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DISCUSSION PAPER SERIES

IZA DP No. 11605

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ABSTRACT

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Several studies have found a positive association between education and health. Confounding factors that a ect both education choices and health, such as (ob- served) parental background and (unobserved) intelligence, may play an important role in shaping this association. In this paper we estimate the impact of education on diseases in old age, accounting for this endogeneity. Our estimates are based on administrative data on men born in 1944–1947, who were examined for military service in the Netherlands between 1961–1965, linked to national death and medication use records. We assume medication use identifies diseases. We estimate a structural model, consisting of (i) an ordered probit model for the educational attainment, (ii) a Gompertz mortality model for survival up to old age, (iii) a probit model for medication use in old age and, (iv) a measurement system using IQ tests to identify latent intelligence. Educational choices, surviving up to old age and medication use all depend on observed individual factors and on latent intelligence. Based on the estimation results, we derive the impact of education on diseases in old age. Our empirical results reveal a strong effect of education on physical diseases, but low or no effect of education on depression and anxiety.

JEL Classification: I14, I24, C35, C38

Keywords: educational inequality, intelligence, medication use, structural equation model

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* We thank R.J.M. Alessie, V. Angelini, R.D. Freriks, L.H. Lumey and T.J. Wans- beek for their helpful comments. We are grateful to participants of the Public Health Seminar at the University of Groningen, as well as the participants of the EuroCim 2018 meeting in Florence and the EuHEA 2018 conference in Maastricht. Financial support from U.S. National Institutes of Health, grant RO1-AG028593, is gratefully acknowledged.

1 Introduction

A large literature has documented a positive association between education and health. Highly educated people may have higher income, savings and retirement benefits, and consequently high-quality health insurance and healthcare over their lifetime (Lochner, 2011). They may be more efficient producers of health, processing health information methodically and adhering carefully to strict treatment regimens of, for instance, diabetes and HIV (Goldman and Smith, 2002). Also, they may have a balanced diet or be more likely to avoid bad habits, such as smoking or overconsumption of alcohol, being more aware of the risks of unhealthy behaviours. However, to what extent this association between education and health outcomes implies causation is under debate. For instance, intelligent individuals may obtain higher education levels and income, and consequently high-quality healthcare; similarly, being born in a wealthy family may have positive effects on both education and quality of diet. In other words, confounding factors, such as intelligence and parental background, may affect both educational attainment and health outcomes, playing an important role in shaping this strong association (Mazumder, 2008, Clark and Royer, 2013, Fletcher, 2015, McCartney et al., 2013). Given the absence of experimental studies of educational impact on health due to, for instance, ethical issues, two approaches have been adopted to isolate the impact of education on health using observational data: instrumental variable (IV) models, including regression discontinuity (RD) designs, and twin studies.

Twin studies compare health outcomes of twins that differ by education level (e.g., Fujiwara and Kawachi, 2009). The usual assumption in such studies is that educational attainment is not affected by any omitted variable that may drive education choices and health status later in life. The motivation behind this assumption is that twins share the same genes, parental background, similar experiences in childhood, and so on. Results from such studies indicate that part of the educational differences in cause-specific mortality disappears when accounting for shared family background (Lundborg, 2013, Amin et al., 2015). However, there are some limitations in this approach (see, for a discussion, Bound and Solon, 1999). Examples include scarce availability of data on twins, low difference in the education level within pairs of twins and potentially low representativeness of the general population, due to, for instance, lower weight at birth and higher probability of premature birth than singletons.

On the other hand, IV models and RD designs (e.g., Clark and Royer, 2013) usually exploit reforms or laws, namely exogenous variations in the minimum school-leaving age, creating two groups that are either affected or not by the reform. In other words, the higher educational attainment is driven by external rather than confounding factors. The estimates based on these studies point towards a small (Lleras-Muney, 2005) or even entirely absent (Arendt, 2005, Clark and Royer, 2013) causal effect of education on health outcomes. The main drawback of this approach is that only the local average treatment effect (LATE) of higher compulsory education can be estimated, since these reforms affect only those who would otherwise drop out of school at the pre-reform minimum school-leaving age. In principle, no conclusions can be formulated on the causal effect of improving the education level from the returns to higher compulsory education estimated from IV models, since no reforms would increase the compulsory education from, say, high school to university.

An alternative approach, which we will employ, is based on structural models in which the interdependence between education, health, and intelligence is explicitly modelled. Structural models to study the education-health association consist of, at least, three parts: the measurement system, the educational attainment model and the health outcome model. The first part, the measurement system, identifies the distribution of unobserved (latent) variables (e.g., intelligence) that may shape the education-health association, accounting for individual characteristics (e.g., parental background) that affect the measures (e.g., IQ tests) of these (latent) variables. The second part models the educational attainment, accounting for observed and these latent confounding factors. In other words, it controls for the non-random selection into education. The third part estimates the probability of a particular health outcome later in life, for a given education level, controlling for the same confounding factors. From the structural model estimates, the average treatment effect (ATE) of attaining a higher educational level on these health outcomes later in life can be derived. Results from such models (Conti and Heckman, 2010, Conti et al., 2010, Bijwaard et al., 2015a,b) show that at least half of the health disparities across educational groups is due to selection in higher education on individual characteristics such as intelligence and parental background.

An advantage of using structural models is that it is possible to estimate both the average treatment effect of education and the distribution of this treatment effect over latent confounding factors (Conti et al., 2010, Heckman et al., 2014, 2016). A drawback is that this approach, to control for all possible sources of endogeneity, needs a rich number of observed, individual, characteristics as well as a measurement system to identify latent confounding factors. Only a few datasets have information on, for instance, a battery of IQ tests, needed to identify the distribution of latent intelligence.

Many studies on the impact of education on health have been conducted to date, using both structural models and IV and twin studies. On the one hand, most of the IV and twin studies (see Galama et al., 2018, for a literature review) are focused on the impact of education on self-reported health outcomes, main causes of diseases, such as obesity or smoking behaviour, and mortality. On the other hand, structural models are mostly focused on general health outcomes early in life (Conti et al., 2010, Heckman et al., 2014, 2016) or gains in life expectancy (Bijwaard et al., 2015a,b).

To our knowledge, no studies have investigated the impact of higher education levels on diseases in old age using a structural model approach. Specifically, in this paper, we estimate a structural model to derive the ATE of higher education levels on different diseases in old age. Moreover, we compare the ATE with the education and diseases association, as given by the raw data. Finally, we also investigate the distribution of the treatment effect over latent intelligence. The results differ with respect to physical and mental health. After controlling for observed confounding factors and intelligence, we have found that the association between education and physical diseases in old age in the structural model is almost identical to the raw differences. This suggests a strong impact of education on physical diseases. However, the estimates using the structural model for depression and anxiety suggest hardly any influence of education on mental diseases. We have found, for physical diseases, higher gains of education for individuals with low intelligence, while, for depression and anxiety, we have found higher gains of education for individuals with high intelligence.

2 Data and descriptive statistics

Data from a large sample from the nationwide Dutch Military Service Conscription Register for the years 1961 – 1965 and male birth cohorts 1944 – 1947 are analysed. All men were called to a military service induction exam, except those living in psychiatric institutions or in nursing institutes for the blind or for the deaf-mute. The vast majority attended the conscription examination around age 18. We have information from the military examinations for 408,015 men. At the military examination, a standardized recording of demographic and socioeconomic characteristics is collected, including education, father's occupation, place and region of birth, date of birth, religion, family size, and birth order. The individuals who attended special schools for disabled or illiterate (28,711 individuals) and the remaining individuals who did not take all the IQ tests (10,431 individuals) were excluded. Family size, religion or season of birth are not available for 186 of the remaining individuals, which were omitted from the data. The final data amount to 368,687 individuals.

For each individual, the educational attainment at age 18 is observed. The education system in the Netherlands, before the Mammoth Act (1968), was characterized by a minimum school leaving age of 14. All children from age 6 to 12 attended elementary school LO (*Lager Onderwijs*). After that, they could choose among three different options (Haak, 1964) : LVO (*Lager Voortgezet Onderwijs*), MVO (*Middelbaar Voortgezet Onderwijs*), and VHMO (*Voorbereidend Hoger- en Middelbaar Onderwijs*). Children choosing LVO attended further years of education at the same elementary school, until the minimum school-leaving age, entering the job market afterwards with no final examination. Children choosing MVO attended either 3 or 4 years of education in a different school, and a final examination at the end of the program. Attending VHMO was conditional on admission. VHMO students spent either 5 or 6 years in preparation to university and were required to pass a final examination. Final examinations of both VHMO and MVO were almost entirely controlled by the government. We decided to group the individuals in three education levels. The primary level includes LO and LVO; the lower and higher levels correspond to MVO and VHMO, respectively. VHMO also includes those few individuals who were already attending university at age 18. We decided to group LO and LVO together because LVO required neither admission nor final examination nor changing school after the LO level.

Three standardized psychometric test scores were also collected at age 18. The first one is the Raven Progressive Matrices test, an abstract reasoning test which does not depend on language skills and measures fluid reasoning. The second is an arithmetic test and the third is a language comprehension test. The scores are only observed in 6 ordered classes, where 1 and 6 are the lowest and the highest class, respectively. The scores correspond to the following percentile ranks. 1: 0 – 10; 2: 11 – 30; 3: 31 – 50; 4: 51 – 70; 5: 71 – 90; 6: 91 – 99. Table A.1 in Appendix A depicts the distribution of the three IQ test scores by education, among the 368,687 individuals in the data. Not surprisingly, IQ scores increase with education.

