ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis Industrial Dynamics and Strategy

How weight influences the rest of your life

Evidence from the Health and Retirement Study

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Abstract

Obesity rates have been rising over the last decade. It has already been established that Body Mass Index (BMI) is negatively related to work productivity and physical health. This paper aims to explore the effect of BMI on life attainment. In this study, life attainment is split into educational attainment and career attainment. Further, it examines whether the effect of BMI on life attainment is mediated through mental health, as established literature states that higher BMIs are closely related to depressive symptoms. To test the relationship between BMI, mental health and life attainment and to obtain more knowledge about the direction of effects, insights from genetic studies and the instrumental variable analysis are used to eliminate reverse causality and omitted-variable bias. Utilizing the longitudinal data and polygenic scores from the Health and Retirement Study, a negative causal effect of BMI on mental health and, in turn, a positive causal effect on educational attainment is found for the elderly, female American demographic.

Keywords: Body Mass Index, Depression, Mental Health, Educational Attainment, Career Attainment

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Introduction

Adult obesity worldwide has almost tripled since 1975 (Ritchie, & Roser, 2019). Established literature (Gates, Succop, Brehm, Gillespie, & Sommers, 2008; Strine, Chapman, Balluz, Moriarty, & Mokdad, 2007; Colditz, 1993) acknowledges the risk of increased body mass on physical abilities. Individuals with a higher Body Mass Index (BMI) tend to have physical limitations or diseases. Other studies show the impact of BMI and the "thin ideal" on mental wellbeing. For example, Klaczynski, Goold and Mudry (2004) identify that having negative feelings about oneself and others as a result of increased weight, is more present in societies that have a negative stigma around heavier bodies. Another example of social stigma can be found in the phenomena that obese people appear to be less productive and are discriminated on the labour market (Kim, & von dem Knesebeck, 2018; Bann, Johnson, Li, Kuh, & Hardy, 2017). For this reasons, this could suggest that increased BMI leads to increased levels of depression, as depressive moods are more elevated among the unemployed population (Stankunas, Kalediene, Starkuviene, & Kapustinskiene, 2006). Furthermore, it is critical to acknowledge the presence of depression in society. In 2017, depression was the second-most occurring mental disease with 3.44% of the world population suffering from it (4.1% female and 2.7% male) (Global Burden of Disease Collaborative Network, 2018). This study also aims to evaluate the relationship between depressive symptoms and life attainment. Fletcher (2007) establishes a negative effect of adolescence depression on their educational attainment. This can be explained through a lack of motivation and life spirit that can exist in cases of depression. The paper addresses examples such as the choice to drop out of high school or whether to enrol for college.

Understanding the effects of higher BMIs is of critical social importance. Firstly, as will be discussed more thoroughly later, there are extensive health costs related to the increase in the percentage of overweight individuals in the population. In addition, the costs attributable to obesity due to inactivity account for an additional financial burden. In 1999, Colditz expresses that the direct costs of obesity defined as BMI>30 total 70 billion in 1995 USD. Additionally, he finds that the direct costs of inactivity (in the workforce) and obesity account for some 9.4% of the national health care expenditures in the United States. Secondly, Stunkard, Faith and Allison (2003) state that obese individuals, from childhood on, are subject to teasing and verbal abuse. This negatively affects their confidence and self-esteem. These experiences contribute to a significantly greater rate of depression experienced by obese individuals (Stunkard, Faith, & Allison, 2003). Moreover, the study finds that treating obesity tends to lead to a decrease in depression in depressed individuals. In contrast, treatment of depression can have adverse effects on obesity. Thus, this implies that treating obesity, especially in higher percentiles of BMI, is an effective tool to combat depression, if applicable.

Despite the social importance, near-future technological development and contemporary culture do not seem to reverse the upward BMI trend. For example, the introduction of the Internet allows for easier and faster communication channels to develop. Similarly, technological inventions integrate more artificial intelligence and require continuously less human intervention or assistance, hence the occupational industry is shifting. In turn, this leads to the corresponding change in food consumption, which has implications for society as a whole. An article by Matusitz and McCormick (2012) addresses the increased use of the Internet to be a cause of a more sedentary society, leading to more obesity. Good, Manning and Salomons (2014) show that general employment has shifted towards, among others, high-paid professionals and managers over the period 1993-2010. Additionally, Ng and Popkin (2012) acknowledge that technology linked with reduced physical activity (PA) and increased sedentary activities dominate the globe. The study shows that occupational PA decreased from 151.7 MET-hours (i.e. kcal/kg) per week to 95.4 (-34.6%) and that domestic PA decreased from 55.6 to 45.2 (-20.5%) MET-hours a week in the United Kingdom between 1961 and 2005. Simultaneously, the food industry changed. This is illustrated by the fact that the number of fast-food outlet sales increased about 300% over the 10-year timespan between 1970 and 1980 (Paeratakul, Ferdinand, Champagne, Ryan, & Bray, 2003). There is a strong association between increased fast food consumption and susceptibility to weight gain and obesity (Anderson, Lyon-Callo, Fussman, Imes, & Rafferty, 2011; Rosenheck, 2008). Additionally, Anderson, Lyon-Callo, Fussman, Imes and Rafferty (2011) show that most individuals stated 'convenience' as the most prevailing motive, which is in line with today's more-demanding society. The combination of the decrease in physical activity and the change in eating behaviour cause the highest level of obesity ever recorded (Ritchie & Roser, 2019).

This paper focuses on the relationship between BMI and mental health, and whether that, in turn, affects life attainment. In this paper, life attainment will be split into educational attainment and career attainment. BMI is generally split into four ranges: A BMI of 18.5 and below indicates underweight, a BMI between 18.5 and 24.9 indicates a healthy weight for one's height, a BMI between 25 and 29.9 indicates overweight, and a BMI of 30 and above indicates obesity (Marengo, 2018). Although there seems little direct reason for weight and height (i.e. the two components that form BMI) to affect life attainment, it is interesting to examine whether the relationship is mediated by mental wellbeing. Mental wellbeing will be conceptualized by life satisfaction and a general mental health score. In short, it will be evaluated whether physical factors significantly influence mental wellbeing, and whether that in turn affects the aforementioned life-performance factors. This paper wants to clarify the direction of effects, as there are studies that discuss 'reverse causality'. Regarding the relationship between BMI and depression, for example, the least well-off members of society suffer a disproportionate share of the burden of diseases, including depression and obesity (Everson, Maty, Lynch, & Kaplan, 2002). Especially those individuals with lower incomes can be more prone to obesity through several mechanisms: lack of access to healthy food, generally unhealthy lifestyles, or psychosocial factors that derive from relative deprivation (Kim, & von dem Knesebeck, 2018). Regarding mental health and life attainment, Ross and Mirowsky (2006) show that depression decreases by education level, and that there is thus reason for reverse causality. Further, it seems plausible that an episode of depression does not prosper one's career attainment. Additionally, the 'pushing' of organizations to make employers operate beyond their sustainable performance level (e.g. in crisis periods with excessive workloads or in competition for a promotion) is one of the key factors for burnouts (Maslach, & Leiter, 1997). These situations appear more frequently in the higher end of career attainment and in (endeavouring) management positions, and thus giving rise to reverse causality for the relationship between depression and career attainment. Finally, Zimmerman and Katon (2005) find that unemployment and financial strain are the two largest contributors to depression.

To obtain causal relationships and to add to the existing literature, this paper uses instrumental variable analysis as its base to answer the following research question:

"To what extent does Body Mass Index have a causal effect on life attainment indicators in a sample of individuals of European ancestry?"

In terms of scientific relevance, this paper aims to add to the established list of variables shown to be affected by enlarged BMI and those that affect life attainment. Moreover, it also tests whether this effect is mediated by mental health. The key contributions of this paper are twofold. Firstly, the use of gene data allows for instrumental variable analysis, and therefore (if successful) allows to interpret the results as causal, contrary to sole correlation as is done in many papers thus far (e.g. Mujahid, Roux, Borrell, & Nieto, 2012). Moreover, it also eliminates the issue of "reverse causality" that was found by Deb, Gallo, Ayyagari, Fletcher and Sindelar (2011). Secondly, the paper focuses on the mediating effects of mental health between BMI and life attainment. This has not been researched extensively yet, and this paper will therefore contribute to the knowledge in this field.

Figure 1 provides a general overview of the paper. Gene data (PGS in *Figure 1*) is used as instruments for the independent variables. The general findings read a negative effect of BMI on mental health and, in turn, a positive effect of stable mental health on life attainment. The overall relationship between BMI and life attainment is negative and is partly mediated by mental health. The results are mostly significant for female respondents, which indicates that females are more affected by societal pressure.

