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# Does higher education matter for health in the UK?

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A B S T R A C T

Using six sweeps of data from the 1958 British National Child Development Study (NCDS), we employ a quasi-parametric approach of propensity score matching to estimate the impacts of higher education attainment on a wide range of health-related outcomes for cohorts at ages 33, 42, and 50. The non-pecuniary benefits of higher education on health are substantial. Cohorts with higher levels of education are more likely to report better health, maintain a healthy weight, refrain from smoking, exhibit a lower frequency of alcohol consumption, and are less likely to be obese. The effects on self-reported health, body mass index (BMI), drinking alcohol increase with age, but continuously decrease with smoking frequency. When considering gender heterogeneity, higher education has a more significant effect on BMI and the likelihood of obesity for males, while it has a greater impact on self-reported health, drinking alcohol, and smoking frequencies for females. Furthermore, we find no significant evidence that higher education reduces the likelihood of depression. The results of the Rosenbaum bounds sensitivity analysis suggest that, although our overall results demonstrate robustness, there may still be unobserved hidden bias in the relationship between higher education and self-reported health.

## 1. Introduction

Education as a way of increasing human capital is a basic factor in the growth process of the aggregate economy. Although predominant studies confer most of the benefits that are likely to be reflected by the pecuniary return since the birth of the human capital theory (Schultz, 1961), it gives 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 and greater political participation. 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 (Grossman, 2006).

According to Cutler et al. (2006), education-health gradients increase when there is knowledge and technology available to prevent or treat because there is a universal demand for better health and those with more education, income, or power are likely to use new knowledge and new techniques more rapidly and effectively (Cutler & Lleras-Muney, 2008; Glied & Lleras-Muney, 2003).

The wider interests stem from the fact whether a positive relationship between education and health exists, then the individual’s educational attainment represents the most obvious means through which policymakers could affect their health (Braga & Bratti, 2013). Although health education gradient may result in part from reciprocal causal effects between educational attainment and health status, other researchers suggest that education does indeed have a causal effect on health (Currie & Moretti, 2003; Wolfe & Zuvekas, 1997). The standard least square estimation may only represent simple correlations and face endogeneity problems, most scholars use the instrumental variable (IV) strategies or regression discontinuity (RD) designs to identify causal effects (Adams, 2002; Clark & Royer, 2013; Glied & Lleras-Muney, 2003; Jürges et al., 2011; Meghir et al., 2018). However, these studies usually differ in terms of econometric specifications and focus only on single or very few health outcomes and behaviours at a particular age.

In this paper, we aim to make contributions to the existing literature in two main respects. First, it adds the growing literature by estimating the impact of higher education on health outcomes in the UK across the ages of 33, 42 and 50. We distinguish between the treated group, consisting of individuals who have completed some form of higher education (HE), and the control group, comprising individuals whose highest

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educational qualification is at least one A-level but who have not pursued further university studies. By including extensive covariates for family background characteristics, personal abilities and health status in childhood and adolescence, we characterise effects commonalities and compare the changes of the health returns of HE and the return to 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, and therefore investigate whether the return gap between genders still exists when the cohorts are up to the age of menopause.

We identify and estimate the treatment effect of HE on health outcomes and health-related behaviours using the propensity score matching (PSM) methodology (Rosenbaum & Rubin, 1983) which is widely applied in statistics and medical literature in both theoretical and empirical works (Dehejia & Wahba, 1999, 2002; Heckman et al., 1997), in evaluating labour market policies (Lechner, 2002; Sianesi, 2004), assessing the effect of college quality (Black & Smith, 2004; Dale & Krueger, 2002, 2014; De Luna & Lundin, 2014), and the wage return to education (Battistin & Sianesi, 2011; Blundell et al., 2005). The treatment effect is defined as the change in health outcomes caused by a potential move from untreated to treated status, or *vice versa*. Our focus in this study is on assessing the average treatment effects on treated assignment (ATT), which quantifies the premium if individuals have been obtained HE attainment relative to their counterparts (non-HE attainment).

To enhance the robustness of our estimation from PSM, we employ two different matching estimators nearest neighbour (NN) and kernel matching with replacement in this paper. Additionally, to address concerns regarding the assumptions of PSM in our study, we facilitate comprehensive evaluations. This includes employing balance tests to check the satisfaction of conditional independence assumption, a “thick-support” region test (Black & Smith, 2004) to check the estimates robustness, and associated Rosenbaum Bounds to check the satisfaction of selection on observable assumption.

Second, we use the National Child Development Survey (NCDS) data that can provide richer data sources on health and health-related variables. We therefore consider a wider set of health variables, in particular (i) general health outcome: self-assessed health; (ii) body weight health outcomes: Body Mass Index (BMI) and obesity; (iii) health-related damaging behaviours: frequency of smoking and drink alcohol; (iv) mental health outcome: depression based on malaise score. All of these health and health behaviours outcomes together provide a more general assessment of the effect of education on health.

Table 1 gives a list of the abbreviations that have been used in this paper. The structure of the rest of this paper is as follows. Section 2 reviews related literature. Section 3 describes the method of PSM, empirical model and data description. The main empirical results are presented and discussed in Section 4. Section 5 outlines the limitations of study and Section 6 highlights the main findings and draws the conclusion.

## 2. Literature review

The available shreds of evidence on the relationship between education and health are controversial in the UK (Jürges et al., 2013; Oreopoulos, 2006; Silles, 2009). Researchers focus on an individual’s general health status usually measured through self-reported heath (SRH) measures[1] or biomarker indicators.[2] Using compulsory schooling law changes as instruments, Oreopoulos (2006) applied an IV regression approach[3] based on the General Household Surveys (GHS) and identifies a positive and significant effect of education on SRH. The study found a negative effect of education on physical and mental disability. Similarly, Silles (2009) using the same method based on data from Health Surveys of England found a positive causal effect of education (year of schooling) on SRH, which is much larger than the OLS estimates. The author further indicated that a strong health gradient is observed for other health measures, such as SRH and smoking behaviour. Using British Household Panel Survey, Contoyannis et al. (2004) divided participants into 4 groups (degree, A-level, O-level, no qualification) by their maximum educational attainment. The authors apply Maximum Simulated Likelihood for a multivariate Probit model and found 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.

By contrast, Jürges et al. (2013) assessed the link of compulsory schooling and health using two nationwide law changes in the minimum school leaving age in the UK as an exogenous variation for education. Their result shows that there is no causal effect between compulsory schooling and the two biomarkers.[4] 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 (2013) studied the changes in the duration of compulsory schooling in the UK and found insignificant evidence of health returns in terms of improved health outcomes or changed health behaviours. The health outcomes they used were objective health measures, such as blood pressure, BMI, and levels of inflammatory blood markers.

Education to some extent induces individuals to have healthy lifestyles. Sabates and Feinstein (2004) proposed a Probit model based on data from the British Household Panel Survey to assess the relationship between education and health, particularly the uptake of health services in the UK. The evidence found that education has a direct effect on preventative health by raising awareness of the importance of undertaking periodic health tests. It might favour mechanisms 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. More patient individuals were more likely to invest in formal education and report better health outcomes (Reyes-Garcia et al., 2007). Schooling directs students’ attention toward the future and, through repeated problem-solving experiences, helps them develop the ability to simulate scenarios effectively (Becker & Mulligan, 1997). This

**Table 1**
Abbreviation table.

| Abbreviation | Full Name |
|---|---|
| BCS | British Cohort Study |
| BMI | Body Mass Index |
| CIA | Conditional Independence Assumption |
| HE | Higher Education |
| NCDS | National Child Development Study |
| NN | Nearest Neighbour |
| OLS | Ordinary Least Squares |
| PSM | Propensity Score Matching |
| SRH | self-reported health |

[1] 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.

