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THE EDUCATION GRADIENT IN HEALTH: THE CASE OF OBESITY IN THE UK AND US

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Abstract

Obesity is gaining increasing attention as an issue requiring public policy initiatives. We examine the determinants of obesity in middle age, with particular attention to the role played by educational attainment. Applying quantile regression methods to longitudinal data sets from the UK and the US, we estimate the schooling effect on the distribution of Body Mass Index (BMI), the primary measure of obesity. Conditioning on childhood BMI and other characteristics of childhood, we confirm health disparities across education groups, establish that this is not a disguised income gradient and extend the current literature by showing that the education effect is greater for the upper quantiles of the BMI distribution, where obesity is indicated. We further show that the finding of variation in health returns to education along the conditional distribution of BMI, which is not revealed by conventional least squares methods, is robust across various specifications and with respect to a test addressing the potential endogeneity of education. Our similar findings across data from the UK and the US, despite the differences in public health policies and means of access to health care services, further reinforce the argument that education, in itself, plays an important role in determining at least this aspect of health status.

Keywords: obesity; Body Mass Index; education; quantile regression.

JEL codes: I12; I14; I26

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1. Introduction

In recent years the proportion of overweight and obese people has substantially increased around the world (Gakidou et al. 2014). In particular the UK and US have seen marked increases in obesity rates over the past few decades. The UK, with an adult obesity rate in England above 25 percent in 2016 (NHS Digital, 2018), has one of the largest proportions of obese adults in Europe. In the US obesity is even more prevalent with a 39.8 percent obesity rate among adults in 2015 and 2016 (Hales et al., 2017). Obesity is known to increase the risk of developing adverse health conditions and thus to ultimately reduce life expectancy. For example, obesity is linked with high blood pressure, coronary heart disease, type 2 diabetes and various types of cancers (National Heart, Lung, and Blood Institute, 1998; HM Government, 2011). The obesity epidemic has thus become a recognised threat to public health and to the financial viability of public-sector health care provision.

An individual's socioeconomic environment and their genetic inheritance are recognised as having causal influence (Amin et al., 2017), but it remains the case that the immediate cause of obesity is an excess of calorific intake relative to energy expenditure. In an "obesogenic environment" (Foresight, 2007; Bissell et al., 2016), with a predominance of sedentary activities and ready access to fast foods, personal lifestyle decisions, particularly with regard to food intake and exercise, are an integral determinant. These decisions may be influenced by, *inter alia*, preferences, family background, personal life experience, income, and health care provision. Which of these potential factors provide(s) the driving force behind the present obesity epidemic is not obvious, but what seems to be increasingly clear for several aspects of health status is the existence of an education gradient: a relationship between the level of educational experience and various health characteristics - see, for example, Conti, Heckman and Urzua (2010), Cutler and Lleras-Muney (2010) and Ayyagari, Grossman and Sloan (2011).

In this study we assess the extent to which an individual's educational attainment is associated with an important aspect of health status in middle age, the propensity to be overweight or obese. Using quantile regression methods, we predict features of the probability distribution of BMI in middle age, with a focus on the obesity-relevant upper tail of the distribution. BMI is measured as weight in kilograms divided by the square of height in meters. In adults aged 20 years and older, overweight is defined as BMI between 25 and 30 and obesity is defined as BMI greater than or equal to 30.

A substantial literature has debated the evidence for a significant relationship between education and obesity. Arendt (2005), Kemptner, Jürges, and Reinhold (2011), Brunello, Fabbri, and Fort (2013) and Fletcher (2015) demonstrate the education effect by showing that the increased educational attainments from exogenous shocks such as schooling law changes have a positive impact on health by reducing the obesity risk. Webbink, Martin and Visscher (2010), Böckerman and Maczulskij (2016) and Kim (2016) find that education effects on BMI also emerge from siblings or twins within a family. Other studies show that the effect of education on overweight status remains persistent even after accounting for income and various other individual characteristics (Cutler and Lleras-Muney, 2010) or for food price and restaurant size factors (Chou, Grossman, and Saffer, 2004). In contrast, some studies have found no education effect on obesity when schooling is increased through the introduction of grammar schools in Germany (Jürges, Reinhold, and Salm, 2011) or the raising of the school leaving age in the UK (Clark and

Royer, 2013). Currently, however, relatively little is known about the effect of education on characteristics, other than the mean, of the probability distribution function for BMI, the most commonly employed indicator of overweight or obese status.

In this study, we estimate the education effect on BMI using quantile regression methods as a novel approach. Many studies have used classical regression methods to estimate the relationship between BMI and education. These conventional approaches model the mean of the BMI distribution, leaving other characteristics of the distribution relatively unexplained. Obesity is, however, associated with the upper tail of the BMI distribution. The education gradient for the conditional mean of BMI, obtained by conventional regression methods, does not necessarily indicate the direction and magnitude of the schooling effect on the upper quantiles, where overweight and obese status is found. We therefore propose to employ quantile regression methods (Koenker and Hallock, 2001; Koenker, 2005) to investigate potential aspects of heterogeneous schooling effects on obesity by estimating the educational gradient at several quantiles of the BMI distribution. We check the robustness of our estimates by employing unconditional quantile regression (Firpo, Fortin and Lemieux, 2009) to recover the effect on the marginal distribution of BMI. In order to deal with the potential endogeneity of educational achievements, we formally test whether the education effect is driven by self-selection bias by comparing the estimates across quantiles of the distribution and also by estimating the schooling effect with instrumental variable quantile regression (Chernozhukov, Fernández-Val, and Kowalski, 2015). By complementing the conventional regression approach with these various quantile regression methods, we are able to provide a more complete picture of the schooling effects on BMI.[1]

For our analysis, we use longitudinal data sets from the UK and the US: the 1970 British Cohort Study (BCS) and the Wisconsin Longitudinal Study (WLS). We first examine the BCS and then the WLS more briefly. The BCS offers extensive information on each respondent's life-long history of BMI, together with other individual and family characteristics. The WLS also provides rich information on educational attainment and other characteristics of the respondent from high school year, alongside their BMI in middle age.