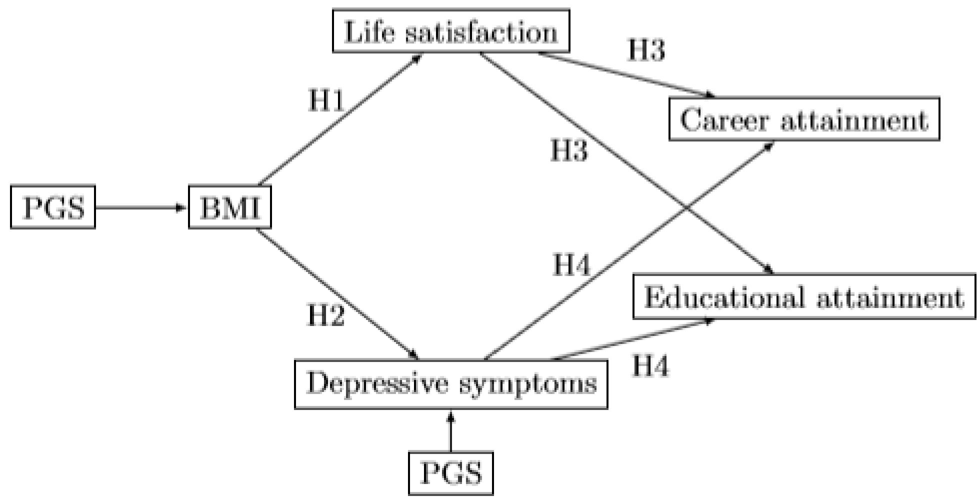

Figure 1: General overview of the research and hypotheses

The structure of the paper will be as follows: After the *Introduction*, existing literature is explored and the hypotheses are formed in the *Theoretical Framework*. Next, the analytical methods are explored in the *Methodology* section and the benefits of gene studies are discussed. Then, the *Data* section explains what data is used and provides more knowledge about gene studies. Further, the results are presented in the corresponding section. Finally, the results and main findings are discussed and limitations of the study and suggestions for future research are addressed.

Theoretical Framework

For the last decade BMI has been steadily rising and obesity levels are higher than ever recorded (Ritchie, & Roser, 2019). A similar trend is present in the research field, as the topic of the effect of weight on life satisfaction, self-esteem, and productivity and co-existing costs has been widely studied in the last decade. For example, Forste and Moore (2012) show lower life satisfaction among overweight and obese adolescents, relative to their normal-weight counterparts. Moreover, the research also find that most of the negative association operates through perception of self, peers, parents, and school. Though there was no gender difference in associations between weight and perceptions, the effect is found to be stronger for women. Also, a study concerning young Australian women shows that obese women are less likely to aspire further education and that they generally are less satisfied with their career or work, partner or closest relationship, social activities, and family relationships compared to women in healthy-BMI categories (Ball, Crawford, & Kenardy, 2012). To continue, Strine, Chapman, Balluz, Moriarty and Mokdad (2007) find a strong, negative association between obesity and life satisfaction. In addition, and perhaps more importantly, the study also finds that life satisfaction is negatively associated with the chance of having asthma, diabetes, arthritis, and heart disease. In addition, Renzano, Wooden and Houng (2010) find that healthy-weight ranged individuals have higher health related quality of life scores (HQoL) than their overweight counterparts. Furthermore, they illustrate that, among the overweight and obese population, physical and mental HQoL scores generally decline with BMI. Interestingly, women reported lower levels of HQoL, on average, compared to men. This indicates a possible link to society's thin ideal and perception of weight, as will be touched upon in the next paragraph. They also show that losing weight can relieve these adverse effects. A four double-blind randomized control trails found that moderate weight loss is associated with noticeably improved HQoL, for obese individuals. Thus, established literature shows a negative relationship between the larger percentiles of BMI and life satisfaction. This provides evidence for the first hypothesis:

Hypothesis 1: "There is a negative relation between Body Mass Index and life satisfaction."

As has already been briefly touched upon earlier in this paper, Forste and Moore (2012) discuss that the relationship between weight and life satisfaction is mediated by perception of self and others. In that light, Strauss (2000) finds that there is no difference in self-esteem scores among 9-to-10-year-old obese and non-obese children. However, in the 4-year follow-up study, obese Hispanic females and obese white females showed significantly decreased levels of self-esteem compared to their non-obese counterparts. Similarly, Tiggemann (2005) finds that there is no relation between BMI and self-esteem at the age of 14, but by the (average) age of 16, heavier girls had lower self-esteem. This suggests a difference in perception of self and/or society for teenagers compared to younger children. Supported by the "thin ideal" as addressed by Klaczynski, Goold and Mudry (2004), it is established that women and girls in postmodern societies are bombarded with messages from the media, parents, and peers that the ideal body is one that is extremely thin. In combination with the Western sense of individualism, the individual itself is to be considered fully responsible for failing to adhere to this body standard. Surprisingly, in their study among undergraduate university students, there is no relationship found between being overweight and self-esteem. However, a negative correlation is found between self-esteem and anti-fat attitudes, negative stereotypes of the obese, and thin idealization. Additionally, Needham and Crosnoe (2005) find a significant relation between BMI and symptoms of depression. However, for female and younger individuals only, again creating the link between different levels of social "fat shaming". They state that the relation is partly mediated through the internalization of others' negative perceptions of themselves, the stress of dieting as an attempt to fit the norm, and a decline in physical health. In the same light, Strauss (2000) establishes that said lower levels in self-esteem result in higher rates of sadness, loneliness, and nervousness. Combining aforementioned theories, this leads to the second hypothesis:

> Hypothesis 2: "There is a positive relationship between Body Mass Index and depressive symptoms."

With respect to productivity at the workplace, Gates, Succop, Brehm, Gillespie and Sommers (2008) find that (severely) obese individuals (i.e. BMI >= 35.0) are significantly less productive compared to healthy-weight individuals. The job types affected most were those with time and physical demands, contrary to the interpersonal and output-related demands, that were not significantly affected by obesity. It is worth noting that physical limitations were of larger concern for plant-based workers compared to office-based workers. Together with the increases in medical costs, work-related productivity losses have a substantial economic impact on society (Lal, Moodle, Ashton, Siahpush, & Swinburn, 2012; Finkelstein, DiBonaventura, Burgess, & Hale, 2010; Hammond, & Levine, 2010). Therefore, reducing obesity can generate positive (non-personal) externalities. With regards to the second part of the research, Judge, Bono, Erez and Locke (2005) find that, in turn, individuals with a more positive sense of self are more likely to pursue their goals. Moreover, to establish the causal effect of self-esteem on life attainment, Kammeyer-Mueller, Judge and Piccolo (2007) show that self-esteem has a positive effect on occupational prestige and income. However, career outcomes did not affect self-esteem. Together, this creates the third and fourth hypothesis, respectively:

> Hypothesis 3: ´Life satisfaction has a positive effect on life attainment."

> Hypothesis 4: "Having depressive symptoms has a negative effect on life attainment."

Combining these four hypotheses, this gives rise to the fifth and last hypothesis:

Hypothesis 5: “There is a negative relationship between Body Mass Index and life attainment.”

Methodology

The general, graphical outline of the research can be found in *Figure 1*. Ultimately, the interest is in the mediator effect of mental health between BMI and life attainment. This paper will use two methods: Ordinary Least Squares (OLS) regression and Instrumental Variable (IV) regression. Performing Ordinary-Least-Squares regression does not allow for causal interpretation of the coefficients. The coefficients can solely be interpreted as an association between the variables. On the other hand, performing an instrumental variable analysis can estimate a causal relationship between variables. To analyse the relationships in this paper, an IV approach is considered when working with independent variables for which a corresponding polygenic score (PGS) is available in the HRS Documentation Report (2018) (See *Figure 1*). More information regarding the dataset is provided in the *Data* section. Using polygenic scores as instruments allows for establishing causal relationships between variables through an IV-analysis, instead of sole association. This aids the aim of the research. However, due to a lack of polygenic scores available for some variables of interest, the IV-method cannot be applied for all. In those case, an OLS regression will be performed.

Assumptions

For the IV-regression to be valid, a set of assumptions is required to hold. As an example, the IV-method for exploring the relationship between BMI and depression is analysed below. Incorporating the polygenic score for BMI, it operates as an instrumental variable to analyse the causal effect of BMI on mental health. The methods are applied in similar ways as is done by Didelez and Sheehan (2007), as the same phenomenon of *Mendelian randomization* can be applied using polygenic scores as the instruments. As presented in the paper, there are three core conditions that need to hold to obtain unbiased causal interpretation of the coefficient: The relevance assumption, the independence assumption, and the exclusion restriction. The first assumption is related to the first stage of the method (i.e. the relationship between PGS of BMI and actual BMI) and states that PGS of BMI and BMI must be related. Note that this does not have to be a causal relationship and can also be mediated through other variables. The stronger the relation, the better. This assumption can be tested by running a simple linear regression between the instrument and the independent variable. The results are presented in *Appendix 5A* and *B*.

The second core condition is exogeneity. There must be no relation between the instrument and confounder U that confounds the relationship between the independent variable and the outcome (Didelez, & Sheehan, 2007). This assumption is reasonably met, given that genes are *per se* exogeneous. Also, though the variables are self-reported, non-random measurement bias seems unlikely for height and weight given the professional nature of the survey. However, the answer regarding mental health are, despite their binary nature, highly subject to the moment of asking the question, but this could tip the scale either way. The life attainment variables are more official in nature, making them more robust, and thus limiting measurement errors. A last criterium is that there should be no simultaneity, meaning that the outcome simultaneously affects the independent variable. This assumption can be tested, because there are polygenic scores available for the dependent variables of this study. The findings are discussed in the *Results* section. Generally, the exogeneity assumption remains a critical limitation to the internal validity of this study.

