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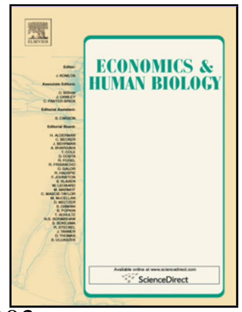

Title: The Long-Run Effect of Education on Obesity in the US

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Highlights

1. The long-run effect of education on BMI is estimated from sibling pairs who reached middle age.
2. The analysis is based on data from the Wisconsin Longitudinal Study collected from 1957 to 1993.
3. An additional year of schooling is associated with a 0.15 reduction in BMI.
4. The negative effect of education is robust across various sibling types and methods.

The Long-Run Effect of Education on Obesity in the US

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Abstract

The proportion of obese population has been gradually increasing in the US over the past few decades. In this study I investigate how education is associated with Body Mass Index (BMI) in later stages of life. BMI, weight(kg)/height$(m)^2$, is the principle measure used for classifying people as obese. Using sibling data and methods that take account of unobserved endowments and environment shared by siblings, I find that there is large variation in BMI between siblings and that education is negatively associated with BMI. One more year of schooling is associated with an estimated reduction of 0.15 in BMI. When considering different education levels, completing college education is associated with 0.7 reduction in BMI relative to high school graduation only. The significant effect of education on obesity that remains in the long-run has policy implications.

Keywords: Obesity, Body mass index, Education
JEL code: I12, I14, I24

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1 Introduction

Obesity prevalence has been steadily increasing in the United States since 1960, when the National Health and Nutrition Examination Survey started to collect data on health and nutritional status of adults. The recent instance of this survey shows an adult obesity rate in 2011-2012 of 34.9%, which is in stark contrast to figures from the earlier surveys. For example, the adult obesity rate was 14.4% in 1976-80 and 22.3% in 1988-1994. The state level data from the Behavioral Risk Factor Surveillance System also show the spread of an obesity epidemic over the last 20 years. In 1990 the highest obesity rate among 45 states was 14%, but in the 2010 survey, 12 states had an obesity rate of 30% or higher.[1] Given the evidence that various diseases and adverse health conditions are associated with obesity (Waaler, 1984; National Institutes of Health, 1998), policy makers and researchers have responded to this growing incidence of obesity by developing plans and targets, as in Healthy People 2020[2], to monitor and promote better public health.

One issue of interest to economists is the observed inequality in overweight and obesity status by education level. The raw data show that obesity is more prevalent among the low educated in the US and other developed countries (Ogden et al., 2010; Cohen et al., 2013), indicating negative correlation between educational attainment and obesity. The correlation between education and obesity, however, may come through three different channels, each having different implications for empirical analysis and policy prescription. First of all, the negative correlation between education and overweight status can be driven by benefits of schooling. Education may induce people to understand the consequences of obesity more easily and help people lead a healthy lifestyle through, for example, restricted diet, regular exercise and routine health check-up as documented by Kenkel (1991), Park and Kang (2008), Fletcher and Frisvold (2009), Lleras-Muney and Cutler (2010), and Eide (2011). Second, the correlation might be induced by reverse causality. That is, having good health in terms of having optimal weight for height may have facilitated educational

[1] The statistics in this paragraph comes from the National Health and Nutrition Examination Survey (NHANES) and the Behavioral Risk Factor Surveillance System (BRFSS).

[2] The Healthy People initiative was started by the US department of health and human services in 1979. One of the goals of the Healthy People 2020 is to achieve health equity, eliminate disparities, and improve the health of all groups.

attainment (Grossman, 2004; Ding et al., 2006). Last but not the least, there may be other factors that influence both schooling and health status such as genetic or other characteristics that may not be readily measurable.

There have been concerted efforts in the economics literature to identify the causal effect of schooling on obesity, based on an understanding of these mechanisms, but empirical findings are inconclusive with regard to the extent of the effect. For instance, Kenkel, Lillard, and Mathios (2006), using the National Longitudinal Study of Youth 1979, find little evidence for an effect of high school completion or receipt of GED (General Educational Development High School Equivalency Diploma) on the probability of being overweight or obese. Using twin data from the National Survey of Midlife Development in the United States, Lundborg (2013) finds no causal effect of schooling on body size. Grabner (2008), in contrast, finds substantial effect of schooling on obesity by using the National Health and Nutrition Examination Survey. The literature which examines data from other parts of the world also finds mixed results. Webbink et al.(2010) find significant effect of schooling for Australian men. Kemptner et al.(2011) find that extended years of compulsory schooling reduce the chance to develop weight problems for people in West Germany. Brunello et al.(2013) and Atella and Kopinska (2014) also find substantial schooling effects on obesity for women living in Italy and other European countries. Clark and Royer (2013) focus on obesity and other health outcomes in the UK and Arendt (2005) for Denmark but both studies find no significant effect of schooling.