Selected demographic and socioeconomic characteristics at the time of military examinations by education level are given in Table A.2 in Appendix A. The general and psychological health evaluations were given by a medical doctor. The urban status of place of birth is defined in five categories: city, urban, urbanized rural, rural, and unknown (Bijwaard et al., 2015b). Rural and unknown are grouped together, forming the category "other", due to small sample size. Father's occupation includes four different categories, ordered from the highest to the lowest level of remunerations and responsibilities: professional, white collar, skilled and unskilled; the fifth category includes individuals whose father's occupation is unknown. Religion was classified, into three categories, as Catholic, Protestant and, grouped together, "other or none". Famine exposure, during the *Hongerwinter*, represents those who were born between November 1944 and March 1946 in the most famine-exposed cities in the Netherlands, namely Amsterdam, Haarlem, Rotterdam, The Hague, Leiden and Utrecht (Ekamper et al., 2014). The reason why famine exposure increases with education is that it implies being born in one the big cities in the Western Netherlands, and men born in these cities have a higher education level.

A subsample of 45,037 of the original sample was linked to the Dutch death register, through to the end of 2014, using unique personal identification numbers. These individuals were originally sampled to study the relation between prenatal famine exposure and mortality (Ekamper et al., 2014). For this reason, all the 25,283 men born in the Western Netherlands, between November 1944 and March 1946, were included in the subsample. The rest of the linked data is composed of a random sample of 10,667 individuals who were born in the same cities but before November 1944 or after March 1946, and a random sample of 9,087 individuals who were born in a different part of the Netherlands in 1944 – 1947. Those who emigrated after age 18 and before 2006 (586 individuals) as well as those whose status (alive, dead, or emigrated) is unknown (4,185 individuals) were excluded. Next, the remaining individuals who attended special schools for disabled or illiterate (2,506 individuals) were excluded. Finally, 1423 remaining individuals were also excluded because information on IQ scores, general or psychological health were missing. The final subsample amounts to 36,337 individuals.

These individuals are also linked to administrative data on medication use. The latter is always prescribed by medical doctors and observed over the period 2006 – 2014, when the youngest were from age 59 (in 2006) to age 67 (in 2014) and the oldest were from age 62 (in 2006) to age 70 (in 2014). Medication use is actually observed for 32,946 individuals only, since 3,391 individuals died before 2006: 10.0% of the individuals with primary education, 9.2% of the individuals with lower education, and 7.5% of the individuals with higher education.

The medication use is observed on annual basis and in Anatomical Therapeutic Chemical (ATC) code, with three levels of classification: the first indicates the anatomical main group, the second the therapeutic subgroup, the third the pharmacological subgroup. We investigate only common diseases that can be uniquely linked to one or more medications in the 3 levels ATC code (see van Ooijen et al., 2015). These diseases and the related medications are listed in Table A.3 in Appendix A. The main assumption is that there is a one-to-one correspondence between using a medication and having the related disease. Table 1 depicts the prevalence of each disease medication by education level in 2006. For all the diseases we consider, we observe a clear educational gradient in medication use, decreasing with increasing education level.

Table 1: Medication use by education level, 2006

	Education level					
	Primary	Lower		Higher		All
			Diff[a]		Diff[a]	
Cardiac diseases	8.5%	6.7%	-1.8%	4.9%	-3.6%	7.3%
Obstructive airway diseases	9.3%	6.8%	-2.5%	6.4%	-2.9%	8.0%
Hypertension	32.5%	30.3%	-2.2%	24.9%	-7.6%	30.6%
Hyperlipidemia	28.2%	24.6%	-3.6%	19.0%	-9.2%	25.5%
Diabetes (type 1 and 2)	10.6%	9.2%	-1.4%	5.4%	-5.2%	9.3%
Depression and anxiety	12.4%	11.6%	-0.8%	10.7%	-1.7%	11.8%
Number of individuals	16,809	10,862		5,275		32,946

[a] Difference with medication use primary education.

Table A.4 in Appendix A demonstrates that the medication use of the linked individuals represents the Dutch population well. For both the age-group 60 – 63 and the age-group 67 – 70 in our sample, the medication use is very similar to the medication use in the Dutch male population for similar age groups.

Selected demographic and socioeconomic characteristics, by education level, for the linked sample with medication use information are given in Table A.5 in Appendix A. The oversampling of individuals from Western Netherlands is easily appreciated from the table. Taller men and men with low birth order tend to have higher education. The education level is also strongly related to father's occupation; men with the highest education tend to have fathers in professional or managerial occupations. As mentioned before, men born in the big cities have higher education levels. Overweight seems to be negatively related to the education level. General health seems only marginally related to education level, but psychological fitness clearly, with the higher the education the higher the psychological fitness.

3 Methodology

We seek to find the impact of education on diseases in old age, identified from medication use. The methodology we use to account for possible confounding of intelligence, affecting both the educational attainment and medication use later in old age, is an extension of the structural equation framework developed by Conti et al. (2010) and Bijwaard et al. (2015a). The structural model is composed of four parts and estimated in two steps through maximum likelihood methods. The four parts comprise: (*i*) an ordered probit model for the educational attainment, (*ii*) a Gompertz mortality model for survival up to old age, (*iii*) a probit model for medication use in old age, and (*iv*) a measurement system using IQ tests to identify latent intelligence.

In our educational choice model we assume, as in standard discrete choice models, that individuals implicitly evaluate the expected consequences of future choices and their costs, including both monetary and psychic costs, to decide whether to continue their schooling. We are agnostic about the decision model used by the individuals and do not observe the cost of education, just like most of the treatment evaluation literature. We do not impose rational expectations. The decision is influenced by latent intelligence, I. Conditioning on intelligence, and observed confounding factors, accounts for all the dependence across educational choices and mortality and medication use. We assume that the value of intelligence is known by the individual but not by the researcher and that it is fixed at the moment an individual makes his schooling and behavioural choices.

After elementary school (LO), the individual can choose whether to stay in the same school (LVO) until the minimum school-leaving age, or to attend either MVO or, conditional on admission, VHMO in preparation to university. Each individual i gains a latent utility E_i^* from education. We assume a linear model, depending on a vector of observed individual characteristics $\boldsymbol{X}_{1i}$ and latent intelligence I_i, for the net utility of each schooling level $E_i^* = \boldsymbol{X'}_{1i}\boldsymbol{\beta} + \gamma I_i + \epsilon_i$, where $\epsilon_i \sim N\big(0, 1\big)$ is an unobserved random variable also affecting utility, which is assumed to be statistically independent of both $\boldsymbol{X}_{1i}$ and I_i. Given I_i and $\boldsymbol{X}_{1i}$, the probability of an individual i choosing education level $E_i = e$ is an ordered probit

$$\Pr\Big(E_i = e|\boldsymbol{X}_{1i}, I_i\Big) = \Phi\Big(b_e - \boldsymbol{X'}_{1i}\boldsymbol{\beta} - \gamma I_i\Big) - \Phi\Big(b_{e-1} - \boldsymbol{X'}_{1i}\boldsymbol{\beta} - \gamma I_i\Big) \tag{1}$$

where b_0, b_1, b_2, b_3 are unknown cut points, $-\infty = b_0 < b_1 < b_2 < b_3 = +\infty$, and with $\Phi(\cdot)$ is the standard normal cumulative density. We define $e = 1, 2, 3$ the primary (LO and LVO), lower (MVO) and higher (VHMO and university) education level, respectively.

Once the individual has decided his education level, future mortality and medication use is potentially causally related to this decision. More importantly, the model allows individuals to select their schooling level anticipating future mortality and/or medication use differences by education levels. This implies that individuals select their schooling level by comparing (future) outcomes by schooling level. To deal with the issue of schooling choice based on future outcomes we use potential outcome models in which we allow observed and unobserved (from the research point of view, but known to the individual) variables to be correlated across schooling levels, mortality rates and medication use. This model is a Roy-type model (Roy, 1951), commonly applied in economics to model choices based on potential outcomes.

We model the probability of surviving until 2006, the first year of observation of medication use. The reason is that low education is associated with premature death before 2006 (see Section 2). Ignoring possible selective attrition due to death before 2006 may bias the estimated effect of education on medication use. To account for this, we include a Gompertz proportional mortality rate differentiated by education level, $\lambda_e\left(t|\boldsymbol{X}_{2i}, I_i, E_i = e\right) = \exp\left(\psi_e t + \boldsymbol{X'}_{2i}\boldsymbol{\kappa}_e + \omega_e I_i\right)$, with shape parameter ψ_e, and its implied survival function

$$S_e\big(t|\boldsymbol{X}_{2i}, I_i, E_i = e\big) = \exp\bigg(-\frac{1}{\psi_e}\Big(\exp\big(\psi_e t\big) - 1\Big)\bigg)^{\exp\Big(\boldsymbol{X'}_{2i}\boldsymbol{\kappa}_e + \omega_e I_i\Big)} \tag{2}$$

depending on observed individual characteristics $\boldsymbol{X}_{2i}$[1] and latent intelligence I_i.

We model the probability of using a particular medication in 2006 through a probit separate by education level. An individual i with education level e who survived up to 2006 is assumed to be affected by a particular disease if the latent utility in using the respective medication m is greater than 0, $U^*_{emi} > 0$. This latent utility linearly depends on I_i and $\boldsymbol{X}_{2i}$, $U^*_{emi} = \boldsymbol{X'}_{2i}\boldsymbol{\varrho}_{em} + \eta_{em}I_i + \varepsilon_{emi}$, with $\varepsilon_{emi} \sim N\big(0,1\big)$. Therefore we have that

$$\Pr\big(U^*_{emi} > 0\big) = \Pr\big(U_{emi} = 1|\boldsymbol{X}_{2i}, I_i, E_i = e\big) = \Phi\big(\boldsymbol{X'}_{2i}\boldsymbol{\varrho}_{em} + \eta_{em}I_i\big) \tag{3}$$

where $U_{emi} = 1$ if the individual i with education level e uses medication m in 2006.

