartile of the family income distribution have lower educational attainments while the negative impact of being from a family that experienced financial difficulties also has a negative effect (-0.528) on education. In addition, for ethnic minorities, individuals with Indian or Chinese parents have significantly higher educational attainments (1.02 and 0.85, respectively). This is in the line with the sense that Asian parents usually encourage their offspring to obtain HE.

Chevalier and Lanot (2002) propose a strategy separating the relative effect of financial situation from family characteristic effects in educational attainments using NCDS and BSC data. They apply an ordered Probit model to estimate the leaving school decision from age 16 to 20 and present a similar result with Harmon and Walker (2000) in that poorer families that are financially constrained are less likely to invest in the human capital of their offspring. However, they also argue that the family characteristic effects dominate the financial constraint effects, mainly the parental education because it is evident that a financial transfer would not lead to a significant increase in educational investment.

Valbuena (2011) adopts an Ordered Logit Model to analyse the relevance of family background and education attainment of offspring use BHPS. In particular, the author finds that parental educational attainment is a strong predictor of the education of their offspring, while the mother's education is the main determinant on the decision of whether to go beyond compulsory education.

Galindo-Rueda et al. (2005) use data from the Youth Cohort Survey (YCS) and the Higher Education Statistics Agency (HESA) to examine how individuals from households with different levels of income have varied in their HE participation likelihood over time. Their results suggest that wealthier areas experience a more rapid increase in the number of students choosing to participate in HE at age 18 between 1996 and 2000. They also conclude that before the introduction of undergraduate tuition fees in 1996, there was a significant class divide in participation which largely reflected pre-existing patterns of educational attainment and economic background.

Chowdry et al. (2010) use a student-level dataset to explore patterns of participation among people from different socio-economic backgrounds in the UK. They use a micro-level linear Probit model with school fixed effects controlling for selection bias of participation in HE. Their result suggests that male/female students from the poorest socio-economic quintile are 40.7% /44.6% less likely to participate in HE than students from the top quintile, respectively.

Other studies have come to similar conclusions. For example, Gayle et al. (2002) using YCS data find that parental education, socio-economic class and State-school attendance all affect HE participation probabilities. Blanden and Machin (2004) find that the expansion of HE in the UK has disproportionately benefited students from wealthier backgrounds after controlling for individual characteristics and prior academic achievement.

4.2.2 Intergenerational educational mobility

The transmission of parental education across generations is also an important related field of the literature. Such education mobility seems to be influenced to a greater extent by levels of educational attainment across generations (Solon, 2002). The issue of intergenerational mobility was raised in UK by Blanden et al (2005), who argue that children from rich families receive the most benefit from the expansion of the HE system. Meanwhile, the gap between children coming from rich and poor backgrounds has widened over time. Recent studies use twins as parents, adoptees method, and instrumental variables to identifying the intergenerational transmission of human capital from parents (Björklund and Salvanes, 2010). Behrman and Rosenzweig (2002) is one of the first papers to use a sample of twin mothers in order to estimate causal effects of parental education on children's education, controlling for confounding genetic bias. However, there is no evidence of an effect between the mother's education and the child's education. Holmlund et al (2008) studying dizygotic twins for mothers and fathers, and find that there is no significant effect of the mother's education on child education outcomes, whereas they do find an effect of the father's education.

The identification of causal effect has also been solved using ‘adoptee’ approaches, for example: Dearden, Machin and Reed (1997) in the UK; and, Sacerdote (2004) and Plug (2004) in the US. Such studies design a natural experiment that adoptees must be randomly assigned to adoptive families to control for heritable effects. This happens because if the adoptees are randomly placed, the causal effects of parental education can be estimated since there is no relation between the biological and adoptive heritable endowments of the adoptees. Sacerdote (2004) and Plug (2004) find a strong positive effect for mother’s education on the child’s highest education attainment. Sacerdote (2004) finds little evidence for a direct effect of parental income on adoptees’ income and education. Björklund et al (2006) and Björklund Jäntti and Solon (2007) investigate a significant positive effect of adoptive father’s education on their child’s education whereas the effect of mother’s education becomes relatively small.

Other studies also create exogenous variation in the form of rules regarding age at school entry rules or compulsory schooling laws in estimating the parameter of interest. The empirical finding is somewhat mixed. Chevalier (2003) uses the change in the compulsory schooling laws in Britain in 1957 as an instrument and finds a large positive effect of a mother’s education on her child’s education but no significant effect of father’s education. Chevalier et al. (2005) further adopt schooling reforms as an instrument using UK LFS data. Their results are in contrast to the previous research and they find that the effect of parental education is insignificant when income measures are included; in other words, family income instead, which turns out to be a stronger effect on the children's educational attainment.

Chevalier et al. (2002) use the UK Labour Force Survey to examine the impact of parental education and income on the probability of a child remaining in school post-16 and also on the probability of attaining five or more GCSEs graded A to C (a standard measure of educational achievement in the UK). Despite large effects of parental education on the children's educational outcomes in the OLS, when instrumenting both education and parental permanent income, the parental education effects become non-significant. Both of these studies are limited by the child outcome variables available in the respective datasets. More evidence applying the IV approach can be found in: Oreopoulos, Page and Stevens (2006) in the US; Carneiro, Meghir and Parey (2007) in the UK; and, Black, Devereux and Salvanes (2005), Holmlund, et al (2008) in the Nordic countries.

4.2.3 Family income and other family background effects

The relationship between parental income and the level of educational attainment is controversial. The fundamental question is whether it is money itself that makes the difference to individual's human capital opportunities. Some argue that a direct relationship exists and others that unobserved factors correlated with both income and attainment drive the relationship. For instance, parental income might indicate the eventual effects of family background on cognitive and non-cognitive ability, and on the parents' tastes for education.

Cameron and Heckman (2002, 2003) use US data to provide empirical evidence suggesting that long-term family permanent income is much more important for individual's educational attainment than short-term credit constraint.[43] Family permanent income actually turns out to be an important predictor for college enrolment. Parents with low education and income are less likely to provide appropriate environment for motivating the young ending secondary school to apply for university education in the long run. Aakvik Salvanes and Vaage (2005) use Norway data and find only a small effect of short-term credit constraints on educational attainment. Even though family income is significant in determining the educational attainment, parental education turns out to be the most important factor. For example, either father or mother with a college degree increases the probability of the child having a college degree by more than 20%.

Although there remain controversies over the effectiveness of family income, other existing literature provide relatively sound evidence from the UK. Gregg and Machin (2000) indicate that low family income does have an independent effect on the children's educational outcomes when controlling for family background and personal ability aspects. Levy and Duncan (2001) using the Panel Study of Income Dynamics adopt sibling variation to eliminate family fixed effects and find that parental income

[43] They argue that the short-term income constraints facing parents at the time of their child's potential enrolment in college have no significant effect on child enrolment once the longer-term constraints are controlled.

has an impact on child's educational outcomes in late years but that the magnitudes of effect are small. Blanden and Gregg (2004) adopt variety of approaches controlling for family background and heterogeneity, and find evidence that family income does have a causal impact on educational attainment, using NCDS, BSC and BHPS data

There are also some literature about family size and birth order (i.e. how many elder siblings), which possibly have effects on educational achievement. For example, family size may have an impact because there is a trade-off between child quantity and quality, while siblings may not receive an equal share of resources devoted to their education.

Black et al. (2005) shows that that educational attainments decline with family size and birth order. Moreover, recent statistical studies also highlight that social class is the strongest predictor of educational attainment in the UK (Cassen and Kingdon, 2007; Dyson et al., 2010).

4.2.4 Personal attributes

More able individuals attempt to signal their ability by acquiring more education than less able individuals (Lang and Kropp, 1986) and an individual's academic ability is an important determinant of enrolment decision of post-secondary graduates (Fuller, Manski, and Wise, 1982).

A number of studies highlight that a variety of cognitive (such as verbal and numeracy ability) and non-cognitive (such as self discipline and perseverance) personal ability and characteristics influence educational attainment and choices. Heckman and Rubinstein (2001) and Heckman et al. (2006) find that non-cognitive skills are quantitatively important determinants of post-secondary educational attainment in the US. Galindo-Rueda and Vignoles (2005) compare the cohort from NCDS in 1958 and BCS in 1970 to find that the role of early cognitive ability to determine educational attainment. Although the authors argue that cognitive ability has declined in importance while family background has become a more important determinant of educational success, it confirms that, for both cohorts, early ability is still a good predictor of educational attainment.[44] Chowdry et al. (2010) state that nearly 40% of the variation of the gap in educational attainment for individuals from different backgrounds at the end of compulsory schooling can be accounted for by prior educational attainment. Collier, Valbuena and Zhu, (2011) use the data from Longitudinal Study of Young People in England (LSYPE) and find all family background variables explain no more than 14% of the variation in the decision to pursue an academic qualification upon completion of compulsory education at age 16. By contrast, educational attainments at the end of the compulsory schooling stage are much powerful predictors for post-compulsory educational choices.

[44] They estimate the probably of attaining a qualification at degree level or higher of males by using cognitive ability index at age 10. The index is constructed by principal components analysis to each cohort survey.

4. 3 The model and methods

4.3.1 The model

In this section I will provide a simple framework that will shed light on decision process of HE attainment in terms of expected return to education. Assuming that the individual deciding whether to go to university is an adult person (age 18) who is endowed with the full ability to commit himself or herself to the effort required by the education system. Consider that each individual lives two periods, and makes the decision of whether attending HE in the first period of his life. At the end of the period, this individual obatined either a HE degree or non-HE qualification (i.e. only A-level qualification). The utility of individual *i* is given as*:*

$U_i = LnC_{1i} + \beta LnC_{2i}$ (4.1)

In period 1, each individual chooses how much to consume C_{1i} of labour income W_{1i}, how much to invest in HE T, and how much to save S_i:

$S_i \leq (W_1 - C_1 - T)$ (4.2)

In Period 2, each individual can consume future expected wage income that depends on how much he/she spends on HE and gross return on savings that he/she brought from the first period:

$C_2 \leq E(W_2) + (1 + r)S_1$ (4.3a)

$E(W_2) = w_1 + \varDelta_i * T$ (4.3a)

where r_e is the return to education. Therefore, the decision problem of each individual is to maximise (4.1) with respect to T, C_{1i} and C_{2i} subject to budget constraint:

$C_2 \leq W_1 + \Delta_i * T + (1+r)(W_1 - C_1 - T)$ (4.3c)

The optimal schooling decision must be a solution to the following maximisation problem:

$MaxL = LnC_{1i} + \beta LnC_{2i} + \lambda(C_2 - W_1 - r_e T - (1+r)(W_1 - C_1 - T))$ (4.4)

$\frac{\partial L}{\partial T}$: $\Delta_i = 1 + r$

The FOC implies the corner condition where T is either zero or full cost of becoming a university graduate. One important feature of this decision rule is that a greater premium as captured by Δ_i (i.e. gross interest rate) will encourage HE attainment, whereas the higher interest rate r will discourage HE attainment. Hence the decision to HE is pursued to the point where its marginal rate of return to education equals the rate of interest.

Assuming that there are HE alternatives, the individual makes the decision of attending HE (T=1) only if expected return to education r_e has to exceed the expected real rate of interest r, since the individual enrolls with a university which can accommodate with the model result, and *vice versa*. However, if individual's r_i^e is greater than r, but he/she does not go for HE (T=0), there must be an error term, since it contradicts the model's result. In other words, the error term e_t is the missing valuation of such individual against going to HE. Hence, the error term can be calculated as follows:

$$e_i = 0, if \begin{cases} r_{e,i} - r > 0 \; and \; T = 1 \\ r_{e,i} - r < 0 \; and \; T = 0 \end{cases}$$

$$e_t = r_{e,i} - r, if \begin{cases} r_e - r < 0 \; and \; T = 1 \\ r_e - r > 0 \; and \; T = 0 \end{cases} \qquad (4.5)$$

Therefore, I can write out the structural model that generates a prediction of individual's decision to HE as follows:

$$T_i = \begin{cases} 1, \;\; if \; d_i > 0 \\ 0, \;\; if \; d_i < 0 \end{cases}$$

$$d_i = r_{e,i} - r + e_i \qquad (4.6A)$$

Where d_i is the threshold value of decision function that determined by difference in rate of return in education and interest rate plus the error term. Hence, if $d > 0$, individual choose to go for HE.