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

[3] 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.

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

assertion found support in the work of Epper et al. (2020), which investigated how individuals' patience levels influenced their rank in wealth and income distributions throughout their lifespans. Their findings showed that individuals with high patience were consistently ranked higher in terms of wealth compared to others. Other study showed individuals in the richest income quintile are equally patient at any age while individuals in the poorest quintile are less patient the older they are (Burro et al., 2022). However, Thompson et al. (2020) argued that childhood social-economic status is negatively associated with patience, creating a significant controversy regarding this causal effect. On the other hand, Stormacq et al. (2019) argued that socioeconomic status does not directly impact health. Instead, potential mediating factors, such as health literacy, habitus (Pampel et al., 2010), and psychological mediators (Griffith et al., 2023), could play pivotal roles in linking socioeconomic status disparities to health and health behaviours.

Cutler and Lleras-Muney (2010) found that higher educated individuals in the US and UK,[5] after accounting for age, gender, and parental background tend to have lower rates of smoking, obesity, and heavy drinking; Additionally, they are more inclined to practice safe driving, live in secure housing, and utilize preventative healthcare. 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. This evidence is however in opposition to Clark and Royer (2013), who show no evidence that education improves behaviours in terms of the dietary regime and regular physical activity in the UK.

HE attainment could be 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) studied a wide range of benefits of HE based on NCDS and BCS. They found that graduates are generally less depressed and present a higher sense of wellbeing than those with lower educational attainment. Feinstein (2002), using data from the NCDS and BCS and matching methods, showed 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 (2007) relied on the 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. They estimated 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) focused 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% of students are marked to have severe social anxiety.

Studies on the effect of higher education on general health status disparities have rarely been found in the literature by adopting PSM or matching related approaches. Conti et al. (2010) went beyond the existing literature which typically estimates mean effects to compute distributions of treatment effects and applied 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 estimated causal effects of education (year of schooling) on adult health and healthy behaviours in a form of matching using the British Cohort Study in 1970. They concluded education has an important causal effect in explaining differences in health behaviours (such as smoking and regular exercise) as well as on some other outcomes (such as obesity poor health and depression). Besides that, they also showed that family background characteristics, and cognitive, non-cognitive, and health endowments developed by early ages, are important determinants of the labour market and health disparities at age 30. 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 callipers. 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.

The literature review examines the relationship between education and health outcomes and draws from a range of studies with diverse methodologies and findings. While some research suggests a positive effect of education on health, particularly in terms of self-rated health and health behaviours, others find mixed or insignificant results. This highlights the need for further investigation.

## 3. Data and methodology

### 3.1. Econometric model

The empirical model takes the following specification:

$$H = C + \beta HE + X\theta + \mu \tag{1}$$

where $H$ is the measured outcome of an individual's general health, health behaviours and mental health. $HE$ is the binary variable that stands for whether an individual obtains HE attainment. $\beta$ is the parameter of interest, which measures the treatment effect of HE on the particular measure of health status and health-related behaviour. $C$ is the constant term and $\mu$ is the error term. $X$ is a vector of confounding variables that can explain variations both in treatment and outcomes variables but themselves are not inversely caused by treatments or outcomes.

### 3.2. Propensity score matching

The impossibility of observing both treatment and control outcomes for each individual is often referred to as the "fundamental problem of causal inference" (Holland, 1986; Rubin, 1974, 1978). PSM is a semi-parametric estimator that was developed by Rosenbaum and Rubin (1983) and applied in statistics and medical literature in both theoretical and empirical works. The matching approach provides one possible solution to the problem of selection bias that has been applied in 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. The effect is only identified if the estimation is under two precise assumptions if one applies matching.

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

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

$$D \perp X \mid p(X) \tag{2}$$

[5] 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.

**Table 2**
Sample size of treat and control groups.

| | 1 or more a-levels | HE degree | Total Sample |
|---|---|---|---|
| Men | 523 | 782 | 1350 |
| Women | 675 | 662 | 1337 |
| All | 1198 | 1444 | 2687 |

2. Unconfoundedness or CIA given the propensity score:

$$D \perp Y1, Y0 \mid p(X) \tag{3}$$

3. Common Support or overlap condition:

$$0 < p(D = 1 | p(X)) < 1 \tag{4}$$

where $D = \{0, 1\}$ is the indicator of exposure to treatment and $X$ is the multidimensional vector of all observable and unobservable pre-treatment characteristics. The potential outcomes are then defined as $Y(D)$.

### 3.3. Data source

The British NCDS 1958 used in this paper is a continuing panel survey of all individuals born in the UK between the 3rd and 9th week of March 1958. There have been 10 follow up sweep surveys available since birth up to 2020. Data was collected from cohort members at multiple time points as they age. These sweep waves can cover various aspects of their lives, including physical and educational development, economic circumstances, employment, family life, health behaviour, wellbeing, social participation and attitudes. In this study. We select the data from sweeps of all cohort members collected at ages 7, 11, 16, 33, 42 and 50. Our criteria for the sweep selection are that information on the cohorts in (i) early age personal ability all childhood sweeps (ages 7 and 11); (ii) health status in childhood and adolescence (ages 7 and 16); (iii) type of secondary school (ages 16); (iv) family backgrounds are observed (age 16); (v) highest educational attainments are observed at age 33 (age 33); and (vi) health-related variables are observed across adult age (age 33, 42 and 50).

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

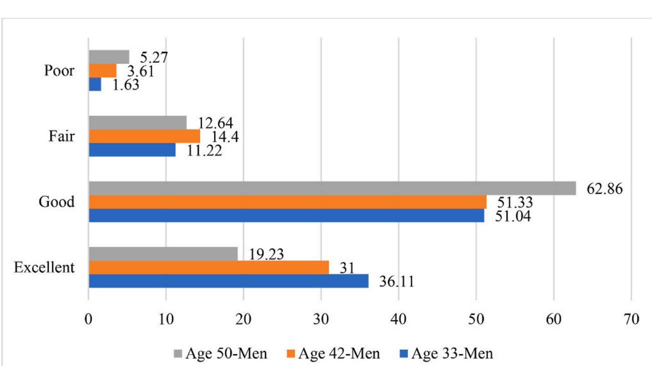


**Fig. 1.** SRH for Men across different ages.

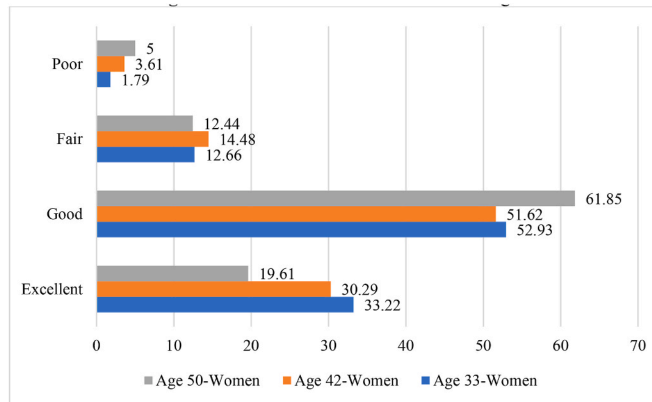


**Fig. 2.** SRH for Women across different ages.

information, educational attainment and subsequent working life. For educational attainment, it contains detailed information on the HE qualifications achieved by each individual up to 2000 (age 42) 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. We define HE attainment in the UK context as the return from undertaking some form of university level or equivalent. Following Blundell et al. (2000), we define 'Non-HE' as individuals who acquired at least one A-level qualification but did not pursue higher education. We assume that individuals stop having further education in 1991 at the age of 33.