We find that the educational gradient exists, but, importantly, is not uniform, across the quantiles of the conditional distribution for BMI. Whereas the schooling effect at the lower tail is negligible, the education effect is significant at the median and, more so, at the 75th percentile of the conditional distribution. The apparent BMI-reducing effect of undergraduate and higher educational attainment becomes larger as we move from the left tail to the right tail of the distribution. An educational gradient for obesity exists because of the effect on the skewness and dispersion of the BMI distribution, as well as on its location. The findings are robust across the analyses of data from the UK and US.

Our finding that advanced levels of education induce a compression of the BMI distribution, as opposed to a simple leftward shift, may have relevance for improved understanding of the mechanics of the education effect, and thence for the design of public health programmes that address obesity.

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[1] Quantile regression has been used in other disciplines, including Rodriguez-Caro et al.(2016). In the economics literature, to our knowledge, this approach has not been used for the study of an education effect on BMI, except for a study of childhood obesity by Stifel and Averett (2009).

The other contribution of our study is that we assess whether an apparent education effect is actually due to income-contingent access to health care. Since income and educational attainment are positively correlated, income-related differential access to health care services is a potential explanation for an education gradient in health characteristics such as obesity. We explore the effect of education on the quantiles of BMI across two countries that have had contrasting health care systems, so are able to compare the education gradients for BMI in these two countries. The UK has maintained a public health care service with universal coverage and largely free at the point of delivery. In contrast, health care in the US has been predominantly a case of private sector provision and fully available only to those who can pay for it, directly or through insurance policies whose availability and benefits are correlated with income level. Our discovery of similar education gradients in both countries suggests that income-related health care access does not, by itself, explain the education gradient in BMI.

This paper is organized as follows. We describe the data in section 2 and present the model in section 3. The empirical findings based on samples from the UK and US are provided in section 4. We consider robustness of our findings with different specifications in section 4 and 5, and conclude in section 6.

2. Data

The data we use come from two longitudinal studies, one from the UK and one from the US. The first is the 1970 British Cohort Study (BCS) and this provides most of our results. The BCS began as the population of all (about 17,000) births in England, Scotland and

Wales in a single week of the year 1970. The respondents have been followed since birth and have now reached middle age.

The BMI and health status of the respondents were recorded in the BCS survey of 2012, when the respondents were 42 years old. The upper panel of Table 1 provides some summary statistics. The BCS is exceptionally rich in providing details of the respondents' family background and childhood characteristics. Additionally, in earlier waves of the BCS, birth weight and BMI at age 10 and 16 have been recorded, along with the BMI of each parent when the respondent was 10 years old. This allows us to trace the dynamic pattern of BMI from childhood to middle age and also through intergenerational transmission.

In studies using other data sources, the BMI mean and median typically lie in the range from 24 to 27, which includes the threshold (BMI=25) of overweight status. In the BCS, the average BMI at age 42 is 26.8, suggesting that a significant proportion of middle-aged UK adults face the risk of adverse health conditions arising from excess weight.

The environmental features that the respondents experienced at birth and through childhood, along with their childhood health records, have been well captured in the several waves of the BCS survey. Other aspects of the parental contribution to the early childhood environment have also been recorded, for example: whether the mother stayed at home during the respondent's pre-school years; whether or not the mother smoked tobacco during that period.

For the BCS respondents, we classify educational attainment into four ordinally ranked categories according to the highest qualification obtained: no academic qualification; General Certificate of Secondary Education (GCSE); Bachelor's degree; higher degree

(MA or PhD). For these respondents, compulsory schooling typically finished at age 16 and was assessed by the GCSE[2], which we select as the reference category of educational attainment for modelling purposes.

The second dataset is the Wisconsin Longitudinal Study (WLS) from the US. The WLS comprises a random sample of 10,317 high school seniors in the state of Wisconsin. The WLS has followed the respondents since their high school senior year in 1957. Since 1975, the WLS has also observed a randomly selected sibling of each respondent. Information on health status, including BMI, was collected in the 1992 survey, and in the 1993 survey for their siblings. Although the WLS is restricted to people from Wisconsin, the average BMI and other empirical findings from this dataset are in line with results from US national data that cover people in the same age group (Kim, 2016).

The lower panel of Table 1 provides summary statistics for key variables, as observed in the WLS. The sample of primary respondents is aged between 52 and 55, somewhat older than in the BCS. Their average BMI is 26.6, close to the average for the BCS data. We convert their educational experience into: high school completion; some college education; BA or higher degree. Our selected reference category is high school completion, with about half of the sample having this as their highest level of educational attainment.

3. Estimation Method

The model that we use to estimate the schooling effect on BMI is

[2] In Scotland, the Scottish Certificate of Education was equivalent.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \delta_1 S_{1i} + \delta_2 S_{2i} + \cdots + \delta_m S_{mi} + e_i. \qquad (1)$$

Here Y_i is BMI for the i^{th} individual in middle-age; $X_i = (X_{1i} \quad X_{2i} \quad \cdots \quad X_{ki})$ are individual and family characteristics, including childhood BMI; $S_i = (S_{1i} \quad S_{2i} \quad \cdots \quad S_{mi})$ are 0/1 dummy variables indicating which schooling level is the highest achieved by an individual when this is not the reference level; e_i is an idiosyncratic error term. Traditional regression modelling specifies $\mathrm{E}(e_i|X_i, S_i) = 0$, making the remainder of the right-hand side in (1) a conditional mean function for Y. The alternative specification: $Q_\tau(e_i|X_i, S_i) = 0$, where $Q_\tau(\cdot)$ indicates the τ-quantile, implies a model for the conditional τ-quantile function, viz:

$$Q_\tau(Y_i|X_i, S_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \delta_1 S_{1i} + \delta_2 S_{2i} + \cdots + \delta_m S_{mi}. \qquad (2)$$

In the case of τ=0.5, (2) is a conditional median function and can be estimated with the Least Absolute Deviations estimator. More generally, the parameters in (2) are estimated by numerical minimisation of $\left\{\tau \sum_{e_i \geq 0} |e_i| + (1-\tau) \sum_{e_i < 0} |e_i|\right\}$.