The structural model is closed by a measurement system to estimate the distribution of latent intelligence I. The measurement system is composed of nine measurement equations, linking the three IQ test scores $q = 1, 2, 3$, separately for each education level, to latent intelligence and observed individual characteristics.[2] This allows controlling for a possible reverse effect of education on intelligence. We assume that intelligence I is normally distributed with zero mean and unknown variance σ^2. The continuous score M^*_{eqi} for an individual i with education level e on IQ test q is not available, but only observed in 6 ordered classes $c = 1, \ldots, 6$. Therefore, nine ordered probit are estimated. The latent variable M^*_{eqi} is defined as a linear combination of observed $\boldsymbol{X}_{1i}$ and I_i, $M^*_{eqi} = \boldsymbol{X'}_{1i}\boldsymbol{\xi}_{eq} + \zeta_{eq}I_i + \tau_{eqi}$, where $\tau_{eqi} \sim N(0, 1)$. Given I_i, $\boldsymbol{X}_{1i}$ and E_i, the probability of an individual i with education level e scoring $M_{eqi} = c$ on IQ test q is

$$\Pr\Big(M_{eqi} = c|\boldsymbol{X}_{1i}, I_i, E_i = e\Big) = \Phi\Big(a_{eqc} - \boldsymbol{X'}_{1i}\boldsymbol{\xi}_{eq} - \zeta_{eq}I_i\Big) - \Phi\Big(a_{eqc-1} - \boldsymbol{X'}_{1i}\boldsymbol{\xi}_{eq} - \zeta_{eq}I_i\Big) \tag{4}$$

where $a_{eq0}, \ldots, a_{eq6}$ are the unknown cut points $-\infty = a_{eq0} < \ldots < a_{eq6} = +\infty$. Since I_i is unobserved, we need to establish its unit of measurement by constraining $\zeta_{11} = 1$.

Following the literature (Heckman et al., 2014, 2016), we jointly estimate the measurement system and the educational attainment model in a first step, using all the men

[1] Note that we use a different set of observed characteristics and different data for (1) education choice and the measurement system and (2) the survival and medication use probability. The first are estimated using the whole sample of recruits, but variables that might be endogenous due to simultaneous causality, namely overweight, general health and psychological health, are excluded ($\boldsymbol{X}_1$). The second are estimated using the linked sample and including these additional health indicators ($\boldsymbol{X}_2$).

[2] We treat intelligence, I, as a latent variable because we aim to control for the effect of observed factors on the measures of I (the IQ scores). Note that for identification we need at least three intelligence tests.

who attended the military examination at age 18. After importing the estimates of the first step in the likelihood, we estimate the probit model for medication use in a second step, using the linked individuals and accounting for survival up to 2006. Assuming that, given $\boldsymbol{X}$, the interdependence among the four parts of the structural model comes from I only and averaging over the distribution of I,[3] the likelihood of the first step is

$$\mathcal{L}_1 = \prod_i \int \Bigg\{ \prod_{e=1}^{3} \Bigg[\prod_{c=1}^{6} \Big[\Pr\big(M_{e1i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{R_{ci}} \Big[\Pr\big(M_{e2i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{A_{ci}} \times \Big[\Pr\big(M_{e3i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{L_{ci}} \Bigg]^{E_{ei}} \Bigg\} \Bigg\{ \prod_{e=1}^{3} \Big[\Pr\big(E_i = e | \boldsymbol{X}_{1i}, I\big)\Big]^{E_{ei}} \Bigg\} dF\big(I\big) \quad (5)$$

where $E_{ei} = 1$ if individual i obtained education level e (i.e., $E_i = e$), and 0 otherwise; $R_{ci} = 1$ if individual i scored c in the Raven test and 0 otherwise; $A_{ci} = 1$ if individual i scored c in the arithmetic test and 0 otherwise; $L_{ci} = 1$ if individual i scored c in the language test and 0 otherwise. Since we assume conditional (on observed characteristics $\boldsymbol{X}$ and latent intelligence I) independence of the events, we do not need any exclusion restrictions for identification.

After importing the estimates of the first step, including the estimated distribution of the latent intelligence $\widehat{F}\,(I)$, we maximize the following likelihood in the second step

$$\begin{aligned}\mathcal{L}_2 = \prod_i \int \Bigg\{ \prod_{e=1}^{3} \Bigg[\prod_{c=1}^{6} \Big[\widehat{\Pr}\big(M_{e1i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{R_{ci}} \Big[\widehat{\Pr}\big(M_{e2i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{A_{ci}} \\ \times \Big[\widehat{\Pr}\big(M_{e3i} = c | \boldsymbol{X}_{1i}, I, E_i\big)\Big]^{L_{ci}} \Bigg]^{E_{ei}} \Bigg\} \Bigg\{ \prod_{e=1}^{3} \Big[\widehat{\Pr}\big(E_i = e | \boldsymbol{X}_{1i}, I\big)\Big]^{E_{ei}} \Bigg\} \\ \times \Bigg\{ \prod_{e=1}^{3} \Bigg[\Big(\lambda_e \Big(t_i | \boldsymbol{X}_{2i}, I, E_i \Big) \Big)^{\delta_i} \left(\frac{S_e\big(t_i | \boldsymbol{X}_{2i}, I, E_i\big)}{S_e\big(18 | \boldsymbol{X}_{2i}, I, E_i\big)} \right) \Bigg]^{E_{ei}} \Bigg\} \\ \times \Bigg\{ \Big[\Pr\big(U_{emi} = 1 | \boldsymbol{X}_{2i}, I, E_i\big)\Big]^{U_{emi}} \\ \times \Big[\Pr\big(U_{emi} = 0 | \boldsymbol{X}_{2i}, I, E_i\big)\Big]^{\big(1 - U_{emi}\big)} \Bigg\}^{E_{ei}\big(1-\delta_i\big)} d\widehat{F}\big(I | T > 2005\big) \quad (6)\end{aligned}$$

[3] Averaging over the distribution of I requires the computation of an integral that cannot be solved analytically. However, Gaussian quadrature can approximate this one dimensional integral very well. Gaussian quadrature is a numerical integration method based on Hermite polynomials. It provides an efficient approximation for evaluating indefinite integrals based on normal distributions. Hence, we estimate the parameters using maximum likelihood on the basis of Gaussian quadrature approximation. The STATA estimation programs are available upon request.

where $\delta_i = 1$ if individual i died before 2006 and where we account for differences in the distribution of I, conditioning on surviving until 2006 ($T > 2005$).[4] The estimated, conditional, distribution of I is defined as

$$d\widehat{F}\big(I|T > 2005\big) = \frac{\sum_{e=1}^{3}\Big[\widehat{\Pr}\big(E_i = e|\boldsymbol{X}_{1i}, I\big)S_e\big(2006|\boldsymbol{X}_{2i}, I, E_i = e\big)\Big]\widehat{f}\big(I\big)}{\int\sum_{e=1}^{3}\Big[\widehat{\Pr}\big(E_i = e|\boldsymbol{X}_{1i}, I\big)S_e\big(2006|\boldsymbol{X}_{2i}, I, E_i = e\big)\Big]\widehat{f}\big(I\big)dI} \tag{7}$$

We estimate the model for each medication use separately, considering $U_{emi} = 1$ if the individual i with education level e uses medication m in 2006. Based on the model estimates, we derive the average treatment effect (ATE) of choosing a higher education level on medication use in old age. The ATE is estimated averaging over the distribution of the observed individual characteristics $\boldsymbol{X}_2$ and the estimated, unconditional, distribution of the latent intelligence I. The ATE is defined as

$$ATE_{1sm} = \int\int ATE_{1sm}\big(\boldsymbol{X}_2, I\big)dF\big(\boldsymbol{X}_2\big)d\widehat{F}\big(I\big) \tag{8}$$

where $ATE_{1sm}\big(\boldsymbol{X}_2, I\big) = \widehat{\Pr}\big(U_{sm} = 1|\boldsymbol{X}_2, I\big) - \widehat{\Pr}\big(U_{1m} = 1|\boldsymbol{X}_2, I\big)$ is the predicted gain, in terms of medication use m, of going from education level 1 (primary) to $s = 2, 3$ (lower and higher, respectively), conditional on observed characteristics $\boldsymbol{X}_2$ and latent intelligence I.

4 Results

The estimated ATEs of choosing a higher education level on medication use, in Table 2, reveal that all physical diseases are highly, and significantly, affected by education. However, the estimated treatment effect of education on depression and anxiety medication is low and, from primary to lower education, not significant. The ATEs of (almost) all diseases do not differ significantly from the raw education-diseases associations (see Table 1). This would indicate that the educational difference we observe in medication use is mainly a true causal effect of education. The only exception is hyperlipidemia medication, for which the ATE from primary to higher education is significantly lower than the observed difference, at the 95% confidence level.

[4]Both an unconditional distribution of I and a conditional distribution of I on surviving up to 18 years old provide similar estimates to the main specification of the model.