I set three research questions to test the association between the determinants of HE participation and other variables. A special focus is paid to the determinants that are related to the individual and family characteristics. First of all:

HYPOTHESIS 1: *Individual's decision to go to HE depends only on their expected return to HE. It is not related to personal and family characteristics.*

According to ex-post rationalization of HE enrolment, the only reason to attend college is the premium betwwen expected return to eduaction and interest rate. Hypothesis 1 is only formulated in terms of the model results. On the other hand, family background has been prominent in models of educational attainment or HE decision. In large number of studies, family background has been measured by family socio-economic indicators. Prior studies indicate that parents with more education and higher income presumably provide more human and material resoureces that could benefit the offspring's academic ability and orientations. Hence, the sencond hypothesis states that:

HYPOTHESIS 2: *Individuals' decision to go to HE depends not only on their expected returns to HE, family characteristics also have an impact.*

As a result, in addtion to the expected return to education, I also take into account the possibility that the perceived return to education can be defined by some sociological model, as follows:

$$T_i = \begin{cases} 1, & if\ d_i > 0 \\ 0, & if\ d_i < 0 \end{cases}$$

$$d_i = r_{e,i} - r + e_i$$

$$r_i^{perc} = r_{e,i} + \lambda' Z_i + \epsilon_i \qquad (4.6B)$$

where Z_i is the vector of family socio-economic variables. As in this case, I obviously expect r_i^{perc}, the return to HE assoicated with family socio-economic background, is perceived by the individual to can sucessfully explain the decision to attend HE. According to the finding of previous studies, measures of family socio-economic background are expected to be positively associated with perceived return to education, and in turn affect decision to HE indirectly.

Furthermore, one can argue that HE is just a filter that sorts on variations in intelligence. Personal cognitive ability is one of the main reasons why HE is rewarded in the labour-market. Individuals with higher cognitive ability will get higher wage returns provided that they participate in HE because HE study acts as a signal that they are worth a higher wage. Therefore, I proposed the third hypothesis:

HYPOTHESIS 3: *More intelligent individuals attempt to signal their cognitive ability by acquiring more education than less able individuals. An individuals' decision to go to HE depends on their perceived return to HE that associated with their cognitive ability.*

In this case, the perceived return to education can be modeled as:

$$T_i = \begin{cases} 1, & if\ d_i > 0 \\ 0, & if\ d_i < 0 \end{cases}$$

$$d_i = r_i^e - r + e_i$$

$$r_i^{perc} = r_i^e + \rho' C_i + \omega_i \qquad (4.6C)$$

where C_i is the vector of personal cognitive variables.

4.3.2 Indirect Inference

II was first introduced by Smith (1993), Gregory and Smith (1991 and 1993), and Gourieroux et al. (1993), and was surveyed by Gourieroux and Montfort 1995. II is a simulation-based method for evaluating or making inferences about the parameters of economic structural models with intractable likelihood functions. It is widely applied in modern economic analysis, including nonlinear dynamic models, and models with latent variables, missing or incomplete data.

When using II for evaluating a structural model, it would bootstrap from the original data or simulate the data from the model when given the set of parameter values and the distributions of the errors. The idea behind II is to obtain a set of auxiliary parameters by estimating an approximate or auxiliary model to form a criterion function. The auxiliary model serves as a window through which to view both the observed data and the simulated data generated by the structural or economic model, and is also characterised by a set of parameters which can be estimated using either observed or simulated data. Therefore, II is to optimally choose the parameters for the auxiliary model so that two sets of the parameter estimations of the auxiliary model are as close as possible.

To be more specific, assume that a set of observations $y_1, y_2 \ldots y_n$ is generated from a structural model and denoted by the probability density function $f(y_n|x_n, \beta)$. Suppose that one can specify an auxiliary model defined by a conditional probability density function $f^a(y_n|x_n, \theta)$, which can be estimated by the quasi (pseudo) maximum likelihood method. The parameter is estimated by maximising a criterion function using the observed data. The auxiliary model can be estimated by maximising the log of the likelihood function to obtain parameter estimates:

$$\hat{\theta} = arg\, max_\theta \sum_{i=1}^{N} log\, f^a(y_i|x_i, \theta) \quad (4.7)$$

where $\hat{\theta}$ serves to capture certain features of the observed data. $\hat{\theta}$ in general is an inconsistent estimator of β. Using the model under $f(y_i|x_i, \beta)$ to simulated paths of length N by drawing independently S times and generate pseudo observations y_n^s. One in turn applies the estimation procedure and the likelihood function based on the simulation given by:

$$\widetilde{\theta}\,(\beta) = arg\max_{\theta} \sum_{s=1}^{S} \sum_{n=1}^{N} logf[y_n(\beta)|x_t, \theta] \qquad (4.8)$$

4.3.3 Model evaluation

The model evaluation procedure is concluded in four steps, as follows:

Step 1: Calculate the errors from the structual model

The idea of PSM methodology is to attempts in non-experimental context to replicate the setup of a randomised experiment. This refers to pair treatment and control units with similar values on the propensity score. It invokes strong ignorability assumptions in order to recover the missing counterfactual so that the outcome would have resulted if an individual had made an alternative choice (i.e. if individual had chosen not to go for HE). For each treated unit (with HE attainment) and control unit (without HE attainment), I calculate the expected return in terms of the difference between actual wage and its counterfactual wage estimated from PSM.: $r_{e,i} = lnwage33 - \_lnwage33$, where $\_lnwage33$ is the counterfactual log wage.

According to the theory, PSM tackles endogeneity bias problem and yields a consistent estimate of the treatment impact conditional on observed covariates. In other words, it computes the return to higher education only owing to HE attainment reasons after controlling other factors including the personal ability and family characteristics. Therefore, idiosyncratic errors e_i can also be calculated based on the equation (3.5) presented in Section 4.3.1. Moreover, I set a vector v_i that include chosen family background variables, and let $r_{e,i}$ and v_i are assumed to be uncorrelated because $r_{e,i}$ computes the return to HE due to 'professional' reasons after adjusting for the personal and family characteristics.

Step 2: Derive the data by bootstrapping

The next step is to draw pseudo samples, and the number of independent draws, S, is set to be 1000. In practice, first of all, I specify a vector v_i to capture family characteristics including family social class, parental education attainment, parents' interest to education and finance constraint. Secondly, I randomly resample the r_i^e, e_i, v_i with replacement from the orginal order, and the size of the resample data equals to the size of the actual data. I repeat this routine by 1000 times. According to Hypothesis 1, the decision to attend HE is entirely based on the ex ante return to education and interest rate: whether $r_i^e + e_i > r$[45] or otherwise. Thus, with bootstraping, each individual from random family backgroud will have decisions only based on expected ruturn to education and repeat this decision process by 1000 times. This assumes that the input variables r_i^e, v_i and e_i are not correlated across people in the true population and gives a sample set of outcomes for T. Lastly, I then estimate the chosen auxiliary regression on this bootstrap sample.

Step 3: Choose the Auxiliary regression

[45] r is the nominal interest rate. By running the model, I set r equals to 5%.

I classify the individual's qualification into two groups: non-HE and HE. Given the binary nature of the dependent variable decision to enroll HE, I employ a binary probit model that defines where the dependent variable can only take two values: 1 if the individual participated in higher education after A-level and 0 otherwise. Therefore, the probability of participating in HE can be modelled as a function as:

$Pr(T_i = 1|r_i^e,\ e_i) = \Phi(\theta X + \varepsilon_i)$ (4.9)

Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The vector X contains a number of control variables that are likely to affect the HE decision, ranging from measures of individual ability, parental background characteristics to regional characteristics and financial constraints, and θ denotes the vector of correspounding parameters.

Step 4: Compute the Wald statistic

Deciding whether to reject or not reject the null hypothesis requires the estimation of the auxiliary model with simulated data. Here, a Wald test statistic is chosen to be the test statistic. T_i $(i = 1, \dots, N)$ is defined as $N \times 1$ vector of observed data and $\widetilde{T_\iota}$ is an $N \times S$ vector of simulated observations generated from the structural model. The sample size of simulated data and the actual data has to be consistent. Under the null hypothesis, the true economic model is the structural model with the given estimates.

I apply the GLS estimates to the auxiliary probit model and compute both coefficients from the actual data and the set of coefficients of pseudo samples and to obtain their distribution, from which we obtained corresponding estimated coefficient θ^a and θ_i, respectively. I also define $\bar{\theta}$ as the average value that is computed from θ_i:

$$\bar{\theta} = \frac{1}{1000}\sum_{s=1}^{1000}\theta_s$$

The Wald statistic is chosen as a metric for measuring the distance between the auxiliary model parameters estimated using the observed data and the simulated data, respectively. The Wald statistic uses the distribution of $(\theta^a - \bar{\theta})$ and the formula of the Wald statistic is specified as:

$$W^a = (\theta^a - \bar{\theta})'\Omega^{-1}(\theta^a - \bar{\theta}) \qquad (4.10)$$

Where Ω the variance and covariance matrix of the distribution of $(\theta_i - \bar{\theta})$. This process measures the distance that the actual estimated coefficient are from the average of the simulated ones.

The following step is to access the combinations of all estimated coefficient the model can fit. For the model to fit the data at the 95% confidence level, it requires the Wald statistic for the actual data to be less than the 95% confidence level of the Wald statistics from the simulated data. Here, transforming the Wald result for the actual data into a normalised t-statistic is recomanded. The transformed Mahalanobis distance can be computed as:

$$\mathrm{T} = 1.645 * \frac{\sqrt{2W^a} - \sqrt{2k}}{\sqrt{2W^{95}} - \sqrt{2k}} \qquad (4.11)$$

where W^{a} is the Wald statistic on the actual data and W^{95} is the Wald statistic for the 95% of the simulated data. If the null hypothesis has not been rejected by the data, the transformed Mahalanobis distance should be less than 1.645. The way is normalised following Le et al. (2012), and Meenagh and Le (2013), so that the resulting t-statistic is 1.645 at the 95% point the distribution, and thus anything falling beyond would lead to the rejection of the model.

4.3.4 Model estimation

Using the notation above, the II estimator is then defined by the solution of:

$$\hat{\beta} = argmin_{\beta} \left(\frac{1}{S}\sum_{s=1}^{S} \widetilde{\theta}\,(\beta) - \hat{\theta}\right)' \Omega^{-1}(\frac{1}{S}\sum_{s=1}^{S} \widetilde{\theta}\,(\beta) - \hat{\theta}) \quad (4.12)$$

Where Ω is a given symmetric positive definite matrix. It chooses the parameters of the underlying economic model so that these two sets of estimates of the parameters of the auxiliary model are as close as possible.

In order to find the minimised distance of those two estimates of the coefficients in the quadratic form (4.2), I use the algorithm based on Simulated Annealing[46] (SA) in which search takes place over a wide range around the initial values, with optimising search accompanied by random jumps around the space[47].

The use of SA attempts to imply the II estimation into practice. It exploits an analogy between the way in which a metal freezes into a minimum energy crystalline structure and search for a minimum in a more general system. Such process in SA can be

[46] The estimation is mainly based on Matlab code file 'run_CalcWald_SA' but only change the up and lower bounds of each coefficient. The file can be easily downloaded from website.

[47] The state in an II estimation procedure can be considered as the set of structural parameters.

considered as the way of finding the minimum Wald statistics implied by the observed and simulated data. At each step, the SA heuristic considers some neighbouring states of the current states, and decides between moving the system to other states or staying in states. These probabilities ultimately lead the system to move to states of lower Wald statistics. Typically this iteration until the quadratic form is minimised, or until a given computation budget has been exhausted.

SA's major advantage over other methods is its ability to avoid becoming trapped at local minima. It then loops over the testing procedure to search for the global minima of Wald statistic. Under the SA algorithm, an initial choice of parameter vector is chosen, and the Wald at that point is evaluated by running through steps 1- 4 above. The algorithm then moves randomly to try a new point in the parameter space. When a new point in the parameter space is found to have a smaller Wald than any point preceding it in the sequence, it is chosen to be the current point from which the search for the minimum proceeds. The algorithm can also move to points which have a larger Wald, although the probability of this happening decreases with the number of points at which Wald statistics have previously been evaluated. Eventually, after a certain number of best points are found, the search is once again widened by increasing the acceptance probability. There are many different available stopping rules for the algorithm. In this study, I set the maximum number of iterations equals to 100.