We are interested in the schooling effects: $\delta_j,\ j = 1,2,\cdots,m$, and investigate how the schooling effect $\delta_j(\tau)$ varies with τ. We focus especially upon the quartiles, $\tau \in (0.25, 0.50, 0.75)$ since these are the basis for commonly used measures of a distribution's location, dispersion and skewness. Following the literature (e.g. Abrevaya and Dahl, 2008), we present bootstrapped standard errors using 1,000 bootstrap replications.

Quantile regression is a useful tool for identifying the impact of education on the whole of the BMI distribution. Since the left and right tails of the BMI distribution both contain regions of unhealthy body size, an ideal education effect would compress the BMI distribution by reducing probability in both tails. However, if the education effect does work in this way, OLS estimators, which model only the conditional mean, are likely to miss important changes in the characteristics of the BMI distribution.

Binary dependent variable models may seem to offer an alternative approach to modelling tail behaviour in the BMI distribution. Cutler and Lleras-Muney (2008) and Webbink et al. (2010), for example, estimate the schooling effect on the probability of being overweight. It has been shown, however (see Yatchew and Chriliches, 1985), that the usual numerical maximum likelihood estimators for binary dependent variable models are inconsistent in the presence of heteroscedastic errors, which is not the case for quantile regression.

Whenever, as here, several linear quantile regressions are estimated for the same dependent variable then some consideration should be given to the problem of crossing quantiles as discussed in Bondell, Reich, and Wang (2010) and Chernozhukov, Fernández-Val, and Galichon (2010). The problem is that if an explanatory variable with unbounded domain is employed in two linear quantile regressions for different quantiles of the same dependent variable then, unless this regressor has equal estimated coefficients in the two regressions, there will inevitably be some, possibly hypothetical, range of regressor values for which the two predicted quantiles are incorrectly ordered. In our case, however, many covariate variables are binary and so have a very restricted domain, limiting the opportunity for predicted quantiles to be incorrectly ordered. We consider this point more fully when discussing the results presented below in section 4.

The last issue that we should consider in the estimation of the education effect is endogeneity bias. Individuals self-select into post-compulsory education levels, and unobserved factors that influence their BMI may also influence their preferences regarding education. We should therefore be cautious about assigning causal interpretation to the reported regressions. We have included an extensive set of covariates to mitigate such bias but, nevertheless, there may remain other, unobserved, factors that make an identification of causality difficult. With this in mind, we consider in a later section whether the magnitude of the education effect at the upper quantiles is big enough to offset omitted variable bias. Provided that any omitted variable bias (i) has the same sign and is of similar magnitude at all quantiles of the BMI distribution and (ii) is not so large as to reverse the sign of estimated coefficients, then a significantly larger estimated effect of education at the upper quantiles, relative to the lower quantiles, indicates an appropriately signed actual education effect at the upper quantiles. We report the relevant test results in the discussion section.

4. The Effect of Education on BMI

4.1 Analysis of the BCS data

We investigate the link between maximum formal educational attainment, typically completed by young adulthood, and BMI in middle age. The OLS regression results from an exploratory baseline specification (not reported) with only schooling variables and a gender indicator reveal that the average BMI at age 42 tends to be smaller as the educational attainment level increases, suggesting that the risk of obesity-related health problems is lower for individuals with relatively high educational attainment. This health inequality by education level is called an “education gradient” in the literature. The quantile regression results for the baseline specification confirm the education gradient: the 25th, 50th and 75th percentiles of the conditional distribution of BMI are negatively associated with educational attainment.

However, rather than a direct causal link between educational attainment and features of the BMI distribution, there may be other confounding factors that are responsible for the BMI effect, correlated with educational attainment and omitted from the baseline specification. In order to reduce the risk of omitted variable bias in estimation of the education effect, we include as control variables several regressors that are potentially causal for adult BMI. Recent literature has noted the presence of inter-generational persistence of health characteristics (Akbulut-Yuksel and Kugler, 2016; Amin et al., 2017); we include parental BMI measurements to control, at least partially, for genetic factors and other factors prompting the inheritance of health characteristics. We also include the respondent’s BMI in childhood and health history prior to adulthood, together with characteristics of the family environment including some relating to the respondent’s early-years experience. Early-years experience is increasingly recognised as a significant causal factor for later-life outcomes, including health status – see Smith (2015) for an introduction to the literature.

