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Abstract

Education is negatively associated with mortality for most major causes of death. The literature ignores that cause-specific hazard rates are interdependent and that education and mortality both depend on cognitive ability. We analyze the education-mortality gradient at ages 18-63 using Swedish register data. We focus on months lost due to a specific cause of death which solves the interdependence problem, and use a structural model that derives cognitive ability from military conscription IQ scores. We derive the educational gains in months lost and the selection effects for each cause of death, and quantify the selection contribution of observed characteristics and unobserved cognitive ability. In a standard Cox model that controls for observed IQ, primary education was associated with 6 months lost when compared to secondary education. In a structural model that accounts for cognitive ability the difference was 43% larger. In addition, the largest educational gains were achieved for the lowest education group in the reduction of external cause mortality. The educational gains in cardiovascular mortality was small, mainly due to large selection effects. These results suggest that educational differences in cause specific mortality may be biased by conventional Cox regression analyses.

Keywords: Cause-specific mortality; causal effect of education; cognitive ability.

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1 Introduction

Disparities in health and mortality across educational groups are striking and pervasive, and are considered one of the most compelling and well established facts in social science and social epidemiology research. It is commonly assumed that a large part of this association derives from the causal effect of education on health outcomes (Hummer and Lariscy 2011). However, evidence is growing in the literature that this assumption might be, at least partly, incorrect (Mazumder 2008; Clark and Royer 2013; Fletcher 2015). The association between health and education may partly be explained by confounding factors such as cognitive ability and parental background that affect both education choices and health (McCartney et al. 2013). Lower cognitive ability as measured by standardized IQ tests is related to adult health (Gottfredson 2004; Deary 2008; Conti and Heckman 2010) and increased mortality (Batty and David 2004; Batty et al. 2007; Calvin et al. 2011; Batty et al. 2009). Because educational attainment and cognitive ability are strongly correlated, it is difficult to separate their effects on health (Auld and Sidhu 2005) or mortality (Deary and Johnson 2010). However, a better understanding of the influence of cognitive ability on shaping the relation between education and mortality is needed to establish potential direct benefits of improvements in education on mortality.

The impact of education on health is likely to differ by disease. Some diseases involve complex treatments which are easier to implement for the high educated, while for other diseases the treatment is simple or hardly effective and knowledge does not affect recovery. This implies that the impact of education on mortality may differ by cause of death. Most of the studies on educational gains in cause-specific mortality ignore that education attainment depends on observed and unobserved factors, such as parental background and cognitive ability, that also influence mortality later in life (e.g. see Huisman et al. 2005; Kulhánová et al. 2014; Mackenbach et al. 2015). Individuals with higher cognitive abilities may not only reach higher education levels but also better health outcomes. Ignoring such confounding in the analysis of the impact of education on cause-specific mortality will bias the estimated impact.

A common approach to investigate educational differences in cause specific mortality is to estimate a proportional Gompertz, or Cox, hazard model for each cause-specific mortality including the education level as one of the explanatory variables. However, a proportional hazard model assumes that the competing causes of death are independent. This implies that the removal of one cause will leave the risk of dying from the other causes unchanged. The interpretation of the coefficients of education in a proportional hazard model is also not obvious in the presence of competing risks, as both the total survival and the cause specific cumulative incidence functions not only depend on the cause specific hazard but also on the hazards of all other causes. Another issue is that not only the scale of the Gompertz mortality hazard but also the shape of the hazard may be affected by education. Estimating separate Gompertz models for each education level (and each cause of death), therefore, captures the impact of education better. A direct way, which avoids these issues, to measure the impact of education on cause-specific mortality is to estimate the months lost due to a specific cause and regress this on the education level.

Standard months lost analysis still does not account for possible confounding of cognitive abilities on the association between education and mortality. The methodology we use to account for the interdependence of education attained and cause-specific mortality rates due to this confounding is an extension of the structural equation framework developed by Bijwaard, van Kippersluis, and Veenman (2015) and Bijwaard et al. (2015). The model consists of three parts: an ordered probit educational attainment depending on latent cognitive ability and childhood characteristics, potential cause-specific mortality hazards depending on the education level, latent cognitive ability, and childhood characteristics, and a measurement system for cognitive ability. We use the observed IQ-score as a measure of the latent, unobserved, cognitive ability. The IQ-score also depends on childhood characteristics. The model allows for interdependencies between educational attainment, IQ-score and cause-specific mortality. Thus, the possible endogeneity of education in the cause-specific mortality hazard is captured by the latent cognitive ability. Based upon the parameter estimates of such a structural model the educational gain of a specific cause of death is defined as the average educational difference in the implied number of months lost from age 18 till age 63 for a specific cause of death.

Our interest is not limited to estimating educational gains, but also in the selection effects of attaining a particular education level. The selection effects are derived from the differences in months lost from the structural model and non-parametric estimates. Comparing these results with the implied months lost based on stratified proportional hazard models, separate by cause of death and stratified by education level (and ignoring the possible endogeneity of education), provide an estimate of the selection on observables. Comparing the stratified results with the results from the structural model provide an estimate of the selection on cognitive ability.

Data from the Swedish Military Conscription Data (1951-1960), linked to administrative Swedish registers, offers the opportunity to investigate the impact of education on cause-specific mortality. We have information on about half a million men who are followed from the date of conscription till the end of 2012, or till death. For those men who die we observe the cause of death and we categorize the causes of death into four categories: neoplasms, cardiovascular diseases, external causes and other causes of death. We distinguish four educations levels, running from less than 10 years of education to at least university. In the analysis we control for the personal characteristics of the men, including parental background and birth order. We also observe the IQ-scores, in nine categories, from an intelligence test conducted at the military examination.

The empirical results show that improving education would lead to two to nine (lowest education group) additional months alive between 18 and 63. The low educated men would gain the most from the reduction of external causes of death (7 months). They would also gain from a reduction in cancer mortality (one month) and a reduction in mortality from other diseases (one month). Although standard Cox proportional hazard analysis would render large educational gains in cardiovascular mortality, we find that the educational gain in cardiovascular mortality is small which is mainly caused by accounting for cognitive ability. For the low educated the selection effects, the effect of selecting themselves into low education, is large for cardiovascular mortality and mortality due to other causes. The selection effect for external causes is negative for this group, caused by selection on cognitive ability, implying that for this group higher cognitive ability leads to a higher mortality due to external causes. For the high educated the educational gains are smaller, around half a month for each cause of death (one month for external causes), and the selection effects are almost negligible.

The paper is structured as follows. In Section 2 we discuss relevant previous research and conceptual framework. In section 3 we present the structural equations framework that we will use to disentangle the relative contributions of cognitive ability and education on the months lost due to each of the five causes of death. Section 4 presents the Swedish Military conscription data including the available register data on parental background and on causes of death. Section 5 presents the results and Section 6 discusses them.

2 Previous Research and Conceptual Framework

Educational attainment is the most commonly used indicator of socioeconomic status in studies of health and mortality (Hummer and Lariscy 2011). There are several reasons why we use education as our measure of socioeconomic status (Hummer et al. 1998; Preston and Taubman 2011). First, educational attainment is usually completed in early adulthood and remains constant over the life course. Second, educational attainment precedes other dimensions of socioeconomic status, such as income, occupation and the accumulation of wealth (Mirowsky and Ross 2003). Third, income and occupation may often respond to health fluctuations, while educational attainment is less prone to such issues of health endogeneity (Smith 2004). Fourth, education is likely to be more relevant then other measures of socioeconomic status for individuals who have retired, who are unemployed or out of the labor force. Finally, when using survey data missing information on educational attainment is much less of an issue in comparison with income and occupation.

Most studies focussing on the educational gradient in health and mortality measure educational attainment with a single indicator of years of completed schooling assuming that each additional year of education confers a monotonic increase in health, see e.g. Elo and Preston (1996) and Lynch (2003). Some other studies suggest that the relationship is not monotonic but instead is a step function that reflects degrees earned (Backlund et al. 1999; Montez et al. 2012). We also base our analyses on four distinct education levels: (*i*) Less than 10 years of education; (*ii*) Secondary education (at most 12 years); (*iii*) Full secondary education (at least 12 years, at most 13 years) and (*iv*) University and PhD.

Cause specific mortality

Evidence suggests differential impact of education on various diseases resulting in different educational cause-specific mortality gradients, Galobardes et al. (2004). The associations for cardiovascular diseases (CVD) appear to be stronger than for total mortality (Kulhánová et al. 2014). The main reason for this is that low education has been linked to cardiovascular risk factors, such as smoking, hypertension and overweight. For cancers the education-gradient varies by cancer type (Galobardes et al. 2004; Kulhánová et al. 2014). Higher mortality for the low educated from lung cancers are clearly related to the higher smoking prevalence of these individuals. The relationship between education level and the mortality rate for other cancers is more complex. Lifestyle differences, such as physical inactivity, might be one reason for this. Death from external causes, including traffic accidents, injuries and, suicides, is a major cause of early death and also depends on education attained (Borrell et al. 2005; Lorant et al. 2005). For traffic accidents differences in exposure, such as different use of protective devices, and differences in susceptibility may explain the educational gradient. Educational differences in mental illness, which is more prevalent among the low educated may explain the educational gradient in suicides.

Cognitive ability

It is obvious that cognitive ability influences educational attainment. It has been established that a strong correlation between cognitive ability and health outcomes exists (Auld and Sidhu 2005; Cutler and Lleras-Muney 2008; Kaestner and Callison 2011). Intelligence, measured by some form of IQ-test(s), is also associated with health outcomes (Gottfredson 2004; Deary 2008; Batty et al. 2009) and mortality (Batty et al. 2007; Batty et al. 2007; Batty et al. 2009; Batty et al. 2009; Calvin et al. 2011). However, isolating a pure measure of intelligence is difficult. Performance on a IQ-test surely depends on cognitive ability but also on other personal characteristics, such as family background. Using a factor model (Anderson and Rubin 1956) that assumes that performance on one or more IQ-tests is driven by, at least in part, by a common unobserved (latent) factor, *cognitive ability*, allows us to estimate the impact of education on cause-specific mortality while accounting for cognitive ability influencing both educational attainment and mortality. Recent papers by Conti and Heckman (2010) and Bijwaard et al. (2015) also use this concept of measuring cognitive ability based on IQ-scores. While cognitive ability cannot be measured directly it accounts for measurement error in the IQ-scores and for the impact of personal characteristics on the IQ-score. Note that we do not include the IQ-score directly in the education equation nor in the cause-specific mortality hazards. We use the IQ-score to measure the latent cognitive ability, which we include in the education equation and the cause-specific mortality hazards.