4.4 Data

4.4.1 Sample selection

In this chapter I will continue to use data drawn from the NCDS. The empirical analysis use information collected when the participants were aged 7, 11, 16, 23 and 33 (Sweep 1 to 5). It matches information on the individuals' highest academic education attainment at age 33 from the fifth sweep. Family background and personal ability variables are collected from the first four sweeps whereas participants who are still in education at the last sweep are dropped. In the main part of the analysis, I only focus on individuals who are studying as the A-level route. In other words, I explore non-HE attainment and define this term as obtained at least one A-level but not continuing to further HE studies. I also explore entry to all forms of HE, which includes diploma, degree level and higher degree level. The initial sample size reported in Chapter One is 2,500, of which 1,131 individuals had a HE qualification and 1,369 individuals obtained at least one A-level. After matching the sample size is reported as 1,109, in which samples within common support area are 1097. Therefore, the final sample includes 1,097 individuals.

4.4.2 Definition of the variables

As determinants of the HE participation decision, I consider a set of individual innate ability characteristics, family background socio-economic characteristics and secondary school characteristics. The family background characteristics are collected from Sweep 2 and 3 of the survey for the period in which the individual grew up and complete compulsory education. Among the variables, I include parental education, parents' interest to education, father's social class group, number of older siblings and financial status. The parental education levels will serve as proxies for the endowment of ability inherited from the parents.

The information on the parents' education is derived from the age that the parents left school, which is reported in Sweep 3. The parental educational attainment is measured as completed years of schooling in their secondary school. NCDS provides rich qualitative information on parental interest in the education at different ages of their offspring. I constructed eight dummies based on the information collected when individuals are at age of 16 to indicate the extent that presents parents are concerned. The father's earnings was reported in 1974 when the child was 16. This measure is usually used as a proxy for family income. However, it is argued that information on a single year is only a crude proxy for the financial situation of the household.[48] I alternatively use dummy as an indicator to assess whether the family was experiencing serious financial difficulties in 1969 or 1974. Finally, dummy variables are used to measure each of the fathers social class.

Information with ability in the childhood is collected from earlier NCDS sweeps. The

[48] The NCDS only records family income when the individual is 16. Since this measure might not reflect living standards earlier in childhood or persistent financial constraint, one alternative method applied by Chevalier and Lanot (2002) attempts to transform this single year earning variable into a continuous one by using additional information extraced from the Family Expenditure Survey.

NCDS contains data on arithmetic and reading tests performed by the children at the aged of 11 as the indicator of individual's early innate ability. I rescale in each of the test results by quantiles to contrsuct dummy variables ranking the individual test results. Moreover, there are six categories of school types reported in NCDS including the missing value. For each of these individuals, it is possible to derive a set of dummy variables indicating whether the individual attended a comprehensive, secondary modern, grammar school, private school, and other types of school.

4.4.3 Descriptive information

Table 4.1 presents a list of the variables available including dummy variable derived from original data, along with their means, standard deviations, and minimum and maximum values. It is noted that statistics because some variables are not consistent with the figure in Chapter 2, as the model suggested, both the actual and counterfactual log wage is required to calcluate the each individual's expected return to education and, in turn, the ex ante decision to HE. Therefore, numbers of observations are dropped due to missing information on target variable (actual and counterfactual log wage). The average of the natural logarithm of actual gross hourly wages is 2.36. By contrast, the average figure of counterfactual wages is 2.32. As can be seen from Figure 1, the distribution of actual and counterfactual wage is somehow very similar across the samples. This evidence suggests that two wage distributions are almost identical if the participants had the tendency to create alternatives to occurred life events. The binary outcome variable is a decision whether or not to participate in HE. There is a larger proportion for attending some form of HE, 59 % against 41 % which is the proportion for not attending the HE.

In addition, less than half of the parents have otained A-level or above qualifications (44 % for father and 43 % for mother, respectively.). About 46 % of individuals choose to attend comprehensive schools, only 7 % secondary mordens, 26 % grammar schools, and 11 % private schools. Regarding to the personal innate ability, most of inviduals in their early age are ranked as in the top two quintiles in math and reading test, while only 7 % of them are ranked as in the bottom two quintiles.

Table 4.2 presents percentage of HE participation disaggregated in different input variables. Overall, the percentage of HE participation (59.43%) is higher than that of non-HE participation (40.57%) in my selected sample. Of the family characteristics inputs, almost all variables have impacts. In particular, indiviuals with parents obtained A-level and above qualifications are more likely have willingness to go into HE. The pattern makes it clear that parents with higher educational attainment also result to a higher HE participation rate for their offsprings. This is somewhat consistant with the idea of intergenerational educational mobility discussed in Section 2. Individuals facing family finance constraints are more likely to stop chasing further study after age 16. Moreover, indiviudals attending comprehensive school had the lowest HE participation rate, while individuals who went throught grammar and private schools had a slightly higher rate. The pattern of decreasing % comes along with increasing birth order postion. It also shows that the gap betwwen individuals from different class background. Individuals who come from Professional or Intermediate families seem to have a higher HE participation. Regarding early personal innate abilities, the patterns at lower quintile are fairly similar across the cohort. Only individuals in the top quintile have a siginificantly larger participation rate.

4. 5 Empirical result

In this section, I will report the results of the II testing and re-estimation that applied to the three hypotheses presented in Section 4.3. Before processing, several tests are designed to assess the explanatory power of Auxiliary model which are presented in Section 5.1. Original observations are calculated and collected from the result obtained in Chapter one. Explanatory dummies, explanatory power and starting calibration coefficients are created and computed in STATA. The performance of model evaluation, and estimation based on Wald Statistic normalised transformed Mahalanobis distance/ t-statistic is calculated in MATLAB[49].

4.5.1 Explanatory power of Auxiliary model

To choose the number of explanatory variables that help explain the HE choices, several models are selected to assess how the actual data overall fit the auxiliary

[49] The MATLAB codes are available on request.

model. Model version (a) only includes parental educational attainment variables; besides parental education, there are 6 variables presenting parental interest to education are added to Model (b). Model (c) contains all family background variables, and model (d) includes all variables described in section 4.3. Thought R^2 or pseudo R^2 are very valuable measures of goodness of fit of a linear regression model, they are far less useful with Probit regression.[50] I therefore imply alternative intuitively appealing ways of assessing the fit of Probit regression model commonly used in literatures.

Table 4.3 summarises the goodness of fits of different auxiliary model. Column 2 specifies which variables are included. Column 3 to 5 indicates the P value of Hosmer-Lemeshow (HL) test, Receiver Operating characteristic (ROC) area and Correct Classification Rate.[51] The results reveal the four models are all adequate models. Nonetheless, Classification correct rate is not sensitive to the increasing relative sizes of explanatory variable. ROC curve area is apparently over the default 50% cutoff.[52] Although Model (a) has the largest HL P-value, the performance of ROC area and Correct Classification rate is the worst among the four models. The reason it has the largest P-value is because it only has 2 degree of freedom. Model (b) performs not as good as model (c) and (d). The models (c) and (d) have almost the same ability to fit the data, but model (d) has a lower HL P-value. It prevails

[50] The pseudo R^2 produced in STATA is based on the log-likelihood statistic, and was not recommended as it lacks an easily understood interpretation. Researchers try to predict the outcome, whereas the model only gives us the probability of the outcome.

[51] Hosmer-Lemeshow test is implemented in STATA using the command **estat gof.**
ROC curve is implemented in STATA using command **lroc**
Correct Classification rate is implemented in STATA using command **estat classification**

[52] 50% is the discrimination one would expect if he tossed a coin to identify positive subjects, rather than use a Probit model.

increasing the number of explanatory variables cannot improve the goodness of fit to the data, but loss more degrees of freedom. As a result, the model (c) would be considered to be adequate to fit the data well. Table 4.4 lists input variables in the Probit model and the corresponding coefficients notation based on the conclusion of goodness of fits tests.

4.5.2 Model Evaluation

(a) Hypothesis 1

The results for model (4.6A)'s t-statistics and confidence intervals for each explanatory variable included in auxiliary model are reported in Table 4.5. Column 2 shows the estimated parameters on the actual data and Colum 3 and 4 present the lower and upper 95% bounds of the estimated parameters on the 1,000 bootstrap samples, respectively. Colum 5 indicates whether each actual parameter is inside the confidence interval calculated from the bootstrapping parameters.

The normalized t-statistics is calculated as 14.59, which indicates the structural model cannot replicate the data as close as to that implied by the auxiliary model. Certain result is evident because 5 out of 16 coefficients obtained from auxiliary model lie outside the confidence interval. Figure 4.3 illustrates the distribution of the coefficient estimated from bootstrap sample data, with red straight line edges the 95 % up and bottom bounds and green line indicate the actual data coefficient position.

On the other hand, the Wald statistic is a measure of the distance between the simulations and the data. The lower the Wald, the better the model can be used for explaining the observed data jointly. Therefore, the p-value is the probability that the model is not rejected by the data and computed by 1-Wald. The Wald statistic is reported as 100 % in Table 4.5, which means the structural model is strongly rejected under the Hypothesis 1 at 95 % confidence level

The result indicates individual's decision to go for HE does not only depend on the expected return to HE and interest rate. It is not surprising that overall the model is rejected. The reason comes with two folds. First, according to large number of literatures, individual's highest education attainment or their decision to HE empirically are more or less determined by other socio-economic variables, such as family and personal characteristics, as discussed in section 2. Second, recalling the ignorability assumption in PSM methodology, realized log wage is assumed to be uncorrelated with treatment status (HE decision), conditional on observed covariates. Therefore, if the assumption holds, expected return to education that obtained from the PSM therefore cannot be used as a predictor to calculate the decision to HE, *ceteris paribus*. The result here is in the line with the ignorability assumption in PSM.

(b) Hypothesis 2

The next step is to test the hypothesis 2**.** Under the hypothesis 2, expected return to education may itself affect directly and combined with some socio-economic characteristics also affect the probability of participating in HE indirectly through a clearly structured path.

Recall the equation (4.6B), socioeconomic related variable vector Z is considered to include parental educational attainment, parental interest to their offspring's education, birth order and family finance status. It obviously generates a different set of errors, e_i^{perc}. Before proceeding it is noted that to choose the starting calibration parameter value is somewhat important; or at least, to ascertain whether there exists a positive or negative association between the decision to participate HE and other socioeconomic variables.

Suppose HE decision outcome is modelled as a function of expected return and expected return to education is modelled as function of socio-economic variables, simultaneously. The equation systems can be specified as follows:

$$T_i = f(\pi_1, r_i^e), \quad r_i^e = g(\lambda, z_i) \quad (4.13)$$

Estimated result from equation (4.13) is inappropriate under hypothesis 2; it only allows a reasonable replication of the educational attainment data. However, the estimated coefficients can be used as a guide as to choose some calibration values that seem to be reasonable. All coefficients are allowed to change[53] by re-estimating the structural model (4.6B) later by choosing different values of coefficients that best match the auxiliary model.

The calibration value is computed using three-stage least square estimation in STATA and the result is shown in Table 4.6. Reading the table, the majority of the effect can be attributed to the direct effect of expected return to education. It reveals a total

[53] In most cases, signs of the coefficient are not allowed to change; otherwise it will violate thesociology theory used in this case.

effect of 85 %. Both of parental education indicators have a positive impact on expected return to education, such effects are expected given a large body of empirical studies. However, the effect of parental interest to education is not statistically significant. On the other hand, finance status exert a somewhat negative impact (significant at 10%) on HE decision, whereas the negative Birth order effect is not statistically significant.

The hypothesis 2 is that if the structural model is correctly specified, the set of calibration coefficient obtained from 3SLS should not differ significantly from those obtained from the auxiliary model using observed data. Table 4.7 summarizes how the test results on calibrated coefficients. Compared with the results in previous model, more coefficients become inside the 95 % bounds, but there is only 2 out of 26 coefficients lie outside the 95 % bounds generated from the simulated data. In particular, Mother's education attainment dummy is found to have the passive pattern in the data compared with the simulated bound. The bad finance indicator is shown to be more negative than that which the structural model could predict. The Wald Statistic reported is not as high as the previous models at 100 % and reduced at 96.67 %. This implies however actual data based on the auxiliary model coefficients still cannot be captured by the corresponding joint distribution generated from model simulation at 5 % confident level.

(c) Hypothesis 3

Similar to hypothesis 2, perceived return to education in hypothesis 3 is a function of personal cognitive ability from age 11 to 16. As a result, the calibration value can be computed from the equation systems designed below:

$T_i = f(\pi_1, r_i^e), \quad r_i^e = g(\rho, c_i) \quad (4.14)$

Table 4.8 list the 3SLS estimation results based on equation (4.14) used as guidance for the calibration value. The bottom quintile of both read score and math score at age 11 are omitted after the estimation. This is possibly due to individuals at these two bottom quintiles only account for 1% of the total sample. Variables include individuals obtaining grade A-C in O-level and A-level Math, read and math score at age 11 in top quintile are all strongly positive associated with expected future wage return (statistically significant at 90 % level). Individual's English language proficiency (Obtaining Grade A-C in O-level and A-level) only has insignificant and small impacts. Individuals' math abilities at age 11 ranked in fourth quintile and lower however, are negatively associated with the expected return.