A third assumption of this method is the exclusion restriction, that entails that the outcome is affected by the instrumental only through the independent variable of interest and not through other variables. Applied to the second hypothesis, this would mean that the BMI genes only affect mental health through its effect of BMI, and no other traits (Didelez, & Sheehan, 2007). Concerns regarding the validity of this assumption are present, i.e. there is a risk of horizontal pleiotropy. Horizontal pleiotropy occurs whenever the associated genes also affect the outcome through another but the pathway of interest (Verbanck, Chen, Neale, & Do, 2018). Genomic regions exerting pleiotropic effects on cardiovascular disease risk (CVD) factors are found, of which a few include obesity (Rankinen, Sarzynski, Ghosh, & Bouchard, 2015). This indicates that there is a causal relationship between BMI genes and CVD. Further, many studies agree that depressions likely arise as a result of cardiovascular disease, specifically coronary artery disease (CAD), but also see depression as an independent risk factor in the pathophysiologic progression of CVD (Zellweger, Osterwalder, Langewitz, & Pfisterer, 2004; Musselman, Evans, & Nemeroff, 1998). Both studies combined creates a causal pathway between BMI and mental health, but now through CVD instead of BMI. Additionally, genetic pleiotropy is also present in depression and CAD (De Geus, 2006), and it seems plausible that heart disease affects one's ability of attaining life goals and can limit options and opportunities. Moreover, the high covariation between obesity and asthma is predominantly caused by shared genetic risk factors for both conditions (Hallstrand et al., 2005). In turn, asthma, but especially dyspnoea, the waking at night with asthma symptoms, and morning symptoms, is significantly associated with depression (Goldney, Ruffin, Wilson, & Fisher, 2003). Evidently, there are other pathways, next to the pathway of interest, between the BMI PGS and depression (i.e. outcome in hypothesis 2). To partly control for this, a binary variable for a history of heart disease is added to the reduced form. With this control variable included, part of the bias is filtered out. Another critical control is that of the 10 principal components, a sample of eigenvectors that function as covariates in association testing in this paper. Adding them to a model adjusts for possible population stratification. A study is said to have population stratification when cases and controls have different allele frequencies attributable to diversity in background population, unrelated to outcome status (Cardon, & Palmer, 2003). This control is common practice in gene studies.

Note: the same assumptions need to hold when exploring the other causal relationships. That is, for relationships between variables of which the independent variables have a polygenic score available. This can be observed in *Figure 1*.

Additionally, the OLS method requires four conditions to hold: Linear relation, statistical independence, no autocorrelation, and homoskedasticity. Autocorrelation will not be discussed, as that does not apply to the data for this paper. Firstly, the linearity assumption will be discussed. The OLS regression allows for linear interpretation of the coefficients. This condition can be evaluated by creating a scatter plot of the dependent and independent variable. The scatterplots for hypothesis 3 and 4 (i.e. the hypotheses that apply linear regression analysis) are shown in *Appendix 3* and do not violate the assumption. Secondly, multivariate normality is assumed and required for the dependent variables. This condition is checked by creating histograms of the variables of interest (*Appendix 4*). Evidently, *age* and *BMI* are rather normally distributed. On the contrary, *earnings* has many high-value outliers and many observations equal to 0. By taking its natural logarithm, the data is more normally distributed as it reduces the outliers and excludes the no-income observations. The latter, of course, needs to be considered when drawing conclusions. Thirdly, the data must not be heteroskedastic, meaning that the error term must not be correlated to the independent variable. This error is statistically controlled for when running the model in STATA by adding ",robust" to the regression. Lastly, for statistical independence the Conditional Independence Assumption (CIA) needs to hold. This assumption is falsified if there are omitted variables other than the variables that are controlled for in the model, that are both related to BMI (i.e. the independent variable) and the mental health score (i.e. the dependent variable). Similar to the independence assumption for the two-stage-least-squared (2SLS) method, this assumption rarely ever holds in reality, and therefore also remains a major limitation for the interpretation of these coefficients.

Even though the mental health variables are either dummies or a sum of a set of dummy variables and they represent the dependent variables for the first part of the research, a(n) (ordered) probit model would therefore be more suitable. However, to stay consistent within the paper and to allow for similar interpretation of the regression coefficients, an OLS model is preferred. For completeness and to check for bias due to omitting information, additional probit models are fitted when testing relationships with dependent variables of a binary or categorical nature. The results can be found in *Appendix 6*. More detailed results are discusses in the corresponding section, but using OLS over probit is not problematic.

Implementation

The instrumental variable method is applied and an example set-up is provided for the second hypothesis (i.e. the effect of BMI on depression). For hypothesis 1, a similar method is applied with the positive mental health indicators as the outcome variable. Hypothesis 4 also follows similar steps, now with PGS of depressive symptoms and depression as the instrument and independent variable, respectively, and the life attainment proxies as dependent variables. The variables will be explored more in depth in the *Data* section. The first stage will be in the form presented below:

$$(1) \qquad BMI_i = \gamma_{BMI} * BMIscore_i + \mu_1 X + \varepsilon_i,$$

Where *BMIscore*$_i$ represents the PGS of individual *i* with respect to BMI, γ_{BMI} is the corresponding coefficient, ε_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_1: age and the ten principal components for identifying population group outliers. The first stage is used to find the predicted values of BMI, which are then used in the second stage:

$$(2) \quad Mental\ health\ score_i = \beta_{MENTALHEALTH} * \widehat{BMI}_i + \mu_2 X + e_i,$$

Where *Mental health score*$_i$ represents the sum of eight binary mental health indicators for each individual *i*, $\widehat{BMI}_i$ are the predicted value of BMI obtained from the first stage, $\beta_{MENTALHEALTH}$ is the corresponding coefficient, e_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_2: age, a binary variable for heart disease, and the ten principal components.

Similar methods are applied when analysing the effect of BMI on life satisfaction (i.e. hypothesis 1). The second part of the research takes on similar methods of using polygenic scores as an instrument to estimate the relationship between mental fitness and educational- and career attainment. However, polygenic scores are only available for having depressive symptoms, not for life satisfaction. Hence, a 2SLS will be implemented for researching the relationship between depressive symptoms and both education and career attainment (i.e. hypothesis 4), while linear regression analysis is applied for the testing of the relationship of life satisfaction on life attainment (i.e. hypothesis 3), due to the unavailability of PGSs for life satisfaction. For the fourth hypothesis, the first stage is represented by the following:

$$\text{(3)}\quad Mental\ health\ score_i = \gamma_{Depression} * Depressionscore_i + \mu_3 X + \upsilon_i,$$

Where *Depressionscore*$_i$ is the PGS for depressive symptoms for individual *i*, $\gamma_{Depression}$ is the corresponding coefficient, υ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_3 : age and the ten principal components. The second stages (one for each proxy of career attainment and educational attainment, respectively) are illustrated below. Note that the analysis is performed only for the currently working in the dataset:

$$\text{(4)}\quad Earnings_i = \beta_{EARNINGS} * Mental\ \widehat{health}\ score_i + \mu_4 X + \Delta_i,$$

Where *Earnings*$_i$ is the total income of individual *i*, $Mental\ \widehat{health}\ score_i$ represents the predicted values obtained from the first stage, $\beta_{EARNINGS}$ is the coefficient of interest, Δ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_4: age, a binary variable for heart disease, and the ten principal components.

$$\text{(5)}\quad Number\ of\ jobs_i = \beta_{NUMBEROFJOBS} * Mental\ \widehat{health}\ score_i + \mu_5 X + \sigma_i,$$

Where *Number of jobs*$_i$ is the total number of jobs of individual *i* has had in his career, $Mental\ \widehat{health}\ score_i$ represents the predicted values obtained from the first stage, $\beta_{NUMBEROFJOBS}$ is the coefficient of interest, σ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_5: age, a binary variable for heart disease, and the ten principal components

$$\text{(6)}\quad Level\ of\ education_i = \beta_{LEVELOFEDUCATION} * Mental\ \widehat{health}\ score_i + \mu_6 X + \theta_i,$$

Where *Level of education*$_i$ is the highest obtained level of education of individual *i*, $Mental\ \widehat{health}\ score_i$ represents the predicted values obtained from the first stage, $\beta_{LEVELOFEDUCATION}$ is the coefficient of interest, θ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_6: age, a binary variable for heart disease, and the ten principal components

$$\text{(7)}\quad Years\ of\ education_i = \beta_{YEARSOFEDUCATION} * Mental\ \widehat{health}\ score_i + \mu_7 X + \sigma_i,$$

Where *Years of education*$_i$ is the total number of years individual *i* followed education, $Mental\ \widehat{health}\ score_i$ represents the predicted values obtained from the first stage, $\beta_{NUMBEROFJOBS}$ is the coefficient of interest, σ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_7: age, a binary variable for heart disease, and the ten principal components

To establish the relationship between the remaining variable (i.e. life satisfaction) and life attainment, simple linear regressions will be performed. There are several ways to operationalize life satisfaction. The example presented below used the proxy of the sum of the two positive indicators of the general mental health score. Similar control variables are added as with the instrumental variable methods and the form is presented below:

$$(8)\quad Earnings_i = \beta_{EARNINGS} * Satisfaction_i + \mu_8 X + \tau_i,$$

Where *Earnings*$_i$ holds the same value as specified before, *Satisfaction*$_i$ is the sum of the two positive indicators of the general mental health score for individual *i*, $\beta_{EARNINGS}$ is the coefficient of interest, τ_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_8: age, a binary variable for heart disease, and the ten principal components. Equations (9), (10), and (11) are the remaining linear regressions that are performed for the other three proxies for life attainment. They follow the same structure and are deducted from (5), (6), and (7), respectively, in similar style as has been done when deducting (8) from (4).

Lastly, hypothesis 5 tests the causal effect of BMI on life attainment. Using similar methods as applied for hypothesis 1,2, and 4 (i.e. combining (1) and (4)-(7)).