Causal inference

Related to this is that the widespread positive education-health/mortality associations may not necessarily reflect beneficial effects of education on health, because cognitive ability influences both education and health outcomes. For example, understanding the doctor better and adhering to complex treatments may be driven by intelligence rather than education (Batty and David 2004), or health literacy which is influenced by to both education and cognitive ability. Thus, the education-health gradient may be in part due to unobserved endowments, such as cognitive capabilities, that affect both education attainment and health. Individuals with higher cognitive skills may not only have better health outcomes but may also have had better schooling opportunities and thus obtain more education. To what degree the education-health associations actually reflect the causal effects of education on health is an important question for understanding the returns to schooling.

In the literature three different approaches have been employed to examine the causal effects of education on health and mortality. The first approach exploits changes in compulsory schooling policies, usually increases in the minimum age or the legally permitted grade to leave school, as instrumental variables for schooling attainment to control for endogeneity, i.e. an uncontrolled confounder affects both the education attained and the mortality. The estimates based on these studies point towards a small effect (Lleras-Muney 2005; Van Kippersluis et al. 2011; Meghir et al. 2013), or even entirely absent (Arendt 2005; Albouy and Lequien 2009; Clark and Royer 2013) causal effect of education on health outcomes. However, a major limitation of using changes in compulsory schooling to detect educational effects on health outcomes, and in particular mortality, is that often only a relatively small part of the population is affected by the laws (Mazumder 2008; Fletcher 2015). Another issue with the instrumental variable methods applied in these studies is that they, implicitly, assume that the compulsory schooling reforms only affect long-term health through their effect on education, ignoring any other contemporary policy changes they may accompany these reforms. Another identification strategy is to use variation in education among siblings, often identical (monozygotic) twins, to difference out the unobserved factors shared by these siblings. These studies obtain estimates of the impacts of the differences in schooling within a pair of identical twins on their health differences at various schooling levels. Results from such studies indicate that part of the educational differences in cause-specific mortality disappears when accounting for shared family background (Behrman et al. 2011; Lundborg 2013; Næss et al. 2012; Amin et al. 2015). These siblings studies also suffer from limited data and issues of generalization, as they only use data on siblings and those families might not represent the general population. A third approach, that we will employ, is based on structural models in which the interdependence between education, health, and cognitive ability is modelled explicitly. Results from such models for health-outcomes (Conti and Heckman 2010; Conti et al. 2010) or for total mortality (Bijwaard, van Kippersluis, and Veenman 2015; Bijwaard et al. 2015) show that at least half of the health disparities across educational groups is due to the selection of healthier, more able individuals into higher education. Hence, in recent years evidence is growing that the presumed health returns to education may be smaller than previously thought.

A clear advantage of our study is the very large sample size. Another advantage is that the data are population based and not prone to self-selection because military conscription was mandatory in Sweden for the included birth cohort. The contribution of this paper is that we develop a new method to estimate the educational gain in cause-specific mortality. The innovative aspects of our method are threefold. First, contrary to the standard literature, we define the educational gains in term of months lost due to a specific cause of death instead of the hazard ratio. The months lost measure are easier to interpret, are additive and are not prone to issues of independence (see below). Second, in the analyses we account for confounding of the cause-specific mortality through (latent) cognitive ability. To this end we extend the structural all-cause mortality model of Bijwaard, van Kippersluis, and Veenman (2015) to cause-specific mortality. The model takes into account that (latent) cognitive ability (and other observed individual characteristics) may affect both the attained education and the cause-specific mortality rates. From the estimated model we derive the educational gain, the causal impact of education on months lost due to a specific cause of death. Third, from the comparison of the results from the structural model and non-parametric results we derive the selection effects (in months lost) of obtaining higher education. Finally, we decompose the selection effects of obtaining higher education into a selection effect on cognitive ability and a selection effects on the observed individual background. In the next section we explain the model and the measure of months lost in more detail.

3 Methodology

The common approach to investigate the educational gradient in cause specific mortality is to estimate Cox proportional hazard models for each cause-specific mortality including the education level as one of the explanatory variables, see a.o. (Næss et al. 2012; Elo et al. 2014; Kulhánová et al. 2014). In these models hazard ratios below one for higher education levels imply that the cause-specific mortality rates are lower for higher education levels. However, a proportional hazard model assumes that the competing causes of death are independent. This implies that the removal of one cause will leave the risk of dying from the other causes unchanged. The interpretation of the coefficients in a competing risks model also requires caution. A particular covariate, say x_l, can appear in several competing hazards. In such a case the vectors β_{lk} convey little information about the effect of the covariate on the probability to die from cause k. Another issue often ignored is that not only the scale of the mortality hazard, but also the shape of the hazard may be affected by education. We estimate stratified proportional hazard models, separate models for each education level (and each cause of death), to account for this.

Months lost due to a specific cause of death

Another measure of the mortality experience is the number of months lost due to a specific cause of death. This quantity has a more natural interpretation and avoids the issues of independence in competing risks proportional hazard models, see Andersen (2013) and Andersen and Canudas-Romo (2013). The months lost can be defined over the whole age distribution or on a segment of the age distribution, e.g. the number of months lost before age 63 (as we will use). Based on the months lost we define the educational gain as the decrease in months lost (from a specific cause of death) when improving the education level. A nice feature of the months lost quantity is that it is an additive measure. The sum over all alternative causes of death within one education level is equal to the total amount of months lost for that education level. The sum of educational gains over all education levels within a cause of death is equal to the total educational impact of that cause of death. The months lost can be calculated using non-parametric methods and based upon estimated hazard coefficients, the implied total survival and the cumulative incidence functions. Non-parametric estimation of the months-lost is straightforward because the survival (Kaplan-Meier) and cumulative incidence functions are straightforward to estimate, see Appendix A.

If all individuals were observed till they die regression analysis on the number of months lost would be easy. However, the individual mortality is often only observed till the end of the observation period. This implies that the age at death is (heavily) censored. The highest age we observe is 63 years. Andersen (2013) demonstrates how, using pseudo-observations, to carry out regression analysis for the months-lost due to a specific cause of death when some of the observations are censored. The idea behind pseuso-observations is closely linked to the Jackknife method and is based on repeatedly dropping one observation and re-estimating the model on the remaining observations[1] The advantage of creating pseudo-observations is that they can be modelled using standard (uncensored) linear models.

[1]We explain this method in more detail in Appendix A.1.

Structural model[2]

Still, this does not account for possible confounding of cognitive abilities, affecting both the educational attainment and the cause-specific mortality. The methodology we use to account for this endogeneity is an extension of the structural equation framework developed by Bijwaard, van Kippersluis, and Veenman (2015) and Bijwaard et al. (2015). The model consists of three parts: (i) ordered probit educational attainment depending on latent cognitive ability and other covariates, (ii) potential cause-specific mortality hazards depending on the education level, latent cognitive ability, and other covariates, and (iii) a measurement system for cognitive ability. The model allows for interdependencies between educational attainment, cognitive ability and cause-specific mortality.

We assume that educational attainment is possibly endogenous and that it depends on observed individual characteristics and on unobserved cognitive ability. The endogeneity of education, correlation between educational attainment and the cause-specific hazards, is captured by latent cognitive ability, which also affects both educational attainment and the cause-specific hazards. We use an ordered probit model and the underlying linear equation of attaining a particular education level is continuous and depends on observed characteristics and the latent cognitive ability θ. The cause-specific mortality is potentially causally related to the education attained.

A common characteristic of mortality data is that not all individuals experience death during the observation period. Such right censoring makes inference based on means unreliable. Another issue is that due to dynamic selection those still alive at age 18, the time the conscripts are observed at the military examination, may not be a random selection of the original birth cohort. We therefore model the cause-specific mortality hazard as this effectively deals with these data issues. The second part of the structural model comprises the potential cause-specific mortality hazards. These hazard rates are potential because each individual's cause-specific mortality is only observed for the actual education level the individual has and not for the alternative education levels the individual could have attained. For all but external causes of death we assume a Gompertz proportional mortality rate, which assumes an exponential increase in the cause-specific mortality by age. A Gompertz mortality rate is known to provide accurate mortality rates for middle aged individuals (Gavrilov and Gavrilova 1991). The potential hazard for each cause of death depends on observed characteristics and on latent cognitive ability θ. We allow both the shape and the scale of the Gompertz hazard to differ by education. We assume that the hazard to die from external causes is exponential, i.e. does not vary by age (but the scale still differs by education). Note that we do not control for personal characteristics, such as marital status, income or occupation, in the hazard rates because these variables are on the pathway from education to cause-specific mortality.

The structural model is closed by a measurement equation linking intelligence (IQ) scores with the latent cognitive ability and observed individual characteristics. We assume a linear relation between the measured IQ depending on observed socioeconomic background and the latent cognitive ability. We use a maximum likelihood estimation method to estimate all the parameters of the model. Thus, we jointly estimate the parameters of the education attainment, the cause-specific mortality hazards and the measurement equation.[3]

Based upon the parameter estimates the educational gain of a specific cause of death is defined as the average educational difference in the implied number of months lost from age 18 till age 63 for a specific cause of death. It is important to note that if the education attainment were completely independent of perceived health gains, i.e. if there is no unobserved cognitive ability that affects both the education attainment and cause specific mortality, we could estimate cause of death hazard models for each education level separately. We use the results of such stratified models, together with the results from non-parametric estimation, to gauge the importance of selection effects.

For each cause of death we can decompose the unconditional (non-parametric) differences in months

[2]The structural model is explained in full detail in Appendix A.2.

[3]We explain this method in more detail in Appendix A.

lost into the educational gain and a residual, which is a selection effect on the basis of cognitive ability and the other observable factors. The *selection effect*, can be further decomposed into a selection on observables, *selection effect observed*, and a selection on latent cognitive ability, *cognitive ability selection effect*. The selection on observables is based on the difference in months lost between the implied education effects of the stratified (by education) Gompertz models and the non-parametric estimates. The selection on cognitive ability is based on the difference in months lost between the educational gain from the structural model and the implied education effects of the stratified (by education) Gompertz models, see Appendix A.3 for the mathematical details.

4 Data

The data come from several Swedish population-wide registers which are linked using unique individual identification. The Swedish Military Conscription Data includes demographic information of the conscripts and information obtained at the military examination, including a battery of intelligence tests. These data are linked to information on the parental socioeconomic situation at birth, the parental education, the education of the individual himself, date of death and the cause of death. The data consist of the population of men born between 1950 and 1984, who were enlisted between 1969 and 2001 in the year they turned 18-20. Military service was mandatory only for men. We selected only those born in 1951–1960, for whom at least one parent is known. We also removed men without a known conscription date.

We aggregated the observed education into four classes: (*i*) Less than 10 years of education (only primary schooling); (*ii*) Secondary education (2 years); (*iii*) Full secondary education (3 years) and (*iv*) Post secondary education (University and PhD). We removed men without a known education level or without an IQ-measurement. We ended up with 446,545 individuals (men) of which 21% belongs to the lowest education group; 36% has finished secondary education (max 12 years); 12% has finished secondary education (13 years) and 30% has (at least) attained 3 years of university. The IQ-measurement was based on a general classification test, which was strongly influenced by the Spearman test and his concept of general ability. It consists of eight subtests which together are assumed to measure general intelligence, g. The test was evaluated as a normalised nine-point scale, added into a sum and then transformed into a nine point scale. We assume that this is close to continuous.