Table 4.9 summarizes the test results on calibrated coefficients for structural model (4.6C). There is only 1 out of 15 coefficients lie outside the 95 % simulation bounds: Mother's education attainment dummy is showing a more positive pattern. On the other hand, with a Wald percentile of 96, jointly, observed data can be explained by the structural model (4.13) at 99 % confident level. The Wald percentile is also reduced compared with model (4.6A) for hypothesis 1.

Although the hypothesis models 2 and 3 with calibration value are still rejected at 95 % overall, it doesn't mean the hypotheses are also rejected. It indicates P-value is even closer to a non-rejection level. One can expect the model (4.6B) and (4.6C) used to explain the data behaviour better in the following case, since these coefficients can be re-estimated by II. This lends credence to the validity of the results and supports the hypotheses.

4.5.3 Model estimation

In this section we report the results for re estimating the hypothesis models by II. The idea of II is to obtain the set of coefficients that minimises the overall Wald statistic. As discussed in Section 3, I attempt to use the SA algorithm to minimize the Wald. In practice, I estimate the model several times, compare the Wald statistics and obtain a set of candidate plausible coefficients. For each of these optimal sets, I run II testing procedure on several times in order to check the robustness of each result. I then vary in the neighbourhood of the resulting estimation values, to ascertain the set of coefficients are close to or around the minimum.

(a) Hypothesis 2

Table 4.10 lists the II estimation results for structure parameters of model (4.6B). Both parental education attainments that positively influence return to education can in turn increase their offspring's participation of HE. The stronger absolute effect and evidence is found when the mother's highest educational attainment is A-level or above based on the II estimates result. This is slightly different from the calibration. According to empirical studies, the birth order of an individual as a direct effect plays an important role in determining the higher education participations (Black, et al. 2005, Dyson, et al., 2010). However, this determinant is not found significant as an indirect effect in the case of II estimation. Significant differences in participation in HE can be attributed to the parental interest in education. Parents with over concerned to education invest has a positive effect in determining offspring's HE participation through the perceived return equation. It is striking that family finance constraint has almost insignificant affect the HE participation decision than one usually expected. The figure is just as half as the calibration in absolute value.

Table 4.11 summarises the corresponding test results once I re-estimate the structural model coefficients. The result is found to have considerably improved after the II estimation is applied. All coefficients lie outside the up and lower 95% bound derived from the simulated data. It demonstrates that the evaluation results based on the II estimates can fit the data better than the calibrated version. Alternatively, in Figure 4.5 from the distribution generated from simulated data, one can see that all actual data (green line) are position in the 95 % bounds. It also prevails that the model successfully passed the joint test as the Wald statistics is 19.45 with a P value equals 80.55%. It concludes these results strongly support hypothesis 2.

(b) Hypothesis 3

Table 4.12 reports the II estimation results for structure parameters of model (4.6C). Focusing on the academic performance, the estimated results show individual's O-level and A-level math ability play much more important role of determining HE participation (change from 7.6% to 16.8% and from 22.1% to 44.5%, respectively), through the return equation. Whereas impact of individual's English language proficiency at O-level and A-level from estimation are relative similar to the calibrated ones. The corresponding coefficients have somewhat ignorable changes. Turning to the early cognitive abilities, estimated coefficients for read sore at top quintile increases from 11.3% to 44.25%, whilst decreases from -14.8% to -25.6% at second lowest quintile. Coefficients for math score at 11 are all round the calibration with no significant changes.

Table 4.13 gives the test results based on the II estimation. The Normalised t-statistic has decreased from 3.89 to 2.18. Though the hypothesis 3 model can somewhat fit the data at least in a moderate level. There is still only 1 out of 15 coefficients lie outside the 95% range derived from the simulated data. Not surprisingly, mother's education attainment ($\boldsymbol{\theta_3}$) shows the passive pattern in the data compared with the simulated bound. Figure 4.6 gives a more straightforward visual analysis of the distribution of coefficients estimated from bootstrap sample data, with red straight line edges the 95 %ile up and bottom bounds and green line indicate the actual data coefficient position. Wald %ile decreases 28.1 (a corresponding P-value = 72%) compared to that of from calibration, which implies the model can jointly capture the observed data in a more proper way.

However, the result is striking that compared to Hypothesis model 1 and Hypothesis models using calibration, after the re-estimation by II method, all the coefficients in the Hypothesis models 2 and 3 pass Wald test quite easily. One possible explanation is that Hypothesis models 2 and 3 allow the derived errors (equation 4.5) of each person to be reduced substantially on re-estimation. Furthermore, re-estimation could possibly reduce the power of the Wald test substantially; and this nonetheless should be investigated in further study.

4.6 Summarizing Remarks and Conclusions

In this chapter I have attempted to build a micro model of HE participation incorporating factors for expected return to HE, and other personal ability and family socio-economic variables based on framework of education decision making behaviour of individual agents. In the model, the participation decision is hypothesised to be a function of: (1) the individual's expected return to HE, (2) expected return but also perceived by family background such as parental influences, household credit constraints, etc.; and, (3) expected return but perceived by personal innate ability and academic performance. I then test these three hypotheses using the 1958 British NCDS dataset. In contrast to the existing literature, this is achieved empirically by adopting the II method to first evaluate the role of the above factors on participating in HE for young cohorts in the 1970s, and I then re-estimate the structural coefficients if the model failed to pass the test. Attempts to apply this new type of method on microeconomic level cross-sectional data is new to the existing literature.

I summarise the findings as follows. First, the model based on Hypothesis 1 fails to pass both the Wald and normalised t-statistic in II. The main powerful conclusion is that Hypothesis model 1 is highly rejected and the power of the test is relatively high. This implies that HE participation does not only depend on an individual's expected return to education, but shoulde more or less relate to other factors as proposed in Hypotheses 2 and 3.

Secondly, Hypothesis 2 model using calibration is rejected by the Wald test at 95 %, but passes the test at more tolerant 99% confidence level. However, the II re-estimation applied on Hypothesis 2 model easily passes the Wald test. Thirdly, although the Hypothesis 3 model is not rejected by the Wald test at 95 percent level, there is a still a coefficient that lies outside the 95% simulation bounds after re-estimation. This result indicates sure that the *predict ability* of the model is uncertain.

The conclusions from the above evidence for the effects of various factors on HE participation are considered to be tentative because the natures of the effects are not simple direct impacts and no studies has attempted to model and test causal effects. In this study, I only attempts to model the expected return to HE in explaining the HE participation behaviour. Because Hypothesis 2 and Hypothesis 3 models are complete hypothesis individually, it is difficult to measure causal effects of different characteristics and it is also difficult to conclude whether these impacts are significant

The magnitude accuracy of these effects also might be under consideration; however, it is evident and confident that the expected return to HE for determining the HE participation are biased in terms of family socio-economic background or personal attribute. It is worth noting that when applying II method to re-estimate the models, all the coefficients in the Hypothesis models 2 and 3 pass Wald test quite easily. This result is ambiguous. The problem is whether the errors term of each person are reduced substantially on re-estimation, or if there is a possibility that re-estimation reduce the power of the Wald test after the re-estimation. One possible explanation is that the power of the test is weak against Hypotheses 2 and 3 models, for both of which the models contain large number of degrees of freedom. These features should be investigated in future study.

This study has observed several limitations. First, the model setup does not directly include personal and family characteristics. Future research could include these agents' heterogeneity dimensions in order to assess the corresponding direct effects. For example, Gallipoli et al. (2007) use a model that incorporates several important mechanisms as essential parts of the lifetime earnings, such as: personal permanent ability, ability transmitted across generations, inter-vivo transfers from parents to offspring permitted to ease liquidity constraints in the education decision, and so on. Secondly, due to the data limitation, this study only focuses on cohorts who participated in HE in the 1970s. As discussed in Chapter 1, the UK's education policy has gradually shifted the burden of funding HE away from the government towards the students and their families. It is, therefore important to examine whether the effect of financial constraint is significant and to what extent the tuition fee can affect HE participation under the changes in the education law. Finally, this study only uses a pooled sample, further research may also consider allowing for gender heterogeneity.

Appendix D Tables and Figures

Table 4.1 Descriptive statistics, NCDS 1958 cohorts

Variable Name	Mean	SD	Minimum	Maximum
Actual log wage	2.36	0.417	0.46	4.48
Counterfactual log wage	2.32	0.422	0.46	4.48
HE decision	0.59	0.491	0	1
Father's highest educational attainment is A-level and above	0.44	0.497	0	1
Mother's highest educational attainment is A-level and above	0.43	0.495	0	1
Father's interest to education at age 16				
Over concerned	0.02	0.137	0	1
Very interested	0.56	0.495	0	1
Some interest	0.16	0.368	0	1
Missing value	0.16	0.361		
Mother's interest to education at age 16				
Over concerned	0.01	0.116	0	1
Very interested	0.58	0.493	0	1
Some interest	0.18	0.383	0	1
Missing Value	0.14	0.349		
Father's social class at age 16				
Professional or Intermediate	0.48	0.499	0	1
Family finance status				
Bad finance at age 11 or 16	0.05	0.222	0	1
Type of secondary school				
Comprehensive	0.46	0.498	0	1
Secondary Morden	0.07	0.256	0	1
Grammar	0.26	0.436	0	1
Private	0.11	0.314	0	1
Birth order /number of older siblings	0.36	0.564	0	3
Personal ability				
Read score				
Bottom quintile	0.01	0.079	0	1
Second quintile	0.05	0.208	0	1
Third quintile	0.12	0.328	0	1
Fourth quintile	0.26	0.442	0	1
Top quintile	0.46	0.498	0	1
Math score			0	1
Bottom quintile	0.01	0.079	0	1
Second quintile	0.05	0.208	0	1
Third quintile	0.12	0.329	0	1

Fourth quintile	0.27	0.442	0	1
Top quintile	0.46	0.498	0	1

Table 4.2 percentage of HE participation

	percentage of HE participation	
	HE	**Non-HE**
Total Sample	59.43	40.57
(No. Obs)	(445)	(652)
Father's highest educational attainment		
O-level	54.31	45.69
A-level and above	65.98	34.02
Mother's highest educational attainment		
O-level	54.36	45.64
A-level and above	66.31	33.69
Father's interest to education at age 16		
Over concerned	71.43	28.57
Very interested	61.64	38.36
Some interest	56.74	43.26
Mother's interest to education at age 16		
Over concerned	60.00	40.00
Very interested	61.54	38.44
Some interest	57.14	42.86
Father's social class at age 16		
Professional or Intermediate	66.16	33.84
Family finance status		
Bad finance at age 11 or 16	49.12	50.88
Type of Secondary School		
Comprehensive	53.56	46.44
Secondary Morden	61.04	38.96
Grammar	65.71	34.29
Private	68.03	31.97
Birth Order /Number of Older Siblings		
0	59.73	40.27
1	57.32	42.68
2	48.78	51.22
3	40.00	60.00
Personal ability		
Read score at age 11		
Bottom quintile	28.57	71.43
Second quintile	40.00	60.00
Third quintile	45.93	54.07

Fourth quintile	58.70	41.30
Top quintile	65.27	34.73
Math score at age 11		
Bottom quintile	46.15	53.85
Second quintile	41.46	58.54
Third quintile	49.21	50.79
Fourth quintile	54.48	45.52
Top quintile	65.43	34.57
Whether obtained O-level English Grade A-C at 14		
Whether obtained O-level Math Grade A-C at 14		
Whether obtained A-level English Grade A-C at 16		
Whether obtained A-level Math Grade A-C at 16		

Table 4.3 Goodness of Fits of Different Auxiliary Model Version

Model	Explanatory variables include	H-L test P-value	ROC area %	Correct Classification %
a	Only Parental education	0.898	0.578	59.43%
b	Parental education; Parental interest in Education	0.5798	0.584	59.53%
c	All family background variables	0.6314	0.609	61.08%
d	All Family background; personal ability variables	0.5012	0.612	61.16%

