Obesity

Effect of Genetic Propensity for Obesity on Income and Wealth Through Educational Attainment

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Objective: This study contributes to the literature on the income and wealth consequences of obesity by exploiting recent discoveries about the genetic basis of BMI.

Methods: The relation between a genetic risk score (GRS) for BMI, which reflects the genetic predisposition to have a higher body weight, and income and wealth was analyzed in a longitudinal data set comprising 5,962 individuals (22,490 individual-year observations) from the US Health and Retirement Study.

Results: Empirical analyses showed that the GRS for BMI lowers individual income and household wealth through the channel of lower educational attainment. Sex-stratified analyses showed that this effect is particularly significant among females.

Conclusions: This study provides support for the negative effects of the GRS for BMI on individual income and household wealth through lower education for females. For males, the effects are estimated to be smaller and insignificant. The larger effects for females compared with males may be due to greater labor market taste-based discrimination faced by females.

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Introduction

The worldwide prevalence of obesity has increased substantially in recent years. The economic consequences of obesity have been widely studied (1). Obesity has been associated with unemployment, lower income, and receiving government benefits (1). The influence of obesity on poorer labor market outcomes is primarily through worsening health (1). Poor health, driven by higher obesity, may lower productivity at the workplace but may also exacerbate taste-based discrimination from employers (2).

One of the major identification issues in this research area is the reverse causality between body weight and labor market outcomes, meaning that lower weight may impact earnings positively but lower earnings may also increase weight. Important factors that are difficult to include in empirical models, such as investments in health capital, further complicate the estimation of these relationships. Leveraging the heritable aspect of obesity, studies have used the weight of a relative as an instrumental variable to infer causality (3). However, vicarious learning and social contagion factors associated with the relative's weight may have an influence on one's own weight. Recently, genetic variants associated with obesity were used as instrumental variables to assess the effect of weight on labor market outcomes (4). However, because of the pleiotropic functioning of genes (genes influencing multiple outcomes simultaneously), it can be questioned whether the exclusion restriction holds in these so-called Mendelian randomization studies (5).

Nevertheless, the heritability of obesity is estimated to be around 40% to 70% (6), and this provides opportunities to make progress in the literature on BMI and labor market outcomes. A 2015 genome-wide association study (GWAS) succeeded in finding several individual genetic variants that are related to BMI (7). Based on the GWAS results, a genetic risk score (GRS) for BMI could be constructed that explained 21.6% of actual BMI (7). The GRS is a weighted sum of multiple genetic variants, and the weights are proportional to the estimated effect sizes in a GWAS (8). Because the GRS is endowed at conception, the GRS for obesity may help to unpack channels through which BMI and labor market outcomes are related. This paper contributes to the literature by using a GRS for obesity as a predictor of educational attainment that in turn influences later-life income and wealth accumulation.

We draw on a longitudinal data set comprising 5,962 individuals (22,490 individual-year observations) from the US Health and Retirement Study

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(HRS). The HRS is a representative panel of Americans older than 50 years of age and their spouses, which offers a fairly unique opportunity to link the GRS for BMI with longitudinal data on later-life income and wealth. Our results show that the mediation path through educational attainment is supported for females but not for males. The results are in line with prior studies indicating that the negative influence of obesity on labor market outcomes is stronger for females than for males (9).

Methods

In our study, we drew on data from the HRS that are representative for the US population older than 50 years and their spouses (10). The HRS focuses on a variety of labor market, health, and retirement outcomes. Genetic data were collected from consenting HRS participants between 2006 and 2012 (11). In this study, we used the GRS for BMI that was released in April 2018. The GRS for BMI is based on results from a GWAS conducted by the Genetic Investigation of Anthropometric Traits (GIANT) consortium (7). The GRS for BMI was merged with the data file provided by the RAND Center for the Study of Aging, which includes the harmonized biennial data of the HRS (1992-2014, version P).