Selected demographic and parental socioeconomic characteristics at the time of military examinations by education level are presented in Table 1. We see a clear positive relation between the maternal socioeconomic status, the paternal education and the education attained by the military conscript. The higher the social class and education of the parents the higher the education level of the conscript. The average IQ-score at age 18 also clearly increases with education attained.

We aggregated the causes of death into four categories: (1) Neoplasms (ICD8 140–240; ICD9 140–240; ICD10 C0–D490) (2) Cardiovascular diseases (ICD8 390–460; ICD9 390–460; ICD10 I); (3) External causes (ICD8 E800–E999; ICD9 E800–E999; ICD10 V–Y), and finally (4) Other causes of death. The death ratios (till the end of the observation period 31/12/2012) differ by education level and by cause of death. For all the four causes of death we observe a clear educational gradient, but much less for neoplasms. For the two groups with the highest education mortality due to neoplasms is the most important cause of death, while for the lower education groups external causes are more important.

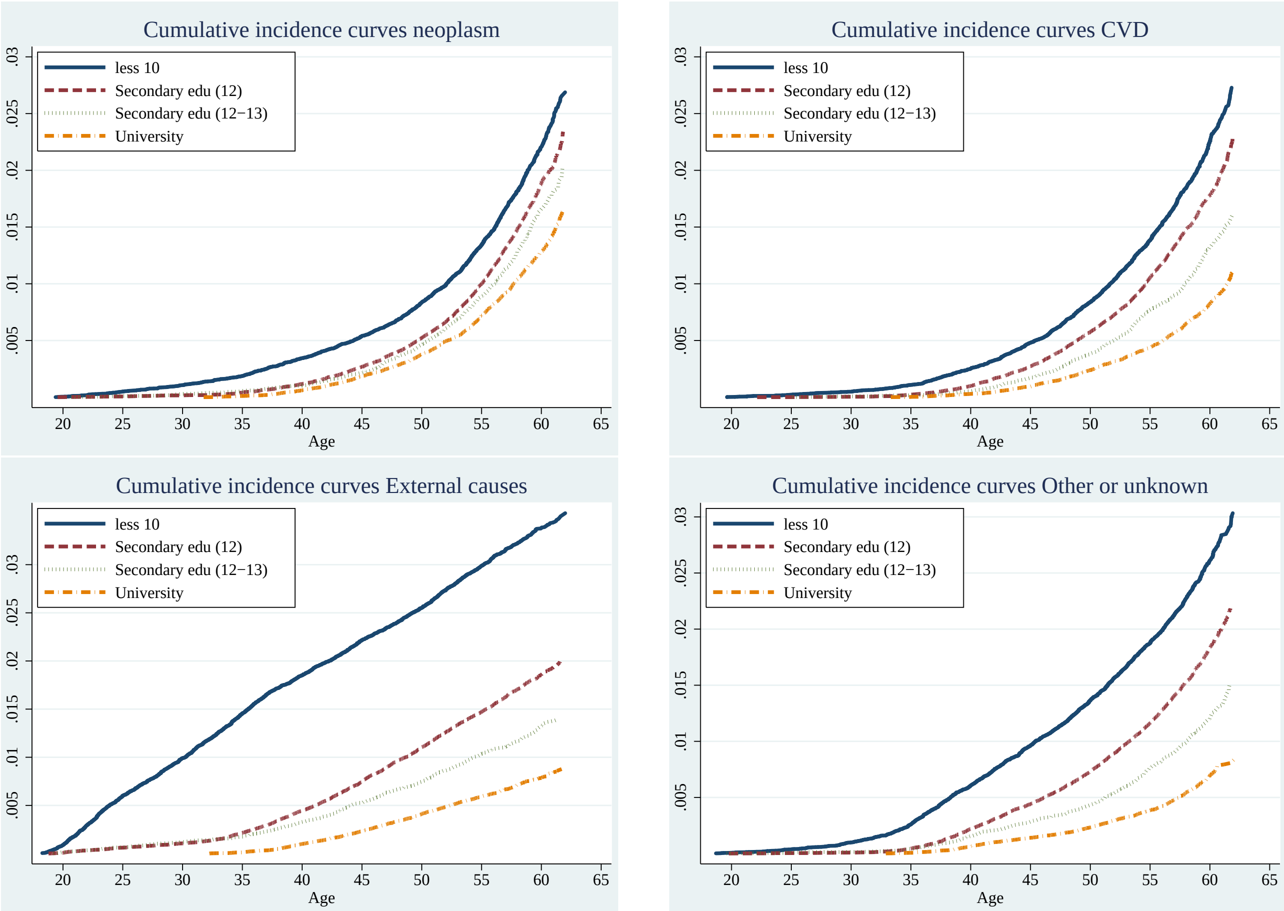
To take the timing of the deaths into account we also calculated the cumulative incidence functions, the probability of dying from a specific cause of death before some age. The (non-parametric) Aalen-Johansen cumulative incidence functions (Aalen and Johansen 1978) depicted in Figure 1 show, again, a clear educational gradient in the probability to die from each of the four causes of death. They also show that external causes of death, such as traffic accidents, suicides and, homicides, play a major role in the early mortality of the lowest educated.

Table 1: Sample characteristics, Swedish Conscripts 1951-1960 ($N = 446,545$)

	Education level			
	primary	secondary (2 years)	secondary (3 years)	university
	Mother's ses			
not classified	4%	4%	3%	3%
unskilled workers	10%	9%	8%	6%
Skilled workers	49%	48%	36%	27%
farmers	19%	15%	13%	11%
non-manual (low)	14%	19%	30%	38%
non-manual (intermediate)	2%	3%	5%	8%
non-manual (high)	1%	1%	4%	6%
	Father's education			
less 9 years	66%	57%	45%	33%
9–10 years	3%	3%	4%	4%
Secondary edu (max 12)	11%	15%	17%	16%
Secondary edu (13)	5%	7%	11%	15%
university	3%	4%	10%	20%
missing	15%	13%	12%	11%
	Birth measures			
mother $<$ 20 at birth	9%	9%	7%	4%
Birth order 1	34%	38%	43%	46%
Birth order 2	31%	33%	33%	33%
Birth order 3	18%	16%	14%	14%
Birth order 4	8%	7%	5%	5%
Birth order $>$ 4	8%	6%	4%	3%
	IQ-measure 18[a]			
average IQ	4.0	4.6	5.7	6.5
	Mortality (age 18–63)			
# of deaths	8,770	9,451	2,506	3,829
deaths per 1000	90.8	59.1	45.3	28.4
	causes of death per 1000 men			
neoplasm	18.2	14.0	13.1	10.0
Cardiovascular diseases	18.4	13.9	10.4	6.3
External causes	31.5	16.5	11.7	6.8
Other causes	22.6	14.7	10.1	5.3
$N =$	96,598	160,000	55,313	134,634

[a] Running from low (1) to high (9).

Figure 1: Cumulative incidence curves by cause of death and education level, Swedish Conscripts 1951-1960



5 Results

Before we turn to discuss the educational gains in months lost we estimate educational differences in causes-specific mortality rates using Cox proportional hazard models, the common approach in the literature (Elo et al. 2014; Kulhánová et al. 2014). In Section 5.2 we discuss the non-parametric estimates of the months lost and the implied educational gain. We also show how these non-parametric educational gains change when we account for observed individual characteristics and for IQ-scores. In Section 5.3 we discuss the estimated educational gains based upon estimated stratified proportional hazards. These proportional hazards models assume that the shape and the scale of the cause-specific hazards differ by education level. They also account for observed individual characteristics. Note that these models ignore that education is possibly endogenous. For comparison we also discuss the results from stratified models including observed IQ-scores. Finally, in Section 5.4 we discuss the results from the structural model, both the educational gains and the selection effects.

5.1 Standard Cox proportional hazard analysis

In using the Cox models we deviate from the standard literature and make an important adjustment. Instead of including three educational dummies, one for each of the three education levels above the lowest, we estimate three separate models with only one educational dummy, for the highest education level based on the data of men with adjacent education levels. This relaxes the assumption of common age-dependence by education level, implicit in the Cox model.[4] This makes comparison of these results with the results from the models for months lost analyses easier.

The results in Table 2 show that across all causes of death educational improvement reduces the mortality hazard, with the strongest educational gains from external causes. The smallest educational gains are found in cancer mortality, consistent with the view that the risk of getting cancer is less affected by healthy lifestyles, except for lung cancer, and that effectiveness of cancer treatment is less influenced by knowledge of the patient. Meghir et al. (2013) also found the lowest gains in cancer mortality using Swedish data. Accounting for maternal socioeconomic status around birth, paternal education and, birth order hardly affects the educational gains, but additionally accounting for differences in intelligence, as measured by the IQ-score, changes the educational gain for half of the causes of death. Including the IQ-score in the controls reduces the estimated educational gain of cardiovascular diseases and other causes of death, but only by a very small amount.

However, using a Cox proportional hazard model assumes that the competing causes of death are independent. This implies that the removal of one cause will leave the risk of dying from the other causes unchanged. The interpretation of the coefficients of education in proportional hazard model is also not obvious in the presence of competing risks, as both the total survival and the cause specific cumulative incidence functions not only depend on the cause specific hazard but also on the hazards of all other causes. A direct way, which avoids these issues, to measure the impact of education on cause-specific mortality is to estimate the months lost due to a specific cause and regress this on the education level.

The Cox models with IQ-scores included in the controls also ignore that cognitive ability not only affects mortality but also educational attainment. The structural model defined in Section 3 accounts for the interdependence of cognitive ability, education and, socioeconomic background, and their joint influence on the cause-specific mortality rates. Before we turn to the results from the structural model, we discuss the results from non-parametric and stratified models and their implied gains in months lost by cause of death.

[4] Estimation of a joint Cox model with three educational dummies does not change the conclusion on the educational gradient in the cause specific hazards. The estimated hazard ratios of secondary education (12-13 years) and of university in a joint model are close to the product of the odds ratios in (1) and (2) and (1) to (3). When accounting for IQ-differences the joint Cox models give slightly larger education effects.

Table 2: Cox hazard odds ratios of education on cause-specific mortality, Swedish Conscripts 1951-1960, age 18–63

	Educational gain[a]		
	(2)	(3)	(4)
	neoplasm		
unadjusted	0.77**	0.87**	0.79**
Controls[b]	0.77**	0.88**	0.79**
Controls and IQ	0.79**	0.90**	0.78**
	cardiovascular diseases		
unadjusted	0.72**	0.72**	0.61**
Controls[b]	0.72**	0.73**	0.63**
Controls and IQ	0.82**	0.78**	0.67**
	external causes		
unadjusted	0.51**	0.69**	0.59**
Controls[b]	0.51**	0.69**	0.59**
Controls and IQ	0.52**	0.74**	0.62**
	other causes		
unadjusted	0.60**	0.65**	0.54**
Controls[b]	0.59**	0.64**	0.54**
Controls and IQ	0.69**	0.70**	0.56**

[a] (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
[b] Controls include: maternal socioeconomic status around birth, paternal education, year of birth and, birth order.
$^{+}p < 0.05, ^{**}p < 0.01$.