Table 4.4 Coefficients used in Auxiliary model

Coefficients	Definition
$\boldsymbol{\theta_0}$	**Constant term**
	Father's highest educational attainment
$\boldsymbol{\theta_1}$	A-level or above
	Mother's highest educational attainment
$\boldsymbol{\theta_2}$	A-level or above
	Father's interest to education at age 16
$\boldsymbol{\theta_3}$	Some interest
$\boldsymbol{\theta_4}$	Very interested
$\boldsymbol{\theta_5}$	Over concerned
	Mother's interest to education at age 16
$\boldsymbol{\theta_6}$	Some interest
$\boldsymbol{\theta_7}$	Very interested
$\boldsymbol{\theta_8}$	Over concerned
	Type of Secondary School
$\boldsymbol{\theta_9}$	Comprehensive
$\boldsymbol{\theta_{10}}$	Secondary Morden
$\boldsymbol{\theta_{11}}$	Grammar
$\boldsymbol{\theta_{12}}$	Private
	Family finance status
$\boldsymbol{\theta_{13}}$	Bad finance at age 11 or 16
	Birth Order
$\boldsymbol{\theta_{14}}$	Number of Older Siblings

Table 4.5 Coefficients estimate based on Calibration and Confidence Interval

Parameters	Actual data Coefficients	95% Lower Bound	95% Upper Bound	IN/OUT
$\boldsymbol{\theta_0}$	0.1311	-0.1753	0.2322	IN
$\boldsymbol{\theta_1}$	0.1644	-0.1469	0.1481	OUT
$\boldsymbol{\theta_2}$	0.1839	-0.1485	0.1414	OUT
$\boldsymbol{\theta_3}$	-0.0020	-0.3246	0.3030	IN
$\boldsymbol{\theta_4}$	0.1127	-0.2651	0.2860	IN
$\boldsymbol{\theta_5}$	0.3968	-0.5999	0.5465	IN
$\boldsymbol{\theta_6}$	0.1103	-0.3104	0.3330	IN
$\boldsymbol{\theta_7}$	0.0259	-0.2900	0.2876	IN
$\boldsymbol{\theta_8}$	-0.2408	-0.6772	0.6350	IN
$\boldsymbol{\theta_9}$	-0.2636	-0.2596	0.2733	OUT
$\boldsymbol{\theta_{10}}$	-0.0521	-0.3264	0.3236	IN
$\boldsymbol{\theta_{11}}$	-0.0069	-0.2916	0.2883	IN
$\boldsymbol{\theta_{12}}$	-0.0292	-0.3364	0.3226	IN
$\boldsymbol{\theta_{13}}$	-0.3239	-0.2965	0.1734	OUT
$\boldsymbol{\theta_{14}}$	0.1282	-0.1226	0.1105	OUT
T-Statistics:	14.59			
Wald Statistics:	100	**P value:**	0%	

Table 4.6 Calibrated Coefficient from 3SLS estimation: Hypothesis 2

Variables	Coefficient	3 SLS Estimation (Use as Calibration)
Return to education	π_1	0.850***
Father's highest educational	λ_1	0.063**
Mother's highest educational	λ_2	0.049*
Father over concerned	λ_3	0.053
Father very interested	λ_4	0.003
Father some interest	λ_5	0.000
Mother is over concerned	λ_6	0.011
Mother very interested	λ_7	0.000
Mother some interest	λ_8	-0.009
Birth order	λ_9	-0.027
Finance status	λ_{10}	-0.121*
Constant	λ_{11}	0.021*
No of Obs		1097

Note ***Significant at the 1 % level; **significant at the 5% level; *significant at 10% level

Table 4.7 Coefficients estimate based on Calibration and Confidence Interval: Hypothesis 2

Parameters	Actual data Coefficients	95% Lower Bound	95% Upper Bound	IN/OUT
$\boldsymbol{\theta_0}$	0.1311	-0.0919	0.3309	IN
$\boldsymbol{\theta_1}$	0.1644	-0.1479	0.1703	IN
$\boldsymbol{\theta_2}$	0.1839	-0.1435	0.1369	OUT
$\boldsymbol{\theta_3}$	-0.0020	-0.2955	0.3213	IN
$\boldsymbol{\theta_4}$	0.1127	-0.2706	0.2552	IN
$\boldsymbol{\theta_5}$	0.3968	-0.5463	0.5496	IN
$\boldsymbol{\theta_6}$	0.1103	-0.3136	0.3067	IN
$\boldsymbol{\theta_7}$	0.0259	-0.2693	0.2754	IN
$\boldsymbol{\theta_8}$	-0.2408	-0.6723	0.6897	IN
$\boldsymbol{\theta_9}$	-0.2636	-0.2704	0.2575	IN
$\boldsymbol{\theta_{10}}$	-0.0521	-0.3517	0.3287	IN
$\boldsymbol{\theta_{11}}$	-0.0069	-0.2882	0.2713	IN
$\boldsymbol{\theta_{12}}$	-0.0292	-0.3140	0.3336	IN
$\boldsymbol{\theta_{13}}$	-0.3239	-0.3772	0.3062	IN
$\boldsymbol{\theta_{14}}$	0.1282	-0.1213	0.1079	OUT
Wald Statistics	96.97	**P-value**	3%	

Table 4.8 Calibrated Coefficient from 3SLS estimation: Hypothesis 3

Variables	Coefficient	3SLS Estimation (Use as Calibration)
Expected return to education	π_2	0.650***
Read score at 11		
Bottom quintile		(omitted)
Second quintile	ρ_1	-0.148
Third quintile	ρ_2	0.028
Fourth quintile	ρ_3	0.024
Top quintile	ρ_4	0.113*
Math score at 11		
Bottom quintile		(omitted)
Second quintile	ρ_6	-0.073
Third quintile	ρ_7	-0.095
Fourth quintile	ρ_8	-0.085
Top quintile	ρ_9	0.100*
O-level English Grade A-C obtained at age 14	ρ_{10}	0.027
O-level Math Grade A-C obtained at age 14	ρ_{11}	0.076*
A-level English Grade A-C obtained at age 16	ρ_{12}	0.006
A-level Math Grade A-C obtained at age 16	ρ_{13}	0.221*

Note ***Significant at the 1% level; **significant at the 5% level; *significant at 10% level

Table 4.9 Coefficients estimate based on Calibration and Confidence Interval: Hypothesis 3

Parameters	Actual data Coefficients	95% Lower Bound	95% Upper Bound	IN/OUT
θ_0	0.1311	-0.0248	0.4627	IN
θ_1	0.1644	-0.1721	0.1656	IN
θ_2	0.1839	-0.1746	0.1668	OUT
θ_3	-0.0020	-0.3786	0.3848	IN
θ_4	0.1127	-0.3257	0.3240	IN
θ_5	0.3968	-0.6258	0.6445	IN
θ_6	0.1103	-0.3833	0.3654	IN
θ_7	0.0259	-0.3354	0.3336	IN
θ_8	-0.2408	-0.7084	0.7770	IN
θ_9	-0.2636	-0.3135	0.3105	IN
θ_{10}	-0.0521	-0.4193	0.4192	IN
θ_{11}	-0.0069	-0.3295	0.3508	IN
θ_{12}	-0.0292	-0.3913	0.3987	IN
θ_{13}	-0.3239	-0.3328	0.3702	IN
θ_{14}	0.1282	-0.1327	0.1295	IN
Wald Statistics	95.9	**P-value**	4.1%	

Table 4.10 II Estimation Results: Family background

Variables	Coefficient	Calibration	Estimates
Father's highest educational	λ_1	0.063	0.147
Mother's highest educational	λ_2	0.049	0.196
Father over concerned	λ_3	0.053	0.066
Father very interested	λ_4	0.003	0.051
Father some interest	λ_5	0.000	0.002
Mother over concerned	λ_6	0.011	0.106
Mother very interested	λ_7	0.000	0.022
Mother some interest	λ_8	-0.009	-8.12e-04
Birth order	λ_9	-0.027	-9.6e-05
Finance status	λ_{10}	-0.121	-0.009
Constant term	λ_{11}	0.021	0.016

Table 4.11 Coefficients estimate based on II estimation and Confidence Interval: Hypothesis 3

Parameters	Actual data Coefficients	95% Lower Bound	95% Upper Bound	IN/OUT
$\boldsymbol{\theta_0}$	0.1311	0.0645	0.5022	IN
$\boldsymbol{\theta_1}$	0.1644	-0.1008	0.1884	IN
$\boldsymbol{\theta_2}$	0.1839	-0.0797	0.2014	IN
$\boldsymbol{\theta_3}$	-0.0020	-0.3078	0.3199	IN
$\boldsymbol{\theta_4}$	0.1127	-0.2967	0.2782	IN
$\boldsymbol{\theta_5}$	0.3968	-0.5759	0.6513	IN
$\boldsymbol{\theta_6}$	0.1103	-0.3185	0.3036	IN
$\boldsymbol{\theta_7}$	0.0259	-0.2947	0.2776	IN
$\boldsymbol{\theta_8}$	-0.2408	-0.6548	0.6437	IN
$\boldsymbol{\theta_9}$	-0.2636	-0.3026	0.3085	IN
$\boldsymbol{\theta_{10}}$	-0.0521	-0.3417	0.3735	IN
$\boldsymbol{\theta_{11}}$	-0.0069	-0.2753	0.3012	IN
$\boldsymbol{\theta_{12}}$	-0.0292	-0.3233	0.3401	IN
$\boldsymbol{\theta_{13}}$	-0.3239	-0.3349	0.2669	IN
$\boldsymbol{\theta_{14}}$	0.1282	-0.1208	0.1199	IN
Wald Statistics:	19.45	**P value**:	80.55%	

Table 4.12 II Estimation Results: personal ability

Variables	Coefficient	Calibration	Estimates
Read score at 11			
Second quintile	ρ_1	-0.148	-0.2555
Third quintile	ρ_2	0.028	0.0194
Fourth quintile	ρ_3	0.024	0.0387
Top quintile	ρ_4	0.113	0.4425
Math score at 11			
Second quintile	ρ_6	-0.073	-0.0533
Third quintile	ρ_7	-0.095	-0.0249
Fourth quintile	ρ_8	-0.085	-0.0056
Top quintile	ρ_9	0.100	0.0845
O-level English Grade A-C obtained at age 14	ρ_{10}	0.027	0.0346
O-level Math Grade A-C obtained at age 14	ρ_{11}	0.076	0.1677
A-level English Grade A-C obtained at age 16	ρ_{12}	0.006	0.0103
A-level Math Grade A-C obtained at age 16	ρ_{13}	0.221	0.4435
constant		-0.064	-0.0492

Table 4.13 Coefficients estimate based on Calibration and Confidence Interval: Hypothesis 3

Parameters	Actual data Coefficients	95% Lower Bound	95% Upper Bound	IN/OUT
$\boldsymbol{\theta_0}$	0.1311	0.0141	0.4887	IN
$\boldsymbol{\theta_1}$	0.1644	-0.1563	0.1733	IN
$\boldsymbol{\theta_2}$	0.1839	-0.1688	0.1819	OUT
$\boldsymbol{\theta_3}$	-0.0020	-0.3732	0.4152	IN
$\boldsymbol{\theta_4}$	0.1127	-0.3275	0.3168	IN
$\boldsymbol{\theta_5}$	0.3968	-0.6200	0.7453	IN
$\boldsymbol{\theta_6}$	0.1103	-0.3901	0.3642	IN
$\boldsymbol{\theta_7}$	0.0259	-0.3313	0.3099	IN
$\boldsymbol{\theta_8}$	-0.2408	-0.7254	0.7969	IN
$\boldsymbol{\theta_9}$	-0.2636	-0.3186	0.3153	IN
$\boldsymbol{\theta_{10}}$	-0.0521	-0.4125	0.4436	IN
$\boldsymbol{\theta_{11}}$	-0.0069	-0.3541	0.3310	IN
$\boldsymbol{\theta_{12}}$	-0.0292	-0.4026	0.3809	IN
$\boldsymbol{\theta_{13}}$	-0.3239	-0.3528	0.3763	IN
$\boldsymbol{\theta_{14}}$	0.1282	-0.1420	0.1416	IN
Wald Statistics	28.1	**P-value**	71.9%	