As shown in Table 2, the overall sample includes 1444 individuals who have a HE qualification and 1198 individuals who obtained at least one A-level but who did not continue into HE.

### 3.4. Health outcomes

The aim of the study is to provide a comprehensive assessment of health outcomes and health-related behaviours. By including a combination of measures, we selected six health-related indicators across different age groups, encompassing various aspects of health and health related behaviours. This encompassed both subjective assessments of health: SRH and objective measures: BMI and Obesity), along with indicators reflecting health behaviours: alcohol and smoking frequency. Furthermore, we included an indicator focusing on mental health status. This diverse selection allows us to explore various health dimensions, covering general health, physical health, mental health, and lifestyle behaviours.

SRH 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. We recode SRH so that a higher number corresponds to better SRH (i.e., 1 = poor, 4 = excellent). Figs. 1 and 2 illustrate the distribution of SRH for different age levels by gender.

BMI is a useful measure of being overweight and obese, it is an estimate of body fat and is a gauge of the risk of diseases that are associated with more body fat. The NCDS records the height and weight of the respondents at all sweeps,[6] except for Sweep 7 in 2004. Table 3 summarises the descriptive statistics of BMI. The measures of BMI can also be used to construct an indicator of being overweight or obese. According to the classification from World Health Organization (WHO), we place measured BMI into four categories, which are: underweight,

[6] We use the following formula to calculate the respondents' BMI: $\mathrm{BMI} = \frac{\mathrm{weight(kg)}}{[\mathrm{height(m)}]^2}$ or $\mathrm{BMI} = \frac{\mathrm{weight(lb)}}{[\mathrm{height(inch)}]^2} \times 703$

**Table 3**
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 |

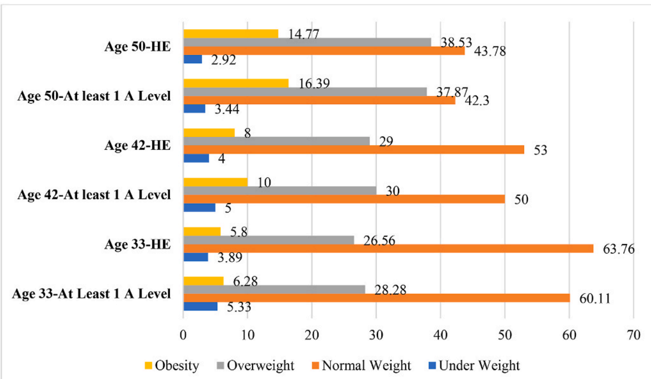


**Fig. 3.** Percentages of obesity by qualifications.

normal weight, overweight, and obesity.[7] Fig. 3 depicts the distribution of obesity by qualifications.

Figs. 4 and 5 illustrate distributions of drinking and smoking frequency. The two data are directly collected from NCDS. The malaise score is calculated from the Malaise Inventory[8] and designed to identify depression in non-clinical settings and indicator of depression (Rutter et al., 1970). Fig. 6 illustrates the distribution of malaise scores at different ages. According to the classification defined in NCDS, individuals responding 'yes' to eight or more of the 24 items are considered to be at risk of depression. We create a binary variable indicating depression = 1 when malaise score $\geq$ 8 and no depression = 0 when malaise score $<$ 8.

### 3.5. Confounding variables

Table 4 presents the descriptive statistics for confounding variables. Confounding variables are considered to influence both the educational decision and health outcomes should be included as regressors. The choice of confounding variables is dictated into five main categories.

1. Demographic characteristics: region of residence at birth, ethnicity.
2. School type: type of secondary school.
3. Early age personal ability: Mathematics score, reading score assessed at age 7 and 11.
4. Family backgrounds: Father's year of education and father's social class, mother's year of education, mother's employment status, number of siblings, parents' interest in participant's education, all at age 16, and family finance status at age 11 and 16.
5. Health status in childhood and adolescence.

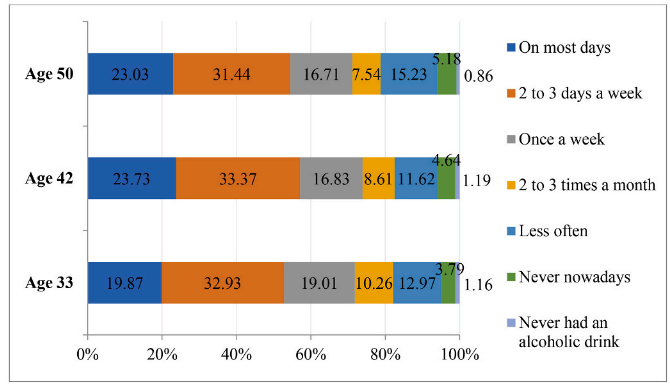


**Fig. 4.** Percentage of drinking alcohol frequency across ages.

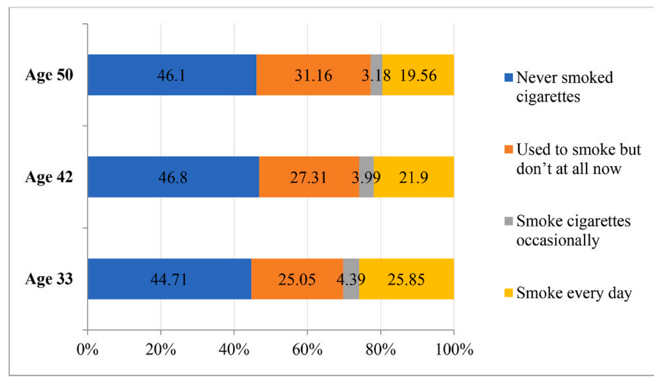


**Fig. 5.** Percentage of smoking frequency across ages.

### 3.6. Controlling health status in childhood and adolescence

There are difficulties in identifying causal relationship between education and health, even with rich set data available for the NCDS. Such relationship does not necessarily demonstrate causality if there is a reverse causation, the education of individuals was influenced by their early life health status. For example, children in poor health are almost certain to miss more days of school due to illness than their healthy peers and may also learn less while they are in school.

According to Conti et al. (2010), family background, and cognitive, noncognitive traits and health endowments are all important determinants of health disparities, the fraction of health gaps by education that can be explained by selection into education on early life endowments and can be attributed to the causal effect of education. We follow Conti et al. (2010) to incorporate confounding variables which aim to control for potential influences on both early health status in childhood and adolescence and education outcomes. These variables include born with low birthweight, maternal heavy smoking during pregnancy, the presence of health conditions and mental health conditions at ages 7, 11, and 16, which aim to control for potential influences on both health status in childhood and adolescence and education outcomes.

We first assess child health before age 7 (educational entrance) with two measures: the infants' low birth weight and maternal behaviour, which is whether the mother smoked after the fourth month of pregnancy. A widely accepted cut-off as being low birth weight is responders

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

[8] It 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.