The regression results are summarized in the upper panel of Table 2. The first column reports the conditional mean effect of education, estimated by least squares. It shows that, conditioning on various childhood and parental characteristics, predicted BMI is negatively associated with educational attainment. The reference education category is GCSE, which corresponds to high school graduation in the US. Thus, relative to GCSE only, having a first degree is associated with a 0.7 decrease in predicted BMI, and having a higher degree induces an even larger decrease of predicted BMI (by 1.34). In this mean regression model, which presumes a pure location shift effect of education, any heterogeneity across different quantiles in the schooling effect cannot be detected. In contrast, the quantile regression results reported in columns (2) – (4), show that statistically significant education effects are observed only at the median (50^{th} percentile) and upper quartile (75^{th} percentile) of the BMI distribution. Moreover, the estimated magnitude of the education effect is larger as one moves toward the right tail of the conditional BMI distribution, where overweight and obesity thresholds are located. Having a BA degree is associated with a 0.4 decrease of median BMI and having a higher degree is estimated to induce a reduction of 1.1. The upper quartile of the BMI distribution is estimated to drop by 0.9 for those with a BA degree – a noticeably larger reduction than is estimated for the median. Because the OLS analysis cannot recognise this compression of the BMI distribution, it under-estimates the extent to which advanced education, by lowering the upper quartile, reduces the incidence of obesity.

To check whether the crossing quantiles problem has empirical relevance, we have investigated whether there is any combination of the binary regressor values which leads to an incorrect ordering of predicted quantiles when the continuous covariates are assigned their sample mean values. We find that the predicted quantiles are correctly ordered in all cases and construe this as evidence that our estimates are sufficiently free from the risk of quantiles crossing within an empirically relevant range of regressor values.

These empirical results clearly indicate that education beyond secondary (high-school) level has a *relevant* impact on the shape of the conditional BMI distribution. If we use the term “obesity-prone” to describe individuals for whom unobserved causal factors are such as to place them at the upper end of a BMI distribution conditioned on their observed factors then we can say that the risk-reducing impact of higher education is greater for the obesity-prone. The evidence for this is that higher education is estimated to displace the median of the conditional BMI distribution more so than the lower quartile and the estimated impact on the upper quartile is even larger.

Another interesting finding in Table 2 is the confirmation that childhood BMI and parental BMI are all significant predictors of BMI in middle age, with own BMI at age 16 estimated as having the larger effect on expected BMI in middle age and also on the quantiles of the distribution function for BMI in middle age. Parental BMI and own childhood BMI all exert a greater effect on the median and upper quartile than on the lower quartile, stretching the distribution for BMI in middle age rightwards, thus increasing the risk of adult obesity. Apart from BMI histories, birth weight and health status[3] at age 10 also induce statistically significant changes in the conditional BMI distribution. The negative effect of low birth weight has been widely studied in the literature, for example in Currie (2011), and this present study adds one more piece of evidence that low birth weight is adversely associated with BMI in later adulthood even after controlling for childhood BMI. The long-run effect of serious ill-health in childhood on BMI in later life also supports the importance of early childhood experience. The covariates introduced in Table 2 reduce the estimated magnitude of the education effect

[3] Health status is measured by an indicator that records when a child either received treatment in hospital, as opposed to general practitioner’s care, or had been taking regular medication since their 5th birthday.

relative to the baseline specification with only schooling and gender variables. Nevertheless, the estimated coefficients continue to suggest that an educational gradient exists and is steeper at the upper tail of the BMI distribution than at the lower tail. Taking the upper quartile as the quantile that has most relevance for the obesity-prone, we see that possession of an undergraduate degree continues to provide a statistically significant improvement in the shape of the BMI distribution .

The presence of significant education effects on adult BMI raises the question of what might be the channels through which education brings benefit to health. One potential channel is the higher expected income resulting from higher educational attainment. Higher income offers enhanced health care access[4], and greater opportunity for choice with regard to food and many life-style decisions. To isolate the education effect from an income effect, we next control for income at age 42. As listed in the lower panel of Table 2, the results show some changes relative to previously estimated coefficients attaching to various education levels in the upper panel of Table 2, but these changes are not substantial relative to standard errors particularly in the upper quartile regression. Even after controlling for income, an educational gradient remains in place with higher education shifting the quantiles leftwards.

4.2 Analysis of the WLS

The modelling for the WLS data has BMI at middle age as the dependent variable. The analysis is based on the primary respondents, who were in the age range 52 to 55 years

[4] Although the UK public sector provides universally available health care through the National Health Service (NHS), higher income offers an opportunity to supplement NHS provision with private sector insurance schemes.

when surveyed. We consider three education levels: high school completion; some college; BA or higher degree. The reference education group is high school completion. The other covariates include age, birth order, IQ scores in high school, and parental income and education. The sibling's BMI is also included to control for unobserved genetic and family characteristics that may be relevant for BMI.

As can be seen in Table 3, the pattern of education effects is quite similar to the results obtained with the BCS data. First, the statistically significant education effects are associated with successful completion of an undergraduate or higher degree course. (An incomplete college education is also estimated to lower the mean, median and upper quartile of the BMI distribution but the estimated effects do not achieve the normal criteria for statistical significance.) Second, the education effect is stronger at the median than at the lower quartile, and stronger still at the upper quartile. As with the BCS data, the effect of completed higher education becomes larger as one moves to the right tail of the conditional distribution.

Because of greater muscle mass, men tend to have higher BMI than women. The quantile regressions show that this gender disparity becomes smaller toward the right tail of the conditional distribution of BMI. Other potential determinants of middle-age BMI include parental income, parental education and own income. We find that parental income is not statistically significant. Parental education is estimated to have a beneficial effect on middle age BMI but at a lower order of magnitude than the effect of own education. As to own income, we find – see the lower panel of Table 3, that an education gradient remains in place after including own income at age 52 with the impact of education continuing to be strongest at the upper quartile of the BMI distribution. Since, hypothetically, there may be reverse causation from obesity to income, we have also considered income earned at an earlier stage of life to control for any long-term income effect.[5] Some, but not all, respondents reported income earned at age 35, and we have found that, in this smaller sample, the education effect remains beneficial and statistically significant at the upper quartile of the conditional distribution for BMI when conditioning on income earned at age 35 as well as at age 52. This evidence suggests that the education gradient is not simply a disguised income gradient, particularly with respect to the obesity-relevant upper quartile of the BMI distribution.