Control

One of the critical advantages of a 2SLS over an OLS regression is that the former enables the obtained regression coefficient to be interpreted as a causal relations, compared to sole associations, given all assumptions hold. An important assumption is the absence of reverse causality, which holds when the independence assumption is verified. Utilizing the polygenic scores for educational attainment and depressive symptoms, a *reverse 2SLS* can be conceptualized. Again, assuming the assumptions for the instrumental variable hold, the 2SLS should not give significant results. In case of significant results, the no-reverse-causality condition of the original test is violated and no conclusions regarding causality can be drawn. For clarifying purposes, the step-by-step method is presented for the reverse causality of depression on BMI, below. A similar method is applied for the second stage (i.e. between educational attainment and mental health). Note, (12) is the same as (3) and simply represents the first stage of an instrumental analysis. Now, the second stage, i.e. (13), differs.

$$(12) \qquad Mental\ health\ score_i = \gamma_{Depression} * Depressionscore + \mu_{12}X + \upsilon_i$$

$$(13) \qquad BMI_i = \beta_{CONTROLBMI} * Mental\ \widehat{health}\ score_i + \mu_{13}X + \varsigma_i$$

Where BMI_i is the total income of individual *i*, $Mental\ \widehat{health}\ score_i$ represents the predicted values obtained from the first stage, $\beta_{CONTROLBMI}$ is the coefficient of interest, ς_i is the error term, and X represents the constant and the control variables with their corresponding coefficients, collectively represented by μ_{13}: age, a binary variable for heart disease, and the ten principal components

Data

Sampling

Basis to this paper is the IV-method to establish causal relationships. This will be done using data from the Health and Retirement Study (HRS) (2018), a longitudinal household survey conducted in the United States, and will combine two publicly available datasets. The RAND HRS Longitudinal File, containing data on 12 survey sessions, or *waves*, completed by 37,495 individuals between 1992 and 2014, is merged with Polygenic Score Data, containing polygenic scores (PGSs) for a variety of phenotypes for HRS respondents who provided salivary DNA between 2006 and 2012, and considered for this research. Variables of interests for this research are BMI, overall mental health score (i.e. the sum of 8 mental health factors), satisfaction (i.e. the sum of the two positive factors for the overall mental health score), dissatisfaction (i.e. the sum of the six negative factors for the overall mental health score), years of education, highest obtained level of education, earnings, number of jobs. These longitudinal variables are obtained from the RAND HRS Longitudinal File. The genetic scores for BMI, Depressive Symptoms, and Educational Attainment are retrieved from the Polygenic Score Data.

The 10 principal components are gathered from the HRS files as well. More generic control- or filter variables are age, gender, industry type, a binary variable for currently working, and a binary variable for having a history of heart disease (i.e. the value of the dummy equals 1 if so, and 0 otherwise). Those are obtained from the RAND HRS Longitudinal File. Lastly, the sample is limited to respondents from European ancestry only, again to limit population stratification.

Polygenic Scores

This research primarily utilizes two sets of SNPs: One for BMI and one for wellbeing. SNPs refer to a specific part of the DNA strand at which two different nucleotides are present in the population (Rietveld, 2019). However, individual SNPs generally only explain about 0.02% of the variance in behavioural outcomes (Rietveld, 2019). Therefore, PGSs will be used instead (see computation below).

Firstly, PGSs for BMI are created using results from a 2015 Genome-wide association study (GWAS) conducted by the Genetic Investigation of Anthropometric Traits. GWAS meta-analysis was performed on a sample of 234.069 individuals. A total of 97 SNPs were reported as genome-wide significant. Secondly, for the analysis for the Subjective Wellbeing PGSs, data is obtained from the 2016 GWAS conducted by the Social Science Genetic Association Consortium. It includes 298.420 European ancestry individuals. Approximately 9.3 million SNPs are included. Adjustments for age, age-squared, sex, and population stratification are included in study-specific GWAS association analyses. Three loci are identified as genome-wide significant. Using all divergent SNPs, a polygenic score is computed. The polygenic score is the sum of the weighted average of the coefficients from the GWAS meta-analyses files corresponding to the phenotype of interest. As per definition by Rietveld (2019), a SNP is defined as a location in the DNA strand at which two different nucleotides are present in the population. Each of the two possible nucleotides is called an allele for that SNP. In case of negative coefficients, the value was converted to its corresponding positive value, and the reference allele is flipped to represent phenotype-increasing PGSs (Okbay, et al., 2016). The formula below illustrates the computation of the polygenic scores:

$$PGS_i = \sum_{j=1}^{J} W_j G_{ji},$$

where *i* represents an individual (*i*=1 to N), *j* is SNP (*j*=1 to J), W_j is the meta-analysis effect size for SNP *j* and G_{ji} is the genotype, or the number of reference alleles (zero, one, or two), for individual *i* at SNP *j*. *Table 1* describes the polygenic-score variables.

Table 1: Descriptive statistics for the polygenic scores (raw data)

Polygenic Scores	N	Mean	Std dev.	Minimum	Maximum
BMI	12,090	0	1	-3.636	4.078
Depressive Symptoms	12,090	0	1	-3.848	3.667
Educational Attainment	12,090	0	1	-3.688	3.801

Longitudinal data

Next to polygenic scores, longitudinal data of the RAND HRS Longitudinal File 2014 is utilized. The data is gathered in biennial *waves*, *Wave 1* being in 1992. This paper uses the most recent *wave* available, being that of 2014 (University of Michigan, Institute for Social Research, 2017). Firstly, BMI is measured in metres per kilogram squared. Beginning in *Wave 3*, the height and weight is asked of the respondents. For further waves, and thus also for the 2014 Wave, the height is taken from previous waves and only weight is asked for again. Secondly, the overall mental health score is computed by the sum of the value of the negative indicators and (1 – the value of the positive indicators), each measuring an individual's mental condition over the course of past week prior to answering the survey. Moreover, *dissatisfied* represents only the sum of the negative indicator scores and is used as a second proxy. Thirdly, life satisfaction is proxied by both aforementioned positive indicator scores individually and their sum (i.e. *satisfied*), that tracks whether respondents enjoyed life for most of the time over the course of the past week and whether they were happy. Fourthly, educational attainment is measured by the total years of education and the highest degree obtained. The highest degree is a categorical variable ranging from no degree (=0) to Law/MD/PhD (=7) and other (=8). Note: Respondents entering from *wave* 8 onwards with a Law/MD/PhD are included in the "other" category. Since this number was insignificantly few (i.e. 21 out of a total of 37,495 observations), the two categories are merged, obtaining both the value 7. Fifthly, career attainment is operationalized by earnings, controlled for by industry type. Industry type is a categorical variable that ranges from values 1 to 19 (*Appendix 1*). Earnings are measured by the sum of the respondent's wage/salary income, bonuses/overtime/pay commission/tips, income from a possible second job or military reserve earnings and professional practice or trade income. Because the variable has many high-value outliers (i.e. extremely right-skewed distribution), the natural logarithm is computed and used in the regression analysis. Since respondents without income are removed from the sample, the analysis is only on respondents with income. Another proxy for career attainment is the number of jobs one has practiced, as it is shown that highly mobile-career employees are generally more successful (Lam,

& Feldman, 2012; Lam, & Dreher, 2004). Lastly, a dummy variable is considered as an indicator for a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems sometime in the past. Lastly, the study will differentiate for gender. The variable *Sex* holds the value 1 for male respondents and 2 for female respondents. According to common practice, missing observation are removed from the sample, and will therefore not be considered in the analysis. *Table 2* gives an overview of the longitudinal variables used in the models and *Table 3* summarizes the control variables. Only 4.4% of the respondents is currently working. Given that the data is a retirement study, this is not surprising. However, it can be problematic because of too small sample sizes.

Table 2: Descriptive statistics of the longitudinal variables (raw data)

Variables	N	Mean	Std dev.	Minimum	Maximum
BMI	9,166	28.023	6.002	11	76.6
Overall mental health	8,939	1.269	1.883	0	8
Dissatisfaction	8,884	1.064	1.517	0	6
Satisfaction	8,908	1.797	0.538	0	2
Level of education	12,090	2.932	1.830	0	7
Years of education	12,060	13.264	2.529	0	17
Earnings	9,259	16,388.16	43,839.11	0	1,000,000
logEarnings	2,895	10.252	1.327	2.302	13.82
Number of Jobs	9,259	2.644	1.684	0	12

Table 3: Descriptive statistics of the control variables (raw data)

Variables	N	Mean	Std dev.	Minimum	Maximum
Age	12,090	78.197	11.939	39	114
Industry	2,307	10.860	4.929	1	19
Currently working	9,169	0.044	0.206	0	1
Heart disease	12,090	0.224	0.417	0	1
Sex	12,090	1.570	0.495	1	2

Principal Components

Principal component (PC) analysis is performed to identify population group outliers and to provide sample eigenvectors as covariates in the statistical model used for association testing to adjust for possible population stratification. Population stratification is a threat to the validity of genetic association studies and GWAS are not immune to it (Uitterlinden, Zillikens, & Rivadeneira, 2013). Controlling for PCs resolves this problem. Description of the PCs are presented in *Appendix 2.*

Results

Part one: Effect BMI on Mental Health

Basis of the analysis is a strong correlation between the BMI SNP and actual BMI. This, namely, is the first stage of the two-stage-least squares regression analysis that is used for both the first and second hypothesis. As evident from *Appendix 5A*, the first stage for the 2SLS regression is sufficiently strong, and the relevance condition is thus satisfied. The same can be concluded for the first stage for hypothesis 4 (*Appendix 5B*). *Tables 4-15* illustrate the results for the second stages of the 2SLS-regressions and the OLS-regressions. For each hypothesis separately (except for 1 and 2), three tables present the corresponding findings for the pooled sample, men only, and women only, respectively. *Table 16* presents the results of the second-stage of the control-regressions. The coefficients should be interpreted as the following: A positive (negative) coefficient represents a positive (negative) relationship between the two variables. If the independent variables increases its value by 1, then the dependent variable increases (decreases) by the absolute value of the coefficient. Only for hypothesis 3, 4, and 5 where log(earnings) is the dependent variable, an increase in the value of the independent variable leads to an percentual increase (decrease) in earnings of β*100%. Specifically, the coefficient in the 2nd row 7th column of *Table 13* (i.e. -0.170) indicates that an increase in BMI by 1, leads to a decrease of 17.0% in income.