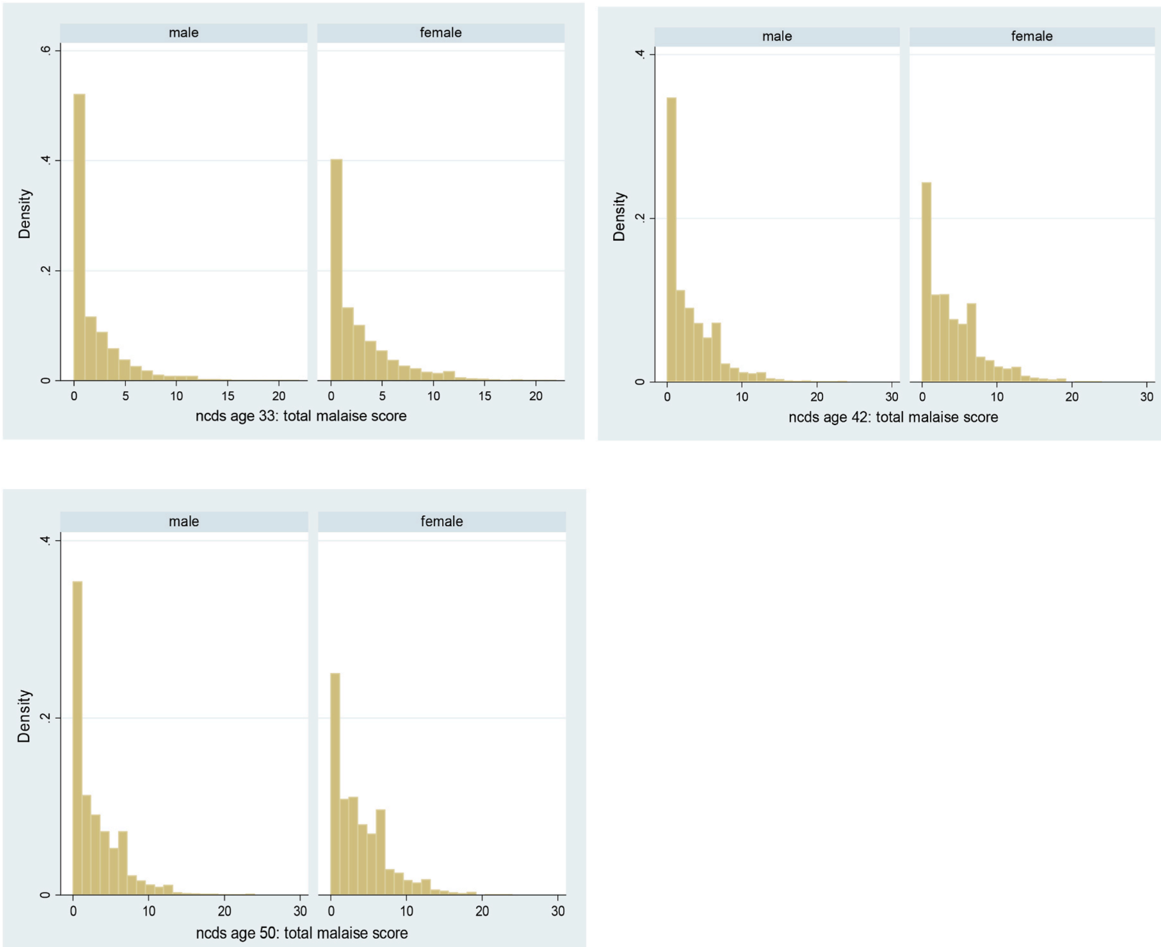


**Fig. 6.** Distribution of the malaise score at different ages.

for whom a birth weight of less than 2500 g. Secondly, an individual's childhood physical and mental conditions are diagnosed and reported in a medical examination from each Sweep.[9] The medical examination is considered as a relatively unbiased measure since it reflects the condition impeding normal functioning, rather than self-evaluation. We created global measures of childhood general health status by separating physical and mental impairments. There are two reasons to construct this measure. On the one hand, it attempts to focus on persistently poor general health. In this case, variables are created to indicate if there is a diagnosis that the child has had health problems during childhood and adolescence at different age stages. On the other hand, an individual with childhood health problems at a single age stage will not necessarily have the same problem across their entire childhood.

Instead of relying solely on health indicators derived from medical examinations, we also incorporate the *Rutter Behaviour Score*, which is an alternative psychological assessment widely accepted and commonly used in health economics studies. The *Rutter Behaviour Scores* reported in the NCDS serve as an index for assessing participants' behavioural difficulties during childhood (Rutter, 1967; Rutter et al., 1970)[10]. We categorize the scores into three levels of severity: "normal" scores, which fall below the 80th percentile; "moderate problem" scores, which fall between the 80th and 95th percentile; and "severe problem" scores, which exceed the 95th percentile. Any missing or incomplete values in health and mental measures are attributed to non-participation and also included in a separate category.

## 4. Empirical analysis

Using the different ages as reference points, the results presented are disaggregated by various educational groups. It is noted the full sample size for both genders is not always equal to the sum of the male and female sub-samples because pooling the samples leads to different matches to those in the sub-sample. Fig. 7 displays distributions of Propensity Scores for the treated and control groups. OLS results are reported together with PSM estimates based on two different matching algorithms discussed. Although suffering endogeneity bias, the parameter of interest in OLS estimates empirically can be interpreted as the average treatment effect (Aizer et al., 2016; Voigtländer & Voth, 2012) and be used to find how the health behaviours change overtime with full controls of confounding variables. We also consider it may not be

[9] 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.

[10] 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.