The similar patterns of education effects across these two countries shed light on the role of education under various education and health systems. For the cohorts, to date, of the WLS, there has been no health care service comparable to the NHS health care service in the UK. The educational systems also differ in that college education has been more common and takes longer in the US than in the UK. Taking both studies together, it seems that tertiary education reduces the obesity risk, regardless of educational system and degree of health care access.

4.3 Robustness of the Estimated Education Effect

For a summary of the key findings from the UK and US datasets, we present estimation results from the quantile regressions in Figure 1. As noted previously, we consider four education levels for the BCS and three education levels for the WLS. For both data sets the reference level for educational achievement is high school graduation. In Figure 1, for a sequence of quantiles from τ=0.05 to τ=0.95, we plot in the two top panels the effects,

[5] Previous studies find that obesity is negatively associated with wages especially among female workers in the U.S. See, for example, Baum and Ford (2004), Cawley (2004), Bhattacharya and Bundorf (2009), and Kan and Lee (2012).

estimated from the BCS data, of having (i) a BA degree and (ii) a higher degree. In the two lower panels we plot the effects, estimated from the WLS data, of having (i) at least a BA degree and (ii) incomplete college education. In each case, the solid line shows the point estimate of the education effect at each quantile, with the shaded grey area representing the 95% confidence intervals. A dashed line, superimposed on the plot, shows the OLS estimate of the effect of education on BMI, with two dotted lines depicting the 95% confidence interval for the OLS estimate.

In each of the panels of Figure 1, the marginal effect of education on BMI is negative for the higher quantiles of the conditional distribution of BMI, which characterise overweight and obese status. The magnitude of the education effect tends to increase toward the right tail of the conditional distribution, indicating a larger effect for those who, because of unobserved factors, face greater health risk from obesity. More precisely, for BCS data, the estimated effect of having BA degree at the 75th percentile is -0.909, while the OLS estimate is -0.720. For the WLS, the effect of having BA degree at the 75th percentile is -0.899 whereas OLS estimate is -0.788.

For both countries, higher education to the level of at least a BA degree seems to generate beneficial effects, compressing the BMI distribution as well as shifting it leftwards. This beneficial compression is not revealed by OLS estimation. OLS estimates may be informative with respect to the conditional mean of the BMI distribution but it is the tails of the distribution that require most attention when investigating problematic health status.

To complement the standard quantile regressions reported above, we have also employed the “recentered influence function” (RIF) regression developed by Firpo, Fortin and Lemieux (2009). Standard quantile regressions can be called “conditional” in the sense that their coefficients give the estimated difference in a quantile value between an individual with the reference level of education and one with some other level of education – conditional on those two individuals sharing common values for the other covariates. The RIF regression estimates an “unconditional quantile regression” whose coefficients are the marginal response of a BMI quantile for the population at large to a marginal change in the proportion of individuals having some particular level of education. We present in Table 4 the estimated responses of the 25th, 50th and 75th percentiles of the BMI distribution. For both data sets the OLS regressions attach a significantly negative coefficient to an increased proportion of undergraduate, or higher, degree holders. The quantile regressions estimate that the upper quartile response to a marginally increased proportion of degree holders is negative, statistically significant at the 5% level and larger than the leftward response of the median or lower quartile, confirming the dominant response pattern – leftward shift plus compression, obtained in the earlier regressions. Whilst the coefficients attaching to an incomplete secondary school or college education are also negative in Table 4, they do not achieve statistical significance. Overall, robustness checking strongly confirms the point that higher education shifts the location of the BMI distribution to the left and also reduces the right-tail dispersion, thus lowering obesity risk.

5. Discussion

In this section, we investigate a potential selection problem arising from tertiary education being an individual’s own choice. As one way to assess the consequences of endogeneity bias in the estimation of an education effect, we formally test whether the education effect at τ=0.75 differs from that at τ=0.25. Using the framework developed in Koenker and Bassett (1978) and Koenker (2005), we report, in Table 5, estimates of the difference in education effects between the 75th and 25th percentiles, with *p*-values for the *F* test of the constraint that the education effect is the same at both quartiles. We employ the specification shown in Table 2 and Table 3, with and without income variables.

We find evidence of a more negative education effect at the upper quartile, compared to the lower quartile, from both the BCS and the WLS data. For the BCS, the null of equal effect at both quartiles is rejected at a 10% significance level for both stages of education when income is excluded from the specification and is rejected at a 10% level for undergraduate education when income is included. Similarly for the WLS, the null of equal impact of completed undergraduate education is rejected at 10% significance with and without income. To the extent that any endogeneity bias is of similar magnitude in both quartile regressions, and not of such a size as to reverse the sign of estimated coefficients, the balance of evidence suggests that, even if our estimates suffer from such bias, education, particularly completion of an undergraduate programme, leads to compression of the BMI distribution, with the upper quartile shifting leftwards more so than the lower quartile.

Additionally, we seek to resolve the endogeneity issue with instrumental variable quantile regression. For the analysis of the BCS, we compress the two college education levels (BA degree and higher degree) into one category of college education. As instruments for college education, we use family size and parental income - in childhood (at age 10 and 16) for the BCS and in high school years for the WLS. We find that for both the BCS and the WLS family size and parental income are significant predictors of educational attainment with first stage *p*-values close to zero. On the other hand, family size or parental income is not associated with middle age BMI, conditioning on individual and other family characteristics listed in Table 2 and 3. Although this is not an exhaustive test for validity of instruments, the findings suggest that our instrumental variables are less likely to be associated with the error term of the BMI quantile regression conditioning on an extensive set of regressors. Using the instrumental variable quantile regression methods developed by Chernozhukov, Fernández-Val, and Kowalski (2015) and Chernozhukov, Fernández-Val, Kowalski, and Han (2018), we provide the estimates of education effect and bootstrap confidence bands in Table 6. For the BCS, the sample has been slightly reduced due to missing data on family size in childhood, but the pattern of education effect is similar to our prior results in Table 2. For the WLS, we find significant effects of education on the conditional distribution of BMI, although the education effect at the 75th percentile is less precisely estimated. The similar patterns of education effects on the conditional distribution of BMI across specifications and for people from the UK and US suggest that the bias in the quantile regression estimates, if any, is not large enough to negate the education effect.