Table 2: Average Treatment Effect in percentage points

	Education level	
	Primary to Lower	Primary to Higher
Cardiac diseases	-1.53^{**}	-2.90^{**}
Obstructive airway diseases	-2.35^{**}	-3.21^{**}
Hypertension	-2.24^{**}	-6.44^{**}
Hyperlipidemia	-2.87^{**}	-7.31^{**}
Diabetes (type 1 and 2)	-1.34^{**}	-4.64^{**}
Depression and anxiety	-0.60	-1.57^{+}

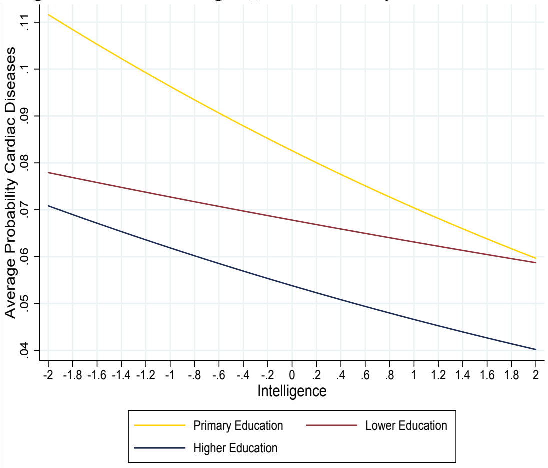
$^{+}p < 0.05$ and $^{**}p < 0.01$

Next, Figure 1 depicts the average predicted probability of each disease, by education, over a significant range of latent intelligence. This range represents around 99% of the population, according to the estimated variance of the latent intelligence distribution, which is reported in Table A.7 in Appendix A. This allows investigating how the treatment effects vary with respect to intelligence. The average predicted probabilities of physical diseases medication use by education generally converge with higher intelligence, providing evidence of decreasing gains from higher education levels. However, the probabilities of depression and anxiety medication use by education diverge with higher intelligence, suggesting that effectiveness of education in preventing depression and anxiety in old age is higher for highly intelligent individuals.

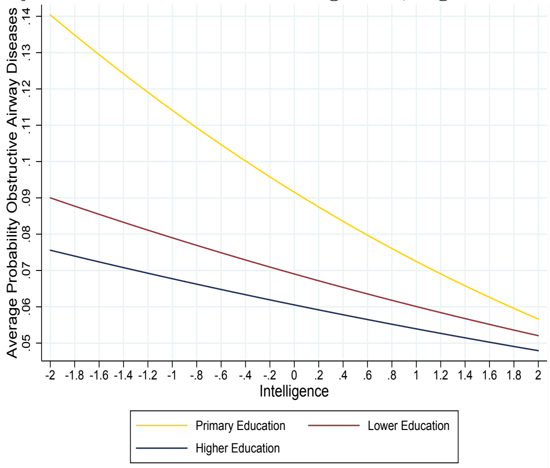
5 Conclusion and discussion

We have estimated a structural model that controls for the effect of observed confounding factors and latent intelligence on educational attainment, survival up to old age and medication use. The latter is used to identify diseases in old age. We have obtained evidence of a strong effect of education on physical diseases. This is in line with recent research on the association between education and health using a structural model approach (Conti et al., 2010). However, for mental health medication, we have obtained results that suggest a weak impact of education on depression and anxiety. To investigate the distribution of the treatment effect of education, we have plotted the average predicted probabilities of

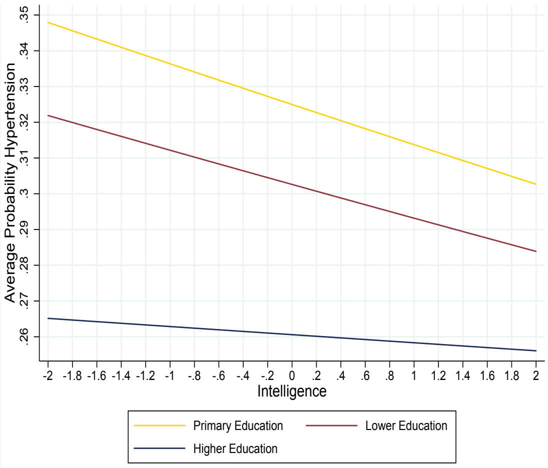
Figure 1: Average probability of medication use, by education and intelligence, age 59-62



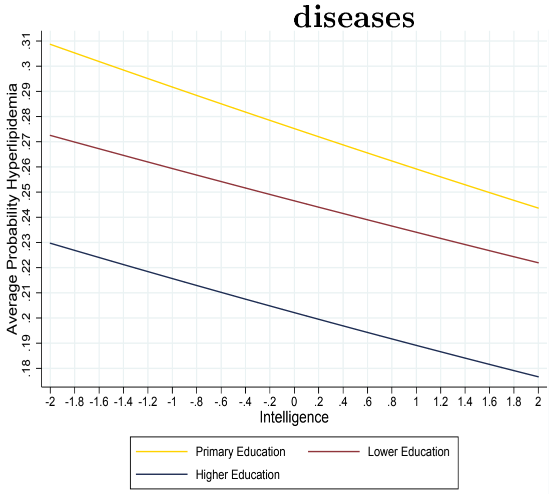
Cardiac diseases



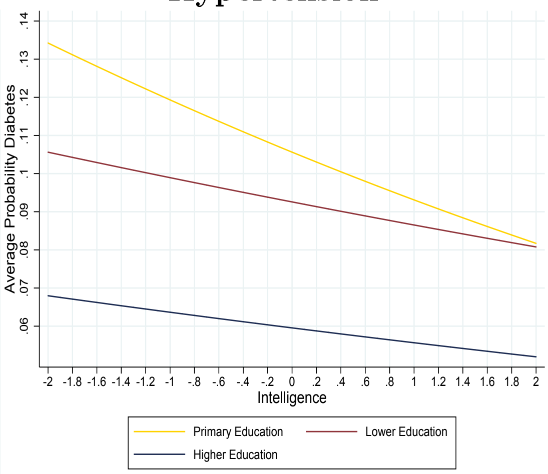
Obstructive airway diseases



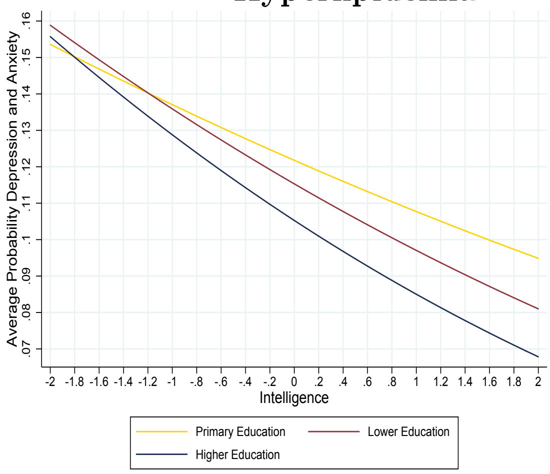
Hypertension



Hyperlipidemia



Diabetes (type 1 and 2)



Depression and anxiety

diseases by education and intelligence. The figures suggest that the effect of education decreases with intelligence for physical diseases but increases with intelligence for depression and anxiety.

Our study has three distinct strengths compared to previous research. First, a clear advantage of the study is the large sample size, which allows the estimation of the detailed structural model with three education levels accounting for confounding in the education attained. Second, the data are population-based and not prone to self-selection because military conscription was mandatory in the Netherlands during the 1960s. Third, our statistical method, using a structural model in which the education attained, mortality and medication use are modelled simultaneously, accounts for the confounding effect of intelligence on both mortality and medication use. This enables us to draw (close to) causal conclusions from our analysis without suffering generalization issues inherent to using compulsory schooling reforms to account for confounding.

Our study also has limitations. First, we do not have military examination information nor other large data containing intelligence tests for women that would allow for similar analyses. Second, the assumption that there is a one-to-one correspondence between using a medication and having the related disease may seem strong, at least for some specific diseases. However, we consider this issue negligible for two reasons. First, assuming that using a particular medication implies having the respective disease is reliable, because the medications observed in the data are always prescribed by a medical doctor. Second, the literature has shown that data on medication use provide good-quality estimates of the prevalence of chronic diseases in the population (Huber et al., 2013, Chini et al., 2011, Maio et al., 2005).

A more substantive issue is that claiming that our main findings represent the causal effect of education may be difficult to justify. Lack of data prevents us to to control for some potentially relevant confounding factors that may significantly shape the education and health association. Conditional on these confounding factors, any association left between education and health would be causal (Heckman et al., 2014). Besides latent intelligence, we account for a large set of observed early-life characteristics, including father's occupation and the urban status of place of birth. However, we do not account for non-cognitive skills, differences in the local economic conditions within the Netherlands and, in the educational attainment model, health early in life.

Unfortunately, measures of non-cognitive skills, such as self-discipline, perseverance and consciousness, are not observed in our data. However, before the Mammoth Act (1968), educational opportunities in the Netherlands were highly unequal and strictly related to the family social class (Prick, 2006, Frijhoff and Spies, 2004) and to the urban status of place of residence, with the majority of rural areas being culturally isolated (Lauwerys and Scanlon, 2013). The estimates of the educational attainment model (see Table A.6 in Appendix A) provide evidence of this, since intelligence I does not affect education choice significantly. Accordingly, in our data, non-cognitive skills are likely to play a minor role in determining education choice.

Non-cognitive skills may still have a direct effect on diseases in old age. Accounting only for psychological health at age 18 is inadequate to capture the multidimensional heterogeneity in non-cognitive skills across individuals. The latter may lead to overestimated effect of intelligence on health outcomes (Conti et al., 2010). Whether non-cognitive skills have a significant and direct impact on health in old age is an open question. In this respect, the literature has only found an indirect (through education), significant, effect of non-cognitive skills on physical health and self-esteem in middle age,[5] and not a direct effect on the same health outcomes (Heckman et al., 2014). However, non-cognitive skills seem to have a significant and direct impact on smoking behaviour in middle age (Heckman et al., 2014).

Differences in local or regional economic conditions at birth and over childhood may also play a role, affecting both education choice and health later in life (Alessie et al., 2017, Heckman et al., 2014). Unfortunately, data on, for instance, provincial unemployment rate are not available for the Netherlands before the 1970s and, therefore, we cannot account for its effect on neither education choice nor health outcomes later in life.