Our outcome variables were the logarithm of individual income and household wealth. Despite the self-reported nature of these variables, these measures are highly reliable (12). Our main predictor was the GRS for BMI, which was standardized to have mean 0 and standard deviation (SD) 1 in the genotyped sample. The mediator was educational attainment in years of education. Because of the time-varying nature of the dependent variables and the time-invariant nature of the GRS for BMI and educational attainment, we used random-effects panel regression (with standard errors clustered at the individual level). In this model, we controlled for current BMI, age, gender, marital status (1 = living together; 0 = not living together), number of children, self-reported health (1 = excellent to 5 = poor), the logarithm of spousal income, industry of occupation (dummies for working in the first sector, second sector, and third sector), job type (dummies for white collar, pink collar, blue collar: services, and blue collar: manual labor), and wave dummies. Moreover, we used 10 principal components of the genetic relationship matrix to control for subtle population stratification. Population stratification may bias estimates between genetic factors (such as a GRS) and outcome variables if genetic differences between subpopulations in the sample are related to unobserved factors not accounted for in the model (such as culture or regional factors). The inclusion of principal components addresses this concern adequately in the HRS (13). A full description of the variables included in the analyses is available in Supporting Information Table S1.

The effect of the GRS for BMI on income and wealth through educational attainment was assessed using the "difference-in-coefficient" approach (14). This approach compares the coefficient of the GRS for BMI in a model with and without the mediating variable. The change in the coefficient for the GRS for BMI due to the inclusion of educational attainment indicates to what extent the mediating variable explains the relationship between the GRS for BMI and the dependent variable. The significance of the mediating effect was assessed using the Karlson-Holm-Breen (KHB) method (15). Based on the assessment that "there is a robust negative correlation between weight and income among women but not men; i.e., higher-income women are less likely to [have obesity]" (1), we performed the regressions in the full sample as well as in sex-stratified subsamples.

Following the recommendations of the genotyping center, the sample was restricted to individuals of European ancestry (16). To ensure that we focused solely on individuals who are active in the labor market, we further excluded individuals older than 65 years of age and those who were retired. For generalizability purposes, individuals (spouses) aged below 50 were also excluded. The final analysis sample included 5,962 individuals representing 22,490 individual-year observations with complete information on all variables included in the regressions. Table 1 presents descriptive statistics of the analysis sample. Correlation tables are available in Supporting Information Tables S2-S4.

Results

Table 2 depicts the main results for the models explaining the logarithm of individual income (Panel A) and the logarithm of household wealth (Panel B). In the full sample, we found a significantly negative association between the GRS for BMI and wealth (Column 1). The relation between the GRS for BMI and income was not significant ($P = 0.196$). The relation between educational attainment and both outcomes was significantly positive (Column 2). Overall, we observed that the indirect relation between the GRS for BMI and individual income as well as household wealth was significantly negative (Column 3). The percentage of mediation was 13.67% and 23.27%, respectively (Column 4).

However, the sex-stratified results indicated that the effect between the GRS for BMI and our outcomes through educational attainment was heterogeneous across sexes. For individual income, the percentage of mediation was 11.29% for males and 17.25% for females. For males, this indirect relationship was not significant at the 5% level ($P = 0.289$). For household wealth, the percentage of mediation was also higher for females than for males (37.09% vs. 12.79%). The indirect relation between the GRS for BMI and this outcome through educational attainment was significant only for females ($P = 0.249$ for males).

Discussion

In this study, we draw on the genetic basis of obesity to study the influence of BMI on income and wealth through educational attainment. Our study provides support for the negative effects of the GRS for BMI on individual income and household wealth through lower education for females. For males, the effects are estimated to be smaller and insignificant. These results are consistent with earlier studies indicating the absence of a negative correlation between weight and income among males (1). Moreover, the larger effects for females compared with males may be due to greater labor market taste-based discrimination faced by females (17).

Our inferences are based on data from individuals aged between 50 and 65 years living in the US. Therefore, the generalizability of our findings to developing countries and younger populations may be limited. Nevertheless, our study clearly warrants further research into what makes individuals with a high genetic propensity for obesity attain a relatively low level of education, e.g., by investigating whether there are