The first hypothesis states that life satisfaction decreases with BMI. *Table 4* shows the results of the pooled sample. Neither of the life-satisfaction proxies provide significant results. Though not significant, the sum of both individual scores (i.e. *satisfaction*) has the lowest p-value. Interestingly, though still insignificant, the relationship is stronger for female individuals. Moreover, the coefficients for all three proxies were positive for males (*Table 5*) and negative for females (*Table 6*), possibly indicating upon an interesting distinction. Further research with a more thorough operationalization for life satisfaction is required to improve the final verdict about the strength of the relationship between BMI and life satisfaction, with respect to gender roles specifically. This concludes that the first hypothesis is rejected, as there is no significantly strong effect measured.

The second hypothesis states a positive relationship between BMI and depression. As evident from *Table 4*, the regression coefficient is positive and significant at a 1% significance level for both the total mental health score and dissatisfaction. This indicates that there is evidence to support an increase in likelihood of having a depression by BMI. Thus, hypothesis 2 is not rejected. However, the gender specific findings (*Table 5 and 6*) reveal that there is no significant relationship between BMI and mental health for men, but for women only. Therefore, there is evidence in favour for the second hypothesis for women, but the hypothesis is rejected for men.

Notice that the findings for the OLS model rather similar to the results of the (ordered) probit model (*Appendix 6*); The sign of the effect remains unchanged, the same relationships are significant, and the magnitude of effects has not changed significantly. Thus, the OLS method is deemed suitable and does not pose a threat to the credibility of the results.

Table 4: Pooled Regression Results between BMI and the Five Mental Health Proxies

	Felt happy	Enjoyed life	Satisfaction	Mental health	Dissatisfaction
BMI	-0.002	-0.002	-0.004	0.045***	0.042***
	(0.002)	(0.002)	(0.004)	(0.013)	(0.011)
Constant	0.881***	0.921***	1.807***	-0.070	-0.308
	(0.090)	(0.075)	(0.147)	(0.506)	(0.414)
Observations	8,919	8,924	8,908	8,939	8,884
R-squared	0.006	0.005	0.007	0.017	0.019

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 5: Regression Results between BMI and the Five Mental Health Proxies, men only

	Felt happy	Enjoyed life	Satisfaction	Mental health	Dissatisfaction
BMI	0.001	0.001	0.002	0.003	0.005
	(0.004)	(0.003)	(0.006)	(0.021)	(0.017)
Constant	0.845***	0.880***	1.725***	1.236	0.985
	(0.144)	(0.116)	(0.230)	(0.789)	(0.650)
Observations	3,667	3,671	3,662	3,676	3,656
R-squared	0.008	0.007	0.010	0.015	0.015

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 6: Regression Results between BMI and the Five Mental Health Proxies, women only

	Felt happy	Enjoyed life	Satisfaction	Mental health	Dissatisfaction
BMI	-0.004	-0.003	-0.007	0.065***	0.062***
	(0.003)	(0.003)	(0.005)	(0.017)	(0.014)
Constant	0.891***	0.931***	1.830***	-0.695	-0.955*
	(0.115)	(0.098)	(0.190)	(0.648)	(0.528)
Observations	5,252	5,253	5,246	5,263	5,228
R-squared	0.009	0.007	0.009	0.025	0.030

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Part two: The effect of Mental Health on Life Attainment

Hypothesis 3 states that there is a positive relationship between life satisfaction and life attainment. As mentioned before, life attainment is split into educational attainment, which is split in level of education and total years of education, and career attainment, which is split into earnings and total number of jobs. Since the combined score *satisfaction* gives most significant results when testing the first hypothesis, this variable is used for the analysis of hypothesis 3. The results of the linear regression models can be found in *Tables 7-9*. The simple regression analysis shows a positive significant relationship between satisfaction and both level of education and total years of education, at a 1% significance level (1% for women, 5% for man). This indicates that individuals with a higher level of life satisfaction are related to higher education attainment. However, the relationship with income and number of jobs, the career-attainment proxies, are not significant, neither for males and females. Thus, there is a relationship between life satisfaction and educational attainment, but not with career attainment. Therefore, hypothesis 3 is partially supported.

Table 7: Pooled Regression Results between Satisfaction and Life Attainment

	Level of education	Years of education	Log(Earnings)	Number of jobs
Satisfaction	0.176***	0.240***	0.084	-0.012
	(0.035)	(0.049)	(0.059)	(0.071)
Constant	4.235***	15.258***	14.681***	0.083
	(0.144)	(0.199)	(0.332)	(0.346)
Observations	8,908	8,882	1,649	2,229
R-squared	0.04	0.045	0.167	0.054

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 8: Regression Results between Satisfaction and Life Attainment, men only

	Level of education	Years of education	Log(Earnings)	Number of jobs
Satisfaction	0.133**	0.195**	1.195*	-0.015
	(0.062)	(0.089)	(0.710)	(0.112)
Constant	3.888***	15.032***	31.177***	0.537
	(0.254)	(0.361)	(2.466)	(0.495)
Observations	3,662	3,652	1.095	1,095
R-squared	0.033	0.033	0.1847	0.049

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 9: Regression Results between Satisfaction and Life Attainment, women only

	Level of education	Years of education	Log(Earnings)	Number of jobs
Satisfaction	0.169***	0.231***	-0.499	0.001
	(0.042)	(0.059)	(0.379)	(0.093)
Constant	4.492***	15.455***	26.657***	-0.304
	(0.173)	(0.236)	(2.127)	(0.488)
Observations	5,246	5,230	1,134	1,134
R-squared	0.062	0.061	0.120	0.075

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

The fourth hypothesis states that depression and life attainment are negatively associated. Again, life attainment is split into educational attainment and career attainment and the same proxy variables are used. With the data on the SNP of Depressive Symptoms available, this hypothesis is researched using a 2SLS regression analysis. The results for the first stage are illustrated in *Appendix 5*. The results for the second stage regressions and the OLS-regressions are presented in *Tables 10-12*. The analysis shows that the effect of general mental health is significant for both the total years of education and highest attained level for level of education, at a 1% significance level. However, if performed per gender, only females show a significant (at 1% significance level) relation between depressive symptoms and educational attainment. Further, a similar (negative) correlation is found using the sum of the six negative mental health indicator scores, now significant regardless of gender. However, mental health has no effect on the number of jobs or income, for either gender. Generally, the fourth hypothesis is rejected for career attainment, only. More research is required to draw conclusions about the effect of mental health on education for men, as half of the proxies show a relation.

Table 10: Pooled Regression Results between (negative) Mental Health and Life Attainment

	Level of education		Years of education		Log(Earnings)		Number of jobs	
Mental health		-0.353*** (0.111)		-0.501*** (0.154)		-0.887 (0.552)		0.017 (0.121)
Dissatisfaction	-0.228*** (0.012)		-0.308*** (0.017)		-0.058 (0.137)		0.001 (0.027)	
Constant	4.879*** (0.127)	5.373*** (0.177)	16.125*** (0.176)	16.828*** (0.247)	29.323*** (1.481)	28.480*** (0.928)	0.077 (0.324)	3.509*** (0.196)
Observations	8,884	12,090	8,858	12,060	2,230	9,169	2,230	9,169
R-squared	0.074	0.048	0.075	0.049	0.150	0.309	0.054	0.011

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 11: Regression Results between (negative) Mental Health and Life Attainment, men only

	Level of education		Years of education		Log(Earnings)		Number of jobs	
Mental health		--0.126 (0.193)		-0.150 (0.270)		-1.385 (0.949)		0.208 (0.206)
Dissatisfaction	-0.242*** (0.021)		-0.339*** (0.032)		-0.323 (0.237)		-0.001 (0.042)	
Constant	4.444*** (0.218)	4.789*** (0.266)	15.819*** (0.303)	16.192*** (0.371)	33.465*** (2.158)	33.007*** (1.369)	0.541 (0.466)	2.557*** (0.289)
Observations	3,656	5,196	3,646	5,182	1,095	3,769	1,095	3,769
R-squared	0.063	0.034	0.065	0.036	0.183	0.320	0.048	0.004

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 12: Regression Results between (negative) Mental Health and Life Attainment, women only

	Level of education		Years of education		Log(Earnings)		Number of jobs	
Mental health		-0.496*** (0.133)		-0.738*** (0.185)		-0.485 (0.678)		-0.092 (0.147)
Dissatisfaction	-0.208*** (0.014)		-0.279*** (0.020)		0.113 (0.163)		-0.003 (0.036)	
Constant	5.141*** (0.155)	5.830*** (0.232)	16.311*** (0.214)	17.369*** (0.322)	25.620*** (2.049)	25.445*** (1.239)	-0.299 (0.452)	4.102*** (0.259)
Observations	5,228	6,894	5,212	6,878	1,135	5,400	1,135	5,400
R-squared	0.085	0.065	0.083	0.065	0.120	0.306	0.075	0.027

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Overall

The overall effect is established using the instrumental variable approach to analyse the relationship between BMI and life attainment. As seen in *Table 13*, this study finds that BMI has a significant negative relationship on level of education and on total years of education, thus on educational attainment in general, at a 1%-significance level. Additionally, there is a significant, positive relationship between BMI and the total number of jobs and earnings, also at a 1%-significance level. This is inconsistent with the literature and the income proxy. It is expected that the number of jobs-proxy, given that the respondents are relatively old, is invalid. As will be touched upon more thoroughly in the *Discussion* section, the career-standards have shifted over time, and number of job transfers perhaps no longer proxies career success for the older demographics. When considering only earnings, there is evidence to support the fifth hypothesis.