Except for height, we do not control for health early in life in the educational attainment model. This, however, should not be a major issue, since the literature has found no remaining association between health early in life and education choice, especially for men, after controlling for early-life environment, parental background and latent skills (Conti et al., 2010). In the medication use and mortality model we do control for health early in life, including height, general health status at age 18 and overweight.

[5]Which, as already mentioned, is likely to not apply to our data.

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Appendix A Additional tables

Table A.1: Distribution of IQ scores by education level, 368,687 individuals

	Education level		
	Primary	Lower	Higher
Raven:			
1 (lowest)	5.2%	1.2%	0.3%
2	14.3%	3.7%	0.9%
3	19.4%	9.3%	3.5%
4	25.3%	20.4%	11.4%
5	26.1%	38.5%	37.9%
6 (highest)	9.7%	27.0%	46.0%
Arithmetic:			
1 (lowest)	7.2%	0.3%	0.1%
2	23.7%	2.9%	0.4%
3	23.9%	9.8%	1.4%
4	23.2%	27.8%	8.0%
5	17.4%	40.7%	38.1%
6 (highest)	4.5%	18.6%	52.1%
Language:			
1 (lowest)	4.9%	0.2%	0.0%
2	21.0%	1.2%	0.2%
3	28.5%	5.4%	0.7%
4	28.8%	20.7%	6.6%
5	14.4%	49.6%	43.4%
6 (highest)	2.4%	22.9%	49.1%
Number of individuals	210,212	107,829	50,646

Table A.2: Sample characteristics by education level, 368,687 individuals

	Education level		
	Primary	Lower	Higher
Average height (cm)	176.8	178.1	179.1
Average birth order	2.8	2.4	2.2
Average family size	4.7	4.0	3.9
Father's occupation:			
Professional	8.2%	17.3%	37.7%
White collar	21.5%	37.5%	38.8%
Farm owner	12.4%	6.6%	5.1%
Skilled	32.6%	22.5%	9.7%
Unskilled	20.1%	11.8%	4.7%
Unknown	5.1%	4.3%	4.1%
Urban status of place of birth:[a]			
City	30.1%	38.0%	42.5%
Urban	19.9%	21.3%	21.9%
Urbanized rural	21.5%	18.6%	17.6%
Other	28.5%	22.0%	18.1%
Religion:			
Catholic	43.3%	38.0%	39.0%
Protestant	40.3%	43.2%	41.2%
Other or none	16.4%	18.7%	19.8%
Famine exposure	5.4%	7.6%	7.9%
Region of birth:			
West	41.9%	48.1%	49.6%
South	24.2%	20.3%	21.6%
East	19.0%	16.0%	14.4%
North	14.9%	15.6%	14.4%
Year of birth:			
1944	23.7%	24.5%	23.7%
1945	22.7%	22.2%	21.2%
1946	30.2%	30.5%	30.8%
1947	23.4%	22.8%	24.4%
Overweight[b]	7.2%	5.8%	5.0%
General health:[c]			
Fit	84.3%	83.4%	83.4%
Almost	6.6%	7.4%	7.3%
Fairly	1.9%	1.9%	1.9%
Unfit	7.2%	7.3%	7.4%
Psychological fitness:[c]			
Fit	75.7%	80.9%	82.7%
Almost	20.1%	16.3%	14.9%
Fairly	0.1%	0.1%	0.1%
Unfit	4.1%	2.8%	2.3%
Number of individuals	210,212	107,829	50,646

[a] City: $>$ 100,000 inhabitants; Urban: cities $<$ 100,000 inhabitants; Urbanized rural: rural communities with $<$ 20% farming population; Rural: rural communities with $>$ 20% farming population.

[b] BMI (Body Mass Index) higher than 25

[c] Not available for all 368,687 individuals (we do not control for health early in life in the first step).

Table A.3: Diseases and relative medication use

Diseases or conditions	Medication use (ATC code)
Cardiac diseases	C01, C03C
Obstructive airway diseases	R03
Hypertension	C02, C03A, C07, C08, C09A,B
Hyperlipidemia	C10
Diabetes (type 1 and 2)	A10
Depression and anxiety	N05B, N06A

Table A.4: Medication use in subsample (Sub) and the Netherlands (NL), in 2007 and 2014

	2007		2014	
	Sub	NL	Sub	NL
	age 60-63	age 60-65	age 67-70	age 65-70
Cardiac diseases:				
C01	6.3%	6.2%	8.4%	7.2%
C03C	2.7%	2.9%	4.6%	3.9%
Obstructive airway diseases:				
R03	8.9%	9.3%	11.8%	11.7%
Hypertension:				
C02	0.8%	0.8%	1.1%	1.0%
C03A	5.6%	5.6%	9.9%	9.1%
C07	20.4%	20.5%	27.7%	25.3%
C08	9.6%	9.6%	15.9%	14.5%
C09A	13.3%	13.1%	20.0%	18.2%
C09B	2.6%	2.5%	3.6%	3.0%
Hyperlipidemia:				
C10	27.4%	27.2%	40.8%	38.0%
Diabetes (type 1 and 2):				
A10	10.0%	10.2%	15.5%	14.0%
Depression and anxiety:				
N05B	8.7%	8.0%	2.0%	1.9%
N06A	5.3%	5.3%	5.5%	5.6%

Source for the Netherlands: CBS

Table A.5: Sample characteristics for the linked individuals by education, 36,337 individuals

	Education level		
	Primary	Lower	Higher
Average height (cm)	177.0	178.1	179.3
Average birth order	2.6	2.2	2.1
Average family size	3.8	3.4	3.4
Father's occupation:			
Professional	9.6%	16.7%	37.9%
White collar	26.7%	43.3%	43.7%
Farm owner	4.9%	2.2%	1.8%
Skilled	35.0%	23.5%	9.5%
Unskilled	17.4%	9.5%	3.4%
Unknown	6.4%	4.9%	3.7%
Urban status of place of birth:[a]			
City	79.4%	86.6%	87.9%
Urban	6.1%	4.6%	4.8%
Urbanized rural	6.6%	4.3%	4.0%
Other	7.9%	4.5%	3.3%
Religion:			
Catholic	34.8%	30.3%	31.5%
Protestant	35.8%	40.0%	39.7%
Other or none	29.4%	29.7%	28.8%
Famine exposure	53.8%	60.4%	59.9%
Region of birth:			
West	83.0%	88.3%	89.2%
South	7.6%	4.9%	5.0%
East	5.5%	3.6%	3.6%
North	3.9%	3.1%	2.2%
Year of birth:			
1944	18.2%	17.5%	17.9%
1945	39.9%	41.6%	40.3%
1946	29.1%	29.3%	29.7%
1947	12.9%	11.6%	12.2%
Overweight[b]	7.6%	6.2%	5.5%
General health:			
Fit	85.0%	83.0%	83.2%
Almost	6.3%	7.4%	7.3%
Fairly	2.0%	2.3%	2.1%
Unfit	6.7%	7.5%	7.4%
Psychological fitness:			
Fit	76.0%	80.9%	82.1%
Almost	19.8%	15.8%	14.9%
Fairly	0.1%	0.1%	0.1%
Unfit	4.1%	3.2%	2.9%
Number of individuals	18,671	11,963	5,703

[a] City: $>$ 100,000 inhabitants; Urban: cities $<$ 100,000 inhabitants; Urbanized rural: rural communities with $<$ 20% farming population; Rural: rural communities with $>$ 20% farming population.

[b] BMI (Body Mass Index) higher than 25

Table A.6: Ordered probit estimates for educational attainment in structural model

	Coeff.	Std. err.
Intelligence	0.0285	0.0184
Height	0.0191**	0.0003
Birth order	−0.0510**	0.0015
Family Size	−0.0379**	0.0012
Professional	0.4148**	0.0059
Farm Owner	−0.5681**	0.0080
Skilled	−0.6570**	0.0056
Unskilled	−0.7399**	0.0067
Unknown	−0.3788**	0.0096
City	0.0544**	0.0060
Urbanized Rural	−0.0578**	0.0063
Other	−0.1260**	0.0065
North	0.0625**	0.0065
South	0.0271**	0.0060
East	−0.0716**	0.0061
Catholic	0.0408**	0.0051
Other or No religion	−0.0349**	0.0059
Birth Year 1944	0.0318**	0.0061
Birth Year 1946	−0.0149**	0.0058
Birth Year 1947	−0.0374**	0.0062
Spring	−0.0095	0.0055
Summer	−0.0181+	0.0057
Autumn	0.0306**	0.0058
Famine Exp.	0.0152	0.0094
Cut Point 1	−0.3709**	0.0093
Cut Point 2	0.6653**	0.0094

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.7: Ordered probit estimates for IQ measurement system, by education level, in structural model: Raven Test