5.2 Months lost due a specific cause

We start with the non-parametric estimation of the educational gains in months lost due to one of the four causes of death. If all individuals were observed till time of death, the impact of education on the month-lost would be easy to obtain. However, the individual deaths are (heavily) censored at the end of the observation window 1/1/2013. This implies that the highest age reached we can observe is 63 years.

We can estimate the effects of covariates, including education, on the months lost using pseudo-observations regression analysis, using the method of Andersen (2013). Table 3 presents the estimated months lost due to each of the considered causes of death by education level and the implied educational gain. The lowest education group clearly looses more months alive between 18 and 63 than the other education groups (22 months compared to only 5 months for the highest education group). We also see a clear difference in the importance of the different causes of death. For the lowest education level external causes explain by far the largest amount of months lost (10 months, 45%), while for the highest education levels cancer mortality contributes relatively more (1.7 months, 34%). The educational gain, depicted in the second panel of Table 3, is the largest for the lowest education group, especially for external causes (6 months). The educational gains for the higher education levels are modest (0.3 to 1.3 months), but still significant.

The third and fourth panel of Table 3 show that the estimated educational gains only slightly change when we include observed individual characteristics (third panel) or both observed individual characteristics and the observed the IQ-score (fourth panel). Accounting for differences in maternal socioeconomic status, parental education and birth order reduces the educational gain from external causes for the lowest education group but increases it for the next education level. Additionally accounting for the IQ-score reduces the educational gain from other causes of death and from cardiovascular diseases (only for the lowest two education levels).

Table 3: Months lost due to cause of death and the educational gain (18-63), Swedish Conscripts 1951-1960, non-parametric model

	Education level[a]			
	(1)	(2)	(3)	(4)
	Months lost			
neoplasm	3.56**	2.47**	2.20**	1.71**
cardiovascular diseases	3.42**	2.45**	1.70**	1.07**
external causes	9.82**	3.75**	2.67**	1.34**
other causes of death	4.90**	2.83**	1.85**	0.97**
Total	21.70	11.49	8.42	5.09
	Educational gain			
neoplasm		1.09**	0.27**	0.48**
cardiovascular diseases		0.98**	0.74**	0.63**
external causes		6.07**	1.08**	1.33**
other causes of death		2.07**	0.98**	0.88**
Total		10.21**	3.07**	3.33**
	Educational gain, controls[b]			
neoplasm		1.04**	0.37**	0.49**
cardiovascular diseases		0.95**	0.75**	0.59**
external causes		5.70**	1.43**	1.31**
other causes of death		2.05**	1.07**	0.92**
Total		9.74**	3.62**	3.31**
	Educational gain, controls and IQ			
neoplasm		1.05**	0.40**	0.52**
cardiovascular diseases		0.79**	0.58**	0.53**
external causes		5.71**	1.51**	1.40**
other causes of death		1.84**	0.83**	0.81**
Total		9.39**	3.33**	3.27**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.

[b] Controls include: maternal socioeconomic status around birth, paternal education, year of birth and, birth order.

$^{+}p < 0.05, ^{**}p < 0.01$.

5.3 Stratified models

The non-parametric approach ignores that other factors also affect the cause-specific mortality. Next we estimate proportional hazard models stratified by education levels for each of the four causes of death, including observed individual information, such as mother's social economic status at birth, father's education, age of the mother at birth, birth order and, birth year dummies. Table 4 presents the estimated hazard ratios of the proportional hazard models, assuming a Gompertz age-dependence for mortality due to neoplasm, cardiovascular diseases and other causes and a constant age dependence, an exponential hazard model, for mortality due to external causes. As separate models are run for each education level, the impact of observed individual characteristics for each education level may differ but also the baseline hazard as reflected in the shape and the scale of the Gompertz hazard. It can indeed be seen that the scale and shape of the Gompertz mortality hazard differ substantially (and, in most cases, significantly), for a given cause of death, among the four educational groups. This justifies stratified estimation by education level.

Mother's socioeconomic status (ses) around birth plays a role in all cause-specific hazards. When the mother of the conscript was a farmer it reduces the hazard of dying from all causes. Unskilled mothers lead to a higher risk of dying from cancers and other causes. For the lowest education group a mother with low non-manual status increases the risk of dying from external causes and from other causes. For the conscripts who went to university a mother with non-manual ses reduces the cardiovascular mortality. The role of the education of the father is more ambiguous. Unknown paternal education almost always increases the mortality risk. For the lowest education group a higher paternal education increases the risk of dying from external causes and other causes. This seems counterintuitive but those men might have failed their parental education prospects as they have a lower education compared to their fathers, which increases mental stress. Men men with 2 years of secondary education born from a young, below 20, mother have an increased risk of dying from external causes and from other causes. Finally, birth order only plays a minor role in explaining the cause-specific mortality by education. We also included year of birth dummies to account for cohort effects.

Based on all the estimated parameters of the cause-specific mortality hazards we calculate the average months lost due to each specific cause of death from age 18 till 63 and how much an individual would gain if he had attained a higher education level, see the first panel of Table 5. After accounting for observed differences the estimated cause-specific months lost for the lowest education group decline compared to the non-parametric estimates. For the other education groups the estimated months lost due to external causes increases. This leads to a reduction in the estimated educational gains for the lowest education group for all causes of death and an increase in the educational gain for external causes for the higher education levels. For the other causes of death the differences between the stratified model and the non-parametric model are small.

We also estimated a stratified model that additionally includes the observed IQ-scores, given in Table B.2 in Appendix B. Although the estimated parameters of the Gompertz hazards change the estimated educational gains do not change, see Table B.3 in Appendix B.

Table 4: Hazard ratios for cause-specific mortality stratified models by education and cause of death, Swedish Conscripts 1951-1960, aged 18–63

	Education level[a]			
	(1)	(2)	(3)	(4)
	neoplasm			
Mother's ses				
not classified	1.103	1.122	1.292	0.988
unskilled workers	1.145	1.018	1.076	1.454^{**}
farmers	0.830^{**}	0.847^{+}	0.789	0.874
non-manual (low)	1.104	1.006	1.025	1.016
non-manual (intermediate)	0.994	1.145	1.137	0.945
non-manual (high)	1.577^{+}	0.976	1.003	0.989
Father's education				
9-10 years	1.054	0.879	1.424^{+}	1.026
secondary edu (max 12)	1.064	0.951	0.895	0.976
secondary edu (13)	1.193	0.997	1.038	1.027
university	1.179	0.961	0.893	1.054
education missing	1.227^{**}	1.113	1.117	1.081
Birth info				
mother < 20 at birth	0.939	1.129	0.968	0.980
birth order 2	0.864^{+}	1.067	1.020	0.994
birth order 3	0.894	1.083	0.991	0.906
birth order 4	0.881	0.932	1.109	0.978
birth order 5 or higher	0.972	1.004	1.081	1.201
Baseline				
constant	-11.334^{**}	-13.747^{**}	-13.562^{**}	-14.426^{**}
Gompertz shape	0.090^{**}	0.131^{**}	0.125^{**}	0.135^{**}
	cardiovascular diseases			
Mother's ses				
not classified	0.962	1.142	1.529^{+}	1.008
unskilled workers	1.055	1.119	1.143	1.055
farmers	0.704^{**}	0.814^{**}	0.780	0.787
non-manual (low)	1.035	0.956	0.859	0.803^{+}
non-manual (intermediate)	1.448	1.030	1.056	0.769
non-manual (high)	1.031	0.990	0.861	0.624^{+}
Father's education				
9-10 years	1.003	1.007	1.157	1.570^{**}
secondary edu (max 12)	1.110	0.968	1.007	0.928
secondary edu (13)	0.932	0.946	0.743	0.991
university	1.123	0.973	1.202	0.875
education missing	1.483^{**}	1.266^{+}	0.974	1.449^{**}
Birth info				
mother < 20 at birth	1.068	1.095	1.017	0.937
birth order 2	0.947	0.972	0.826	0.848^{+}
birth order 3	0.915	0.986	0.918	0.931
birth order 4	0.716	1.107	1.064	0.765
birth order 5 or higher	1.003	1.170	1.045	0.824
Baseline				
constant	-11.988^{**}	-13.790^{**}	-14.042^{**}	-15.053^{**}
Gompertz shape	0.101^{**}	0.130^{**}	0.132^{**}	0.143^{**}

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included.
$^{+}p < 0.05, ^{**}p < 0.01$.

Table 4: Hazard ratio stratified models (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
	external causes (exponential)			
Mother's ses				
not classified	0.799^{+}	1.133	1.031	1.213
unskilled workers	0.943	1.125	0.769	1.112
farmers	0.645**	0.858^{+}	0.932	1.076
non-manual (low)	1.190**	0.931	0.878	1.026
non-manual (intermediate)	1.142	1.068	1.036	1.280
non-manual (high)	1.078	0.801	0.819	1.009
Father's education				
9-10 years	1.098	1.165	1.019	1.043
secondary edu (max 12)	1.253**	1.063	1.256	0.842
secondary edu (13)	1.386**	1.093	1.011	0.840
university	2.120**	1.203	1.402^{+}	0.822
education missing	2.403**	1.504**	2.019**	1.194
Birth info				
mother < 20 at birth	1.066	1.275**	1.082	1.128
birth order 2	1.091	1.080	0.991	1.005
birth order 3	0.921	1.109	0.833	0.997
birth order 4	0.893	1.118	0.988	1.189
birth order 5 or higher	1.552**	1.381**	0.990	0.914
Baseline				
constant	−7.141**	−7.678**	−7.926**	−8.700**
	other causes of death			
Mother's ses				
not classified	1.180	1.269**	1.109	0.933
unskilled workers	1.260**	1.333**	1.222	1.057
farmers	0.565**	0.577**	0.723^{+}	0.815
non-manual (low)	1.146^{+}	0.998	1.089	1.066
non-manual (intermediate)	1.272	1.309^{+}	1.388	0.919
non-manual (high)	1.157	0.769	1.061	0.802
Father's education				
9-10 years	0.935	0.951	1.051	0.784
secondary edu (max 12)	1.128	1.095	1.086	1.346**
secondary edu (13)	0.995	0.977	1.390^{+}	1.190
university	1.481**	1.258^{+}	1.244	0.887
education missing	1.583**	1.388**	1.619**	1.477**
Birth info				
mother < 20 at birth	0.981	1.202^{+}	1.278	1.122
birth order 2	0.974	1.028	1.180	0.848
birth order 3	0.987	1.070	0.790	0.952
birth order 4	0.894	0.944	0.890	0.773
birth order 5 or higher	1.106	0.956	1.161	0.850
Baseline				
constant	−10.290**	−12.320**	−12.855**	−14.131**
Gompertz shape	0.067**	0.102**	0.102**	0.116**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included.
$^{+}p < 0.05$, $^{**}p < 0.01$.