Table 13: Pooled Regression Results between BMI and Life Attainment

	Level of education		Years of education		Log(Earnings)		Number of jobs	
BMI	-0.087***	-0.077***	-0.113***	-0.096***	-0.197***	-0.170***	0.039***	0.037***
	(0.011)	(0.012)	(0.015)	(0.017)	(0.054)	(0.055)	(0.012)	(0.012)
Mental health		-0.161***		-0.220***		-0.514***		-0046***
		(0.010)		(0.014)		(0.043)		(0.009)
Constant	8.110***	7.675***	20.314***	19.650***	33.998***	34.208***	2.140***	2.181***
	(0.417)	(0.475)	(0.567)	(0.632)	(2.071)	(2.108)	(0.446)	(0.454)
Observations	12,090	8,939	12,060	8,913	9,169	8,852	9,169	8,852
R-squared	0.052	0.070	0.052	0.070	0.313	0.319	0.013	0.013

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 14: Pooled Regression Results between BMI and Life Attainment, men only

	Level of education		Years of education		Log(Earnings)		Number of jobs	
BMI	-0.104***	-0.095***	-0.137***	-0.120***	-0.239***	-0.224**	0.031	0.025
	(0.018)	(0.020)	(0.025)	(0.027)	(0.087)	(0.089)	(0.019)	(0.016)
Mental health		-0.172***		-0.243***		-0.672***		-0.044***
		(0.018)		(0.026)		(0.073)		(0.016)
Constant	8.441***	7.884***	21.023***	20.134***	39.334***	40.051***	1.701**	1.880**
	(0.674)	(0.775)	(0.931)	(1.035)	(3.321)	(3.374)	(0.723)	(0.742)
Observations	5,196	3,676	5,182	3,666	3,769	3,635	3,769	3,635
R-squared	0.040	0.061	0.041	0.061	0.326	0.336	0.005	0.007

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Table 15: Pooled Regression Results between BMI and Life Attainment, women only

	Level of education		Years of education		Log(Earnings)		Number of jobs	
BMI	-0.075*** (0.014)	-0.065*** (0.016)	-0.095*** (0.018)	-0.082*** (0.021)	-0.155** (0.068)	-0.128* (0.069)	0.045*** (0.015)	0.046*** (0.148)
Mental health		-0.146*** (0.012)		-0.198*** (0.016)		-0.396*** (0.053)		-0.032*** (0.011)
Constant	7.848*** (0.521)	7.527*** (0.596)	19.768*** (0.701)	19.341*** (0.791)	30.038*** (2.630)	30.160*** (2.680)	2.281*** (0.559)	2.201*** (0.567)
Observations	6,894	5,263	6,878	5,247	5,400	5,217	5,400	5,217
R-squared	0.068	0.081	0.066	0.080	0.310	0.312	0.029	0.067

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Now, the mental health score is added to the last model (even column in *Tables 13-15*) to see for a change in effect of BMI. The effect of BMI on life attainment becomes smaller when controlled for the mental health score, but the effect remains significant. From the table, it can be concluded that mental health has a significant, negative effect on life attainment. This is also reflected by the increase in R-squared, indicating that more variation is explained when mental health is considered. Together, this reveals that the effect of BMI is overestimated (i.e. upward bias) and that part of the variance is explained by mental health.

Control

The use of instrumental variables enables conclusions on causation, instead of speaking of a sole relationship or association between variables. This method comes with the assumption that the first stage is a sufficiently strong, showing correlation between the instrument and the dependent variable. Another assumption for using instrumental variables is that there is no correlation between the instrument and other variables. If this holds, there should be no reverse causality between the dependent and independent variable. As explained in the *Methodology* section, a reverse 2SLS can be performed, since gene data on BMI, Depressive Symptoms, and Educational Attainment has been obtained. If the "reverse tests" show significant results, this indicates upon the existence of reverse causality in the "original tests", meaning that the assumption is violated.

The first-stage results can be found in *Appendix 5C* and the second-stage results are presented in *Table 16*. The relevance assumptions are verified. As visible in *Table 16*, the causal effect of mental health on BMI is insignificant, meaning that there is no evidence to reject the exogeneity assumption for the method applied in hypothesis 1 and 2. Similar control is performed for the second part of this research. The causal effect of educational attainment on both the mental health score and satisfaction is significant at 1%. Therefore, there could be reverse causality in the relationship between mental health and educational attainment and possibly between mental health and career attainment, too. This doubts the validity of the PGS of depressive symptoms for the instrumental-variable approach. Hence, causal-relation conclusions cannot be drawn. Thus, the interpretation of the regression coefficients for hypothesis 3 and 4 ought to be altered to association instead of causation.

Table 16: Pooled Control Regression Results

	BMI	Mental health	Satisfaction
Mental health	0.118		
	(0.427)		
Level of education		-0.344***	0.033***
		(0.045)	(0.013)
Constant	36.586***	3.011***	1.525***
	(0.707)	(0.274)	(0.078)
Observations	9,166	8,939	8,908
R-squared	0.048	0.008	0.004

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Discussion

The aim of this study is to analyse the effect of BMI on life satisfaction. As the world-population is getting heavier and has reached its all-time high, it is key that effects of such changes are researched. It is evident from established research that BMI is positively related with mental health problems. This is already a problem itself, because it generates high medical cost for treatment and creates inefficiencies in workforce productivity, but depletion of mental health can also have further (negative) implications for an individual's life. This paper studies the effect of education and career choices and achievements and attempts to answer the main research question: *"To what extent does Body Mass Index have a causal effect on life attainment indicators in a sample of individuals of European ancestry?"* Most relations are established using instrumental variable regression, utilizing PGSs as the instrument, or ordinary least squares regression. The general findings are discussed below.

Firstly, the effect of BMI on mental health is established through the first and second hypothesis. Further, it is found that BMI is associated with negative mental health indicators (e.g. feeling down, feeling lonely, etc.), but there is no relation with positive mental health indicators (e.g. feeling happy, enjoying life). This implies that increased BMI operates as a "dissatisfier" for mental health; Heavier individuals are sad more often, but not less happy. However, this only holds for the female respondents, as the male counterpart of the study showed no relationship between BMI and mental health. This is consistent with existing literature, which shapes the view that not weight itself, but the associations and behaviours attached to it by society are what takes a toll on mental health, instead. Mostly women feel concerned about their weight and "fat shaming" is more dominant in female spheres.

The second part of the research revealed a positive relationship between mental health and life attainment. This seems plausible, because mental stability reduces stress levels and allows for better focus at the workplace, for example. Noticeably, this effect was present regardless of gender. Moreover, feeling mentally stable also positively affects confidence in oneself overall. This, in turn, allows for more ambitious educational goals. However, as is also evident from the literature, especially females are prone to psychological instability in their puberty and young adolescence stage of life. In these stages of life, educational development and course of direction of the life one wants to live are central. Contrary to career development, which primarily starts in a later stage in life.

Also, the general effect of BMI on life attainment is significant. However, the R-squared (i.e. a score that shows the percentage of variance in the dependent variable explained by the independent variable) is approximately just over 0.05 for educational attainment and 0.14 and 0.01 for earnings and number of jobs, respectively, which suggests that BMI only has marginal influence of the total variance of life attainment. However, the R-squared of educational attainment and earnings increase to 0.07 and 0.15, respectively, when controlled for the general mental health score. Together with a simultaneous decrease in the effect of BMI, this indicates that part of the effect of BMI was captured by BMI, but it is actually as a cause of mental health.

This study aims at explaining causal relationships between variables. More specifically, it attempted to examine the causal effect of BMI on life attainment, mediated through mental health. Accordingly, the instrumental variable method is applied according to the Mendelian Randomization method. Though the findings are generally in line with established literature, there are three limitations regarding the internal validity of the study. Firstly, as mentioned in the *Methodology* section, there are many assumptions regarding the applied methods. Only if all hold, the coefficient is unbiased, and one can interpret them as causal. In that section, it becomes evident that, firstly, the independence assumption is posing a critical threat to the internal validity of the method and that this assumption cannot be tested. The control test shows significant results, implying that reverse causality could be present in the second stage of the research (the results were insignificant for the first part). This would falsify the independence assumption and ultimately remove the chance of exploring causal relationships. However, a critical note should be placed: As this control method also applies the instrumental variable approach, these coefficients can also only be interpreted as causal when all assumptions hold, meaning that there is similar bias when interpreting these coefficients as there is for the "main" methods. Secondly, the exclusion restriction is another assumption that cannot be tested, but is probably falsified for this study specifically. Horizontal pleiotropy opens additional pathways between BMI and the dependent variable of interest, causing bias in the coefficients in the section *Results*. Even though a control for heart disease is considered, it is generally impossible to establish and map all pathways and more research in the field of gene studies is required. Thirdly, linear regression is applied for exploring relations when the independent variable did not have a PGS available. This method does not allow for causal interpretation of the coefficients to begin with, but also struggles with the independence assumption of the independent variable. Omitted variable bias is a critical limitation to linear regression models (Heckman, 1979) and reverse causality is too (Kramer, et al., 2002).