In this study I investigate whether and to what extent, if any, education is associated with Body Mass Index (BMI), a primary measure of obesity. Using sibling data from the Wisconsin Longitudinal Study (WLS), I attempt to estimate the schooling effect by controlling for family characteristics that have formed and nurtured early lives of individuals. This method is useful to eliminate family-level confounding factors that have been discussed in the recent literature as a potential determinant of adult health. See, for example, Case, Lubotsky, and Paxson (2002), Case, Fertig, and Paxson (2005), Fuchs (2004), and Cutler and Glaeser (2005). This approach, however, can be potentially inconsistent if between-siblings variation is caused by individual level heterogeneity. By including an extensive set of individual characteristics measured through high school years, I attempt to alleviate part of this omitted variable bias.

The main findings are as follows. The sibling-based estimates indicate that one more year of schooling is associated with a reduction of 0.15 in BMI, conditioning on other individual characteristics. In a model with schooling level indicators, most of the schooling effect emerges at the margin of completing college or higher education levels. Having a BA or higher degree is associated with a 0.7 reduction in BMI. These estimates from sibling-comparison come out 77% to 86% smaller than the conventional least squares estimates. When stratified by sibling types, schooling effects are statistically significant across same-sex and opposite-sex sibling pair samples, but larger for the opposite-sex sibling pairs. For a sensitivity test of the estimates, the alternative approach, the random effect estimation with a proxy of family fixed effects, is also used. The estimates are robust across these two estimators. Similar findings are discovered for the probabilities of being overweight or obese. This study extends the literature by providing new evidence on the long-term effect of education on BMI based on the analysis of sibling pairs. The present study shows that, despite substantial effect of family background, there exists large variation of BMI in middle age between siblings and that educational attainment explains part of this BMI variation. College education effects that remain significant in later stages of life offer some support to the notion that policy intervention through educational program in adulthood can be useful in addressing health inequalities that may have arisen from childhood across families with different backgrounds.

The remainder of the paper is organized as follows. Section 2 describes the data and section 3 presents an empirical framework. The empirical findings are discussed in section 4 and 5. The estimation of the schooling effects on the probability of being obese and overweight is also conducted in section 5. Section 6 provides discussion on the possible mechanisms of schooling effects and section 7 concludes.

2 Data

The data used in this study come from the Wisconsin Longitudinal Study (WLS). The WLS is a longitudinal survey of 10,317 randomly selected men and women who graduated from Wisconsin high schools in 1957. Most of the respondents are white with very few from other ethnic groups.[3] The WLS has followed the respondents in 1975, 1992 and 2004 since the first survey in 1957. From 1977, the WLS also surveyed one randomly selected sibling for each primary respondent. In 1992 and 1993, health outcomes as well as other extensive information were collected from the primary respondents and their siblings. The sample extracted for this study consists of 5,722 respondents and siblings from the 1992 and 1993 surveys when most of the people in the sample had reached their early fifties. For more information on the WLS, see Herd et al.(2014).

As the primary respondents were restricted to high school graduates in Wisconsin, although their siblings were not, one may raise concerns about sample selection. Wisconsin has provided a favorable environment for human capital investment since the rise of public secondary schooling in 1910s. For example, it was one of the few states that set the minimum school leaving age at 16 since 1945, while many states maintained younger ages (mostly at 14) even in 1975 (Oreopoulos, 2003). There may be several factors that contribute to this generous public schooling education in Wisconsin. Since public secondary schooling is intergenerational redistribution of resources from elderly to children, community characteristics may play an important role as documented in Poterba (1997) and Goldin and Katz (1999). The relatively homogeneous communities of Wisconsin, in terms of race (mostly white) and religion (41% Catholic, 31% Lutheran, and 10% United Methodist), may have supported human capital investment for local community children. In addition, returns to education were relatively high for cohorts who were born in the Midwest between 1930 and 1939 (Card and Krueger, 1992), and thus the opportunity cost of dropping out from high school was very high for high school students in the WLS. Considering these characteristics of the state, the samples of students selected from high school senior years in 1957 may not be very different from those who were not sampled. Nevertheless, the small fraction of high school dropouts are excluded as results for this sample can be different from those of the literature, and empirical findings of this study are compared to previous findings from nation-wide data throughout the paper.

The summary statistics are provided in Table 1. BMI is measured as weight in kilograms divided by height in meters squared. The recommended range of BMI

[3] There are 4 families with fathers from Asia and the rest of the families have fathers who are originally from Europe.

is between 18.5 and 25. A BMI between 25 and 30 is considered overweight, and a BMI equal to or above 30 is considered obese. The accumulation of body fat beyond overweight or obese threshold has been documented to present various health problems and increase mortality risk. The diseases and adverse health conditions associated with obesity include high blood pressure and high cholesterol, heart disease, stroke, type 2 diabetes and certain types of cancer (National Institutes of Health, 1998). The mortality rates by BMI for different causes are provided in Waaler (1984).

In this study overweight is defined as having a BMI of 25 or higher for comparison with the previous studies. See, for example, Kenkel, Lillard, and Mathios (2006) and Webbink, Martin, and Visscher (2010). Note that the BMI in the WLS is based on self-reported height and weight. The average BMI in the sample of the WLS is 26.70. The fractions of people who are classified as overweight and obese are 0.65 and 0.23, respectively. Consistent with findings from nation-wide data, men tend to have a higher BMI than women.[4] The average BMI for men is 27.46 and is 26.04 for women. About 77% of men are classified as overweight, and only 54% of women are overweight. The obesity rates are also larger for men than women with 25% of men and 20% of women being obese. The fractions of overweight and obese people among non-Hispanic whites from nation-wide data such as the 2011-12 National Health and Nutrition Examination Survey (NHANES) are 0.67 (BMI$\geq$ 25) and 0.32 (BMI$\geq$ 30) respectively. The overweight and obese population from the WLS is about 2% to 9 % lower than from the NHANES.