Figure 4.2 Actual wage VS Counterfactual wage distribution

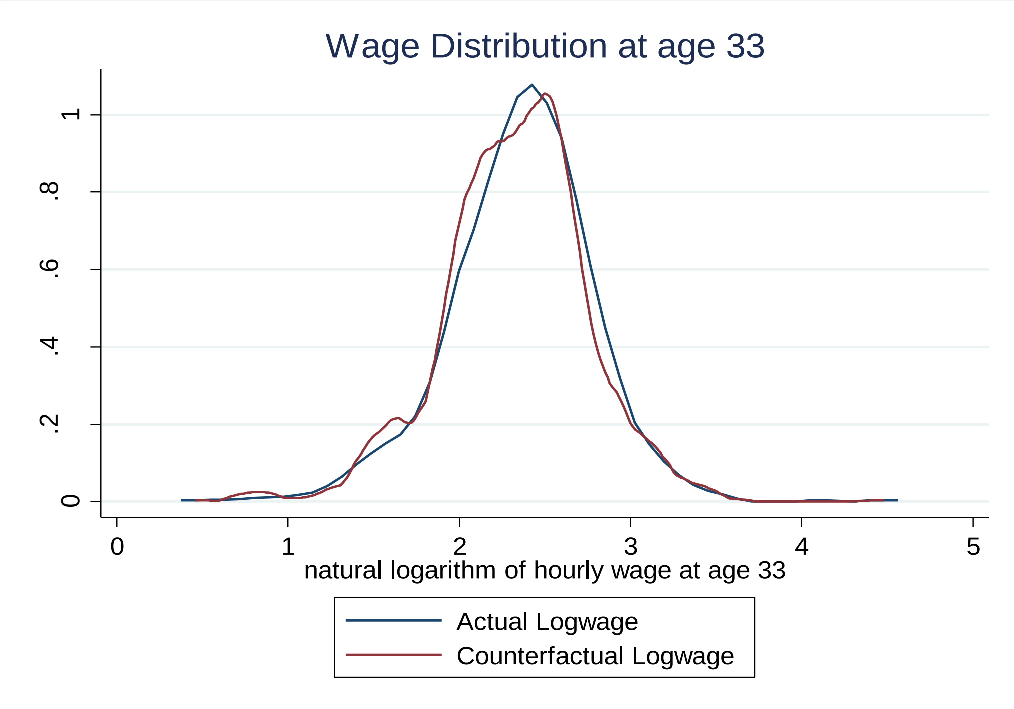
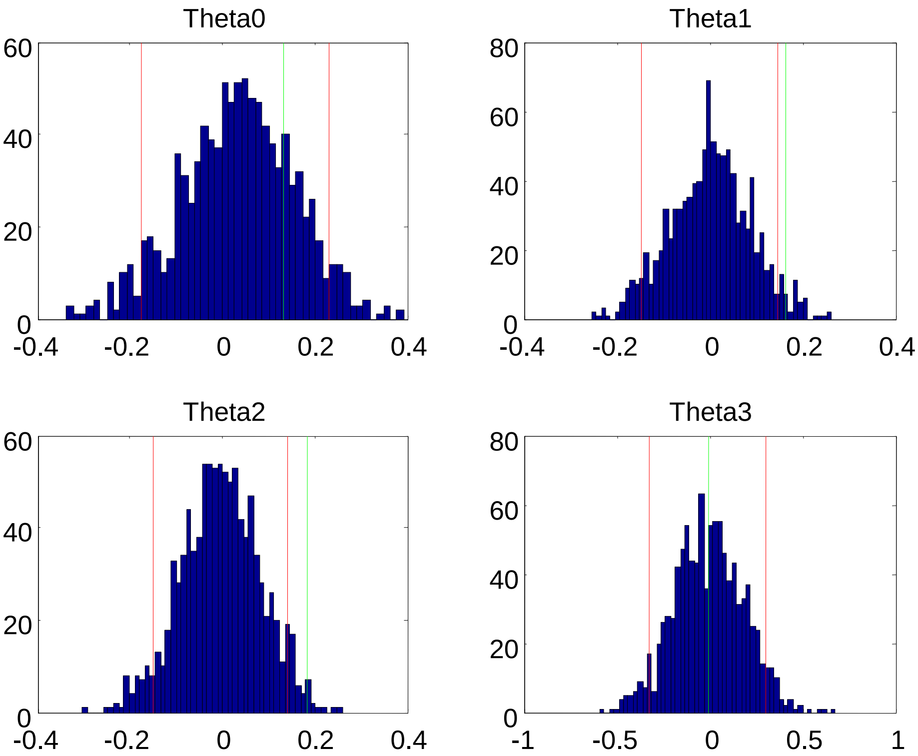
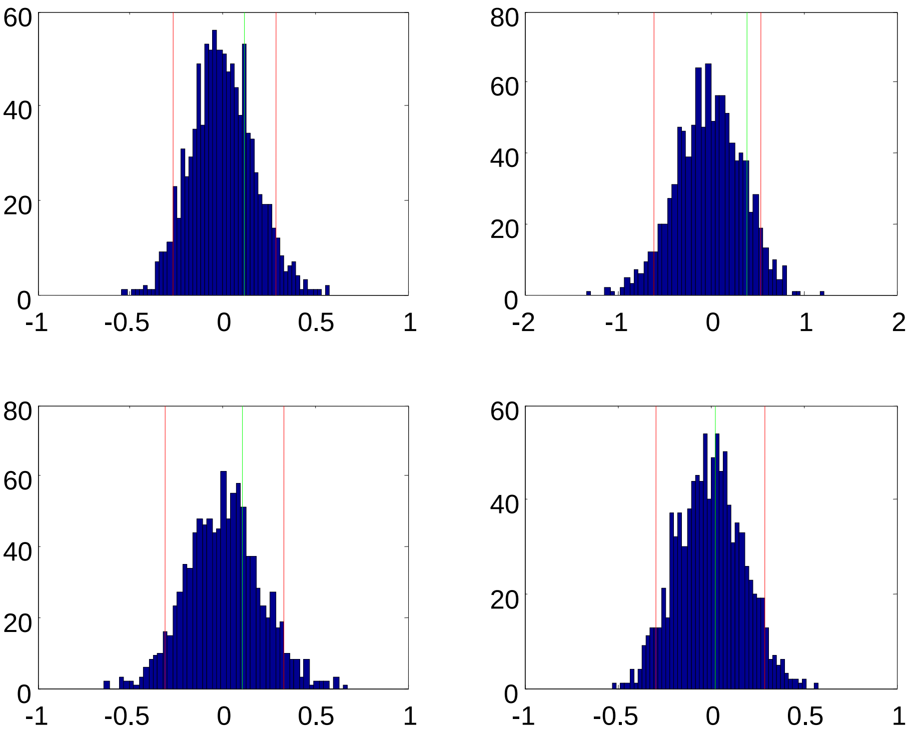
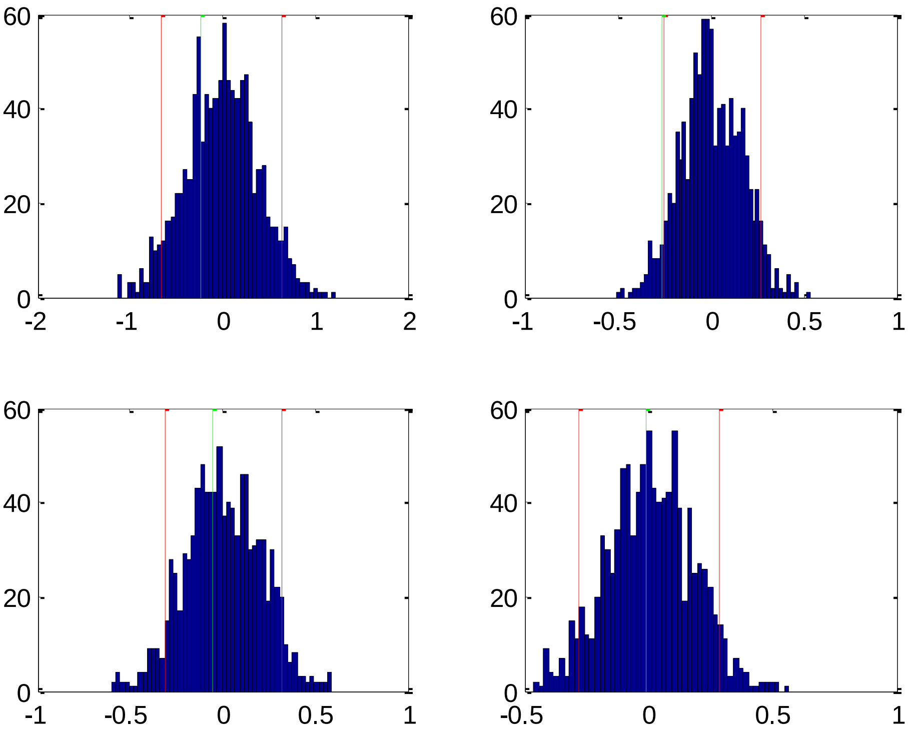


Figure 4.3 Distribution of Coefficient from Simulation Data, Model 3.6A







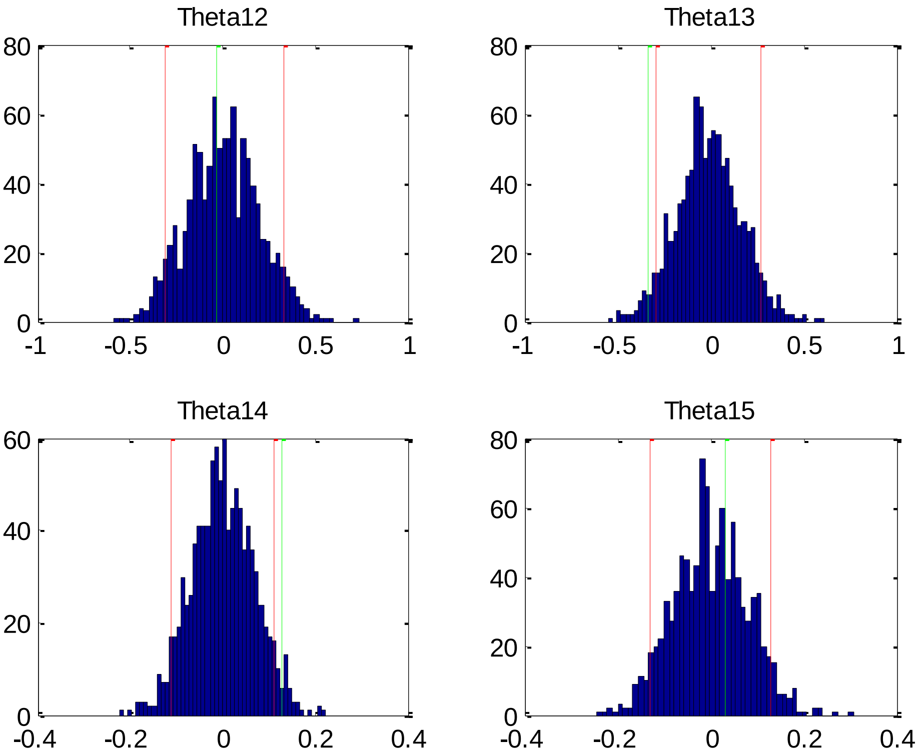


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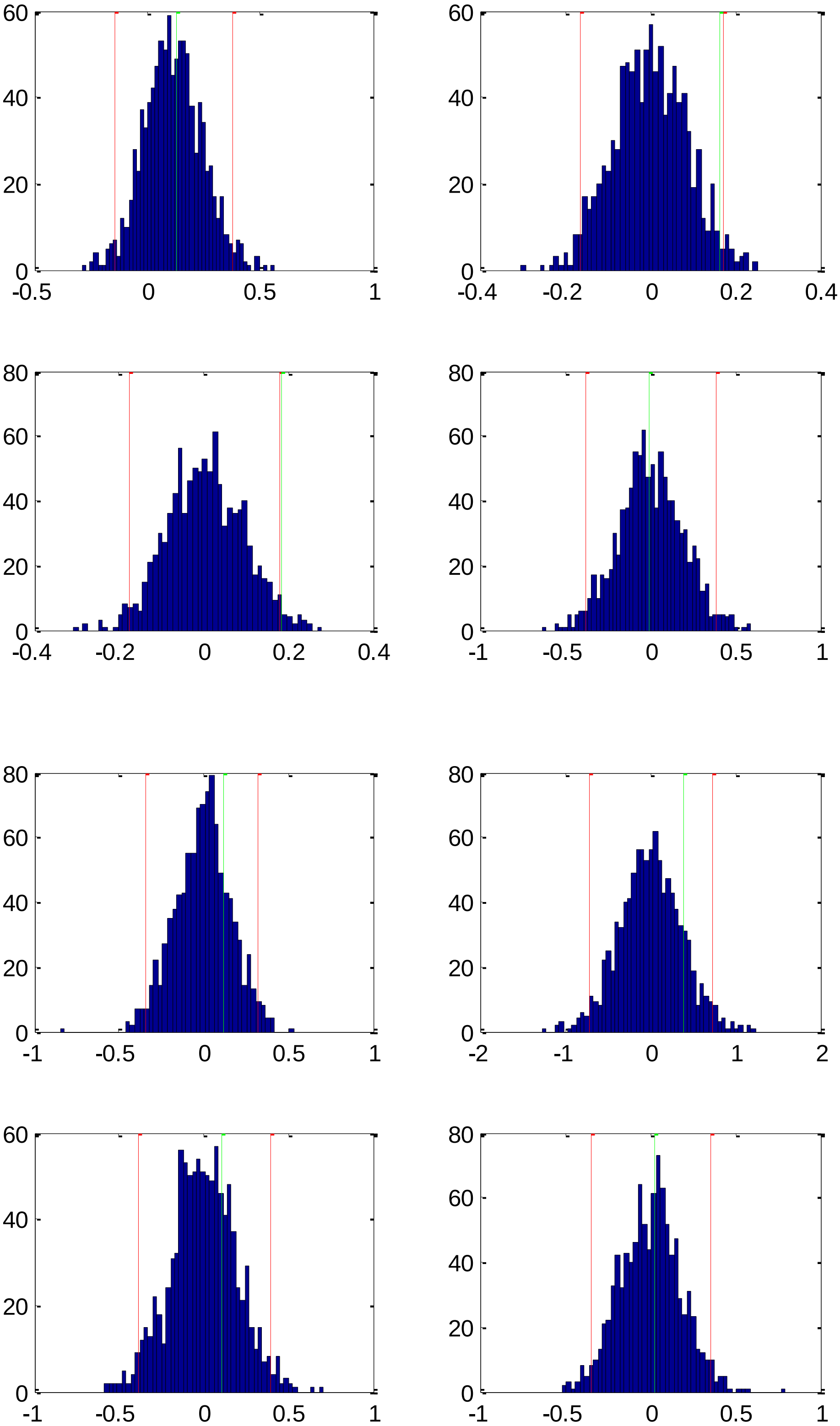
Figure 4.4 Distribution of Coefficient from Simulation Data, Hypothesis 2 Model using Calibration