Table 5: Months lost due to cause of death and the educational gain (18-63), Swedish Conscripts 1951-1960, aged 18–63

	Education level[a]			
	(1)	(2)	(3)	(4)
	Stratified model			
		Months lost		
neoplasm	3.41	2.46	2.19	1.74
cardiovascular diseases	3.32	2.48	1.73	1.08
external causes	9.55	5.06	3.57	2.12
other causes of death	4.78	2.82	1.82	0.97
Total	21.06	12.82	9.31	5.92
		Educational gain		
neoplasm		0.95^{**}	0.26	0.45
cardiovascular diseases		0.84^{**}	0.75^{+}	0.64^{+}
external causes		4.49^{**}	1.49^{**}	1.45^{**}
other causes of death		1.95^{**}	1.00^{**}	0.85^{**}
Total		8.24^{**}	3.51^{**}	3.39^{**}
	Structural model			
		Months lost		
neoplasm	3.45	2.32	2.19	1.69
cardiovascular diseases	2.48	2.18	1.76	1.15
external causes	11.26	4.52	3.59	2.58
other causes of death	3.45	2.44	1.82	1.15
Total	20.63	11.45	9.37	6.57
		Educational gain (months)		
neoplasm		1.13^{**}	0.13	0.50^{+}
cardiovascular diseases		0.30	0.42	0.61^{+}
external causes		6.74^{**}	0.93^{**}	1.01^{**}
other causes of death		1.01^{**}	0.62^{**}	0.67^{**}
Total		9.18^{**}	2.09^{**}	2.80^{**}

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
$^{+}p < 0.05, ^{**}p < 0.01$.

5.4 Results structural model

The stratified model ignores that education may depend on unobserved factors, such as cognitive ability, that also affect the cause-specific mortality hazards. Next we estimate the structural model, in which the three components of the model, the education attainment, the IQ-measurements and the cause-specific mortality hazards, are interdependent through the unobserved latent cognitive ability, θ, as discussed in Section 3. For most causes of death and education levels, higher cognitive ability reduces the hazard. However, cognitive ability only significantly reduces the risk of dying from cancer for men with 2 years of secondary education.[5] This reflects that higher intelligence has little influence on cancer-survival. For the lowest education group death due to external causes increases with cognitive ability. Not surprisingly, cognitive ability is positively related to the education attained and the IQ-score.

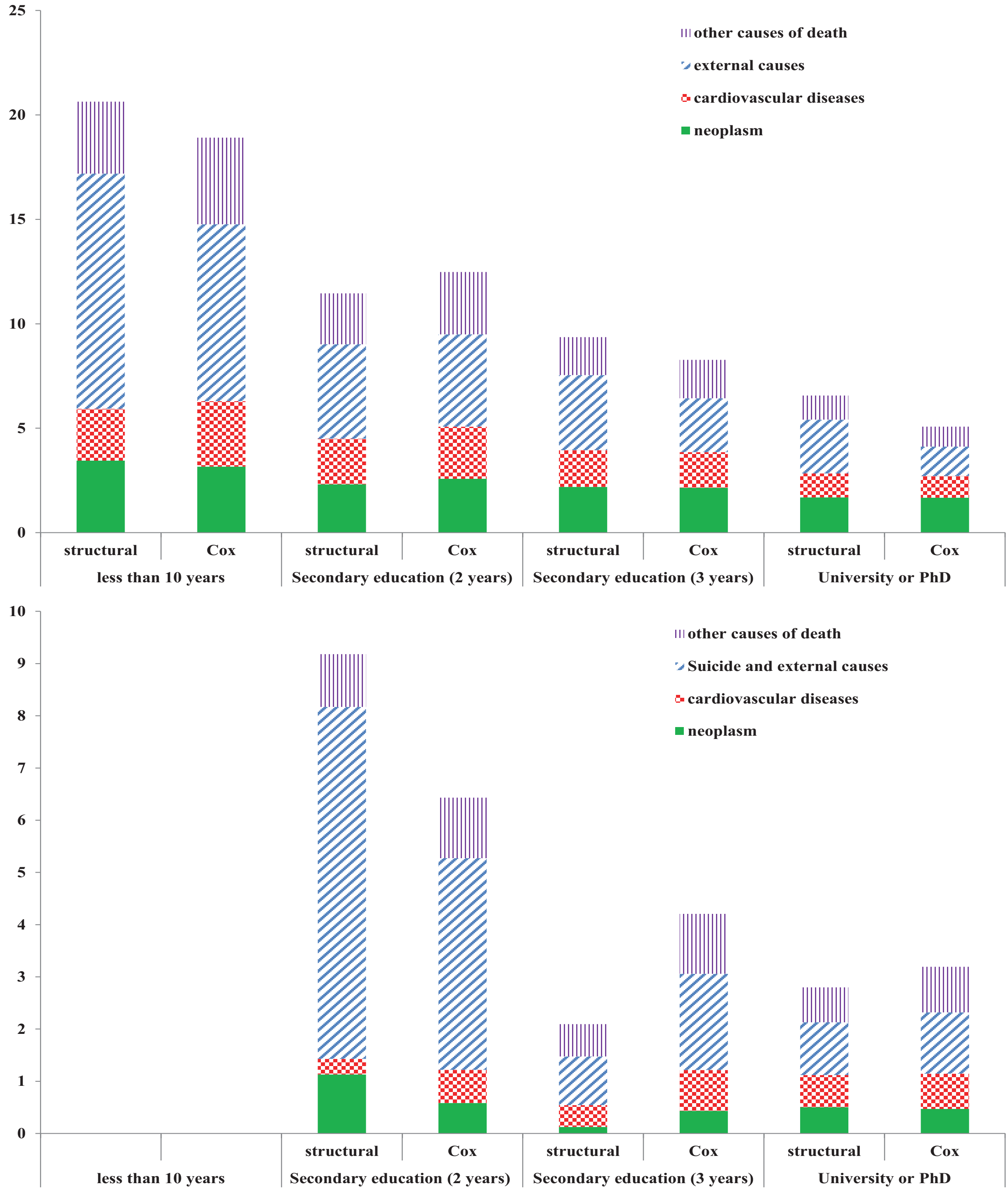
Based on the estimated coefficients of the structural model we calculate the average number of cause-specific months lost from age 18 till age 63 and the implied educational gains. Compared to the results from the stratified model both the months lost and the implied education gains changes the most for external causes, see the second panel of Table 5. For the lowest education group 55% of the months lost till age 63 is due to external causes, such as traffic accidents and suicides. For the other education groups about 40% of the average time lost is due to these mortality causes. Although the amount of time lost due to cancers decreases with the education level the relative importance increases with the education level, from 17% for the low educated to 26% for the men who went to university. The amount of months lost from death of cardiovascular diseases and other diseases both show an educational gradient and their relative importance in the total time lost by education level is rather stable.

The educational gain of the structural model provides the causal impact of education on the months lost, i.e. it gives how many months an individual would have gained in survival for a specific causes of death if he had attained a higher education level. The education gains are the largest for external causes. A low educated man would have gained almost seven additional months from a reduction in mortality due to external causes if he had taken secondary education, which is 75% of the total gain he would had had. Only the gain in cancer survival for the low educated is also larger than one month. All the other educational gains are smaller than one month. The educational gain for cardiovascular diseases is small, 0.2 to 0.6 months. This rather low impact of education on cardiovascular mortality is probably because we can only follow the conscripts till age 63, before the bulk of heart attacks hits these men. The same holds for cancer mortality.

Based on the estimation results from the Cox models we could also estimate the implied months lost and educational gains. In Figure 2 we compare the results from the structural model with the implied estimated months lost and educational gains from the Cox model that accounts for childhood characteristics and the IQ-score, see Table 2 for the estimated hazard ratios. The estimated Cox models, that ignore that the socioeconomic status and IQ also affect the education attained, imply a lower amount of months lost between age 18 and 63 year (except for men with secondary education), especially for deaths due to external causes. The implied educational gain for the men with the lowest education level is higher when using Cox models, but lower for the other two education levels. This is mainly caused by a difference in educational gain from external causes.

[5]See Table B.4 in Appendix B. The other coefficients only change a little and the full table of estimated coefficients is given in also given in Table B.4.

Figure 2: Months lost and educational gains (18–63): Structural model versus Cox models, Swedish Conscripts 1951-1960



Notes. The first panel depicts the months lost by education level for the structural model and the Cox model. The second panel depicts the implied educational gains in months lost, i.e. the gain months lost of moving up one education level.

We are also interested in the selection effects, the gain in months lost by individuals selecting themselves into a higher education level. This gain is caused by the fact that individuals with different education levels also differ in other aspects that influence their survival. For each cause of death we derive the total selection effects from the difference between the non-parametric educational gains in Table 3 and the educational gains from the structural model, see Appendix A.3 for the details. Table 6 presents these selection effects and the further decomposition of the selection effects into selection on observables (from the stratified models) and selection on (latent) cognitive ability.

The selection effects are, in general, smaller than the educational gains. We find positive selection effects, education is related to factors that also decrease the cause-specific mortality, and negative selection effects, education is based on factors that increase the cause-specific mortality. Most of the selection effects are positive. The selection effect for external causes of death for the low educated men who improve their education from less than 10 years to secondary education is negative (and slightly negative for neoplams). From the lower part of Table 6, the selection on cognitive ability, we see that this negative selection is caused by a negative impact of cognitive ability (despite a positive selection on observed individual characteristics). We find the largest selection effects for the lowest education group for cardiovascular mortality and mortality due to other causes. These positive selection effects are mainly due to selection on cognitive ability. We find little selection effects for the highest educational improvement.

Table 6: Selection effects in months lost (18-63), Swedish Conscripts 1951-1960

	Education level[a]		
	(2)	(3)	(4)
	Total selection effect		
neoplasm	−0.04	0.15	−0.02
cardiovascular diseases	0.68^{+}	0.33	0.02
external causes	-0.67^{+}	0.15	0.32
other causes of death	1.06^{**}	0.36	0.21
Total	1.03^{**}	0.98^{+}	0.53^{+}
	Selection effect on observed factors		
neoplasm	0.13	0.01	0.03
cardiovascular diseases	0.14	−0.01	−0.01
external causes	1.58^{**}	−0.41	−0.11
other causes of death	0.12	−0.02	0.02
Total	1.97^{**}	−0.44	−0.07
	Selection effects on cognitive ability		
neoplasm	−0.18	0.14	−0.06
cardiovascular diseases	0.54^{+}	0.34	0.03
external causes	-2.25^{**}	0.57^{+}	0.43^{+}
other causes of death	0.94^{**}	0.38	0.19
Total	-0.94^{**}	1.42^{**}	0.60^{+}

[a] (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
$^{+}p < 0.05, ^{**}p < 0.01$.