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	1.0000		0.8525^{**}	0.0079	0.8406^{**}	0.0155
Height	0.0212^{**}	0.0005	0.0174^{**}	0.0006	0.0122^{**}	0.0010
Birth Order	-0.0320^{**}	0.0021	-0.0352^{**}	0.0032	-0.0460^{**}	0.0052
Family Size	-0.0227^{**}	0.0017	0.0160^{**}	0.0026	0.0284^{**}	0.0040
Professional	-0.0104	0.0125	0.0510^{**}	0.0126	0.0403^{+}	0.0147
Farm Owner	-0.4585^{**}	0.0122	-0.0938^{**}	0.0191	-0.2214^{**}	0.0315
Skilled	-0.3183^{**}	0.0098	-0.0641^{**}	0.0130	-0.0633^{+}	0.0231
Unskilled	-0.4467^{**}	0.0109	-0.1603^{**}	0.0158	-0.1374^{**}	0.0311
Unknown	-0.3092^{**}	0.0148	-0.0250	0.0206	-0.0957^{+}	0.0311
City	0.0930^{**}	0.0092	0.0243	0.0119	0.0257	0.0177
Urbanized Rural	-0.1111^{**}	0.0093	-0.0819^{**}	0.0129	-0.0452	0.0200
Other	-0.1219^{**}	0.0093	-0.1230^{**}	0.0133	-0.1401^{**}	0.0213
North	-0.1568^{**}	0.0097	-0.2117^{**}	0.013	-0.1564^{**}	0.0204
South	0.0384^{**}	0.0089	0.0888^{**}	0.0125	0.0257	0.0185
East	-0.1672^{**}	0.0089	-0.0824^{**}	0.0126	-0.0583^{+}	0.0199
Catholic	0.0669^{**}	0.0076	0.0075	0.0103	-0.1121^{**}	0.016
Other or No religion	0.0035	0.0091	0.0154	0.0115	0.0506^{+}	0.0172
Birth Year: 1944	-0.0528^{**}	0.0092	-0.0758^{**}	0.0126	-0.0218	0.0198
Birth Year: 1946	-0.0395^{**}	0.0086	-0.0171	0.012	-0.0046	0.0187
Birth Year: 1947	-0.5038^{**}	0.0091	-0.3846^{**}	0.0126	-0.3508^{**}	0.0196
Spring	0.0259^{+}	0.0083	0.0388^{**}	0.0111	0.0394	0.0172
Summer	0.0460^{**}	0.0084	0.0641^{**}	0.0114	0.0440	0.0178
Autumn	-0.0430^{**}	0.0087	-0.0455^{**}	0.0118	-0.0323	0.0177
Famine Exp.	0.0446^{+}	0.0153	0.0198	0.0184	0.0287	0.0279
Cut Point 1	-2.8750^{**}	0.0207	-3.0144^{**}	0.0228	-3.6347^{**}	0.0507
Cut Point 2	-1.8312^{**}	0.0201	-2.2575^{**}	0.0205	-2.9606^{**}	0.0411
Cut Point 3	-1.0273^{**}	0.0199	-1.5075^{**}	0.0193	-2.1982^{**}	0.0361
Cut Point 4	-0.1296^{**}	0.0198	-0.6405^{**}	0.0187	-1.3183^{**}	0.0336
Cut Point 5	1.1568^{**}	0.0201	0.6394^{**}	0.0187	0.0591	0.0324

$^{+}p < 0.05$ and $^{**}p < 0.01$

Through the measurement system, we estimate the normal distribution $N\left(0, \sigma^2\right)$ of the latent intelligence I. The estimated variance is $\widehat{\sigma}^2 = 0.7652$, with standard error 0.0009.

Table A.8: Ordered probit estimates for IQ measurement system, by education level, in structural model: Arithmetic Test

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	2.0094**	0.0172	1.6023**	0.0207	1.2326**	0.0292
Height	0.0338**	0.0008	0.0250**	0.0009	0.0152**	0.0012
Birth Order	−0.0486**	0.0032	−0.0541**	0.0046	−0.0652**	0.0062
Family Size	−0.0577**	0.0027	0.0212**	0.0036	0.0285**	0.0049
Professional	−0.0073	0.0194	0.0414	0.0180	−0.0634**	0.0183
Farm Owner	−0.4529**	0.0196	0.3153**	0.0277	0.1385**	0.0380
Skilled	−0.6208**	0.0165	−0.1347**	0.0202	−0.0507	0.0288
Unskilled	−0.8591**	0.0186	−0.2999**	0.0244	−0.1509**	0.0378
Unknown	−0.6982**	0.0228	−0.1732**	0.0289	−0.2845**	0.0377
City	0.0141	0.0139	−0.1024**	0.0165	0.0043	0.0217
Urbanized Rural	−0.0966**	0.0141	−0.0555+	0.0180	−0.0407	0.0245
Other	−0.0798**	0.0142	−0.0428	0.0185	−0.1380**	0.0261
North	0.0745**	0.0147	−0.0028	0.0179	0.1472**	0.0255
South	0.2683**	0.0135	0.3437**	0.0174	0.0284	0.0224
East	−0.0005	0.0134	0.0738**	0.0177	0.0011	0.0242
Catholic	−0.0401**	0.0115	0.0425+	0.0143	−0.3123**	0.0199
Other or No religion	−0.2102**	0.0136	−0.0749**	0.0156	−0.0068	0.0210
Birth Year: 1944	0.0967**	0.0139	−0.0050	0.0173	−0.0082	0.0239
Birth Year: 1946	−0.1119**	0.0130	−0.0976**	0.0164	−0.0465	0.0226
Birth Year: 1947	−0.5113**	0.0139	−0.4240**	0.0177	−0.2184**	0.0241
Spring	−0.0209	0.0124	0.0179	0.0152	0.0010	0.0210
Summer	−0.0167	0.0126	0.0533**	0.0157	0.0235	0.0216
Autumn	−0.0464**	0.0131	−0.0594**	0.0163	−0.0308	0.0217
Famine Exposure	0.0253	0.0228	0.0474	0.0246	0.0526	0.0335
Cut Point 1	−4.0855**	0.0405	−5.0297**	−0.0552	−5.1710**	0.1138
Cut Point 2	−2.0925**	0.0364	−3.3975**	−0.0385	−4.0634**	0.0736
Cut Point 3	−0.7894**	0.0352	−2.0762**	−0.0310	−3.2626**	0.0602
Cut Point 4	0.5811**	0.0350	−0.4839**	−0.0261	−2.0546**	0.0489
Cut Point 5	2.5064**	0.0375	1.4682**	−0.0283	−0.2099**	0.0415

$^{+}p < 0.05$ and $^{**}p < 0.01$

Through the measurement system, we estimate the normal distribution $N\left(0, \sigma^2\right)$ of the latent intelligence I. The estimated variance is $\widehat{\sigma}^2 = 0.7652$, with standard error 0.0009.

Table A.9: Ordered probit estimates for IQ measurement system, by education level, in structural model: Language Test

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	1.4201**	0.0087	0.9650**	0.0092	0.6296**	0.0111
Height	0.0281**	0.0006	0.0195**	0.0007	0.0084**	0.0009
Birth Order	−0.0667**	0.0025	−0.0463**	0.0034	−0.0645**	0.0049
Family Size	−0.0334**	0.0021	0.0101**	0.0027	0.0262**	0.0038
Professional	0.0483+	0.0149	−0.0357+	0.0136	−0.0816**	0.0139
Farm Owner	−0.3879**	0.0149	0.1134**	0.0211	−0.0172	0.0299
Skilled	−0.5160**	0.0125	−0.0674**	0.0141	−0.0444	0.0217
Unskilled	−0.6342**	0.0140	−0.0990**	0.0170	0.0209	0.0293
Unknown	−0.4798**	0.0178	−0.1231**	0.0218	−0.2363**	0.0286
City	0.0500**	0.0112	−0.0201	0.0128	0.0133	0.0170
Urbanized Rural	−0.0750**	0.0113	−0.0172	0.0140	−0.0695**	0.0193
Other	−0.0788**	0.0113	−0.0442+	0.0144	−0.0970**	0.0203
North	0.0457**	0.0115	−0.1108**	0.0139	−0.0615+	0.0196
South	0.1182**	0.0108	0.1523**	0.0134	0.0084	0.0174
East	−0.0734**	0.0106	0.0332	0.0137	−0.0111	0.0191
Catholic	−0.1119**	0.0091	−0.2012**	0.0110	−0.2305**	0.0152
Other or No religion	−0.1377**	0.0107	−0.1075**	0.0120	−0.0229	0.0164
Birth Year: 1944	−0.0484**	0.0111	−0.1135**	0.0134	−0.0956**	0.0185
Birth Year: 1946	−0.0758**	0.0104	−0.0765**	0.0127	−0.0465+	0.0177
Birth Year: 1947	−0.6106**	0.0110	−0.4157**	0.0136	−0.3043**	0.0187
Spring	−0.0331**	0.0099	0.0109	0.0118	0.0035	0.0163
Summer	−0.0198	0.0100	0.0440**	0.0121	0.0470+	0.0169
Autumn	−0.1387**	0.0104	−0.1046**	0.0126	−0.0664**	0.0168
Famine Exposure	−0.0160	0.0182	−0.0105	0.0191	0.0576	0.0260
Cut Point 1	−3.7284**	0.0286	−4.3022**	0.0387	−4.2774**	0.0857
Cut Point 2	−2.0512**	0.0266	−3.2788**	0.0259	−3.6243**	0.0510
Cut Point 3	−0.7942**	0.0260	−2.2866**	0.0222	−2.9929**	0.0382
Cut Point 4	0.6234**	0.0260	−1.0634**	0.0204	−1.8897**	0.0315
Cut Point 5	2.3057**	0.0276	0.7052**	0.0201	−0.1924**	0.0296

$^{+}p < 0.05$ and $^{**}p < 0.01$

Through the measurement system, we estimate the normal distribution $N\left(0, \sigma^2\right)$ of the latent intelligence I. The estimated variance is $\widehat{\sigma}^2 = 0.7652$, with standard error 0.0009.