The average years of schooling in the WLS are 13.90, which indicates some years of college education beyond the compulsory schooling level. About half of the sample are high school graduates and 31 percent of the sample holds a college or higher degree. There are a few people (1% of the sample) who did not complete high school education based on the 1992 survey, and they have been excluded from the sample as some of them reported completion of high school education in the earlier survey in 1975.

[4]Higher BMI for men may reflect the fact that men have more muscle mass than women on average. In the sense that BMI is based on weight and height, not the fraction of muscle mass relative to body fat, its information value can be reduced. See, for example, Burkhauser and Cawley (2008) which explains in detail the limitation of BMI. However, BMI has been widely used in the medical literature for obesity measure due to its considerable predictive value for morbidity and mortality. See Waaler (1984) for a seminal work.

As of 1992, when the respondents and their siblings were interviewed for schooling and health outcomes, people in the WLS were 52 years old on average. Their average birth order is 2.46, and the median birth order is 2. Half of the sample have 1 or 2 siblings in a family, and 30% have 3 or 4 siblings. Other individual characteristics include IQ scores tested in high school years. Information on parental income is extracted from the Wisconsin Tax Data for the year 1957 when the primary respondents were in their senior high school year. Parental income ranges from $100 to $99,800 and the average income is $6,462. Parental education indicates years of schooling for the head of the household in 1957.

3 Empirical Model

The health status H_i for individual i is modeled as a function of individual and family characteristics X_i and schooling S_i with an additive idiosyncratic error term ζ_i,

$$H_i = X_i\beta + S_i\delta + \zeta_i. \tag{1}$$

As a measure of health status, this study focuses on BMI. An individual's health evolves gradually through their life course, and the schooling experience of early life may be one of the determinants of health status in later years, along with other factors that are represented by individual and family characteristics. Indeed, the simple stratification of BMI by schooling level reveals strong negative correlation between schooling and BMI. This correlation arises if education affects health and thus BMI.[5] On the other hand, the correlation may arise due to the opposite direction of causality. That is, excess weight in high school years may hinder an individual's mobility and productivity, which results in lower educational attainment. There are some studies that show a weight effect on educational achievement, although the evidence is inconclusive. For example, Kaestner and Grossman (2009) find no statistically significant effect of weight on children's educational achievement. In our

[5] There are two approaches in the literature to explain how education affects health: the productive efficiency and allocative efficiency hypotheses. For a review of these two approaches, see, for example, Grossman (2006). In the productive efficiency hypothesis (Grossman, 1972), an increase in educational attainment improves efficiency of health production. The allocative efficiency hypothesis considers different sets of inputs and knowledge (Kenkel, 1991) in health production by education level.

sample from the WLS, the weight and height were measured when people reached middle age. Therefore the weight effect in younger years has not been explored due to data restrictions, but the possibility of this reverse causality cannot be ruled out.

Apart from interaction between education and weight, there can be other factors that are associated with both schooling and weight but are left in the error term of the equation (1). For example, there can be resources and inputs provided through childhood, and genetic endowment and family environment that are shared by siblings. Such factors are likely to help individuals obtain educational attainment and build healthy body shape. Some of these confounding factors, if not all, may be controlled for by including observable individual and family characteristics in the empirical model. In order to identify the causal effect of schooling on weight, the omitted variable bias should be addressed in the estimation. In this study I use family fixed effect estimation and exploit variations of education and BMI between siblings within a family for the estimation of schooling effect.

The extended health regression model that incorporates family fixed effects is as follows.

$$y_{ij} = X_{ij}\beta + S_{ij}\delta + \gamma\mu_j + \varepsilon_{ij}, \tag{2}$$

where y_{ij} is BMI for individual i ($i = 1, 2$) from family j, X_{ij} is a vector of observed individual level covariates and S_{ij} is schooling. μ_j is an unobserved family effect and ε_{ij} is idiosyncratic error term. The unobserved component μ_j can be positively correlated with schooling S_{ij} while it is negatively correlated with y_{ij}. To accommodate this possibility and distinguish negative from positive correlation, γ is multiplied with μ_j. An example of the unobserved family characteristics contributing to μ_j is perseverance or time preference. Parental discipline and training can help children build up their self-control skill and learn value of the future reward for hard work. If children with high self-control skill and low future discount rate are more likely to exert constant efforts to pursue higher degree level and maintain healthy body shape, the unobserved component $\gamma\mu_j$ that raises BMI (low perseverance or high discount rate) is negatively correlated with schooling. As schooling is negatively correlated with BMI a priori, the negative correlation between the unobserved factor and schooling leads to overestimation of schooling effect from the OLS.