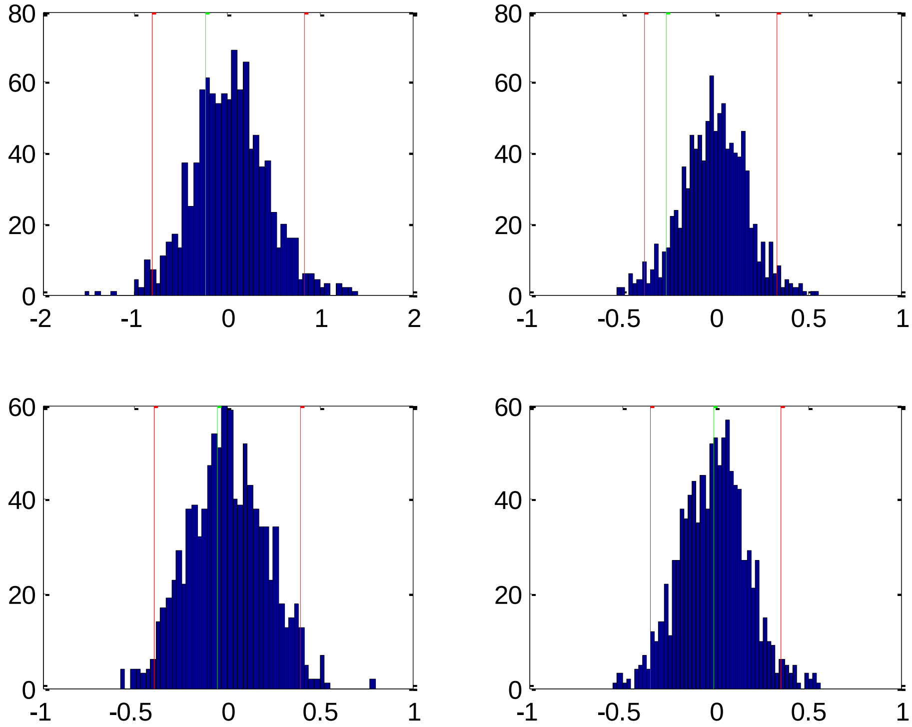

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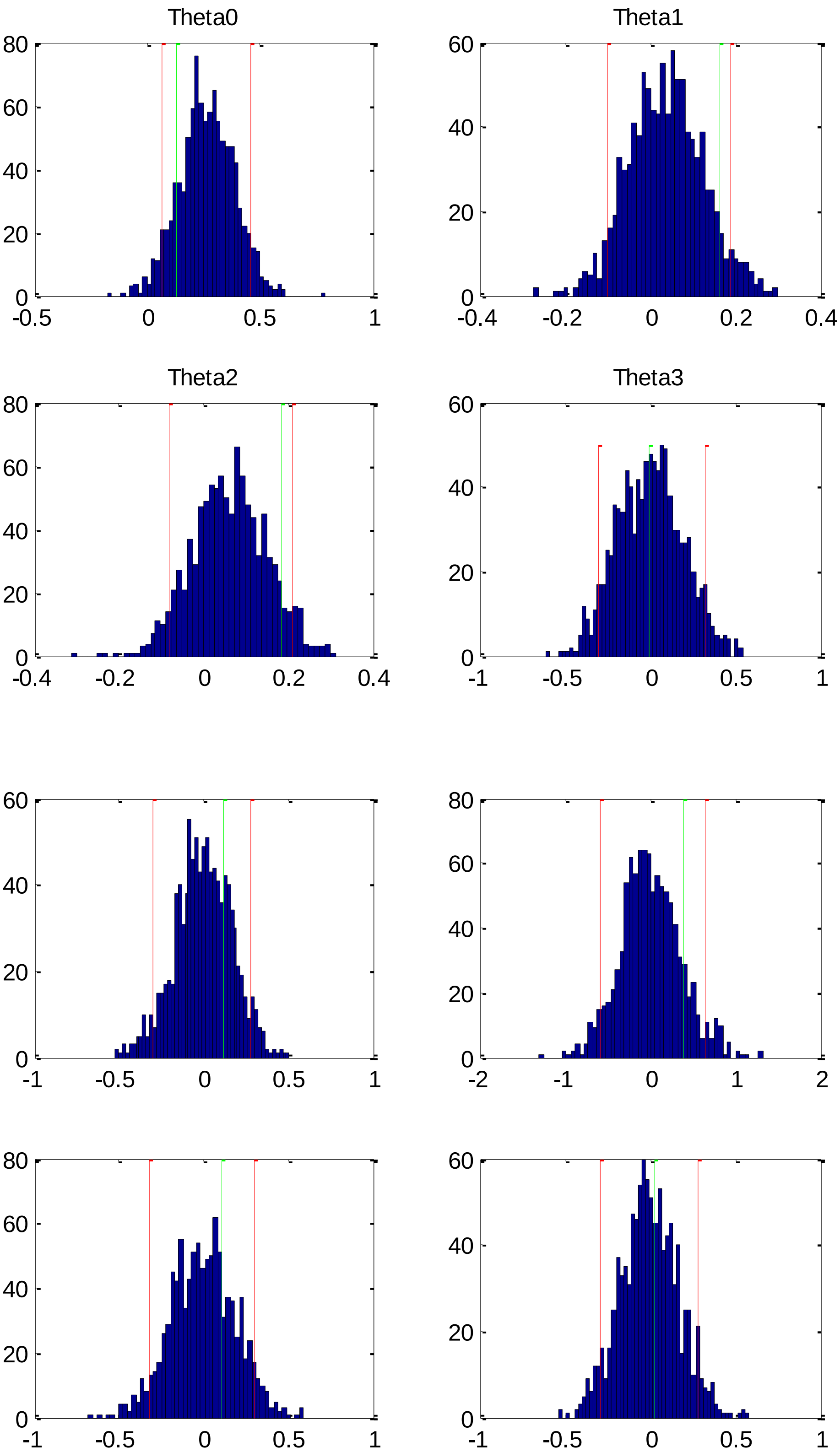
Figure 4.5 Distribution of Coefficient from Simulation Data, Hypothesis 2 model by II estimation