6. Conclusion

We provide a more comprehensive view of the education gradient in obesity with two novel approaches. First, we show that higher education not only relocates the BMI distribution but also compresses it and reduces its right-hand skew by inducing a leftward shift of the upper tail, more so than for the lower tail. The lowering of the right-hand skew in the BMI distribution, which cannot be detected by traditional least-squares regression, is especially relevant for the reduction of obesity risk. These findings, which are confirmed by several robustness checks, emerge from both UK and US data, substantiating a beneficial education gradient in obesity risk. From the perspective of public health and policy intervention, it is noteworthy that the beneficial education effects are stronger for those individuals where unobserved factors have placed them in the upper tail of a BMI distribution conditioned on their observed characteristics.

Second, we examine potential sources of education gradient by comparing two countries that have distinct health care systems as a natural experiment. The apparently beneficial influence of education on health indicators is sometimes ascribed to factors associated with education – such as higher income or improved access to health care. We find that the educational effect remains even after an extensive set of covariates, including income, are employed. The fact that we get similar conclusions from UK and US data sets, where only the former has offered universal health care access, free at the point of delivery over the lifetimes of these respondents, argues against the education effect being simply due to greater health care access for the better educated.

We do not offer a rationalisation for the observed education gradient, leaving this for further research. Hopefully, we have made a case that the influence of education level on obesity risk is a worthwhile focus for research and, potentially, a basis for evidence-based public health policy.

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Table 1. Summary Statistics

Variables	Mean	Std Dev.
	The British Cohort Study	
Male	0.402	0.490
Asian	0.014	0.117
Higher degree	0.069	0.254
BA degree	0.306	0.461
Dropout	0.185	0.389
Mother's age at birth <20	0.067	0.250
Birth weight	3.339	0.517
Father's school leaving age	15.620	1.247
Being ill at 5	0.011	0.107
Family Income at 10	137.158	54.084
BMI of Mother at 10	23.178	3.573
BMI of Father at 10	24.311	2.815
BMI at 10	16.826	2.072
Being ill at 10	0.059	0.235
Family Income at 16	234.905	120.278
BMI at 16	20.689	2.570
Being ill at 16	0.240	0.427
BMI at 42	26.528	5.162
Income at 42	48,028.52	28,660.51
Sample Size	1,295	
	The Wisconsin Longitudinal Study	
Male	0.480	0.499
Years of Schooling	13.803	2.337
BA or higher degree	0.299	0.458
Some college	0.160	0.367
High school	0.541	0.498
Age	52.485	0.567
BMI	26.594	4.411
Birth order	2.369	1.696
Parental income	64.540	59.408
Parental education	9.911	3.443
Sample Size	3,065	

Notes: Mean and standard deviations are provided. BMI is measured in kg/m^2. In the BCS, income at 42 is annual income, while family income at 10 and 16 are weekly income. Sample size for income at 42 is 959. In the WLS, parental income is annual income measured in 1957 hundreds of dollars.

Table 2. OLS & Quantile Regressions of BMI on Educational Levels from the BCS

Explanatory Variables	(1) OLS		(2) 0.25 Quantile		(3) 0.50 Quantile		(4) 0.75 Quantile	
Model A								
Male	1.364*	(0.257)	1.758*	(0.232)	2.036*	(0.257)	1.564*	(0.349)
Asian	0.815	(1.074)	0.435	(0.914)	1.100	(1.052)	-0.013	(1.368)
Higher degree	-1.338*	(0.518)	-0.064	(0.421)	-1.041*	(0.371)	-1.082†	(0.663)
BA degree	-0.720*	(0.302)	-0.186	(0.297)	-0.495	(0.303)	-0.909*	(0.411)
Dropout	-0.414	(0.346)	0.227	(0.349)	-0.052	(0.335)	0.012	(0.513)
Mother's age at birth <20	1.098*	(0.509)	0.876*	(0.414)	0.647	(0.743)	0.889	(0.745)
Birth weight	-0.454†	(0.249)	-0.395†	(0.220)	-0.519*	(0.232)	-0.374	(0.361)
Father's school leaving age	-0.117	(0.109)	-0.071	(0.088)	-0.118	(0.093)	0.018	(0.163)
Seriously ill at 5	-1.371	(1.185)	-1.218	(1.469)	-0.880	(1.389)	-1.613	(1.465)
Family Income at 10	-0.397	(0.381)	0.055	(0.313)	-0.228	(0.398)	-0.766	(0.610)
BMI of Mother at 10	0.146*	(0.036)	0.089*	(0.035)	0.180*	(0.041)	0.182*	(0.051)
BMI of Father at 10	0.171*	(0.046)	0.151*	(0.048)	0.184*	(0.051)	0.237*	(0.057)
BMI at 10	0.394*	(0.070)	0.262*	(0.078)	0.175†	(0.097)	0.456*	(0.133)
Being ill at 10	0.927†	(0.539)	0.733	(0.667)	1.401*	(0.691)	1.165*	(0.577)
Family Income at 16	0.070	(0.282)	-0.266	(0.238)	0.124	(0.327)	0.113	(0.438)
BMI at 16	0.611*	(0.056)	0.436*	(0.062)	0.704*	(0.078)	0.708*	(0.093)
Being ill at 16	0.208	(0.291)	0.109	(0.275)	0.014	(0.328)	-0.081	(0.402)
Intercept	4.280	(2.634)	7.183*	(2.362)	3.026	(2.848)	0.043	(3.766)
Sample Size	1,295		1,295		1,295		1,295	
Model B								
Higher degree	-1.025†	(0.574)	-0.109	(0.541)	-0.598	(0.506)	-0.954	(0.812)
BA degree	-0.769*	(0.345)	-0.298	(0.373)	-0.245	(0.327)	-1.098*	(0.562)
Dropout	-0.554	(0.404)	0.284	(0.416)	0.246	(0.447)	0.039	(0.634)
Income at 42	-0.313	(0.246)	-0.014	(0.222)	-0.262	(0.261)	-0.213	(0.356)
Sample Size	959		959		959		959	