The parameter of interest in this study is δ, the effect of schooling on BMI. The statistical significance of the estimated parameter from the above approach depends on the degree of variation in BMI between siblings. To support this notion, I first show the correlation of BMI and schooling level between siblings in Table 2. Across sibling types, the correlation is between 0.17 and 0.27 for BMI, and 0.30 to 0.41 for schooling. This implies there is variation in these key variables. Following Price and Swigert (2012), I next examine the distribution of BMI difference between siblings. The Figure 1 plots distributions of the BMI difference by sibling types using a kernel density. For illustration, I also show the difference in BMI among twin and half-sibling sample although their sample sizes are very small.[6] The distributions in Figure 1 show that there is a large difference in BMI overall regardless of the sibling types. This is consistent with the results in Price and Swigert (2012) that analyze a sibling sample from the National Longitudinal Survey of Youth 1979 Survey.

The family fixed effect estimation, however, has limited ability to remove the omitted variable bias. The unobserved components at the individual level may remain in the error term even after the first differencing between siblings. In addition, the family fixed effect regression is more vulnerable to bias from measurement error in schooling (Bound and Solon, 1999; Neumark, 1999). Nonetheless, the sibling comparison can be useful if the sibling-based estimates are smaller than those from the conventional least squares regression as noted in Bound and Solon (1999). The estimates across these two specifications are compared to confirm that the sibling-based estimates are indeed smaller. Considering the potential caveat regarding the family fixed effect estimation, the schooling effect estimated with this approach can be considered as an upper limit of the return to schooling.

The recent literature supports the use of family fixed effects by providing evidence of a tight link between family characteristics and children's health. Among others, Case, Lubotsky, and Paxson (2002) show that permanent income measured as lifetime average of family income has persistent effects on children's health through adolescent years. Another important determinant of health status discussed in the obesity literature is genetic inheritance. Cutler and Glaeser (2005), analyzing the Minnesota Twin sample, show that among various health behaviors and outcomes, BMI is explained mostly by genetic factors. About 72 percent of BMI variation across people is estimated to come from genetic difference with the classical approach on heritability. Fuchs (2004) also emphasizes the importance of genes in explaining the

[6] I have 92 observations for twin sample and 66 observations for half-sibling sample.

variation of health outcomes across individuals. Finally, the other interesting findings by Case, Fertig, and Paxson (2005) add further evidence that supports the empirical framework adopted in this study. They show that mother's education and family characteristics are related to children's health at age 42 through its effect on health in early childhood. This implies that, with a lack of data on health in childhood, controlling for family characteristics is vital in isolating the effect of education from long-term family effects on health.

4 Results

I start by presenting the estimation results from OLS regression to illustrate the magnitude of the correlation between education and BMI in Table 3. Education may affect BMI through various channels such as job, income or marital status. Consequently any attributes accumulated after high school years are likely to result from post-secondary education, especially labor market outcomes. The primary goal of this study is to find the overall effect of education on BMI that incorporate the direct and indirect effect of education. Therefore the explanatory variables are restricted to individual and family characteristics up to high school years. The covariates include age, age squared, a male indicator, birth order, IQ scores and parental income and education. IQ scores and parental income are from high school years. Conditioning on these characteristics, one more year of schooling is estimated to reduce BMI by 0.17. I next examine the schooling effect on BMI with schooling dummy variables. The education levels are "high school completion only", "some college education without BA degree", and "college education with BA or higher degree". The omitted category of education level in the regression is high school completion. This approach is convenient in capturing a nonlinear effect of schooling on BMI as it allows the schooling effect to differ by levels. Column 3 of Table 3 shows that, compared to high school graduates, people who have some college education or higher tend to have better status in their BMI than their counterparts, but only college graduates with BA or higher degree have a statistically significant effect.

The second column in Table 2 shows health returns to schooling from sibling comparison. The estimated effect of one more year of schooling on BMI is -0.147 and statistically significant. The alternative specification of schooling effect with school level dummy variables presented in column 4 of Table 3 reveals similar findings. The schooling level is negatively associated with BMI such that the average BMI decreases as one moves from having a high school degree to having some college education to having college, or higher, education. The largest schooling effect emerges from the college or higher education levels. Having a college degree as opposed to only a high school education is associated with a BMI reduction of 0.7.[7]

The schooling effects across different sibling types are presented in Table 4. About half of the sample has same-sex sibling pairs, and the rest of the sample has opposite-sex sibling pairs with a brother and a sister in a family. I further break down the same-sex siblings into brother or sister pairs. In columns 4 and 5 of Table 4, we find that schooling effects are similar across sibling types with a slightly bigger effect for opposite-sex sibling pairs. Consistent with the results from the full sample, the schooling effect comes from college education resulting in at least a BA degree. One notable finding is the significant effects of schooling from the opposite-sex sibling pairs. In general, as people age, their BMI tends to increase, though at a decreasing rate. Regardless of age, however, men are more likely to have higher BMI. In the sample of the WLS, men also tend to obtain higher schooling levels than women. The significant estimates of schooling effects on BMI from the opposite-sex sibling sample even in the presence of these disparities confirm that the college education effect is not derived from a gender effect.[8]

The possible sources of variation in schooling and BMI that I consider in the regression are IQ scores and birth order. In the literature, cognitive skills have been discussed as a potential channel of the schooling effect on health. Due to restricted data on both cognitive ability and health outcomes, it has been difficult to obtain empirical evidence on the mechanism of an education effect on health working through cognitive ability. With IQ scores that were taken in high school years as a proxy of cognitive ability, I find that BMI is significantly correlated with IQ scores. However,

[7]The negative schooling effects at the higher education levels are also presented clearly with a further breakdown of college education categories into BA degree only and higher degree levels. Although the results are not reported in the table, they show that the average BMI is lower with advanced educational attainments compared to college education only.