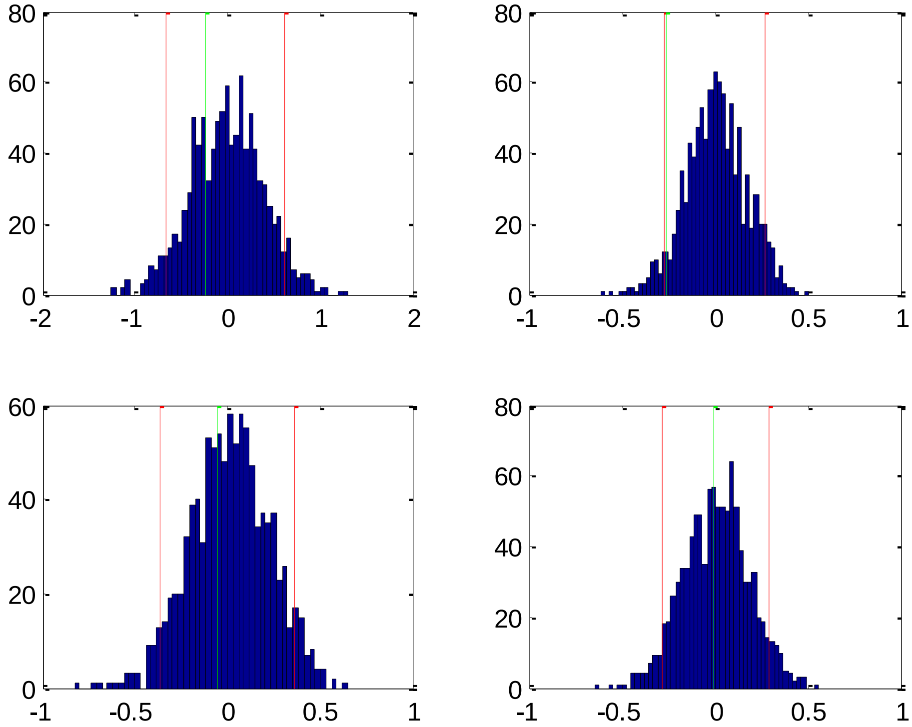

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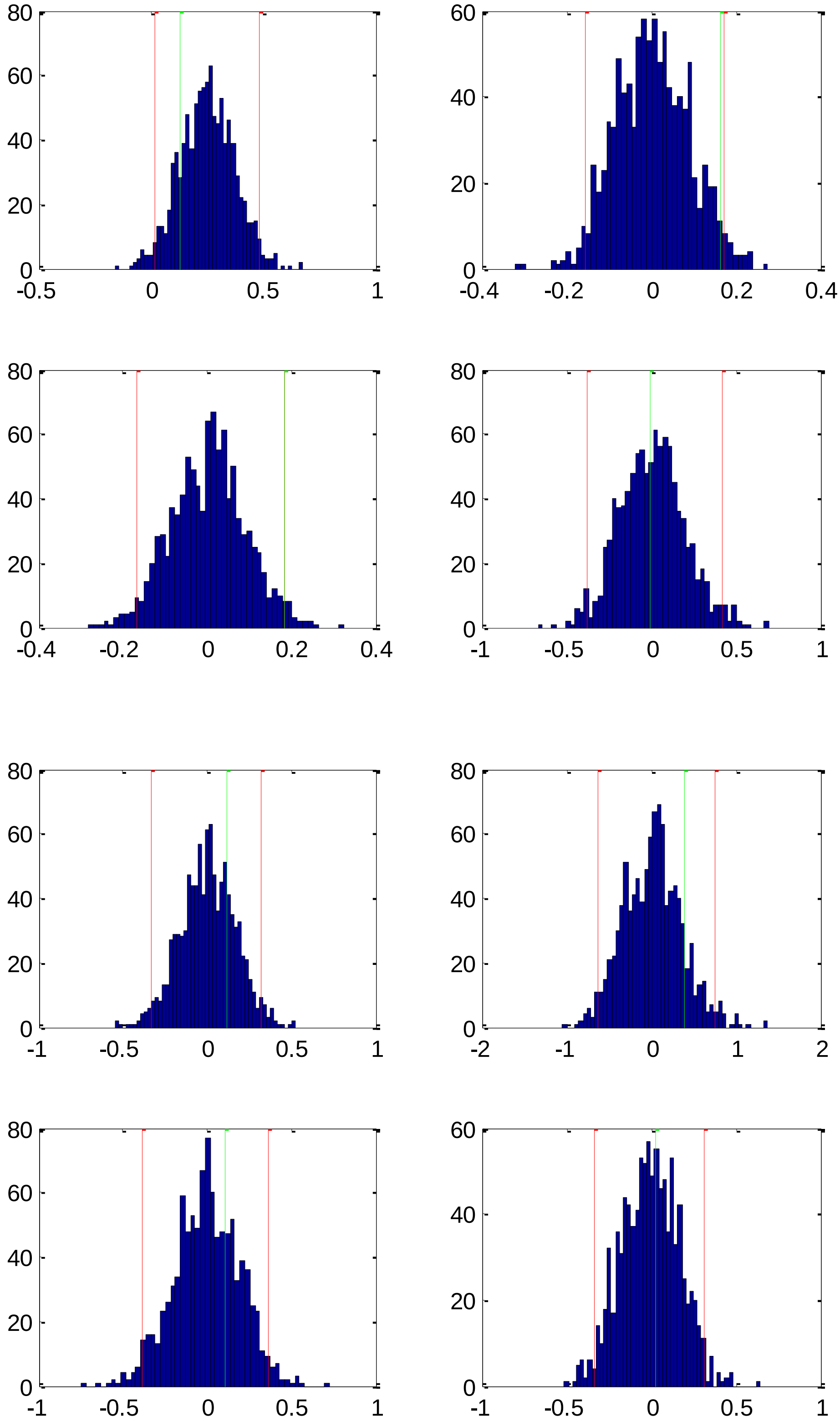
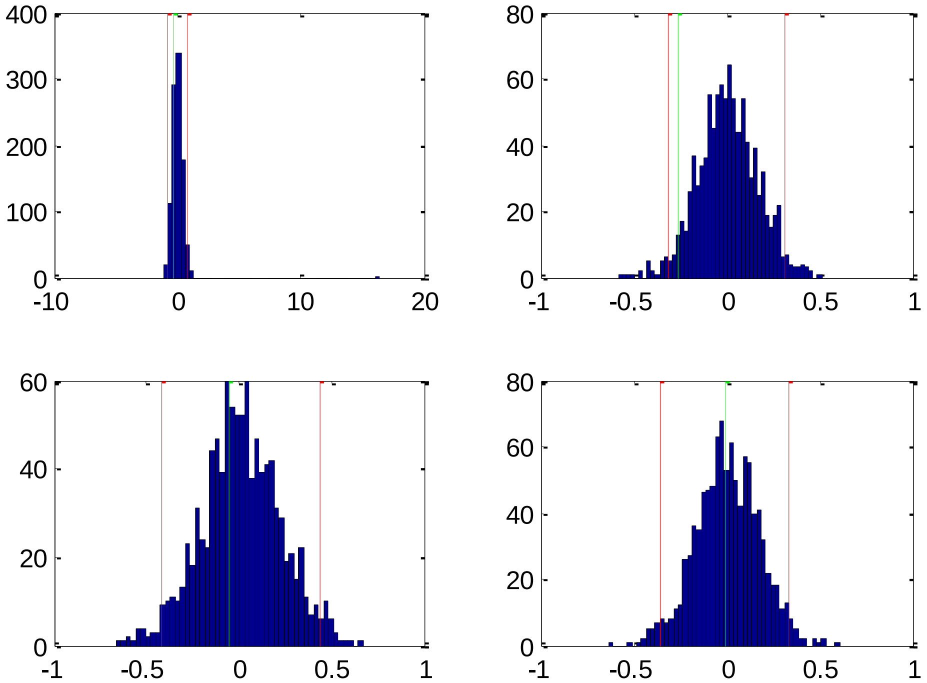
Figure 4.6 Distribution of Coefficient from Simulation Data, model (3.6A) by II estimation

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Chapter 5: General conclusion

5.1 Concluding comments

This thesis examines both pecuniary and non-pecuniary return to HE in the UK and it empirically tests the model of demand for HE origins from human capital theory. All three empirical chapters use data from the British 1958 NCDS.

This study contributes to the literature in a number of ways. Firstly, the analysis of Chapter Two uses PSM regressions to estimate the returns to highest academic qualifications. After an extensive review of the empirical and methodological literature in this field, the first investigative chapter of this thesis exploits the rich dataset to examine returns to education in the UK for from 33 to 50 years of age. By this time, individuals should have enough labour market experience since completing their education to provide an accurate assessment of the value of their qualifications in the labour market.

It is clear from Chapter Two that there is a variation in returns to education across the cohort, and the overall returns to educational qualifications at each stage of the educational process remain sizeable and significant, even after allowing for heterogeneity. The return rises with the greater disparity of the educational groups as age increases. Compared with leaving school at 16 without qualifications, the average incremental return at age 33 to O-levels is 13 %, for A-levels it is 33 %, and for HE it is 50 %. When the cohorts were at age 42, the return incremental to O-levels is around 16 %, for A-levels it is almost 40 %, and for HE it is about 58 %. On the other hand, in order to judge the impact of education on earning over lifetime, I restrict the sample to those individuals who attended all three follow up surveys after age 33, and re-estimate by using PSM. The result is relatively similar to that of the whole sample. This suggests that result there has been an increase in earnings over time for individuals who attained a higher educational attainment, which is highly robust.

The results also show that females with HE attainments usually enjoy higher returns than males, and the gender gap constantly increases over the years. For example, when comparing A-levels with HE attainment, on average females enjoy a 7 % premium over males. However, when comparing individuals with O-levels or no qualifications, the wage gap is not significant. This finding reflects a tendency for lower educated women to gain less wage growth than men. I further argue that females without HE are lower paid, and this is due to the number of females who re-entered the labour market in their late thirties and early forties. Females without HE attainment are more likely to suffer an interruption in employment because of maternity and motherhood in their thirties. When they return to the labour market, they can hardly be paid relatively fair and high wages due to their lack of work experience, they also have fewer chances for promotion.

Obviously HE offers much more possibilities to get better job, a higher income, and consequently achieve significant material benefits. But there are many non-monetary reasons why individuals decide to achieve HE. The non-monetary benefits of education have attracted the attention in this thesis because they represent the positive impacts on utility which are not captured by traditional economic measures. Most of the research has aimed at establishing causal links between an individual's education and health outcomes, as well as at evaluating particular effects. Chapter 3 starts by reviewing the large literature of the impact of education on health outcomes. However, a weakness of the most existing evidence to date is that much of the assessment of the effects of education has measured education in terms of years of schooling. This has commonly been investigated as a simple linear effect, without distinguishing the relative benefit of educational participation at some particular stage. Chapter Three also extended the analysis to later sweeps of the NCDS survey. This will allow for a wider range of outcomes to be considered and also allows for an analysis of the various ages at which these outcomes occur.

The findings from Chapter Three suggest that attending HE may be an effective way to improve population health and reduce the likelihood of health damaging behaviours. In particular, by using the conventional OLS approach I find considerable evidence that education is strongly associated with health and risky health behaviours. Furthermore, the effects of education remain after the introduction of controls for socio-economic background and prior health conditions. By applying the PSM approach, I find that a substantial element of this effect is causal. In more detail, HE has significantly positive impact on individual's general health status in terms of self assessed health status. Higher educated individuals have better general health conditions and this impact increases as the cohorts grow older. Associational evidence shows a negative relationship between education and obesity, such that more education is associated with less obesity. The causality of education on obesity is significant when individuals were middle aged. The estimated effect is about -12.3 % for males and -10.7 % for females at age 42, and -13.6 % for males and -11.4 % for females at age 50. Moreover, HE also has substantial effects on initiation, cessation, and frequency of smoking and drinking alcohol. It is striking that the impact of HE on reducing the likelihood of depression in UK is insignificant. This may happen because HE attainment results in a higher occupation in the labour market and this leads to higher levels of stress. There may be existing trade-offs between stress and satisfaction of higher occupation that may lead to an ambiguous relationship between educational success and mental health. I also exhibit some robust evaluations and evidence of the quantitative effects of education assessed in terms of covariates balance and sensitivity to the unobserved hidden bias. The problem arises from the general health indicator including SRH, BMI and likelihood of obesity. It indicates that these results are relative vulnerable to unobserved bias when conducting R-bounds analysis. The robustness of the effects on general health indicators may be of interest in future research.

According to human capital theory, investment in education would not occur unless the individual's future earnings stream following the extra investment is higher than it would have been had he or she not invested. Therefore, if one compares the ex ante expected earnings streams with and without investment, they would only be equal at a positive rate of return. This is the yield of the investment that is the most appropriate way to measure the decision of education. In contrast to existing literature that explores associations between HE participation and other factors, and which attempts to find the casual effects, in Chapter 4 I investigate the possibility that an individual's expected future returns to HE itself can determine the decision of HE participation. The participation decision is hypothesised to be a function of: (1) the individual's expected return to HE; (2) the expected return perceived by family socio-economic characteristics; and, (3) expected return perceived by early cognitive ability and academic performance. The three hypotheses are derived from the results obtained from the microeconomics framework of education decision making behaviour of individual agents. To test these hypotheses, I apply the Indirect Inference method to evaluate each hypothesis model and re-estimate the model to see if it fails to pass the test. I am the first to attempt to introduce this new type of method on microeconomic level cross-sectional data.

The main powerful conclusion is that the model of hypothesis one is highly rejected and the power of the test is relatively high. This shows that the model fails to pass both the Wald and normalized T-statistic. The conclusions for the models of hypotheses two and three are ambiguous. Both models use calibration coefficients and again fail to pass the Wald test; however, when I re-estimate all of the coefficients in the hypothesis model, both models two and three pass quite easily. On the one hand, because the natures of the effects are not simple direct impacts and causal effects of family and personal characteristics on HE participation are unclear, the accuracy of these effects might be under consideration. On the other hand, re-estimation seems to reduce the power of the II test substantially, and this should be further investigated.

5.2 limitations

Various limitations may exist in this study. The primary limitation of this study, then is the limitation of the data used. The estimates sample is only selected as the participants who were born in the 1950s, it may not reflect impact of recent the policy reform, especially introduction of the tuition fee in 1998. Secondly, the estimates take no account of the actual amount of time spent to achieve the different qualifications, hence the earnings forgone are not considered. Thirdly, comparisons may be alternatively made if we use additional rate of return in terms of incremented annually rather than on overall basis. While such an annualisation is reasonably straightforward for academic qualifications that generally studied on a full-time and uninterrupted basis. Last but not the least, I do not include psychic costs of studying and the effort needed to obtain different qualifications; these might also considerably differ between qualifications and thus contribute to explain differential returns.

5.3 Policy implications

Although the work of this study is not sufficient to inform policy, I draw the following policy implication relative to the study results. Based on the result from Chapter 4, HE participation has been the preserve of higher socio-economic groups in the UK, although the participation has risen substantially in recent decades, the relative position of lower socio-economic groups in terms of HE participation is still poor. The policy response has been to expand HE further, in an attempt to widen access to previously under-represented groups.

However, the introduction of tuition fees for HE have been considered as a barrier to finance this expansion. There are obvious arguments that this will have acted to depress demand for HE among lower socio-economic and poorer students. In fact the empirical evidence suggests that the private financial rate of return to HE in the UK is substantially high than that to non-HE. This implies that individuals would still be willing to invest in their own higher education, even if the government continuously cut subsidies and they are hence required to pay a greater cost. Furthermore, as long as the return to a HE has remained high throughout the period and there is evidence that the policy of expanding HE has not led to a collapse in the economic value of HE, the increasing HE subsidies are necessarily justified. On the other hand, even if it accepts positive non-financial impact of HE on health disparities, HE subsidies may be considered as the last resort if there is no alternative less expensive method to acquire the skills that ultimately affect health and individuals are aware of the health benefits of HE. It is considered public expenditures on NHS and health care is still a straightforward way.

5.4 Future work

This thesis raises a number of questions that should be considered in future work. Firstly, I might keep track of the returns to more recent cohorts of individuals (e.g. BCS70 and the Millennium Cohort Study) with available data to continue to study the returns to education and the demand and supply of qualifications in the labour market. Evidence shows that participation has recently increased, and will remain so in the future. However, following the changes in the fees structure of HE over recent years, it is predicted that participation rates and the number of graduates will decline in the future. This should include estimates of the variance in returns. It is, therefore, important to examine the magnitude of returns to HE and the extent to which they have changed over the generations in order to examine the effect of the government's policy of HE.

In relation to non-pecuniary returns, more research is required to understand the mechanisms or mediate the effects through which these outcomes occur. According to the previous literature, the estimates of the effect to HE on health damaging behaviours may nonetheless not be fully identified. In some studies, behavioural patterns (such as smoking and drinking) are considered as the mechanism by which education can improve health. Another limitation of this present analysis is that it is restricted to finding an average return to HE. However, it may not be the case that each level of qualification affects outcomes by the same magnitude. Therefore, further research needs to be developed to account for this issue.

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