6 Conclusion and discussion

A large literature documents that higher levels of education are associated with a lower mortality. These educational gains may differ by cause of death. Possible mechanisms include occupational risks, health behavior, the ability to process information and cognitive ability (Cutler and Lleras-Muney 2008). It is commonly acknowledged that education, childhood background and IQ-scores are correlated. These factors are likely to influence cause-specific mortality too. Our findings confirm a strong selection into education based on parental background and cognitive ability. Accounting for this selection leads to a reduction of educational gains, especially for the low educated. This challenges the large educational impacts on cause specific hazards reported in the literature (Huisman et al. 2005; Kulhánová et al. 2014; Mackenbach et al. 2015).

Our contribution to the literature is twofold. First, we define the educational gains of different causes of death in terms of months lost instead of hazard ratios. Second, we use a structural model to estimate the educational gains accounting for interdependence of cognitive ability and education and their joint influence on each cause specific mortality. Specifying the educational gains in terms of months lost due to a specific cause of death instead of the odds of dying from such a cause in a Cox proportional hazard model has two advantages. First, a Cox model ignores that the competing causes of death are often interdependent and, second, the interpretation of the coefficients in a Cox model is difficult as the probability of dying from one particular cause depends on the hazards of dying from all other causes. The months lost due to a specific cause of death takes the interdependence into account, especially in our structural model, and the interpretation is very simple. Another advantage of the months lost measures is that they are additive, both over the causes of death and over the education levels. The advantage of using a structural model is that it explicitly accounts for cognitive ability that affect both educational attainment and cause-specific mortality.

Our empirical results reveal that the largest educational gains in months alive can be achieved by the low educated men in the reduction of external causes of death, such as traffic accidents and suicide. They would gain seven months between 18 and 63 if they had had secondary education. The other education groups would also gain the most from improving their education level from the reduction of traffic accidents and suicide. But, they would only gain one month between age 18 and 63. For this age range the educational gains in the reduction of cardiovascular and cancer mortality is rather small (less than one month).

Comparing our estimated months lost from the structural model to non-parametric estimated months lost provides the selection effects of the observed educational gains. These selection effects can be further decomposed into selection on observed childhood characteristics and selection on unobserved cognitive ability by also comparing to estimated months lost based on stratified (by education level) proportional hazard models. Most of the selection effects are positive, implying that education attainment is based on factors that reduce (cause-specific) mortality.

Although a direct comparison with previous results is not possible, because we define the cause-specific educational gains in terms of months lost instead of in hazard ratios, we can draw some general conclusions. Based on our standard Cox proportional hazard analyses we get results similar to previous results, with large educational gains for all main causes of death and education levels. Based on these hazard ratios the educational gains seems rather stable over the education levels. However, only after translating these to educational gains in months lost shows that the low educated gain the most (especially, due to external causes). Accounting for confounding changes the conclusion even more. Meghir et al. (2013) is the only other previous paper accounting for possible confounding in the causes-specific mortality rate and the attained education. They exploit a compulsory schooling reform in Sweden that increased the affective number of compulsory schooling years from 7 or 8 years to 9 years. They did not find any significant educational impact on cancer or circulatory diseases. Our results for the low educated (less than 10 years of schooling) from the structural model shows that the educational gain from cancers and cardiovascular diseases is rather small when accounting for cognitive ability confounding is in line with their results. However, we still found rather large educational gains for the low educated (mainly due to an increase in the educational gain due to external causes). For the higher educational levels, which were not affected by the compulsory schooling reform, the educational gains are lower.

Our study has four distinct strengths compared to previous research. First, a clear advantage of the study is the very large sample size, which allows the estimation of the detailed structural model with four education levels and four causes of death 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 Sweden during the 50s. Third, our statistical method, using a structural model in which the education attained and the cause-specific mortality are modelled simultaneously, accounts for the confounding effect of intelligence on cause-specific mortality. This enables us to draw causal conclusions from our analysis, without suffering generalization issues inherent to using compulsory schooling reforms to account for confounding. Fourth, contrary to the standard literature on causes of death (competing risks) analysis we define the educational gains of causes of death in terms of months lost due to each specific cause of death instead of the hazard ratio. This quantity has a more natural interpretation and avoids the issues of independence in competing risks proportional hazard models. The months lost can be defined over a segment of the age distribution. The months lost quantity is an additive measure. The sum over all alternative causes of death within one education level is equal to the total amount of months lost (and the educational gain) for that education level and the sum of educational gains over all education levels within a cause of death is equal to the total educational impact of that cause of death.

Our study also has limitations. First, we do not have military examination information or other large data containing intelligence test for women that would allow for similar analyses. and Second, the follow-up time is relatively short with a maximum age of 63. A fruitful avenue for future research would be to investigate the data again in, say, ten years from now, when the cohort has reached 73 and the distribution of the causes of death (more cardiovascular and cancer death) may have changed. Second, although we controlled for some parental background, through paternal education and maternal socioeconomic status, we might have ignored important family characteristics we did not observe. Neither could we account for unobserved family characteristics. However, Elo et al. (2014) have found that once observed parental education and socioeconomic status is controlled for the unobserved family factor do not matter for the education mortality association. Third, although military conscription was mandatory in Sweden, men with severe mental disabilities or severe chronic diseases were exempted from the military examination. Thus, our results only apply to those who had no severe mental or chronic diseases at age 18.

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Appendix A Methodology

The standard approach to analyse cause-specific mortality is to formulate a competing risks model with an independent Cox proportional hazard model for each cause-specific mortality. The cause-specific hazard of dying from cause j for an individual with characteristics X is

$$\lambda_j(t|X) = \lambda_{0j}(t)\exp\bigl(\beta_j'X\bigr),$$

with $\lambda_{0j}(t)$ is the age-dependence of the mortality rate, common for all individuals. The cause-specific hazard gives the mortality rate due a particular cause conditional on not having died from any other cause previously. The interpretation of the coefficients in such a competing risks model requires caution, Thomas (1996). A particular covariate, say x_l, can appear in several competing hazards. In such a case the vectors β_{lj} convey little information about the effect of the covariate on the probability to die from cause j. The reason is that that probability depends not only on the hazard to die from cause j but also on the hazard to die from all the other causes. Thus, despite that in a Cox analysis for competing causes of death it is assumed that the causes are independent many measures of the importance of the specific causes depend on all other hazards.

Note that total hazard of dying is the sum of all cause-specific hazards and the total survival function, the probability to survive up to age t, is equal to

$$S(t|X) = \exp\Bigl(-\sum_j \int_0^t \lambda_j(s|X)\,ds\Bigr). \tag{A.1}$$

A direct way to measure the impact of education on cause-specific mortality is to calculate the months lost due to a specific cause. The months lost due to cause j is (from τ_0 to τ_1, e.g. from age 18 till age 63) are directly related to the cumulative incidence functions

$$L_j(\tau_0,\tau_1) = \int_{\tau_0}^{\tau_1} F_j(s)\,ds \tag{A.2}$$

This measure is related to the mean life time, or the restricted mean life time (from τ_0 to τ_1), see Andersen (2013). The sum over all causes of the months-lost due to each specific cause is equal to the total expected months lost between τ_0 and τ_1, which is τ_1 minus the restricted mean life time. Non-parametric estimation of the months-lost is straightforward because the survival (Kaplan-Meier) and cumulative incidence functions (Aalen-Johansen, Aalen and Johansen 1978) are also straightforward to calculate. If we do not have ties in observed ages of death the Kaplan-Meier estimator of the, total, survival is

$$S(t) = \prod_{s\le t}\Bigl(1-\frac{d(s)}{Y(s)}\Bigr) \tag{A.3}$$

with $d(s)$ is the number of deaths at age s and $Y(s)$ is the number of people still alive at age s. From the Nelson-Aalen estimate of the cumulative hazard for cause j,

$$\Lambda_j(t) = \sum_{s\le t}\frac{d_j(s)}{Y(s)} \tag{A.4}$$

with $d_j(s)$ is the number of deaths due to cause j at age s, the Aalen-Johansen estimate of the cumulative incidence of cause j is

$$F_j(t) = \sum_{s\le t} S(s_-)\bigl[\Lambda_j(s)-\Lambda_j(s_-)\bigr] \tag{A.5}$$

with s_- is the age just before s and an estimate of the months lost is

$$L_j(\tau_0,\tau_1) = \sum_{\tau_0\le s\le\tau_1} F_j(s-)(s-s_-) \tag{A.6}$$

Appendix A.1 Using pseudo observations

If all individuals were observed till they the impact of education on the month-lost would be very easy to obtain. However, common for survival analysis, the individual deaths are (heavily) censored at the end of the observation window 1/1/2013. This implies that the highest age reached we can observe is 63 years. We will use pseudo-observations to account for censoring. Andersen (2013) has shown that with pseudo-observations regression analysis for the months-lost due to a specific cause of death is very simple, even when some of the observations are censored. The idea of pseudo-observations is closely linked to the Jackknife-method, (Efron 1982). If the sample contains n individuals the jackknife uses n deterministically defined subsamples of size $n-1$ obtained by dropping in turn each of the n observations and re-estimate the model. The advantage of creating pseudo-observations is that they can be modelled using standard (uncensored) linear models. For the estimation of the years lost the pseudo-observation for each individual is calculated as

$$J_k^i = n\hat{L}_k(18,63) - (n-1)\hat{L}_k^{(-i)}(18,65), \qquad i = 1,\ldots,n \tag{A.7}$$

where $\hat{L}_k^{(-i)}(18,63)$ is the estimator of months-lost from the sample without the i^{th} individual and $\hat{L}_k(18,65)$ the full sample estimate. We regress these obtained months-lost on the education indicator using a GLM approach.[6]

Appendix A.2 Structural model

The methodology we use to account for this endogeneity is an extension of the structural equation framework developed by Bijwaard, van Kippersluis, and Veenman (2015) and Bijwaard et al. (2015). The model consists of three parts: (i) ordered probit educational attainment depending on latent cognitive ability and other covariates, (ii) potential cause-specific mortality hazards depending on the education level, latent cognitive ability, and other covariates, and (iii) a measurement system for cognitive ability. The model allows for interdependencies between educational attainment, cognitive ability and mortality.

Educational attainment
Define the indicator of education, D, taking the value k if the individual has attained education level k $(1,\ldots,4)$: $D = k$ if $\zeta_{k-1} < D^* \leq \zeta_k$ with $D^* = \gamma' X + \alpha_D\theta + \nu_D$, which is continuous and depends linearly on the (vector of) observed characteristics X and latent intelligence θ and where $\zeta_0 = -\infty$ and $\zeta_4 = \infty$. Because we assume that ν_D is normally distributed we have an ordered probit model for the educational attainmente. Therefore the probability that an individual has attained education level k $\Pr(D = k)$ is given by

$$\Phi(\zeta_k - \gamma' X - \alpha_D\theta) - \Phi(\zeta_{k-1} - \gamma' X - \alpha_D\theta), \tag{A.8}$$

with $\Phi(\cdot)$ as the standard normal cumulative density. Once the individual has decided his education level, future mortality is potentially causally related to this decision.