[8]For possible heterogeneous schooling effect by gender, I estimate the schooling effect by including an interaction term with gender and years of schooling. On average, the schooling effect on BMI is larger for women than men as it is often documented in the literature, but the difference in schooling effects between men and women is small.

conditioning on education level, the IQ scores are not statistically significant any more in the regression. Consequently the estimates of schooling effect are similar without IQ scores. The findings in Table 3 and 4 suggest that the schooling effect on BMI does not merely reflect an ability effect. Kenkel, Lillard, and Mathios (2006) also find similar results, using the National Longitudinal Study of Youth 1979, by showing that a proxy of cognitive skills is not associated with obesity status.

The birth order that I include in the model is a linear order of birth, ranging from 1 to 11 in the sample of the WLS. About 50 percent of the sample had two siblings. The first-born child may have a better chance to have a higher level of schooling due to restricted resources available for educational investment. There is empirical evidence that birth order is significantly associated with schooling in the U.S. for the cohorts that I examine in this study. See, for example, Behrman and Taubman (1986) and Kim (2010). The birth order is also strongly correlated with BMI, more so among women. Conditioning on age, age squared and education levels, women with higher birth order tend to have lower BMI. For example, last-born women tend to have slimmer body shape than first-born women. The OLS regression results in Table 3 show that birth order is significantly associated with BMI, although the substantial proportion of birth order effect is explained away with family fixed effects.

The credence of the sibling-based estimates depends on whether the within-family estimates are smaller than OLS estimates, as discussed in Bound and Solon (1999). The results in Table 3 show that the size of the estimated return to schooling becomes smaller once we control for family fixed effects. However, the differences in the estimated schooling effect between OLS and between-sibling comparisons were not statistically significant when the Hausman-Wu test was conducted for model specification test. This implies that, although the upper limit of the schooling effect is narrowed with sibling-based estimates, the within family estimation approach is not necessarily better positioned to resolve the endogeneity issue.

The estimation results in Table 3 and 4 are in line with previous findings of the literature. In particular, the magnitude of the schooling effect on BMI is quite similar to those from analyses of various health surveys in the U.S. Grabner (2008) finds that the estimated effect of schooling on BMI is -0.133 from OLS using data from the National Health and Nutrition Examination Survey.[9] Cutler and Lleras-Muney

[9] Note that height and weight measures in the National Health and Nutrition Examination Survey

(2008) show similar results using several waves from the National Health Interview Survey. They find that one more year of schooling is associated with a decrease of BMI by 0.127 from the full specifications of OLS. The college education effect on BMI from the alternative specification in Table 2 is also consistent with prior results. For example, Chou, Grossman, and Saffer (2004) find that, using survey data from the Behavioral Risk Factor Surveillance System, the OLS estimate of the college education effect on BMI is -1.15. This is comparable to -0.922, the OLS estimate in this study.

5 Robustness Check

5.1 Random Effect Estimation

For a robustness check of the schooling effect from the family fixed effects specification, I employ an alternative approach in this section. Following Ashenfelter and Rouse (1998), I gauge the unobserved component μ_j using the mean years of schooling at the family level.

$$\mu_j = \theta(\frac{S_{1j} + S_{2j}}{2}) + v_j. \tag{3}$$

The family level shared characteristics, such as perseverance or time preference, are aggregated into average sibling education level. Substituting for μ_j in the health regression model (2) with equation (3) results in

$$y_{ij} = X_{ij}\beta + S_{ij}\delta + \gamma\theta(\frac{S_{1j} + S_{2j}}{2}) + \gamma v_j + \varepsilon_{ij}. \tag{4}$$

I estimate the above model (4) with the random effect generalized least squares (GLS). Although this method rests on a stronger assumption than the fixed effect estimator, this approach presents a direct measure of the correlation between BMI and a proxy of family fixed effect using the coefficient of average schooling years of the family.

Table 5 presents estimation results. The first and second columns show linear and nonlinear schooling effects from the full sample. The regression includes the

were from the medical exam not from self-report unlike the ones in the WLS. The similar sizes of the schooling effect on BMI across these two studies indicate that the bias from the measurement errors in the self-reported height and weight from the WLS is small, if any.

family-level mean years of schooling and individual and family characteristics that are previously used in the OLS. Conditioning on these covariates, an additional year of schooling is associated with a reduction of BMI by 0.137. In columns 3 and 4, I next split the sample by sibling gender into same-sex or opposite-sex sibling pairs for estimation of the schooling effects. The estimates of college education effects are quite similar to those from the fixed effect regressions.