**Table 4**
Descriptive statistics for confounding variables.

| Variable | Mean | S.D | Variable | Mean | S.D |
|---|---|---|---|---|---|
| **White** | 0.987 | 0.115 | **Father's social class in 1974** | | |
| **Mathematics ability at 7 years** | | | Professional | 0.034 | 0.181 |
| 5th quintile (highest) | 0.194 | 0.395 | Intermediate | 0.132 | 0.338 |
| 4th quintile | 0.114 | 0.318 | Skilled Non-manual | 0.063 | 0.244 |
| 3rd quintile | 0.271 | 0.445 | Skilled manual | 0.298 | 0.458 |
| 2nd quintile | 0.141 | 0.348 | Semi-skilled non-manual | 0.010 | 0.010 |
| 1st quintile (lowest) | 0.280 | 0.449 | Semi-skilled manual | 0.087 | 0.281 |
| **Reading ability at 7 years** | | | Unskilled | 0.036 | 0.185 |
| 5th quintile (highest) | 0.192 | 0.394 | Missing, or unemployed or no father | 0.34 | 0.474 |
| 4th quintile | 0.132 | 0.339 | Number of siblings in 1974 | 1.743 | 1.512 |
| 3rd quintile | 0.263 | 0.44 | **Father's interest in education** | | |
| 2nd quintile | 0.209 | 0.407 | Expects too much | 0.024 | 0.153 |
| 1st quintile (lowest) | 0.204 | 0.403 | Very interested | 0.262 | 0.440 |
| **Mathematics ability at 11 years** | | | Some interest | 0.249 | 0.433 |
| 5th quintile (highest) | 0.194 | 0.396 | **Mother's interest in education** | | |
| 4th quintile | 0.202 | 0.402 | Expects too much | 0.037 | 0.188 |
| 3rd quintile | 0.171 | 0.376 | Very interested | 0.349 | 0.477 |
| 2nd quintile | 0.202 | 0.401 | Some interest | 0.346 | 0.476 |
| 1st quintile (lowest) | 0.231 | 0.422 | | | |
| **Reading ability at 11 years** | | | **Region in 1974** | | |
| 5th quintile (highest) | 0.159 | 0.365 | North West | 0.116 | 0.320 |
| 4th quintile | 0.191 | 0.393 | North | 0.075 | 0.264 |
| 3rd quintile | 0.241 | 0.428 | East and West Riding | 0.087 | 0.281 |
| 2nd quintile | 0.168 | 0.374 | North Midlands | 0.076 | 0.265 |
| 1st quintile (lowest) | 0.241 | 0.428 | East | 0.086 | 0.280 |
| Comprehensive school 1974 | 0.467 | 0.499 | London and South East | 0.160 | 0.367 |
| Secondary modern school 1974 | 0.170 | 0.376 | South | 0.063 | 0.243 |
| Grammar school 1974 | 0.087 | 0.281 | South West | 0.068 | 0.251 |
| Private school 1974 | 0.06 | 0.214 | Midlands | 0.101 | 0.301 |
| Other school 1974 | 0.017 | 0.130 | Wales | 0.058 | 0.234 |
| **Father's age in 1974** | 46.64 | 6.39 | Scotland | 0.111 | 0.315 |
| **Mother's age in 1974** | 43.56 | 5.700 | Other | 0.100 | 0.299 |
| **Mother employed in 1974** | 0.657 | 0.475 | **Father's years of education** | 7.904 | 1.622 |
| **Bad finances in 1969 or 1974** | 0.114 | 0.317 | **Mother's years of education** | 7.916 | 1.376 |
| **Childhood and adolescence health indicators** | | | | | |
| **Born at Low birth weight (<2500g)** | 0.063 | 0.137 | | | |
| **Mother smoked heavily during pregnancy** | | | | | |
| Non-smoker | 0.664 | 0.269 | **Rutter Behaviour Score 7** | | |
| Medium smoker | 0.157 | 0.357 | Normal | 0.608 | 0.451 |
| Heavy smoker | 0.123 | 0.264 | Moderate problem | 0.086 | 0.564 |
| Variable smoker | 0.056 | 0.235 | Severe problem | 0.041 | 0.452 |
| **General health 7** | | | Missing or Incomplete | 0.265 | 0.504 |
| Good | 0.780 | 0.255 | **Rutter Behaviour Score 11** | | |
| Abnormal | 0.067 | 0.229 | Normal | 0.554 | 0.425 |
| Missing Value | 0.153 | 0.152 | moderate | 0.077 | 0.527 |
| **General health 11** | | | Severe problems | 0.038 | 0.460 |
| Good | 0.705 | 0.296 | Missing or Incomplete | 0.331 | 0.489 |
| Abnormal | 0.094 | 0.251 | **Rutter Behaviour Score 16** | | |
| Missing Value | 0.201 | 0.175 | Normal | 0.486 | 0.477 |
| **General health 16** | | | moderate | 0.098 | 0.551 |
| Good | 0.693 | 0.256 | Severe problems | 0.030 | 0.445 |
| Abnormal | 0.106 | 0.230 | Missing or Incomplete | 0.386 | 0.532 |
| Missing Value | 0.201 | 0.193 | | | |

appropriate to show the percentage change of the treatment effects of HE on ordered categorical outcomes. After matching, we tabulate the total matched sample and calculate the fraction of each ordered categorical outcome for both treatment and control groups. It is a straightforward measure of percentage change of the treatment effects across ages.

### 4.1. Self-reported health

As shown in Table 5, OLS estimates for the age group of 33 is about 0.064 for the whole sample, 0.037 for male, and 0.079 for female participants. Generally, the impact on individuals aged 42 and 50 exhibits some similarity to that at age 33. Higher education (HE) exerts a more pronounced influence on females than on males. All estimated ATT coefficients are statistically significant, in particular effects are significant at the 5% level for females across all ages under both NN and Kernel matching method, while for others, they attain at least a significance level of 10%. The effects on the pooled sample across ages have no significant differences: 0.08 at age 33, 0.08 at age 42, and 0.09 at age 50. The results stress the importance of taking sex heterogeneity into account while the effects show monotonic increases with age. 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 at age 50.

Table 6 shows 41.9% of 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% points. On the other hand, when measuring the risk of poor health status, the risk is more than doubled from 0.9% (with HE) to 2.6% (with non-HE). For females, the fraction of the 'excellent' category is 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 across the age. Higher educated cohorts have better general health conditions and this impact increases as cohorts get older. The results are somewhat consistent with the previous finding by Ross and Wu (1995), and White et al. (1999), which suggest that education has a strong and positive effect on adult SRH. Our results also align with Oreopoulos (2006), identifying a positive and significant effect of education on SRH using data from the General Household Surveys in the UK, as well as with Silles (2009), who used data from the Health Surveys of England.

### 4.2. BMI and obesity

When turning to PSM estimates with the inclusion of full controls for covariates, the estimated coefficient from PSM has no significant difference compared to the OLS result at age 33 in pooled samples (see Table 7). HE 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 are statistically significant.