TABLE 1 Descriptive statistics of analysis sample

	Full sample, $N_{individuals} = 5{,}962$, $N_{individual\text{-}wave} = 22{,}490$				Male, $N_{individuals} = 2{,}790$, $N_{individual\text{-}wave} = 10{,}543$				Female, $N_{individuals} = 3{,}172$, $N_{individual\text{-}wave} = 11{,}947$			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Logarithm of individual income	8.925	3.609	0.000	15.691	9.079	3.838	0.000	15.691	8.789	3.388	0.000	13.321
Logarithm of household wealth	12.106	1.535	0.000	18.322	12.212	1.461	0.000	17.507	12.013	1.591	0.000	18.322
Years of education	13.601	2.415	0.000	17.000	13.771	2.587	0.000	17.000	13.452	2.241	0.000	17.000
GRS for BMI	−0.013	0.995	−3.636	3.911	−0.019	0.989	−3.297	3.911	−0.008	1.000	−3.636	3.637
BMI	27.458	5.050	15.300	63.200	27.887	4.464	15.300	57.400	27.080	5.489	15.700	63.200
Age	57.427	4.004	50.000	65.000	57.738	3.897	50.000	65.000	57.152	4.078	50.000	65.000
Gender (1 = male; 2 = female)	1.531	0.499	1.000	2.000	1.000	0.000	1.000	1.000	2.000	0.000	2.000	2.000
Living together (1 = yes; 0 = no)	0.822	0.383	0.000	1.000	0.894	0.308	0.000	1.000	0.757	0.429	0.000	1.000
Number of children	2.938	1.779	0.000	19.000	2.885	1.754	0.000	16.000	2.985	1.800	0.000	19.000
Self-reported health (1 = excellent – 5 = poor)	2.243	0.940	1.000	5.000	2.262	0.946	1.000	5.000	2.225	0.935	1.000	5.000
Logarithm of spousal income	5.482	5.115	0.000	14.334	5.812	4.935	0.000	13.514	5.191	5.251	0.000	14.334
Industry (first sector)	0.080	0.271	0.000	1.000	0.139	0.346	0.000	1.000	0.028	0.165	0.000	1.000
Industry (second sector)	0.157	0.364	0.000	1.000	0.219	0.414	0.000	1.000	0.103	0.304	0.000	1.000
Industry (third sector)	0.763	0.425	0.000	1.000	0.642	0.479	0.000	1.000	0.869	0.337	0.000	1.000
Job type (white collar)	0.385	0.487	0.000	1.000	0.175	0.380	0.000	1.000	0.359	0.480	0.000	1.000
Job type (pink collar)	0.298	0.457	0.000	1.000	0.054	0.226	0.000	1.000	0.406	0.491	0.000	1.000
Job type (blue collar: services)	0.104	0.306	0.000	1.000	0.356	0.479	0.000	1.000	0.149	0.356	0.000	1.000
Job type (blue collar: manual labor)	0.213	0.409	0.000	1.000	0.415	0.493	0.000	1.000	0.086	0.281	0.000	1.000

Descriptive statistics for wave dummies and 10 principal components are not reported here but are available upon request from the authors.
SD, standard deviation; Max, maximum; Min, minimum.

TABLE 2 The relationship between GRS for BMI and the logarithm of individual income and logarithm of household wealth through educational attainment

	(1)	(2)	(3)	(4)
Sample	The direct relation between the GRS for BMI and the dependent variable (model without mediating variable)	The relation between educational attainment and the dependent variable (model with mediating variable)	The indirect relation between the GRS for BMI and the dependent variable through educational attainment	The indirect relation (3) as percentage of the direct relation (1)
Panel A: Logarithm of individual income				
Full sample	−0.054	0.089***	−0.007*	13.67%
	(0.042)	(0.020)	(0.003)	
Males only	−0.039	0.069**	−0.004	11.29%
	(0.064)	(0.026)	(0.004)	
Females only	−0.074	0.122***	−0.012*	17.25%
	(0.055)	(0.030)	(0.005)	
Panel B: Logarithm of household wealth				
Full sample	−0.067***	0.164***	−0.013*	23.27%
	(0.019)	(0.009)	(0.005)	
Males only	−0.084***	0.151***	−0.009	12.79%
	(0.028)	(0.012)	(0.008)	
Females only	−0.058**	0.180***	−0.018**	37.09%
	(0.025)	(0.014)	(0.007)	

Standard errors are in parentheses.
$^{***}P<0.001$; $^{**}P<0.01$; $^{*}P<0.05$.
Full regression results are available in Supporting Information Tables S5-S6.

characteristics (such as personality traits) genetically related to BMI as well as to educational attainment. Moreover, future studies may explore the feasibility and desirability of testing for one's GRS for BMI at a young age to plan interventions to improve educational attainment and subsequently later-life income and wealth. O

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