Potential mortality hazards
The second part of the structural model comprises the potential cause-specific mortality hazards. These hazards are potential because each individual's mortality is only observed for the actual education level and not for potential alternatives in education level. For each education level we choose a Gompertz mortality rate. Let t be the age of the individual, with the potential hazard for education level k to die from cause c $\lambda_c^{(k)}(t) = \exp(a_{kc}t + \beta_{kc0} + \beta_{kc}' X + \alpha_{kc}\theta)$ depending on observed characteristics X and latent cognitive ability θ. The shape of the hazard is captured by a_{kc} and the scale of the

[6] Parner and Andersen (2010) and Overgaard et al. (2015) provide an STATA procedure to estimate the years/months lost based on pseudo observations.

hazard by β_{kc0}. The effect of latent cognitive ability on the hazard is captured by α_{kc}. We assume that that hazard to die from external causes is exponential, i.e. does not vary by age.

IQ-measurements
The structural model is closed by a measurement equation linking intelligence (IQ) scores with the latent cognitive ability and observed individual characteristics, with $M = \delta' X + \alpha_M \theta + \nu_M$ where ν_M is normally distributed.

We use a maximum likelihood estimation method to estimate all the parameters of the model. For the structural model, we jointly estimate the parameters of the education choice, the cause-specific mortality hazards and the measurement equation.

Appendix A.3 Educational gain and decomposition of the difference in months lost

Based upon the estimated parameters of the structural model we can derive the total survival, cumulative incidence functions and the months lost due to a specific cause of death. The total survival for education level (k) is (suppressing the dependence on individual factors)

$$S^{(k)}(t) = \exp\Big(-\sum_c \int_0^t \lambda_c^{(k)}(s)\, ds\Big) \tag{A.9}$$

the cumulative incidence function, the probability of dying from cause c before time t

$$F_c^{(k)}(t) = \int_0^t \lambda_c^{(k)}(s) S^{(k)}(s)\, ds \tag{A.10}$$

and the months lost due to cause c is (from τ_0 to τ_1, e.g. from age 18 till age 65)

$$L_c^{(k)}(\tau_0, \tau_1) = \int_{\tau_0}^{\tau_1} F_c^{(k)}(s)\, ds \tag{A.11}$$

We define the educational gain of a specific cause of death, c, as the average gain in months lost due to a specific cause of death if an individual improves his education from level k to $k+1$

$$G_c^k(\tau_0, \tau_1) = \int\int \mathrm{E}\Big[L_c^{(k+1)}(\tau_0, \tau_1|X, \theta) - L_c^{(k)}(\tau_0, \tau_1|X, \theta)\Big] dF_{X,\theta} \tag{A.12}$$

where X are the included covariates and θ is the value of the latent cognitive ability. We integrate over the joint distribution of the covariates and the latent cognitive ability for the whole population $F_{X,\theta}$ to obtain the *average treatment effect* of improving education with one level.

Our interest is not limited to estimating these educational gains but also in estimating the selection effects. For each cause of death we can decompose the unconditional (non-parametric) differences in months lost into the educational gain and a residual, which is a selection effect on the basis of cognitive ability and the other observable factors.

The decomposition of the non-parametric estimates of months lost in (A.6)

$$G_{AJ,c}^k(\tau_0, \tau_1) = G_c^k(\tau_0, \tau_1) + \varepsilon^k\,(X, \theta) \tag{A.13}$$

where $G_{AJ,c}^k(\tau_0, \tau_1) = \Big[L_c^{(k+1)}(\tau_0, \tau_1) - L_c^{(k)}(\tau_0, \tau_1)\Big]$ represents the non-parametric differences in months lost from τ_0 to τ_1 (18–65), $G_c^k(\tau_0, \tau_1)$ is the treatment effect in (A.12) from the structural model and $\varepsilon^k\big(X, \theta\big)$ represents the selection effect on the basis of observable characteristics X and cognitive ability θ. All these measures are defined for an improvement of the educational level from level k to $k+1$.

The *selection effect*, $\varepsilon^k\big(X,\theta\big)$, can be further decomposed into a selection on observables, *selection effect observed*, and a selection on latent cognitive ability, *selection effect intelligence*

$$\begin{aligned}\varepsilon^k\big(X,\theta\big) &= G^k_{AJ,c}(\tau_0,\tau_1) - G^k_c(\tau_0,\tau_1) &\text{(A.14)}\\ &= \Big[G^k_{AJ,c}(\tau_0,\tau_1) - G^k_{sep,c}(\tau_0,\tau_1)\Big] + \Big[G^k_{sep,c}(\tau_0,\tau_1) - G^k_c(\tau_0,\tau_1)\Big] &\text{(A.15)}\end{aligned}$$

where

$$G^k_{sep,c}(\tau_0,\tau_1) = \int \mathrm{E}\Big[L_c^{(k+1)}(\tau_0,\tau_1|X) - L_c^{(k)}(\tau_0,\tau_1|X)\Big] dF_{X|D=k}(x), \quad \text{(A.16)}$$

is the gain in months lost based on the estimated separate proportional cause-specific mortality hazard models, i.e. the models that ignore the influence of cognitive ability on the education choice and on the mortality. The first part of (A.15) measures the selection on cognitive ability and the second part the selection on observed characteristics. We integrate over the joint distribution of the covariates given education level k $F_{X|D=k}(x)$.

Appendix B Additional tables and figures

In Table B.1 we present the estimated odds ratios of the ordered probit education choice and IQ-measurements, both for the stratified model (in which they are independent from the cause of death hazards) and for the structural model (in which they are related to the cause of death hazards through the latent cognitive ability). In Table B.2 we present the hazard ratios in the stratified model including IQ-effects. The implied months lost and educational gains are shown in Table B.3. In Table B.4 we present the hazard ratios in the structural model (including the effect of cognitive ability).

Table B.1: Estimated coefficients (IQ) and odds ratios of ordered probit education level, stratified and structural model, Swedish Conscripts 1951-1960, aged 18–63

	Education (odds ratio)		IQ	
	Stratified	Structural	Stratified	Structural
Cognitive ability		2.234^{**}		1.370^{**}
Mother's ses				
not classified	0.975^{**}	0.972^{**}	-0.153^{**}	-0.154^{**}
Unskilled workers	0.988^{+}	0.986	-0.040^{**}	-0.040^{**}
Farmers	1.018^{**}	1.020^{**}	0.278^{**}	0.277^{**}
non-manual (low)	1.493^{**}	1.659^{**}	0.680^{**}	0.679^{**}
non-manual (intermediate)	1.687^{**}	1.934^{**}	0.844^{**}	0.845^{**}
non-manual (high)	1.906^{**}	2.246^{**}	1.031^{**}	1.033^{**}
Father's education				
9-10 years	1.299^{**}	1.394^{**}	0.430^{**}	0.431^{**}
secondary edu (max 12)	1.330^{**}	1.434^{**}	0.406^{**}	0.404^{**}
secondary edu (13)	1.618^{**}	1.839^{**}	0.684^{**}	0.685^{**}
University	2.266^{**}	2.800^{**}	1.122^{**}	1.125^{**}
edu missing	1.126^{**}	1.162^{**}	0.155^{**}	0.153^{**}
Birth info				
mother $<$ 20 at birth	0.709^{**}	0.649^{**}	-0.497^{**}	-0.496^{**}
birth order 2	0.880^{**}	0.852^{**}	-0.219^{**}	-0.217^{**}
birth order 3	0.808^{**}	0.766^{**}	-0.394^{**}	-0.392^{**}
birth order 4	0.740^{**}	0.685^{**}	-0.592^{**}	-0.590^{**}
birth order 5 or higher	0.675^{**}	0.610^{**}	-0.816^{**}	-0.814^{**}
ξ_1	-0.691^{**}	-1.077^{**}		
ξ_2	0.365^{**}	0.265^{**}		
ξ_3	0.735^{**}	0.747^{**}		
constant			5.092^{**}	5.421^{**}

In a stratified model the IQ-measurement and the ordered probit education equation are estimated separately. In the structural model they are estimated jointly with the cause-specific mortality, see Appendix A.2. Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.2: Hazard ratio for cause-specific mortality models including IQ based upon stratified model by education and cause of death, Swedish Conscripts 1951-1960, aged 18–63