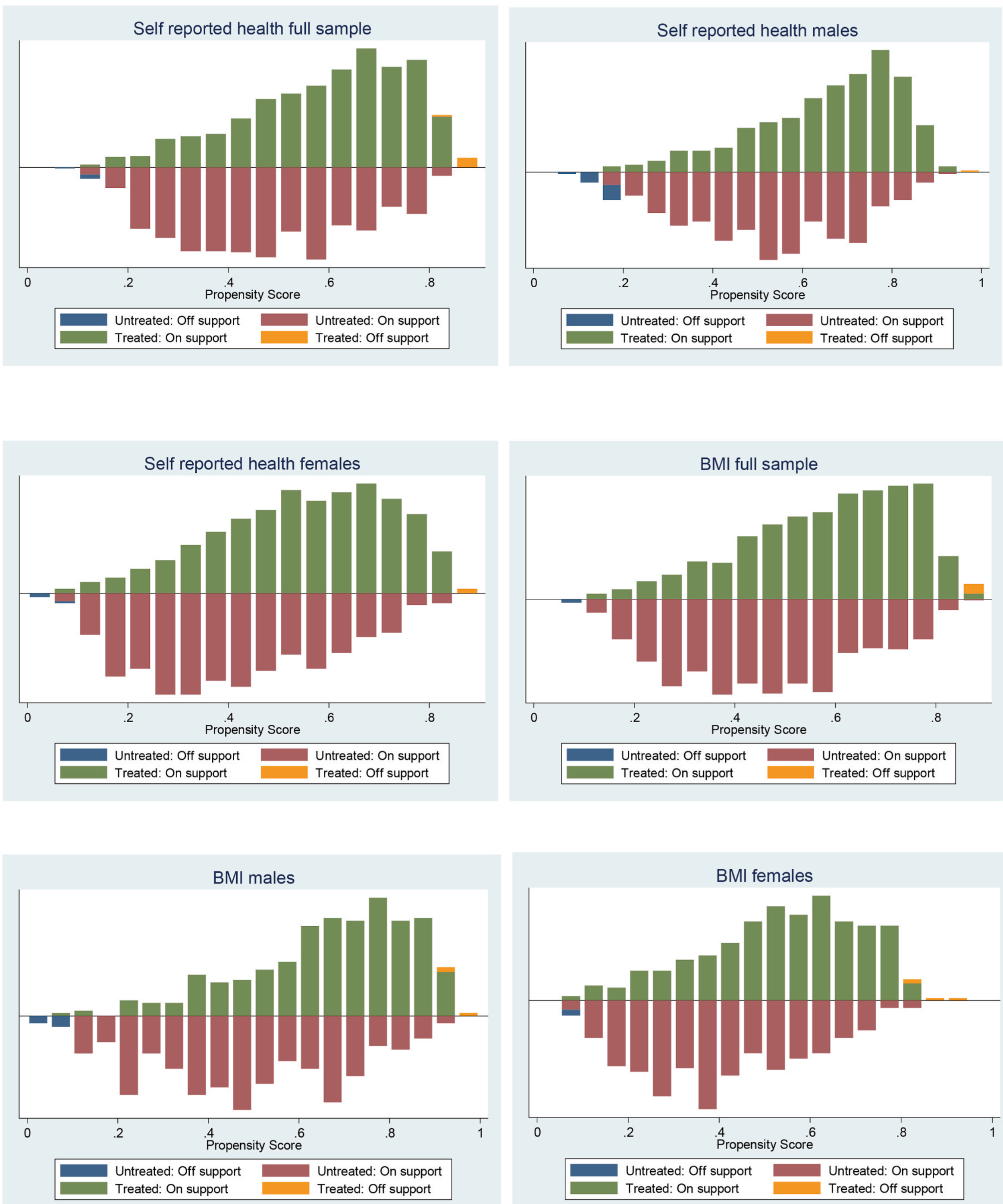


**Fig. 7.** Propensity score distributions and common support regions

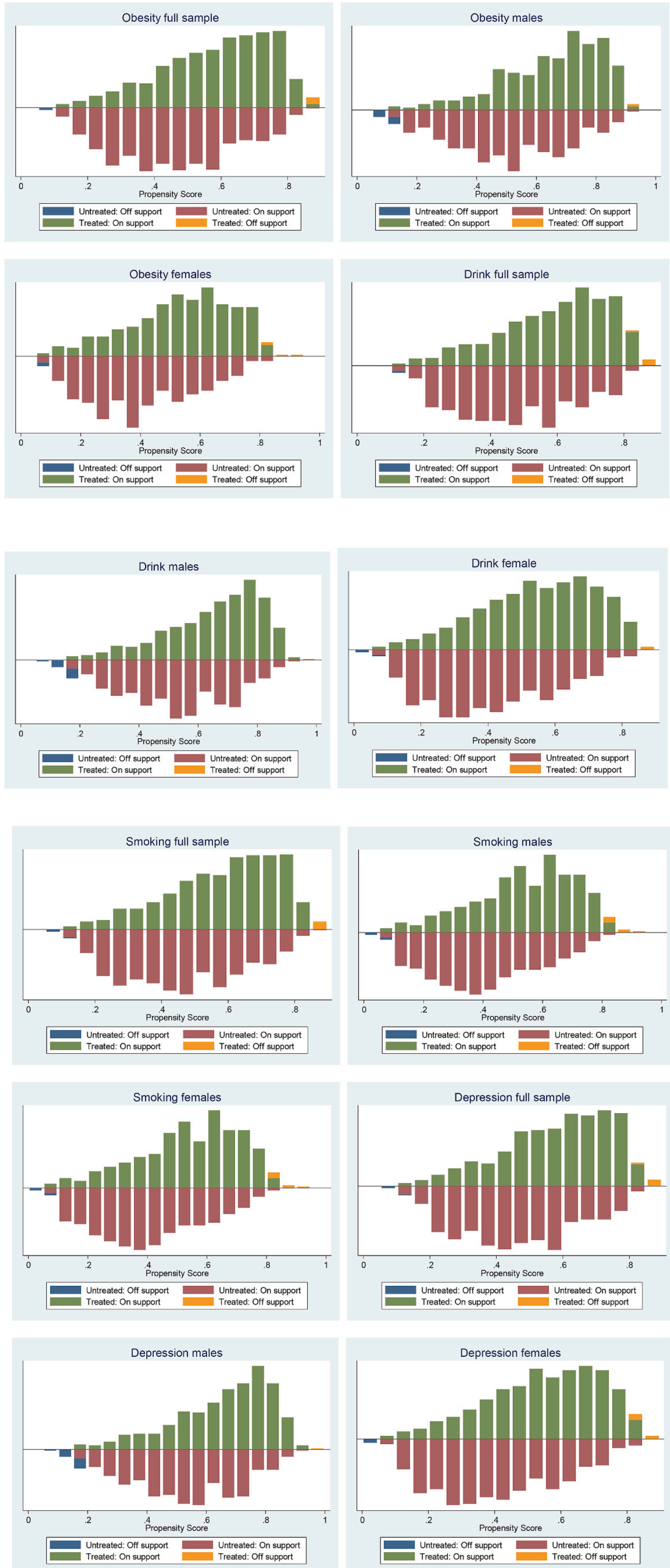


**Fig. 7.** (*continued*).

**Table 5**
Causal effects of HE on self-reported health.

| Age | Baseline OLS | | | PSM NN | | | PSM Kernel | | |
|---|---|---|---|---|---|---|---|---|---|
| | Full | Male | Female | Full | Male | Female | Full | Male | Female |
| 33 | −0.064 | −0.0365 | −0.079 | −0.081* | −0.078* | −0.118** | −0.078** | −0.070* | −0.111** |
| | (0.142) | (0.105) | (0.134) | (0.049) | (0.071) | -(0.075) | (0.034) | (0.054) | (0.067) |
| 42 | −0.065** | −0.0521 | −0.0832** | −0.085** | −0.090* | −0.135** | −0.081** | −0.090** | −0.131** |
| | (0.034) | (0.053) | (0.045) | (0.051) | (0.057) | (0.074) | (0.045) | (0.05) | (0.071) |
| 50 | −0.067* | −0.059 | −0.086* | −0.091* | −0.102* | −0.167** | −0.090* | −0.100* | −0.165** |
| | (0.054) | (0.083) | (0.072) | (0.07) | (0.075) | (0.076) | (0.072) | (0.064) | (0.069) |

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

**Table 6**
Fraction of total matched sample under NN with replacement, self-reported heath.

| | Male | | | Female | |
|---|---|---|---|---|---|
| | HE | Non HE | | HE | Non HE |
| | | | **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%) |
| Matched sample | 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%) |
| Matched sample | 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%) |
| Matched sample | 504 | 201 | | 478 | 234 |

The HE reduces BMI figure up to 0.472 at age 42 and 0.617 at age 51 in pooled samples. As the cohorts grow older, males get more benefits 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 much as that of females.

We also consider the effects of HE on the threshold of obesity. The ATTs are insignificant when the cohorts are aged 33. Once cohorts grow to age 42, the marginal effects become −0.123 for males and −0.107 for females, both significant at the 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 has a significant but small restraining effect on obesity growth for individuals at age 42 and 50. Our results share similarities with the study of Johnston et al. (2015), indicating that more educated individuals are less likely to be obese in the UK. Zhu et al. (2015) also concluded that educational inequalities in obesity were significant for both female and male in Scotland, while considering overall socioeconomic position,[11] the inequalities in obesity were more indicative and consistent in females.

### 4.3. Drinking and smoking frequency

Likewise, the results for OLS show a positive impact of HE on the incidence of smoking (see Table 8). Cohorts with HE attainment reduce ranging 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 females are nearer to “never smoke” compared to males. Attending HE can significantly gain a 0.204 margin for females. 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, we do not find any significant effects of HE on reducing the frequency of smoking behaviour when the participants enter their 50s for both genders.