Notes: * indicates statistical significance at the 5% level and † for 10% level. For quantile regressions, bootstrapped standard errors are in parentheses, using 1,000 bootstrap replications. Model B also includes the covariates listed in Model A. For both models, the reference education level is GCSE. Each of family income at 10 and 16 is the logarithm of family income. Income at 42 is the logarithm of income earned at 42.

Table 3. OLS & Quantile Regressions of BMI on Educational Levels from the WLS

Explanatory Variables	(1) OLS		(2) 0.25 Quantile		(3) 0.50 Quantile		(4) 0.75 Quantile	
Model A								
Male	1.433*	(0.155)	2.204*	(0.140)	1.886*	(0.170)	1.129*	(0.251)
BA or higher	-0.788*	(0.204)	-0.442*	(0.149)	-0.553*	(0.243)	-0.899*	(0.301)
Some college	-0.232	(0.222)	0.096	(0.198)	-0.039	(0.245)	-0.326	(0.372)
Age	0.344*	(0.137)	-0.039	(0.117)	0.345*	(0.167)	0.624*	(0.215)
Birth order	-0.104*	(0.047)	0.020	(0.048)	-0.099*	(0.046)	-0.139*	(0.061)
IQ scores	0.002	(0.006)	-0.007	(0.005)	0.001	(0.006)	0.002	(0.010)
Parental income	-0.061	(0.125)	0.039	(0.088)	-0.098	(0.132)	-0.134	(0.167)
Parental education	-0.080*	(0.025)	-0.047*	(0.020)	-0.089*	(0.028)	-0.068†	(0.036)
Sibling's BMI	0.190*	(0.016)	0.141*	(0.014)	0.173*	(0.019)	0.228*	(0.027)
Intercept	4.399	(7.350)	21.865*	(6.203)	4.245	(9.096)	-8.306	(11.43)
Sample size	3,065		3,065		3,065		3,065	
Model B								
Male	1.442*	(0.172)	2.133*	(0.156)	1.878*	(0.203)	1.228*	(0.285)
BA or higher	-0.817*	(0.219)	-0.433*	(0.169)	-0.488*	(0.252)	-0.957*	(0.319)
Some college	-0.110	(0.240)	0.175	(0.202)	-0.008	(0.243)	-0.268	(0.431)
Income at 52	-0.073	(0.050)	-0.027	(0.062)	-0.064	(0.054)	-0.027	(0.102)
Sample size	2,565		2,565		2,565		2,565	

Notes: * indicates statistical significance at the 5% level and † for 10% level. Standard errors are in parentheses; for quantile regressions, these are bootstrapped, using 1,000 bootstrap replications. Model B also includes the covariates listed in Model A. For both models, the reference education level is high school completion. All income variables are in logarithms.

Table 4. OLS & Unconditional Quantile Regression of BMI on Educational Level

Explanatory Variables	(1) OLS		(2) 0.25 Quantile		(3) 0.50 Quantile		(4) 0.75 Quantile	
BCS								
Higher degree	-1.338*	(0.518)	-0.246	(0.374)	-0.696†	(0.364)	-1.056*	(0.429)
BA degree	-0.720*	(0.302)	-0.477*	(0.220)	-0.283	(0.201)	-0.563*	(0.281)
Dropout	-0.414	(0.346)	0.192	(0.242)	-0.053	(0.237)	-0.213	(0.337)
Sample Size	1,295		1,295		1,295		1,295	
WLS								
BA or higher	-0.788*	(0.204)	-0.064*	(0.029)	-0.112*	(0.039)	-0.176*	(0.053)
Some college	-0.232	(0.222)	-0.014	(0.031)	-0.006	(0.041)	-0.088	(0.059)
Sample Size	3,065		3,065		3,065		3,065	

Notes: * indicates statistical significance at the 5 % level and † for 10 % level. The estimates of unconditional quantile regressions and the standard errors in parentheses in columns 2 to 4 are obtained using the 'rifreg' STATA procedure developed by Firpo, Fortin and Lemieux (2009). The reference education level is GCSE for the BCS and high school completion for the WLS. Each estimated regression also included all other variables listed in Table 2 for the BCS and Table 3 for the WLS.