	Education level[a]			
	(1)	(2)	(3)	(4)
	neoplasm			
Mother's ses				
not classified	1.101	1.109	1.290	0.989
unskilled workers	1.147	1.015	1.074	1.456**
farmers	0.830**	0.857+	0.789	0.867
non-manual (low)	1.099	1.024	1.022	1.008
non-manual (intermediate)	0.985	1.169	1.134	0.935
non-manual (high)	1.558+	0.997	1.000	0.978
Father's education				
9-10 years	1.041	0.889	1.428+	1.020
secondary edu (max 12)	1.060	0.959	0.896	0.971
secondary edu (13)	1.182	1.011	1.038	1.018
university	1.144	0.979	0.895	1.041
education missing	1.223**	1.113	1.118	1.078
Birth info				
mother < 20 at birth	0.943	1.116	0.969	0.989
birth order 2	0.866+	1.062	1.019	0.997
birth order 3	0.896	1.071	0.992	0.912
birth order 4	0.883	0.914	1.112	0.987
birth order 5 or higher	0.967	0.978	1.083	1.219
IQ-level[b]				
IQ 1	1.178	1.297+	1.145	0.899
IQ 2	0.957	1.105	0.650	0.660
IQ 3	1.018	1.111	1.008	1.050
IQ 4	1.002	1.001	0.964	0.809
IQ 6	0.855	0.897	1.020	0.953
IQ 7	1.180	0.974	0.935	1.029
IQ 8	1.456+	0.890	0.936	1.031
IQ 9	1.599	0.708	0.999	1.009
Baseline				
constant	−11.358**	−13.755**	−13.536**	−14.411**
Gompertz shape	0.090**	0.131**	0.125**	0.135**
	cardiovascular diseases			
Mother's ses				
not classified	0.947	1.100	1.505+	1.005
unskilled workers	1.059	1.106	1.147	1.055
farmers	0.715**	0.838**	0.804	0.794
non-manual (low)	1.084	0.999	0.894	0.815+
non-manual (intermediate)	1.528**	1.080	1.099	0.783
non-manual (high)	1.107	1.046	0.902	0.638+
Father's education				
9-10 years	1.021	1.031	1.174	1.581**
secondary edu (max 12)	1.143	0.991	1.016	0.932
secondary edu (13)	0.966	0.977	0.757	1.003
university	1.173	1.015	1.236	0.896
education missing	1.476**	1.264**	0.979	1.456**
Birth info				
mother < 20 at birth	1.058	1.068	0.994	0.924
birth order 2	0.940	0.962	0.816+	0.843+
birth order 3	0.893	0.960	0.895	0.922
birth order 4	0.692**	1.056	1.026	0.757
birth order 5 or higher	0.945	1.091	0.985	0.811
IQ-level[b]				
IQ 1	1.991**	2.160**	1.755	0.801
IQ 2	1.376**	1.601**	2.036**	1.087
IQ 3	1.289**	1.193+	1.280	1.226
IQ 4	1.259**	1.071	1.282	0.805
IQ 6	1.102	0.828+	0.917	0.825
IQ 7	0.990	0.956	0.985	0.867
IQ 8	0.771	0.957	0.957	0.903
IQ 9	1.549	1.100	1.089	0.714+
Baseline				
constant	−12.215**	−13.882**	−14.118**	−14.920**
Gompertz shape	0.101**	0.130**	0.132**	0.143**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
[b] Running from low to high, with level 5 as reference category.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table B.2: Hazard ratio stratified models including IQ (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
	external causes (exponential)			
Mother's ses				
not classified	0.798^{+}	1.110	1.026	1.212
unskilled workers	0.944	1.120	0.768	1.109
farmers	0.644**	0.879^{+}	0.951	1.099
non-manual (low)	1.160**	0.962	0.899	1.051
non-manual (intermediate)	1.105	1.110	1.061	1.321^{+}
non-manual (high)	1.012	0.837	0.845	1.049
Father's education				
9-10 years	1.073	1.183	1.035	1.060
secondary edu (max 12)	1.235**	1.080	1.263^{+}	0.852
secondary edu (13)	1.344**	1.124	1.023	0.861
university	1.953**	1.248^{+}	1.433^{+}	0.858
education missing	2.380**	1.504**	2.029**	1.209
Birth info				
mother $<$ 20 at birth	1.082	1.249**	1.070	1.097
birth order 2	1.100^{+}	1.071	0.983	0.994
birth order 3	0.934	1.089	0.822	0.980
birth order 4	0.913	1.082	0.965	1.161
birth order 5 or higher	1.576**	1.319**	0.955	0.883
IQ-level[b]				
IQ 1	1.186^{+}	1.418**	1.391	0.781
IQ 2	1.002	1.640**	1.403	0.910
IQ 3	1.026	1.436**	1.207	1.059
IQ 4	1.016	1.229**	1.112	1.084
IQ 6	1.052	1.073	1.096	0.857
IQ 7	1.480**	1.017	0.813	0.858
IQ 8	1.702**	0.949	0.904	0.736**
IQ 9	2.359**	0.849	1.110	0.711^{+}
Baseline				
constant	-7.222^{**}	-7.840^{**}	-7.958^{**}	-8.556^{**}
	other causes of death			
Mother's ses				
not classified	1.164	1.228^{+}	1.095	0.932
unskilled workers	1.266**	1.320**	1.229	1.054
farmers	0.575**	0.596**	0.729^{+}	0.842
non-manual (low)	1.209**	1.046	1.100	1.108
non-manual (intermediate)	1.353^{+}	1.379**	1.397	0.968
non-manual (high)	1.267	0.815	1.073	0.854
Father's education				
9-10 years	0.953	0.974	1.050	0.803
secondary edu (max 12)	1.164^{+}	1.121	1.088	1.371**
secondary edu (13)	1.041	1.013	1.389^{+}	1.236
university	1.575**	1.323**	1.234	0.954
education missing	1.580**	1.385**	1.614**	1.504**
Birth info				
mother $<$ 20 at birth	0.968	1.168^{+}	1.278	1.074
birth order 2	0.965	1.015	1.179	0.834^{+}
birth order 3	0.961	1.041	0.786	0.926
birth order 4	0.859	0.899	0.884	0.745
birth order 5 or higher	1.035	0.891	1.137	0.807
IQ-level[b]				
IQ 1	1.742**	2.010**	1.909	0.996
IQ 2	1.261**	1.555**	1.775**	0.849
IQ 3	1.167^{+}	1.284**	1.150	1.347
IQ 4	1.101	1.162^{+}	0.995	1.073
IQ 6	0.875	0.958	0.939	0.879
IQ 7	0.637**	0.777**	1.023	0.852
IQ 8	0.992	0.866	1.150	0.657**
IQ 9	0.944	0.749	1.287	0.556**
Baseline				
constant	-10.397^{**}	-12.427^{**}	-12.917^{**}	-13.964^{**}
Gompertz shape	0.067**	0.102**	0.102**	0.116**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
[b] Running from low to high, with level 5 as reference category.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table B.3: Months lost due to cause of death and the educational gain (18-63) based upon stratified model (by education and cause of death) including IQ, Swedish Conscripts 1951-1960

	Education level[a]			
	(1)	(2)	(3)	(4)
	Months lost			
neoplasm	3.41	2.45	2.19	1.74
cardiovascular diseases	3.31	2.48	1.73	1.09
external causes	9.59	5.05	3.56	2.12
other causes of death	4.76	2.82	1.82	0.97
Total	21.07	12.80	9.31	5.92
	Educational gain			
neoplasm		0.96	0.26	0.45
cardiovascular diseases		0.83	0.75	0.64
external causes		4.54	1.49	1.45
other causes of death		1.94	1.00	0.86
Total		8.27	3.51	3.40

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
$^{+}p < 0.05,^{**} p < 0.01$.

Table B.4: Hazard ratios for cause-specific mortality in structural model, Swedish Conscripts 1951-1960, ages 18–63

	Education level[a]			
	(1)	(2)	(3)	(4)
	neoplasm			
Cognitive ability	1.012	0.854**	1.017	1.075
Mother's ses				
not classified	1.103	1.120	1.291	0.985
Unskilled workers	1.145	1.018	1.076	1.454**
Farmers	0.830**	0.845+	0.789	0.874
non-manual (low)	1.106	0.972	1.028	1.032
non-manual (intermediate)	0.997	1.093	1.142	0.963
non-manual (high)	1.582+	0.920	1.009	1.012
Father's education				
9-10 years	1.055	0.858	1.427+	1.036
secondary edu (max 12)	1.066	0.928	0.897	0.987
secondary edu (13)	1.196	0.955	1.043	1.044
University	1.184	0.891	0.900	1.082
edu missing	1.228**	1.099	1.118	1.084
Birth info				
mother < 20 at birth	0.937	1.163+	0.965	0.971
birth order 2	0.863+	1.080	1.019	0.990
birth order 3	0.893	1.103	0.989	0.900
birth order 4	0.880	0.955	1.106	0.967
birth order 5 or higher	0.970	1.038	1.077	1.183
Baseline				
constant	−11.358**	−13.819**	−13.565**	−14.489**
Gompertz shape	0.090**	0.131**	0.125**	0.136**
	cardiovascular diseases			
Cognitive ability	0.723**	0.672**	0.755**	0.884
Mother's ses				
not classified	0.969	1.135	1.539+	1.014
Unskilled workers	1.064	1.118	1.148	1.056
Farmers	0.693**	0.810**	0.784	0.786+
non-manual (low)	0.978	0.876+	0.812	0.783**
non-manual (intermediate)	1.340	0.918	0.976	0.746
non-manual (high)	0.955	0.853	0.779	0.600**
Father's education				
9-10 years	0.961	0.947	1.111	1.543**
secondary edu (max 12)	1.071	0.910	0.959	0.911
secondary edu (13)	0.871	0.849	0.686+	0.963
University	0.992	0.806	1.059	0.837
edu missing	1.448**	1.226**	0.958	1.443**
Birth info				
mother < 20 at birth	1.139	1.180+	1.069	0.952
birth order 2	0.969	1.002	0.840	0.853
birth order 3	0.946	1.034	0.945	0.942
birth order 4	0.751**	1.178	1.112	0.780
birth order 5 or higher	1.065	1.270**	1.105	0.845
Baseline				
constant	−12.329**	−13.934**	−13.997**	−14.982**
Gompertz shape	0.102**	0.130**	0.132**	0.143**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included.
$^{+}p < 0.05, ^{**}p < 0.01$.

Table B.4: Hazard ratios structural models (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
	external causes (exponential)			
Cognitive ability	1.200**	0.745**	0.812**	0.665**
	external causes (exponential)			
Mother's ses				
not classified	0.794**	1.128	1.041	1.232
Unskilled workers	0.939	1.124	0.771	1.114
Farmers	0.650**	0.856+	0.934	1.075
non-manual (low)	1.230**	0.867+	0.841	0.950
non-manual (intermediate)	1.197	0.971	0.977	1.165
non-manual (high)	1.128	0.709	0.760	0.897
Father's education				
9-10 years	1.124	1.107	0.990	0.993
secondary edu (max 12)	1.281**	1.011	1.211	0.797+
secondary edu (13)	1.444**	1.002	0.951	0.771+
University	2.272**	1.036	1.271	0.717**
edu missing	2.429**	1.464**	1.995**	1.182
Birth info				
mother < 20 at birth	1.030	1.353**	1.124	1.181
birth order 2	1.078	1.107+	1.002	1.025
birth order 3	0.905	1.153+	0.853	1.033
birth order 4	0.870	1.177+	1.020	1.260
birth order 5 or higher	1.502**	1.477**	1.033	0.985
Baseline				
constant	−6.975**	−7.787**	−7.894**	−8.429**
	other causes of death			
Cognitive ability	0.703**	0.655**	0.927	0.695**
Mother's ses				
not classified	1.191	1.261+	1.112	0.947
Unskilled workers	1.271**	1.331**	1.223	1.059
Farmers	0.555**	0.574**	0.724+	0.815
non-manual (low)	1.078	0.908	1.072	0.988
non-manual (intermediate)	1.169	1.157	1.359	0.837
non-manual (high)	1.066	0.655+	1.034	0.714
Father's education				
9-10 years	0.892	0.891	1.039	0.746
secondary edu (max 12)	1.085	1.025	1.072	1.275+
secondary edu (13)	0.925	0.871	1.359+	1.094
University	1.299+	1.030	1.202	0.778
education missing	1.543**	1.341**	1.611**	1.459**
Birth info				
mother < 20 at birth	1.053	1.302**	1.296	1.175
birth order 2	0.999	1.061	1.185	0.866
birth order 3	1.023	1.126+	0.797	0.987
birth order 4	0.942	1.009	0.901	0.819
birth order 5 or higher	1.181+	1.043	1.179	0.917
Baseline				
constant	−10.686**	−12.473**	−12.847**	−13.886**
Gompertz shape	0.068**	0.102**	0.102**	0.116**

[a] (1) less than 10 years; (2) Secondary education (2 years); (3) Secondary education (3 years); (4) University or PhD.
Reference categories for the parental background are: Skilled mother and less than 9 years of education for the father. Year of birth dummies also included.
$^{+}p < 0.05$, $^{**}p < 0.01$.