Turning to the fraction changes of each category for matched samples in Table 9, males with HE are more likely to quit smoking than the ones without HE at age 33. Occasional smoking frequency for HE participants is less than that for Non-HE participants, whereas daily smoking frequency for both groups is almost the same. For females, the daily smoking frequency for the HE group is higher than that for the non-HE group, but the occasional smoking frequency does not have significant differences. Moreover, the quit-smoking fraction of the non-HE group is higher than the HE group is because people in the HE group are more likely to be a non smoker. As the participants get older, the differences between the two groups become smaller. It is found that at age 50, the fraction of four categories for both treated and control groups are almost equivalent.

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 & Lleras-Muney, 2010). Our result also shows that young cohorts with higher levels of education are more likely to abstain from smoking and decrease their alcohol consumption frequency. However, the impact is diminishing as individuals are getting older. In particular, HE does not effectively affect smoking behaviour when cohorts are in their age 50.

### 4.4. Depression

The OLS results find a negative relationship between HE and depression shown in Table 10. These associations vary significantly for

[11] Socioeconomic position was assessed by the highest educational qualification, occupational social class and household income.

**Table 7**
Health and education relationship: HE to BMI and Obesity.

| | OLS | | | PSM NN | | | PSM Kernel | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | BMI | | | | |
| Age | Full | Male | Female | Full | Male | Female | Full | Male | Female |
| 33 | −0.259* | −0.342* | −0.102 | −0.297* | −0.355** | −0.136 | −0.301** | −0.360** | −0.138 |
| | (0.165) | (0.229) | (0.108) | (0.192) | (0.152) | (0.362) | (0.114) | (0.140) | (0.245) |
| 42 | −0.546** | −0.550** | −0.482** | −0.472** | −0.529** | 0.377** | −0.475** | −0.528** | 0.376** |
| | (0.181) | (0.24) | (0.147) | (0.031) | (0.040) | (0.035) | (0.115) | (0.124) | (0.103) |
| 50 | −0.330* | −0.467** | −0.632** | −0.617** | −0.859** | −0.481** | −0.601** | −0.821** | −0.424** |
| | (0.206) | (0.279) | (0.273) | (0.242) | (0.364) | (0.127) | (0.211) | (0.301) | (0.114) |
| | | | | | Obesity | | | | |
| 33 | −0.032* | −0.071** | −0.041 | −0.026 | −0.064 | −0.015 | −0.024 | −0.06 | −0.015 |
| | (0.028) | (0.04) | (0.044) | (0.032) | (0.076) | (0.06) | (0.029) | (0.070) | (0.061) |
| 42 | −0.075** | −0.108** | −0.087** | −0.110** | −0.123** | −0.107** | −0.101** | −0.119** | −0.100** |
| | (0.029) | (0.039) | (0.433) | (0.052) | (0.051) | (0.046) | (0.050) | (0.049) | (0.042) |
| 50 | −0.065** | −0.116** | −0.079* | −0.124** | −0.136** | −0.114** | −0.118** | −0.130** | −0.109** |
| | (0.035) | (0.047) | (0.049) | (0.064) | (0.059) | (0.045) | (0.061) | (0.048) | (0.039) |

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

**Table 8**
Health and education relationship: HE to drinking and smoking frequency.

| | OLS | | | PSM NN | | | PSM Kernel | | |
|---|---|---|---|---|---|---|---|---|---|
| Age | Full | Male | Female | Full | Male | Female | Full | Male | Female |
| | | Alcohol Drinking Frequency | | | | | | | |
| 33 | −0.178* | −0.032 | −0.286** | −0.231** | −0.073 | −0.255** | −0.214** | 0.067 | −0.245** |
| 42 | −0.232* | −0.138 | −0.262** | −0.301** | −0.156* | −0.416 | −0.294** | −0.148* | −0.409* |
| 50 | 0.263** | 0.1298 | 0.3615** | −0.358** | −0.201* | −0.474** | −0.345** | −0.194* | −0.456** |
| | Smoking Frequency | | | | | | | | |
| 33 | −0.141* | −0.134** | −0.150** | −0.145** | −0.082 | −0.204** | −0.141** | −0.08 | −0.200** |
| 42 | −0.101* | −0.093* | −0.129** | −0.093** | −0.053 | −0.106** | −0.088** | −0.048 | −0.101** |
| 50 | −0.098* | −0.073* | −0.116** | −0.074 | −0.046 | −0.097 | −0.071 | −0.039 | −0.089 |

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

different ages. HE has a larger impact on depression for females at age 33 than for males. For the PSM estimates, all of the estimated coefficients appear to be negative but insignificant, ATT is only significant for females at age 33. The PSM results suggest that most of the depression-education gradient in OLS comes from selection rather than causation. A general increase in the malaise score and depression indicator over time for both genders, but we found no evidence to suggest that HE carries potential impacts on reducing the likelihood of depression. In contrast to previous research evidence (Bynner et al., 2002; Feinstein, 2002), our findings do not suggest a significant impact of HE on the reduction in depression. This however aligns with the study by McCloud et al. (2023), which found no evidence that symptoms of common mental disorders differed between students in higher education and non-students.

Feinstein (2002) found that the health-related benefits are most pronounced when individuals progress from level 0 to level 1. The impact of Level 3 or 4 academic qualifications or higher-level vocational qualifications on depression is not as substantial as the effect of Level 1 qualifications. Gardner and Oswald (2002) discovered that individuals with higher education levels generally experience lower stress scores. They proposed that this educational advantage in stress reduction could be linked to improved economic status. However, their findings also revealed a unique pattern: individuals with degrees report higher stress levels compared to those with intermediate qualifications (A-level equivalence). This observation suggests a non-linear U-shaped relationship between education and stress, indicating that stress tends to decrease with education until reaching degree level, after which it experiences a slight increase. The impact of HE on depression is ambiguous since there may be contrasting mechanisms.

HE attainment is associated with more control over working standards and thus has a positive effect on mental health and reduces rates of morbidity (Clark & Royer, 2013; Marmot et al., 1991); on the other hand, higher occupational attainment also leads to higher levels of stress (Rose, 2001). It is believed that there could 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 & Oosterbeek, 1998).

### *4.5. Robustness test*

PSM relies on the CIA, which assumes that treatment assignment is independent of potential outcomes given observed covariates. We ensure compliance with the aforementioned three assumptions in PSM. Hence, to further test the credibility of the estimated results, we conduct the Covariate balancing test (as shown in Table A.1 in Appendix) and the thick region test (as shown in Table A.3) and examine the sensitivity of the results due to unobserved heterogeneity by Rosenbaum Bounds (as shown in Table A.2).

Balance tests indicate that there are few systematic differences in the distribution of covariates between the treatment and the control groups and clearly show that the matching procedure is fairly successful in terms of balancing the distribution of covariates between the two groups. The results of the Rosenbaum Bounds analysis indicate that, apart from the SRH, the estimated results appear to be robust to the presence of unobserved heterogeneity. However, the treatment effect on SRH may indeed be influenced by unobservable factors that are not accounted in our analysis. This suggests a possibility of reverse impact from higher education to SRH due to the presence of unobservable variables that could underlie the association between higher education and self-reported health.