Table A.10: Gompertz proportional mortality rate estimates, by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.1974^{**}	0.0313	-0.1317^{**}	0.0412	-0.1040	0.0775
General Health: Unfit	0.1107	0.0631	0.2649^{**}	0.0753	0.0847	0.1287
Psych. Health: Unfit	0.0785	0.0558	0.2262^{**}	0.0734	-0.0790	0.1311
Overweight	0.1935^{+}	0.0807	0.3257^{**}	0.1094	0.2129	0.1942
Height	-0.0092^{+}	0.0037	-0.0037	0.0048	0.0011	0.0078
Birth Order	-0.0209	0.0172	0.0340	0.0261	0.0386	0.0436
Family Size	0.0021	0.0182	-0.0307	0.0256	-0.0734	0.0421
Professional	-0.0759	0.0906	-0.0832	0.0905	0.1668	0.1106
Farm Owner	-0.0889	0.1263	0.1050	0.2147	0.5121	0.3436
Skilled	0.0132	0.0610	0.0730	0.0770	0.2914	0.1629
Unskilled	0.0858	0.0716	0.1014	0.1059	-0.0224	0.2895
Unknown	0.2694^{**}	0.0937	0.1864	0.1339	0.3333	0.2374
City	0.0866	0.1201	0.1111	0.1834	0.2242	0.2895
Urbanized Rural	0.0381	0.1351	0.0339	0.2148	0.0157	0.3595
Other	0.1601	0.1313	0.0948	0.2189	0.3900	0.3600
North	0.2393	0.1326	-0.1341	0.2209	-0.3611	0.4113
South	-0.1493	0.1180	-0.0550	0.1741	0.0876	0.2520
East	0.1939	0.1203	0.1628	0.1934	-0.1167	0.3306
Catholic	0.0477	0.0593	-0.0196	0.0778	0.2824^{+}	0.1247
Other or No religion	0.1019	0.0592	0.0222	0.0741	0.1893	0.1223
Birth Year: 1944	0.0187	0.0733	0.1179	0.0970	0.0744	0.1594
Birth Year: 1946	-0.1041	0.0679	-0.2082^{+}	0.0889	0.0964	0.1388
Birth Year: 1947	-0.0157	0.0968	-0.0652	0.1347	-0.1882	0.2197
Spring	-0.0032	0.0656	0.0081	0.0843	0.1118	0.1371
Summer	-0.0051	0.0688	-0.1062	0.0935	-0.1242	0.1543
Autumn	0.0634	0.0669	-0.0674	0.0884	-0.0812	0.1406
Famine Exposure	-0.0338	0.0754	-0.0159	0.0991	-0.1115	0.1542
Constant	-10.1426^{**}	0.2019	-10.1978^{**}	0.2765	-10.3806^{**}	0.4496
Shape	0.0881^{**}	0.0025	0.0889^{**}	0.0033	0.0860^{**}	0.0052

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.11: Probit estimates for cardiac diseases, by education Level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.0854^{**}	0.0180	-0.0371	0.0256	-0.0715	0.0474
General Health: Unfit	0.0340	0.0390	0.0249	0.0501	0.1360	0.0766
Psych. Health: Unfit	0.0894^{**}	0.0329	0.0809	0.0475	0.0740	0.0762
Overweight	0.1223^{+}	0.0504	0.3770^{**}	0.0665	0.2350^{+}	0.1157
Height	-0.0045^{+}	0.0022	-0.0037	0.0030	-0.0027	0.0049
Birth Order	0.0110	0.0100	0.0507^{**}	0.0163	-0.0066	0.0276
Family Size	0.0103	0.0110	-0.0488^{**}	0.0160	-0.0406	0.0257
Professional	0.0174	0.0524	0.0039	0.0540	0.1168	0.0681
Farm Owner	-0.1572	0.0805	-0.1327	0.1502	0.6444^{**}	0.2049
Skilled	0.0540	0.0361	0.0389	0.0478	0.1712	0.1048
Unskilled	0.0490	0.0433	0.0575	0.0661	0.3413^{+}	0.1451
Unknown	0.0659	0.0610	0.0559	0.0875	0.1959	0.1527
City	-0.0721	0.0694	0.0678	0.1105	0.2042	0.1880
Urbanized Rural	-0.0914	0.0790	0.0607	0.1311	0.2395	0.2152
Other	-0.1173	0.0798	0.0955	0.1361	0.0637	0.2460
North	0.0080	0.0879	-0.1365	0.1345	-0.3427	0.2716
South	-0.0078	0.0679	-0.0180	0.1029	0.0223	0.1607
East	-0.0045	0.0766	-0.1260	0.1278	-0.0914	0.2063
Catholic	0.0254	0.0354	0.0141	0.0477	-0.0467	0.0752
Other or No religion	0.0592	0.0356	-0.0173	0.0462	-0.1554^{+}	0.0752
Birth Year: 1944	-0.0075	0.0458	0.1128	0.0620	-0.0309	0.0956
Birth Year: 1946	-0.0669	0.0400	-0.0400	0.0536	-0.1741^{+}	0.0875
Birth Year: 1947	-0.1632^{**}	0.0587	-0.0429	0.0811	-0.2587^{+}	0.1321
Spring	0.0230	0.0394	-0.0628	0.0538	-0.0046	0.0868
Summer	0.0045	0.0414	-0.0446	0.0569	-0.0960	0.0943
Autumn	-0.0363	0.0412	-0.0958	0.0550	0.0664	0.0833
Famine Exposure	0.0245	0.0456	-0.0290	0.0609	-0.0648	0.0971
Constant	-1.4256^{**}	0.0934	-1.4589^{**}	0.1355	-1.6659^{**}	0.2308

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.12: Probit estimates for obstructive airway diseases, by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.1276^{**}	0.0178	-0.0720^{**}	0.0251	-0.0593	0.0433
General Health: Unfit	0.2355^{**}	0.0359	0.3039^{**}	0.0459	0.4171^{**}	0.0651
Psych. Health: Unfit	0.0608	0.0322	0.0527	0.0470	0.0417	0.0696
Overweight	0.0548	0.0503	-0.0578	0.0798	0.0859	0.1136
Height	-0.0040	0.0022	-0.0008	0.0029	-0.0127^{**}	0.0045
Birth Order	0.0124	0.0099	-0.0069	0.0163	0.0070	0.0257
Family Size	0.0030	0.0108	0.0148	0.0153	-0.0364	0.0238
Professional	0.1147^{+}	0.0498	0.0232	0.0537	-0.0327	0.0606
Farm Owner	-0.0063	0.0736	-0.1312	0.1458	0.1214	0.2200
Skilled	0.0062	0.0358	0.0683	0.0475	-0.2192^{+}	0.1087
Unskilled	0.0898^{+}	0.0423	0.1105	0.0647	-0.2605	0.1735
Unknown	0.1450^{+}	0.0584	0.0870	0.0873	-0.0191	0.1468
City	0.0933	0.0697	0.0301	0.1093	0.1042	0.1653
Urbanized Rural	0.0162	0.0782	-0.0631	0.1334	0.2714	0.1903
Other	-0.0410	0.0791	0.1673	0.1305	0.0515	0.2207
North	0.0262	0.0850	-0.0090	0.1234	-0.2286	0.2420
South	-0.0039	0.0670	-0.1809	0.1082	0.1687	0.1457
East	0.1005	0.0728	-0.1788	0.1270	0.0001	0.1837
Catholic	-0.0677^{+}	0.0343	-0.0353	0.0474	-0.0114	0.0712
Other or No religion	-0.0641	0.0349	-0.0220	0.0459	0.0386	0.0675
Birth Year: 1944	-0.0473	0.0457	0.0278	0.0618	0.0074	0.0915
Birth Year: 1946	-0.0436	0.0391	-0.0616	0.0538	-0.0753	0.0787
Birth Year: 1947	-0.1603^{**}	0.0571	-0.0970	0.0799	-0.0739	0.1181
Spring	0.0526	0.0383	0.0306	0.0535	-0.0591	0.0800
Summer	0.0086	0.0404	0.0320	0.0567	-0.0289	0.0831
Autumn	-0.0896^{+}	0.0408	-0.0249	0.0549	-0.1192	0.0799
Famine Exposure	-0.0335	0.0446	-0.0601	0.0605	0.0660	0.0899
Constant	-1.4401^{**}	0.0935	-1.5812^{**}	0.1346	-1.5359^{**}	0.2087

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.13: Probit estimates for hypertension, by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.0317^{+}	0.0130	-0.0277	0.0174	-0.0071	0.0302
General Health: Unfit	-0.0039	0.0287	0.0305	0.0348	0.0299	0.0514
Psych. Health: Unfit	0.0061	0.0246	0.0210	0.0333	0.0567	0.0500
Overweight	0.2703^{**}	0.0377	0.4471^{**}	0.0513	0.4515^{**}	0.0784
Height	-0.0084^{**}	0.0016	-0.0084^{**}	0.0020	-0.0083^{**}	0.0031
Birth Order	-0.0041	0.0075	-0.0111	0.0112	0.0089	0.0173
Family Size	-0.0168^{+}	0.0080	-0.0287^{**}	0.0107	-0.0605^{**}	0.0163
Professional	-0.0354	0.0378	0.0034	0.0367	0.0228	0.0425
Farm Owner	-0.2061^{**}	0.0545	-0.1853	0.0989	-0.0166	0.1606
Skilled	-0.0123	0.0260	0.0369	0.0327	0.1736^{**}	0.0666
Unskilled	-0.0285	0.0314	0.0291	0.0457	-0.0491	0.1075
Unknown	0.0498	0.0446	0.1601^{**}	0.0601	0.0683	0.1017
City	0.0750	0.0512	0.0309	0.0732	0.0947	0.1091
Urbanized Rural	0.0610	0.0577	0.0016	0.0867	0.1632	0.1301
Other	0.0848	0.0576	-0.0571	0.0902	0.0140	0.1454
North	-0.0269	0.0620	0.1066	0.0866	0.1112	0.1412
South	0.0444	0.0484	0.0781	0.0701	0.0155	0.1042
East	0.0048	0.0543	0.0229	0.0835	-0.0340	0.1244
Catholic	-0.0381	0.0255	0.0229	0.0325	0.0841	0.0482
Other or No religion	-0.0294	0.0258	-0.0072	0.0316	-0.0508	0.0475
Birth Year: 1944	-0.0068	0.0332	0.0497	0.0425	-0.0598	0.0629
Birth Year: 1946	-0.1528^{**}	0.0290	-0.1612^{**}	0.0367	-0.1270^{+}	0.0550
Birth Year: 1947	-0.1588^{**}	0.0413	-0.1092^{+}	0.0549	-0.2224^{**}	0.0817
Spring	0.0226	0.0286	0.0112	0.0367	0.0319	0.0554
Summer	-0.0397	0.0301	0.0091	0.0390	-0.0144	0.0587
Autumn	-0.0713^{+}	0.0296	-0.0798^{+}	0.0376	0.0409	0.0543
Famine Exposure	-0.0205	0.0329	0.0474	0.0420	-0.0098	0.0619
Constant	-0.3469^{**}	0.0682	-0.4591^{**}	0.0913	-0.5763^{**}	0.1400