5.2 Overweight and Obesity

In this section, I examine the effect of schooling on the probability of being overweight and obese to facilitate comparison with the previous literature. It is also useful from the perspectives of other public health literature as morbidity and mortality rates are documented to increase substantially when BMI exceeds the overweight threshold (National Institutes of Health, 1998; World Health Organization, 2000). The presentation of schooling effects on obesity and overweight status will provide additional evidence regarding the impact of schooling on health.

Note that for empirical analysis I define overweight status as a BMI greater than or equal to 25 and obesity as a BMI greater than or equal to 30, following the previous economics literature. According to this definition, obese persons are a subset of those who are overweight. The estimation results are reported in Table 6. I present the results from the family fixed effect regression along with the results from the linear probability model and probit model for the ease of comparison with the previous findings (Chou, Grossman and Saffer, 2004; and Kenkel, Lillard and Mathios, 2006). In the top panel of Table 6 are the estimated effects of one more year of schooling on the probability of being overweight or obese. The estimated schooling effects are quite similar across overweight and obesity probabilities. They range from -0.010 to -0.018 depending on specifications, and they are all statistically significant at the 5% level. Note that, consistent with BMI results, the cross-sectional regression generates larger estimates than family fixed effects regression.

Panel B of Table 6 shows how the impact of education does not accrue homogeneously throughout the levels of educational experience. The apparent significance of years of schooling in Panel A is seen in Panel B to reflect the statistically significant impact of experiencing education to at least the level of college completion.

The differences in the estimates from the linear probability model and the fixed effect model indicate possible endogeneity of schooling as in the BMI results. For example, the estimated effect of college education on the probability of being overweight or obese from the linear probability model is -0.091(overweight) and -0.060(obese). Once unobserved family fixed effects are controlled for, the estimates are reduced to -0.066 and -0.047, but both remain significant at the 5% level. It can be interpreted that completing college education decreases the probability of being overweight by about 0.07 and being obese by 0.05 relative to high school education only. These results on the whole imply beneficial effects from schooling against the risk of developing overweight and obese status.

The heterogeneous effects of schooling that arise across different schooling levels corroborate some previous findings. Chou, Grossman, and Saffer (2004) show that the high school completion and college education have substantial effect on the probability of being obese based on analysis of people aged 18 years and older drawn from the Behavioral Risk Factor Surveillance System. Cutler and Lleras-Muney (2008) also find significant effect of education on obesity from the National Health Interview Survey, and conclude that schooling has a larger effect for the better educated. Kenkel, Lillard, and Mathios (2006) find little effect of schooling at the lower levels of education both with linear probability models and instrumental variable approaches. They show that the marginal effect of high school completion and GED receipt on either overweight or obesity rates is negligible for people aged about 36 from the sample of the National Longitudinal Survey of Youth 1979.

6 Discussion

The health return to schooling, in terms of reduced BMI and lowered risk of obesity status, is robust across various specifications, suggesting that part of the disparity in health status by education levels can be induced by schooling. This evidence for a beneficial effect of schooling on BMI raises the question of how and why education affects health. I have investigated two of the potential channels for a schooling effect and briefly summarize the results here. One aspect of schooling benefits is income and access to health care. The better educated individuals are more likely to have higher income and be able to access to better health care. The income gradient in obesity is typically observed in the basic national statistics. See, for example, Healthy People 2010 Final Review.[10] I have explored this channel by controlling for individual's wages earned in the year when their BMI was measured, but found that the income effect does not explain away the schooling effect. The size of the schooling effects remains the same while the income effect is estimated to be negligible. Nevertheless, this does not fully exclude the possibility of an income effect as the current income may not fully reflect the path of previous income.

Another potentially relevant mechanism is the social network or peer effect. Education may sort people into different social classes or peer groups in which people develop different norms of lifestyle and health standard. In addition, the networks formed by the more educated may provide a better chance to have relatively more effective financial, physical or emotional support to promote health status.[11] Among various social networks, family members might affect each other the most. In particular, siblings may provide peer acceptance or disapproval of each other's body size and promote resemblance if desirable (Webbink et al. 2010). With the family fixed effects regression that has been used through this study, the mean levels of BMI among siblings are accounted for implicitly. For explicit controlling of peer effect at the family level, I have included a sibling's BMI as an additional regressor in the OLS regression. The variation in sibling's BMI explains some of the schooling effect but the schooling effect remains substantial and significant.

Neither of the above mechanisms completely explains the schooling effect on BMI. Instead several mechanisms that are not discussed here may be involved as well as the two channels mentioned above. Nonetheless, what appears clear from this study is that education plays a significant part to bring about lower BMI, reduced risk of obesity, and thus better health status.

7 Conclusion

This study uses an empirical framework that emphasizes the importance of unobserved ability and environment in the formation of human and health capital. Using

[10] The final review of Healthy People 2010 can be accessed at the following web address: http://www.cdc.gov/nchs/healthy_people/hp2010/hp2010_final_review.htm.

[11] In the medical literature, the evidence on the effect of social and emotional support on health status and mortality is well documented. See, for example, Berkman (1995) for a review.

data of siblings who are likely to share genetic inheritance and family background, I find that there is large variation in schooling and BMI between siblings even among the same-sex siblings. This implies that environment and endowments provided by parents and the intricate interactions within a family have limited impacts on children's education and health in adulthood. On the other hand, the significant long-run effect of schooling at the college education level on later life BMI suggests that post-secondary education plays a crucial role in reducing the risk of having excess weight in middle age.