Other forms of limitations of this study are found within the dataset and variables. The first is in regard to the way of proxying the mental health scores. In the HRS dataset, the questions in the survey regarding mental health stated the following, to which the respondents had agree or disagree with: "Much of the time during the past week …". This score is limiting in the sense that it is prone to emotional bias depending on the timing of the interview. Also, the score is updated once every two years (i.e. every wave), with is very infrequent compared to the rather limiting timeframe on which the answer to the question is based (i.e. the past week). Further, the binary form is limited because it excludes any form of nuance. Also, by summing the binary indicators, the number of different values is limited. A larger array of scores will probably explain a larger part of the variance and decrease the standard error. Hence, the chances of reaching significant results would be larger. Another limitation comes about from the sampling of the HRS dataset. As depicted by *Table 3*, the respondents ranged between an age of 39 and 114, which is a relatively old sampling group. Society and corresponding norms and values are presumably different now than forty years ago. This implies that societal view towards overweight individuals and the implications on mental health could differ, too. Similarly, education norms and career behaviour have also changed over the course of time, possibly explaining the opposing signs for the effect of mental health on earnings and number of jobs. Lastly, BMI is not a perfect indicator for obesity, as it does not consider body composition (i.e. the percentage of fat vs lean body mass) (Johansson, Böckerman, Kiiskinen, & Heliövaare, 2009). Therefore, very lean individuals could score high for BMI if they have a lot of muscle mass.

Lastly, the main improvement for follow-up research are analysing mental health more thoroughly, improving research on pleiotropy, differentiating for age categories and culture, and choosing another measure for obesity. Firstly, a strong limitation of this study is the rather superficial and binary way of computing mental health scores. An improvement would be to analyse each individual's mental health through a certified general practitioner (GP) or specialist over a longer period of time. Also, individuals could be rated on more indicators than on the 8 that are currently considered for the mental health score. When doing so, introducing a larger scale, for example from 0 to 100, increases the spread of values for mental health status. Generally, a wider spread in independent variables provide more accurate coefficients. This will, thus, improve accuracy for hypothesis 3 and 4. Similarly, the same applies for life satisfaction. Secondly, pleiotropy is a problem that needs additional researching. The occurring of pleiotropy in genes makes that there are additional pathways between the instrument and the outcome. If more of such cases are established, they can be controlled for in the model (as has been done with heart disease). This will remove part of the bias and makes for more accurate coefficients. Thirdly, an interesting continuation of this study would be to redo it for different age groups and environments specifically. Previous literature shows that the norms and values in society and external pressure about fitting in lead the effect of BMI on mental health. Therefore, the follow-up study could see if such norms differ per age category. Moreover, an individual fixed-effects model could be performed by tracking individuals and the findings can be applied to identify the critical indicators for changing societal norms. Lastly, BMI is a sub-optimal measure for obesity, as it does not consider the fat to muscle ratio. Perhaps a better measure would be waist circumference or waist-to-hip ratio. It would be interesting to compare the results of a replication study, using those measures instead, to this study and to check the robustness of the findings.

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Appendix

Appendix 1: Overview of profession categories

Value	Corresponding profession
1	Agriculture/Forest/Fish/Hunting
2	Mining
3	Utilities
4	Construction
5	Manufacturing
6	Wholesale Trade
7	Retail Trade
8	Transport/Warehousing
9	Information
10	Finance/Insurance
11	Real estate/Rental/Leasing
12	Professional/Scientific/Technical Services
13	Management/Admin/Support
14	Educational Services
15	Healthcare/Social Assistance
16	Arts/Entertainment/Recreation
17	Accommodation/Food Services
18	Other Services
19	Active Duty Military

Appendix 2: Description Principal Components

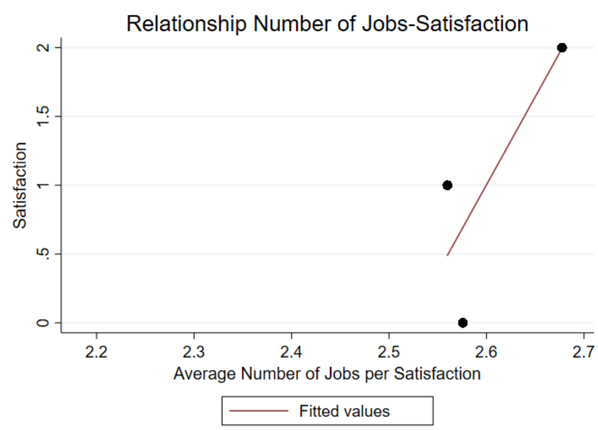
	N	Mean*	Std dev.	Minimum	Maximum
PC1_5A	12,090	0	0.009090	-0.037	0.050
PC1_5B	12,090	0	0.009095	-0.056	0.016
PC1_5C	12,090	0	0.009095	-0.024	0.021
PC1_5D	12,090	0	0.009095	-0.047	0.034
PC1_5E	12,090	0	0.009095	-0.046	0.011
PC6_10A	12,090	0	0.009095	-0.032	0.035
PC6_10B	12,090	0	0.009095	-0.044	0.045
PC6_10C	12,090	0	0.009095	-0.034	0.037
PC6_10D	12,090	0	0.009095	-0.036	0.035
PC6_10E	12,090	0	0.009095	-0.042	0.030

* all smaller than $1*10^{-7}$

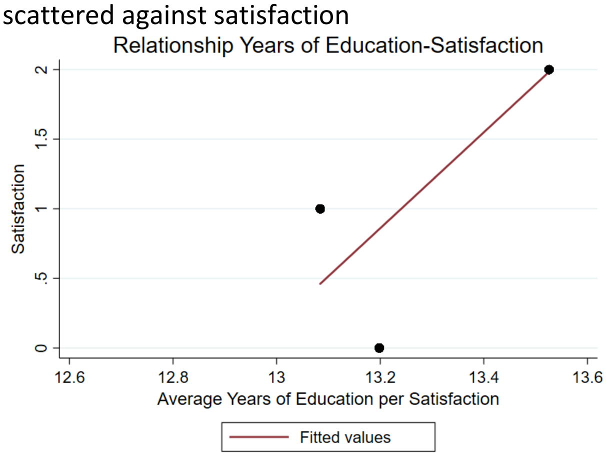
Appendix 3: Scatterplots linearity assumption hypothesis 3 (A-D) and 4 (E-H)

A: Average earnings by satisfaction scattered against satisfaction

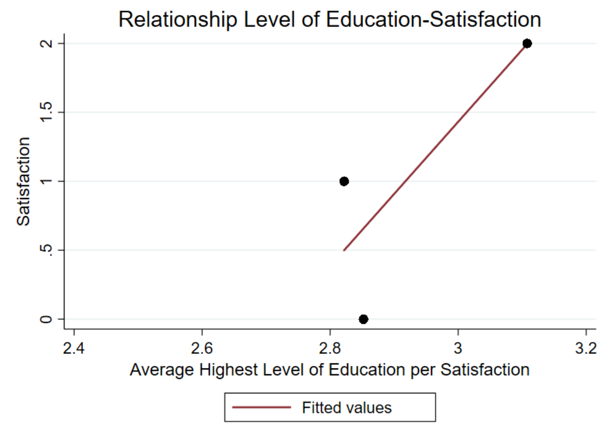
B: Average number of jobs by satisfaction scattered against satisfaction



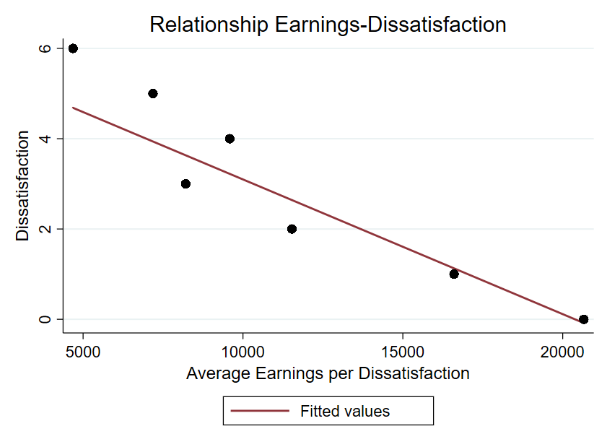
C: Average years of education by satisfaction scattered against satisfaction



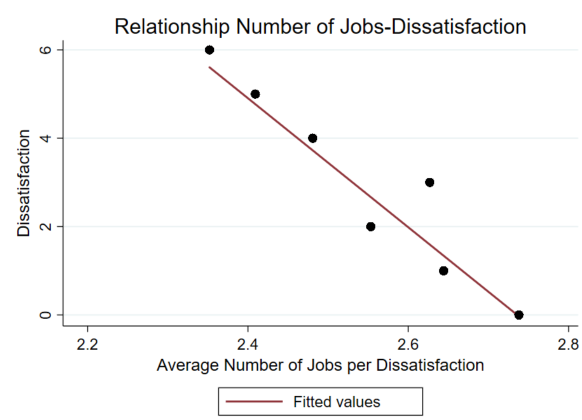
D: Average highest level of education by satisfaction scattered against satisfaction