Table 5. Testing Equality of Quartile Regression Coefficients

	$\delta_{j,0.75} - \delta_{j.0.25}$ with [p-values]			
Explanatory Variables	(1)		(2)	
A. BCS				
Higher degree	-1.018	[0.060]	-0.845	[0.156]
BA degree	-0.723	[0.058]	-0.800	[0.076]
Includes income at 42	no		yes	
Sample Size	1,295		959	
B. WLS				
BA or Higher	-0.456	[0.052]	-0.524	[0.039]
Some college	-0.421	[0.115]	-0.442	[0.136]
Includes income at 52	no		yes	
Sample Size	3,065		2,565	

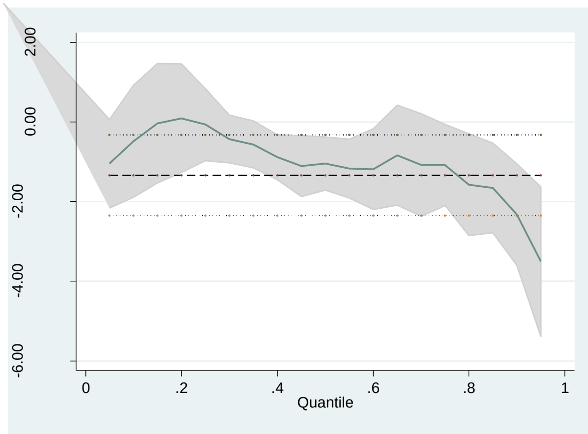
Notes: Each cell reports the estimated difference, $\delta_{j,0.75} - \delta_{j.0.25}$, between the effects of education level j on the upper and lower quartiles of the BMI distribution. The figures in parentheses are p-values for testing the null hypothesis of zero difference. All explanatory variables listed in Table 2 (BCS) and Table 3 (WLS) are included in the quantile regressions. All income variables are in logarithm.

Table 6. Instrumental Variable Quantile Regression of BMI on Educational Level

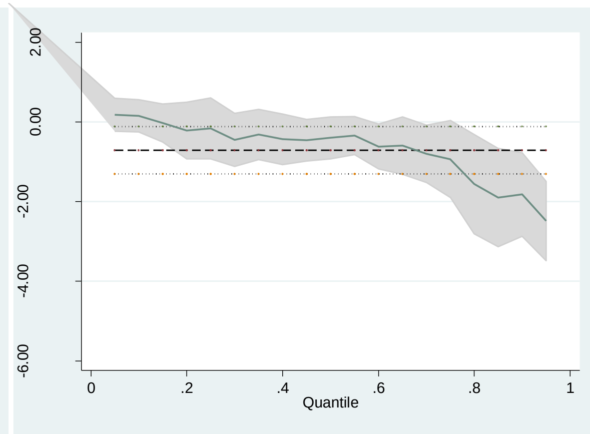
Explanatory Variables	(1) 0.25 Quantile	(2) 0.50 Quantile	(3) 0.75 Quantile
BCS			
BA or higher	-2.147	-3.204*	-7.091*
Lower confidence band	[-5.484]	[-7.010]	[-12.539]
Upper confidence band	[0.626]	[-0.662]	[-1.350]
Sample Size	1,285	1,285	1,285
WLS			
BA or higher	-4.513*	-5.252*	-0.579
Lower confidence band	[-9.564]	[-8.805]	[-10.958]
Upper confidence band	[-3.178]	[-1.387]	[4.065]
Sample Size	3,065	3,065	3,065

Notes: * indicates statistical significance at the 5 % level. Instrumental variable quantile estimates and 95% confidence bands (lower and upper bands) are estimated with 'cqiv' STATA procedure, for uncensored data, developed by Chernozhukov, Fernández-Val, Kowalski and Han (2018). Instrumental variables are family size and parental income in childhood for the BCS and in high school years for the WLS. The reference education level is GCSE for the BCS and high school completion for the WLS. Each estimated regression also included other variables listed in Table 2 for the BCS and Table 3 for the WLS.

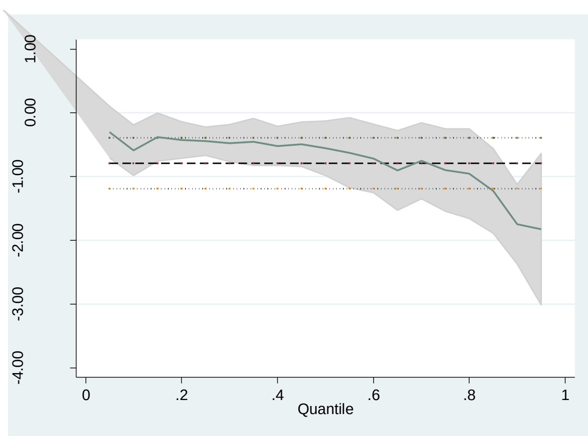
Figure 1. All-quantiles regression coefficients for BMI.



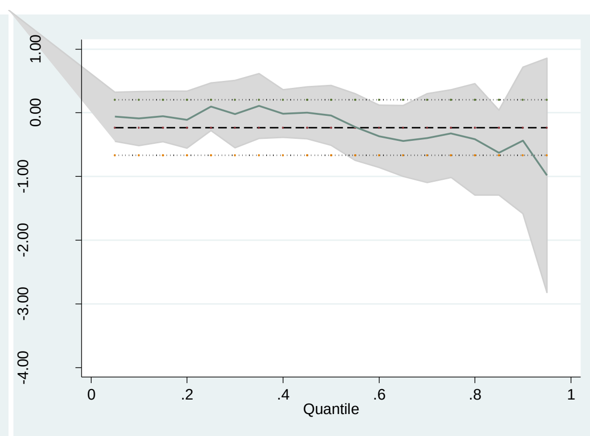
a. Effect of Higher degree (BCS)



b. Effect of BA degree (BCS)



c. Effect of BA+ degree (WLS)



d. Effect of Some college (WLS)

Notes: The estimated effects of education level on BMI quantiles from τ=0.05 to τ=0.95 are illustrated for the BCS in the top panel and for the WLS in the lower panel. The solid line is the point estimate of the education effect at each quantile, with the shaded grey area representing 95% confidence intervals. A dashed line shows the OLS estimate of the education effect with two dotted lines depicting 95% confidence interval. The reference education level is high school completion for the WLS, GCSE for the BCS.