The empirical findings of this study of middle aged adults are in line with previous findings of the literature derived from samples of younger adults. Since the results are based on people whose high school education was in Wisconsin, we need to exercise some caution when quantifying the schooling effect more widely. Nevertheless, these findings shed light on various aspects of the overall return to schooling. The benefit of schooling may exceed the pecuniary return that is typically observed in the labor market. In the presence of peer effects and the consequent social multiplier effect, the impact of education on public health may be even larger.

The findings here imply scope for policy intervention even in adulthood in reducing the health gradient, although policy intervention made in childhood can be more efficient and effective as documented in recent studies by Belfield and Kelly (2013) and Mora, Llargues, and Recasens (2015). The role of education may warrant increased emphasis in the current health-related policies such as Healthy People 2020. Various educational and informational programs accompanied by close health monitoring could be designed to target less educated people to compensate for the lost benefits of formal post-secondary schooling. This may facilitate a reduction in the large disparity of health status across education level groups and achieve an overall improvement in public health, with consequent substantial benefit to social welfare. Given the limitation of this study in which individual level heterogeneity such as details of food consumption and health behaviors is not explored, more efforts are required for future research to draw a complete picture of the effects of education on obesity and the underlying mechanisms.

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Table 1.
Summary Statistics of the WLS

Variables	Mean (Standard Deviation)
Body Mass Index (BMI)	26.71 (4.53)
Overweight (BMI≧25)	.65 (.48)
Obese (BMI≧30)	.23 (.42)
Years of Schooling	13.90 (2.36)
High school	.51 (.50)
Some college	.17 (.38)
College or higher	.31 (.46)
Age	52.06 (4.60)
Birth order	2.46 (1.65)
IQ scores	103.88 (14.93)
Parental income	6,462.37 (6116.47)
Parental education	9.90 (3.44)
N	5,722

Notes: The data set is from the Wisconsin Longitudinal Study. BMI and education variables are from the 1992 and 1993 surveys. IQ scores are from the 1957 (primary respondents) and 1977 (siblings) surveys and all other variables are from the 1975 survey. BMI is measured in kg/m^2.

Table 2.
Correlation between siblings

Variables	All	Brothers	Sisters	Mixed
Body Mass Index (BMI)	.208	.267	.199	.172
Years of Schooling	.362	.411	.390	.304
N	3,005	692	851	1,462

Notes: The mixed sample consists of brother-sister pair siblings. N indicates the total number of families.

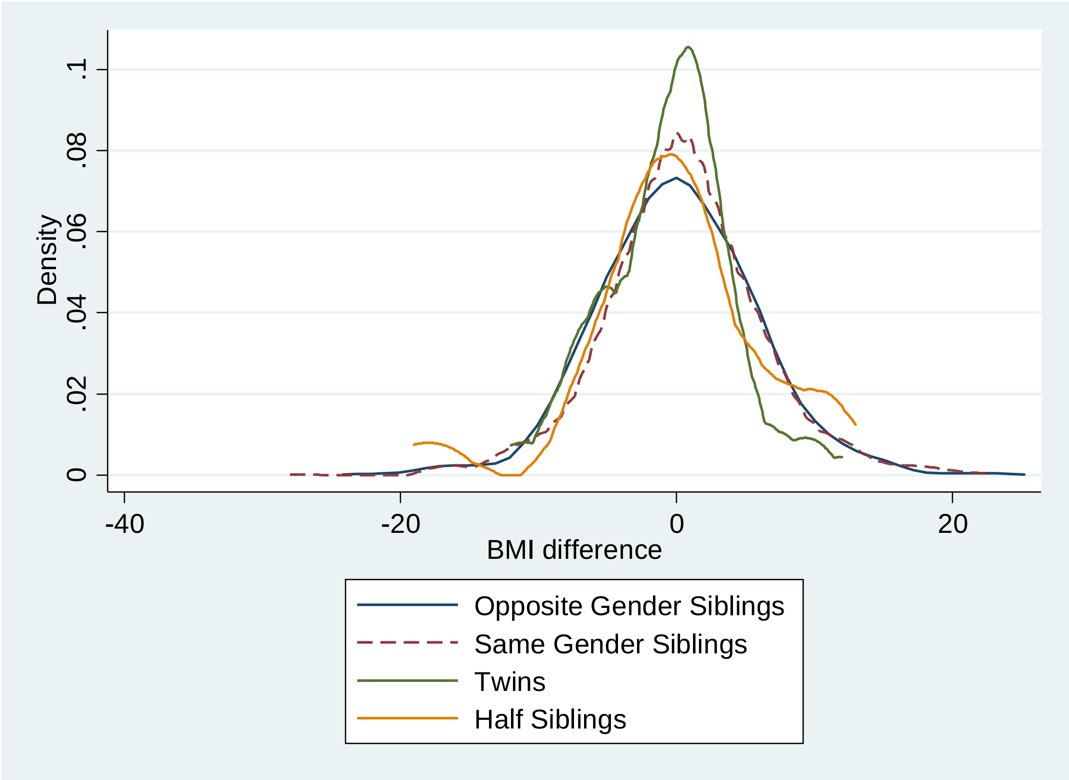

Figure 1. Distribution of the difference in BMI between siblings

Notes: A pair of a brother and a sister is grouped into opposite gender siblings. The half siblings are those who do not share biological mother or father.