**Table 9**
Fraction of total matched sample under NN with replacement: drinking and smoking frequency.

| | Male | | Female | | |
|---|---|---|---|---|---|
| | HE | Non-HE | | HE | Non-HE |
| | **Drinking Frequency** | | | | |
| | | | **Age 33** | | |
| Once a day | 143 (26.5%) | 105 (30.5%) | | 65 (14.6%) | 85 (19.8%) |
| 2–3 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%) |
| Matched Sample | 539 | 344 | | 445 | 429 |
| | | | **Age 42** | | |
| Once a day | 141 (29.9%) | 104 (36.1%) | | 104 (24.6%) | 110 (28.3%) |
| 2–3 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%) |
| Matched Sample | 472 | 288 | | 423 | 389 |
| | | | **Age 50** | | |
| Once a day | 181 (39.2%) | 133 (43.8%) | | 106 (25.2%) | 99 (26.4%) |
| 2–3 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%) |
| Matched Sample | 462 | 300 | | 421 | 375 |
| | **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%) |
| Matched Sample | 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%) |
| Matched Sample | 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 |

Additionally, we follow Black and Smith (2004) and estimate the ATTs on the region of thick-support, which is defined as the region with an estimated propensity score in the interval by $0.33 < \widehat{P}(X) < 0.67$. The thick-support estimates in the majority of the cases seem fairly robust compared to the estimates based on the entire common support region. Most 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 propensity score.

## 5. Limitation

The findings of this study face limitations. Despite our efforts to control for covariates as described in Section 3.5, the results of the Rosenbaum Bounds analysis reveal a potential concern: the treatment effect on SRH appears to be relatively sensitive to unobserved heterogeneity. In essence, there may be unobservable factors not considered in our analysis that are associated with both education and health. This suggests that our results could be susceptible to unobserved bias, with the possibility of a reverse effect from higher education to SRH due to the presence of unobserved confounders that may influence both an individual's educational attainment and their health status. The robustness of the effects on general health indicators is a topic of interest for future research.

Secondly, while the inclusion of confounding variables is a valuable step in mitigating reverse causality, it should be noted completely ruling out this problem is still challenging. Unobserved factors, such as genetic endowments or changing time preferences (Fuchs, 1982; Becker & Mulligan, 1997) may also drive education and health status at the same time. Controlling factors that affect economic status or health in early life may settle issues of causality, but the long-run impact of early-life nutrition and health interventions will not be fully realised over the life time. Hence our results hinge on whether the unobserved factors are adequately proxied in the data, which could be biased.

In future studies, we could explore alternative methods that account for the possibility of selection on unobservable variables, such as instrumental variables (Albarran et al., 2020) and regression discontinuity design (Matthay et al., 2019). This also remains an open question that researchers could investigate in future research endeavours.

**Table 10**
Health and education relationship: HE to depression.

| | OLS | | | PSM NN | | | PSM Kernel | | |
|---|---|---|---|---|---|---|---|---|---|
| | Full | Male | Female | Full | Male | Female | Full | Male | Female |
| **Age 33** | 0.097** | 0.080* | 0.113** | −0.007 | −0.001 | −0.026** | −0.006 | −0.001 | −0.021* |
| | (0.034) | (0.052) | (0.044) | (0.009) | (0.01) | (0.013) | (0.009) | (0.01) | −0.013 |
| **Age 42** | 0.082* | 0.078** | 0.120* | −0.011 | −0.006 | −0.073 | −0.01 | −0.006 | 0.07 |
| | (0.05) | (0.045) | (0.097) | (0.049) | (0.026) | (0.093) | (0.049) | (0.026) | (0.093) |
| **Age 50** | 0.104* | 0.094* | 0.123* | −0.018 | −0.012 | −0.107 | −0.015 | −0.01 | −0.102 |
| | (0.084) | (0.072) | (0.094) | (0.064) | (0.053) | (0.105) | (0.064) | (0.053) | (0.105) |

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

Another potential limitation is the focus on British data, which may introduce country-specific cohort effects. For example, since all participants were born in 1958, the educational attainments of this cohort could uniquely impact the estimated effects on their health outcomes. While the association between education and health likely operates similarly across different groups and birth years, the results in this paper pertain specifically to the 1958 cohort and may not be directly generalisable to other populations.

## 6. Conclusion

One 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 benefits of educational participation at some particular stage. By using the longitudinal survey of NCDS data with different sweeps, this paper adopts a quasi-parametric approach of PSM to estimate the relationship between HE attainment and a very wide range of cohorts' health-related outcomes across different ages. 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 heterogeneity bias and measurement errors. Moreover, another key contribution is that we have also highlighted the importance of investigating whether there are incremental returns to HE within the lifetime of cohorts.

We draw the following conclusions from our empirical evidence. HE is positively associated with 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. Evidence confirms a positive effect of education on obesity while higher education tends to have a lower BMI index. Such effects are significant when individuals are in their 40s and 50s. HE also has a substantial impact on initiation, cessation, and frequency of smoking and drinking alcohol, however, the effects on reducing the frequency of smoking are decreasing as cohorts are getting older.

In general, this paper suggests that attending HE is an effective way to improve general health status and reduce the likelihood of health-damaging behaviours. This finding is consistent with the fundamental causes of disease hypothesis (Link & Phelan, 1995), which suggests that education gives an individual a wide range of 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. We support the view that education has a positive effect on an individual's health outcomes and reduces damaging health behaviours.

On the other hand, it is striking that the impact of HE on reducing the likelihood of depression in the UK is insignificant. This may happen because HE attainment results in a higher occupation in the labour market and this led to higher levels of stress. There could be existing trade-offs between stress and satisfaction in higher occupation that may lead to an ambiguous relationship between educational success and mental health.

## Ethics statement for 'does higher education matter for health in the UK?'

1.Purpose and Rationale: This research paper seeks to investigate the relationship between higher education attainment and health outcomes in the UK. The objective is to discern whether individuals with higher educational qualifications have better health outcomes compared to those with lower or no qualifications. Understanding this relationship can provide valuable insights into the broader determinants of health and help inform public policy.
2.Participant Welfare: This research utilized secondary data sources, eliminating direct interaction with participants. The datasets used were publicly available and did not contain personally identifiable information."
3.Data Privacy and Confidentiality: To maintain the confidentiality of any personal or sensitive information, all data was anonymized and securely stored. Access to this data was limited to the primary research team. The results are presented in aggregate form, ensuring that individual identities are protected and cannot be deduced from the research findings.
4.Potential Risks and Mitigation: The potential risks associated with this research were minimal due to the nature of the study. Any data used was handled with utmost care to ensure privacy and confidentiality. If any sensitive topics emerged during data analysis or discussions, they were approached with sensitivity and discretion.
5.Feedback and Dissemination: The research findings are available to the public and have been disseminated through academic publications. Participants, if directly involved, were offered a summary of the results to ensure they were informed of the study's outcomes.
6.Collaboration and Transparency: This research was conducted in a transparent manner, with methods and findings open to scrutiny. Collaborators, if any, were informed of all ethical considerations, and consensus was achieved on all protocols.
7.Conclusion: The research titled "Does higher education matter for health in the UK?" was carried out adhering to the highest ethical standards, ensuring the dignity, rights, safety, and well-being of all involved or implicated. Any ethical considerations, where relevant, were pre-approved by Cardiff Metropolitan University.

## CRediT authorship contribution statement

**Bomin Liu:** Writing – review & editing, Validation, Project administration, Methodology, Investigation, Formal analysis. **Sisi Ji:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Zheyi Zhu:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2024.101642.

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