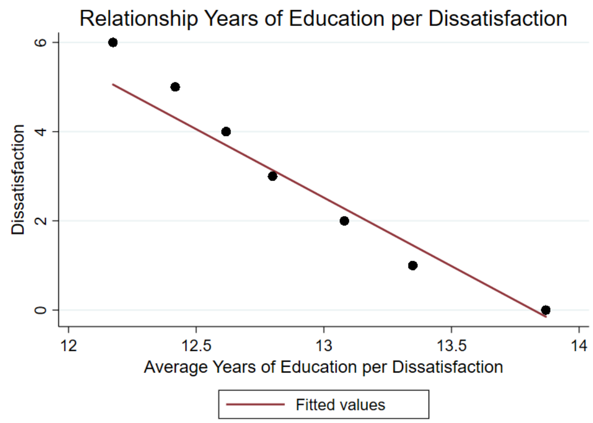
E: Average earnings by dissatisfaction scattered against dissatisfaction



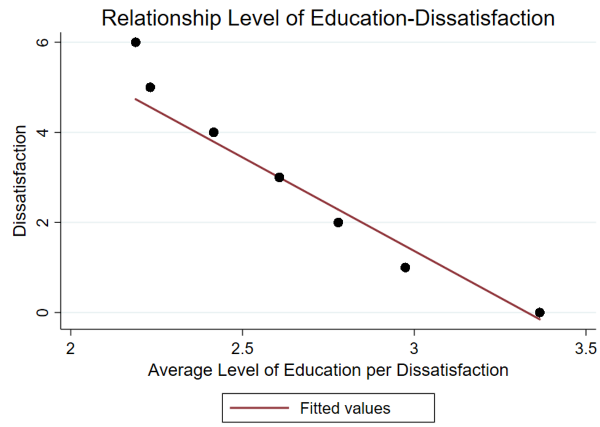
F: Average number of jobs by dissatisfaction scattered against dissatisfaction



G: Average years of education by dissatisfaction scattered against dissatisfaction

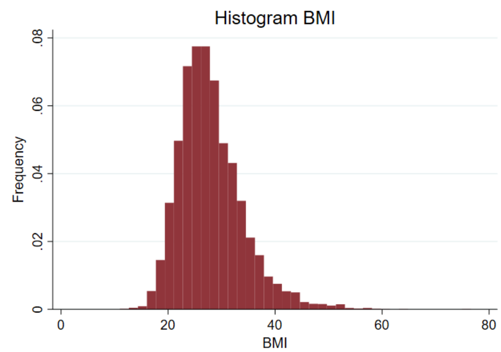


H: Average highest level of education by dissatisfaction scattered against dissatisfaction

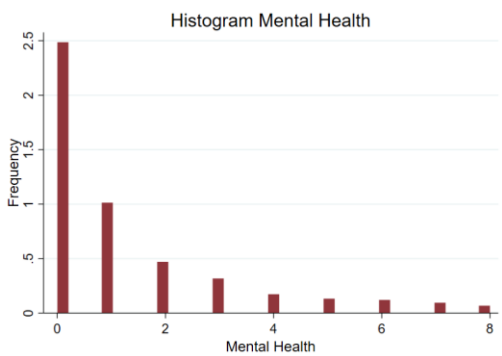


Appendix 4: Histograms multivariate normality assumption

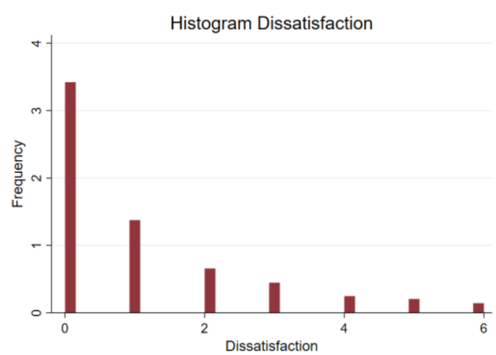
A: BMI



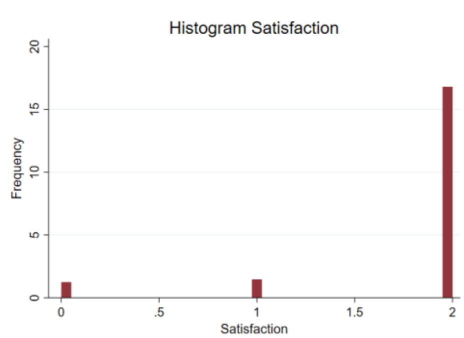
B: Overall mental health score



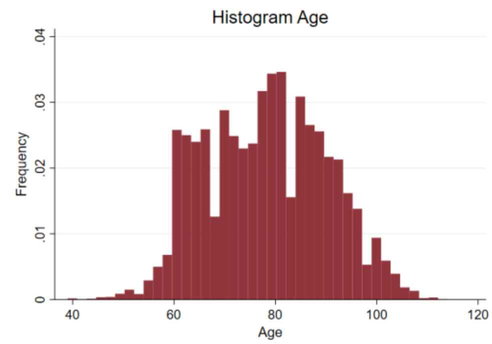
C: Dissatisfaction



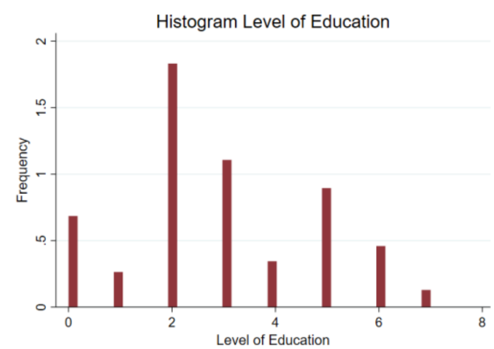
D: Satisfaction



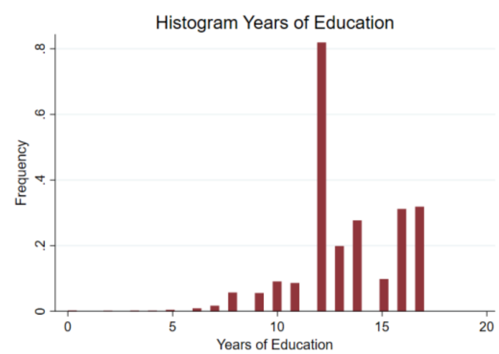
E: Age



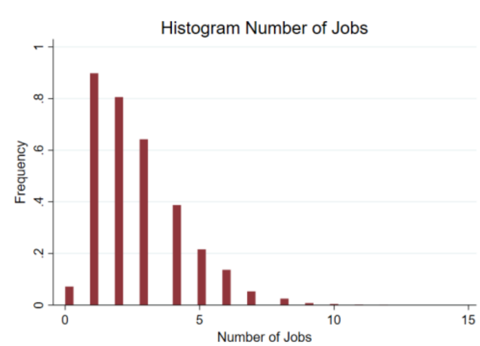
F: Highest level of Education



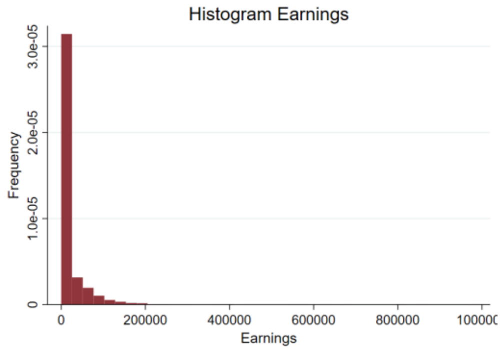
G: Years of Education



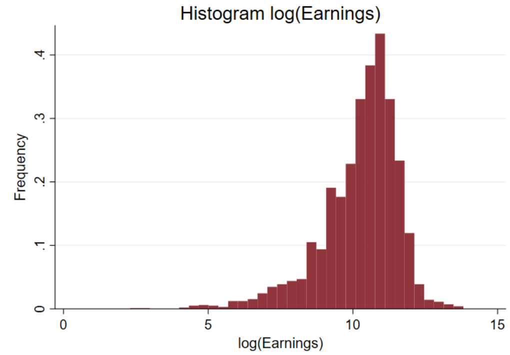
H: Number of Jobs



I: Earnings



J: log(Earnings)



Appendix 5: The results for the first-stages of the two-stage-least-squares regressions

A: Relevance BMI Polygenic Score

	BMI (pooled)	BMI (men only)	BMI (women only)
BMI PGS	1.555***	1.368***	1.684***
	(0.063)	(0.085)	(0.884)
Constant	36.431***	35.868***	36.728***
	(0.419)	(0.582)	(0.575)
Observations	9,166	3,807	5,359
R-squared	0.108	0.110	0.111
F-stat	87.63***	37.59***	53.03***

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

B: Relevance Depressive Symptoms Polygenic Score

	Depressive (pooled)	Depressive (men only)	Depressive (women only)
Depressive PGS	-0.155***	-0.147***	-0.159***
	(0.021)	(0.030)	(0.028)
Constant	1.308***	1.053***	1.462***
	(0.143)	(0.216)	(0.189)
Observations	8,939	3,676	5,263
R-squared	0.008	0.010	0.008
F-stat	5.81***	2.92***	3.52***

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

C: Relevance Control first stages

	Depressive (pooled)	Level of education (pooled)
Depressive PGS	-0.155***	
	(0.021)	
Educational attainment PGS		0.461***
		(0.016)
Constant	1.308***	5.060***
	(0.143)	(0.103)
Observations	8,939	12,090
R-squared	0.008	0.106
F-stat	5.81***	124.76***

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses

Appendix 6: Results *(Ordered) Probit Analysis*

	Felt happy	Enjoyed life	Satisfaction	Mental health	Dissatisfaction
BMI	-0.011	-0.011	-0.014	0.031***	0.033***
	(0.012)	(0.013)	(0.011)	(0.008)	(0.08)
Constant	1.167***	1.383***			
	(0.453)	(0.497)			
Observations	8,919	8,924	8,908	8,939	8,884
Pseudo R-squared	0.008	0.009	0.007	0.006	0.007

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are presented in parentheses