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.14: Probit estimates for hyperlipidemia, by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.0492^{**}	0.0134	-0.0407^{+}	0.0181	-0.0480	0.0321
General Health: Unfit	0.0034	0.0294	0.0262	0.0362	-0.0401	0.0554
Psych. Health: Unfit	-0.0242	0.0252	-0.0552	0.0350	-0.0459	0.0541
Overweight	0.1189^{**}	0.0389	0.2940^{**}	0.0529	0.2194^{**}	0.0843
Height	-0.0129^{**}	0.0017	-0.0190^{**}	0.0021	-0.0184^{**}	0.0033
Birth Order	0.0050	0.0076	-0.0002	0.0116	0.0337	0.0181
Family Size	0.0045	0.0082	-0.0108	0.0111	-0.0162	0.0173
Professional	-0.0352	0.0391	-0.0160	0.0380	-0.0091	0.0452
Farm Owner	-0.2069^{**}	0.0568	-0.2992^{**}	0.1069	-0.0339	0.1718
Skilled	0.0452	0.0267	-0.0267	0.0340	0.0530	0.0717
Unskilled	0.0678^{+}	0.0320	-0.0085	0.0475	-0.0351	0.1134
Unknown	0.0907^{+}	0.0457	0.0845	0.0625	0.1315	0.1060
City	-0.0071	0.0519	0.0156	0.0768	0.2034	0.1176
Urbanized Rural	0.0027	0.0584	0.0608	0.0901	0.2086	0.1384
Other	-0.0527	0.0589	0.0419	0.0943	-0.0501	0.1581
North	0.0873	0.0630	-0.0600	0.0928	0.0153	0.1584
South	0.0559	0.0493	0.0481	0.0730	0.1197	0.1102
East	-0.0335	0.0561	0.0023	0.0874	0.2408	0.1282
Catholic	-0.0048	0.0262	0.0284	0.0339	-0.0080	0.0510
Other or No religion	0.0236	0.0265	0.0667^{+}	0.0328	-0.1070^{+}	0.0509
Birth Year: 1944	0.0187	0.0340	0.0268	0.0441	-0.0078	0.0664
Birth Year: 1946	-0.0768^{**}	0.0297	-0.0814^{+}	0.0381	-0.1008	0.0578
Birth Year: 1947	-0.1110^{**}	0.0425	-0.0960	0.0574	-0.2906^{**}	0.0884
Spring	0.0193	0.0294	0.0265	0.0383	-0.0664	0.0590
Summer	0.0162	0.0307	0.0120	0.0407	-0.0128	0.0617
Autumn	-0.0599^{+}	0.0304	-0.0186	0.0389	-0.0944	0.0580
Famine Exposure	0.0175	0.0337	0.0516	0.0437	-0.0002	0.0657
Constant	-0.6105^{**}	0.0697	-0.6991^{**}	0.0954	-0.9000^{**}	0.1502

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.15: Probit estimates for diabetes (type 1 and 2), by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.0728^{**}	0.0171	-0.0383	0.0232	-0.0347	0.0461
General Health: Unfit	-0.0206	0.0374	0.0957^{+}	0.0451	0.0727	0.0755
Psych. Health: Unfit	0.0313	0.0316	0.0171	0.0443	0.1248	0.0730
Overweight	0.4187^{**}	0.0437	0.5138^{**}	0.0595	0.4825^{**}	0.1017
Height	-0.0061^{**}	0.0021	-0.0127^{**}	0.0027	-0.0071	0.0047
Birth Order	-0.0298^{**}	0.0100	-0.0167	0.0152	-0.0066	0.0274
Family Size	0.0083	0.0103	-0.0110	0.0143	-0.0400	0.0251
Professional	0.0127	0.0486	0.0017	0.0494	0.0340	0.0656
Farm Owner	-0.1326	0.0755	-0.1666	0.1476	0.1812	0.2492
Skilled	-0.0105	0.0339	0.0391	0.0435	0.1145	0.1012
Unskilled	0.0284	0.0404	0.0724	0.0598	0.1743	0.1496
Unknown	0.0064	0.0581	0.0346	0.0816	0.2667	0.1397
City	-0.0615	0.0652	-0.1240	0.0965	-0.0075	0.1667
Urbanized Rural	-0.1465	0.0757	-0.0744	0.1133	-0.4859^{+}	0.2452
Other	-0.2154^{**}	0.0770	-0.3547^{**}	0.1283	-0.1194	0.2233
North	0.1010	0.0801	0.1392	0.1181	0.1337	0.2181
South	-0.0895	0.0662	-0.0152	0.0974	-0.0640	0.1732
East	-0.0414	0.0728	0.0919	0.1121	0.1020	0.1948
Catholic	-0.0207	0.0335	0.0336	0.0441	-0.0133	0.0742
Other or No religion	0.0343	0.0332	0.0870^{+}	0.0418	-0.0305	0.0711
Birth Year: 1944	-0.0269	0.0429	0.0112	0.0573	-0.0719	0.0969
Birth Year: 1946	-0.1697^{**}	0.0381	-0.0772	0.0492	-0.0969	0.0841
Birth Year: 1947	-0.2204^{**}	0.0551	-0.0963	0.0750	-0.3045^{+}	0.1333
Spring	-0.0100	0.0371	-0.0178	0.0495	0.0235	0.0844
Summer	-0.0217	0.0389	0.0415	0.0518	0.0073	0.0893
Autumn	-0.0265	0.0383	-0.0367	0.0506	-0.0440	0.0842
Famine Exposure	-0.0599	0.0428	0.0777	0.0568	-0.0170	0.0956
Constant	-1.0832^{**}	0.0871	-1.2808^{**}	0.1213	-1.4567^{**}	0.2135

$^{+}p < 0.05$ and $^{**}p < 0.01$

Table A.16: Probit estimates for depression and anxiety, by education level, in structural model

	Primary Educ.		Lower Educ.		Higher Educ.	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Intelligence	-0.0730^{**}	0.0162	-0.1007^{**}	0.0217	-0.1216^{**}	0.0372
General Health: Unfit	0.0905^{**}	0.0345	0.1201^{**}	0.0418	0.1108	0.0613
Psych. Health: Unfit	0.1343^{**}	0.0294	0.1553^{**}	0.0397	0.0990	0.0601
Overweight	-0.0991^{+}	0.0496	−0.0277	0.0673	0.0388	0.1015
Height	-0.0040^{+}	0.0020	-0.0070^{**}	0.0026	0.0014	0.0038
Birth Order	0.0154	0.0091	0.0085	0.0138	0.0495^{+}	0.0213
Family Size	−0.0107	0.0099	0.0087	0.0133	−0.0398	0.0203
Professional	−0.0099	0.0472	0.0388	0.0448	0.0375	0.0519
Farm Owner	−0.0661	0.0680	−0.1421	0.1249	−0.2469	0.2230
Skilled	0.0439	0.0322	−0.0456	0.0412	−0.0451	0.0862
Unskilled	−0.0048	0.0393	−0.0223	0.0574	0.1217	0.1256
Unknown	0.0889	0.0543	−0.0870	0.0789	−0.2773	0.1459
City	−0.0063	0.0619	−0.0250	0.0913	−0.1855	0.1286
Urbanized Rural	−0.0950	0.0710	−0.1485	0.1126	−0.0733	0.1558
Other	−0.0789	0.0712	0.0369	0.1121	−0.1171	0.1768
North	−0.0398	0.0788	−0.1274	0.1112	-0.4451^{+}	0.2117
South	0.0186	0.0593	−0.0684	0.0900	0.0296	0.1269
East	−0.0509	0.0682	−0.1525	0.1079	−0.1023	0.1505
Catholic	0.0010	0.0313	−0.0746	0.0411	−0.0341	0.0605
Other or No religion	-0.0767^{+}	0.0323	0.0430	0.0390	0.0581	0.0578
Birth Year: 1944	−0.0114	0.0416	−0.0689	0.0546	−0.0444	0.0803
Birth Year: 1946	0.0131	0.0361	−0.0387	0.0453	−0.0364	0.0671
Birth Year: 1947	−0.0295	0.0512	−0.0364	0.0682	0.0198	0.0982
Spring	0.0667	0.0356	−0.0519	0.0455	−0.0653	0.0678
Summer	0.0458	0.0373	−0.0860	0.0488	−0.1029	0.0719
Autumn	−0.0115	0.0370	-0.1320^{**}	0.0472	-0.1655^{+}	0.0682
Famine Exposure	−0.0182	0.0407	−0.0545	0.0523	−0.0156	0.0769
Constant	-1.1727^{**}	0.0842	-1.1123^{**}	0.1140	-0.9440^{**}	0.1680

$^{+}p < 0.05$ and $^{**}p < 0.01$