Table 3.
Estimates of Schooling Effects on BMI

Explanatory	OLS	FE	OLS	FE
Variables	(1)	(2)	(3)	(4)
Years of schooling	-.169*(.029)	-.147*(.043)		
Some college			-.214 (.167)	.014 (.224)
College or higher			-.922*(.155)	-.710*(.229)
Age	.099 (.126)	.109 (.142)	.099 (.126)	.112 (.142)
Age squared	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.001 (.001)
Male	1.54*(.119)	1.43*(.160)	1.53*(.119)	1.41*(.159)
Birth order	-.105*(.039)	-.043 (.114)	-.104*(.039)	-.040 (.114)
IQ scores	.002 (.004)	.002 (.007)	.002 (.004)	.000 (.007)
N	5,722	5,722	5,722	5,722

Notes: Standard errors are in parentheses. For fixed effect regressions, standard errors are adjusted for within family correlation. *N* indicates sample size. Columns 1 and 3 are from OLS regressions and columns 2 and 4 are from family fixed effects regressions. OLS regression also includes parental income and parental education. * indicates statistical significance at the 5 percent level.

Table 4.
FE Estimates of Schooling Effects on BMI by Sibling Types

Explanatory Variables	All (1)	Brothers (2)	Sisters (3)	Same-sex (4)	Opp-sex (5)
Some college	.014 (.224)	-.311 (.411)	.096 (.500)	-.060 (.335)	.077 (.300)
College or higher	-.710*(.229)	-.594 (.406)	-.716 (.506)	-.665†(.329)	-.768*(.320)
Age	.112 (.142)	.303 (.277)	.253 (.264)	.245 (.202)	-.026 (.201)
Age squared	-.001 (.001)	-.003 (.003)	-.002 (.002)	-.002 (.002)	.000 (.002)
Male	1.41*(.159)				1.41*(.160)
Birth order	-.040 (.114)	.201 (.205)	-.328 (.227)	-.091(.157)	.010 (.167)
IQ scores	.000 (.007)	-.009 (.012)	.003 (.015)	-.004 (.009)	.005 (.010)
N	5,722	1,302	1,617	2,919	2,803

Notes: Standard errors that are adjusted for within family correlation are presented in parentheses. N indicates sample size. All results are from family fixed effects regressions. Column 2 is for brother sibling sample, column 3 for sister sibling sample and column 5 for brother/sister sibling sample. * indicates statistical significance at the 5 percent level and † for 10 percent level.

Table 5.
GLS Estimates of Schooling Effects on BMI

Explanatory	All	All	Same-sex	Opp-sex
Variables	(1)	(2)	(3)	(4)
Years of schooling	-.137*(.041)			
Some college		-.108 (.172)	-.243 (.246)	.019 (.240)
College or higher		-.731*(.205)	-.653*(.292)	-.769*(.289)
Age	.104 (.113)	.106 (.113)	.175 (.161)	.031 (.156)
Age squared	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.001 (.001)
Male	1.51*(.116)	1.50*(.115)	1.62 (.183)	1.41*(.150)
Birth order	-.101*(.037)	-.099 (.037)	-.078 (.053)	-.126*(.053)
IQ scores	.002 (.004)	.002 (.004)	.002 (.007)	.003 (.006)
N	5,722	5,722	2,919	2,803

Notes: Standard errors that are adjusted for within family correlation are presented in parentheses. The regressions also include mean years of schooling at the family level, parental income, and parental education. Column 3 is for brother sibling or sister sibling sample and column 4 for brother/sister sibling sample. * indicates 5 percent significance level.

Table 6.
Estimates of Schooling Effects on Probabilities of Overweight and Obesity

	Overweight (BMI≥ 25)			*Obesity* (BMI≥ 30)		
Explanatory	(1)	(2)	(3)	(4)	(5)	(6)
Variables	LPM	FE	probit	LPM	FE	probit
A. Model I						
Years of schooling	-.017*	-.016*	-.018*	-.012*	-.010*	-.012*
	(.003)	(.004)	(.003)	(.003)	(.004)	(.003)
B. Model II						
Some college	-.016	.008	-.016	-.011	.001	-.011
	(.017)	(.024)	(.018)	(.016)	(.022)	(.015)
College or higher	-.091*	-.066*	-.097*	-.060*	-.047*	-.059*
	(.016)	(.025)	(.017)	(.015)	(.023)	(.014)
N	5,722	5,722	5,722	5,722	5,722	5,722

Notes: Standard errors are in parentheses. For fixed effect regressions, standard errors are adjusted for within family correlation. Model I presents linear schooling effect and Model II presents nonlinear schooling effect with schooling dummy variables. The results in columns 1 and 4 are from linear probability models and columns 2 and 5 from family fixed effects regressions. The results in columns 3 and 6 reports marginal effects from probit models. Other explanatory variables included in the regressions are age, age squared, male indicator, birth order, IQ scores, parental income and parental education. * indicates statistical significance at the 5 percent level.