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The impact of mental problems on mortality and how it is moderated by education*

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Abstract

Mental disorders have a large impact on invalidity and mortality. Poor mental health is associated with low education, which is also associated with poor health and higher mortality. The association between mental health and mortality may, therefore, be partly explained by the increased incidence of mental problems of the low educated. An important issue is that mental health problems, education attainment and mortality may all depend on the same observed and unobserved individual factors. Such confounding renders both the incidence of mental health problems and education endogenous in the mortality analysis. We account for both the selective incidence of mental health problems and selective educational attainment by using a correlated multistate model for the mental health (hospitalization) process (both admittance an discharge) and mortality with a re-weighting technique (inverse propensity weighting) based on the probability to attain higher education.

We use Swedish Military Conscription Data (1951-1960), linked to the administrative Swedish death and National Hospital Discharge registers. We observe the timing of admittance and discharge from mental hospitals, the moment and cause of death and the education level. We estimate the effect of mental hospitalization and education on the morality rate and how the effect of mental hospitalization is moderated by education. Our empirical results indicate a strong effect of both mental hospitalization and education on mortality. Mental hospitalization affects mortality due to external causes of death in particular. Only for the low educated improving education moderates the impact of mental hospitalization on mortality. We also found that ignoring confounding would overestimate the impact of mental hospitalization on mortality. Accounting for confounding in mental hospitalization seems to be more important than accounting for selective educational attainment.

JEL classification: C41, I14, I24.
Keywords: Mental health; Education; Mortality; Timing-of-events; Inverse propensity weighting

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1 Introduction

Mental disorders represent an important share of the burden of diseases, invalidity and mortality, (Vos et al., 2015). Recent studies have found that one in five individuals had a mental disorder in the preceding year in the Netherlands (23%) and in Germany (24%) (Andrade et al., 2000). Mental health is not only very prevalent it is also very disabling with psychiatry disorders interfering with occupational role dysfunction for 35% of the cases, and leading to physical disability in 48%. The World Health Organisation (WHO) estimated that neuropsychiatric disorders accounts for 13% of all the daily adjusted life years disability. Because several mental disorders turn out chronic and because a major part of the treatment aims at caring and not curing, this group of diseases ranked as one of the most costly diseases, accounting for 28% of all health care costs. Higher mortality risks for people with mental disorders are well recognized, (Chesney et al., 2014, Gale et al., 2012, 2014, 2010, Harris and Barraclough, 1998, Lawrence et al., 2010). Mental illness may directly affect physical health or the prognosis of a disease. The side effects of psychotropic treatment may also lead to higher mortality. People with mental illness are more likely to smoke, drink alcohol, and use drugs (Lasser et al., 2000, Lawrence et al., 2009). Inequalities are found for morbidity, risk factors, disability and health care use.

A large literature has documented a positive association between education and health. Highly educated people have higher income, savings and retirement benefits, and consequently high-quality health insurance and healthcare over their lifetime (Clark and Royer, 2013, Fletcher, 2015, Mazumder, 2008, McCartney et al., 2013). Education, is also related to socio-psychological problems. Low educated people are more likely to be unemployed which may cause psychological stress. The well-educated usually report a greater sense of control over their lives and their health (Ross and Wu, 1995). Social psychiatry has long noted the association between socio-economic status and mental disorders. Thus, an important reason why well educated people have better health might be that educational status affects mental health. It has also been established that lower educated have more mental health problems (Halpern-Manners et al., 2016, Søndergaard et al., 2012). However, little attention has been paid to investigate how education shapes the impact of poor mental health on mortality. We try to fill this gap by estimating the impact of both mental health and education on the mortality hazard, including education as a moderator of the impact of mental health on mortality.

Recent research (Behrman et al., 2011, Bijwaard and van Kippersluis, 2016, Tansel and Keskin, 2017) has shown that education influences both entry and discharge from hospitals. We use admittance and discharge to mental hospitals, i.e. the time spend in mental hospital, as our indicators of poor mental health. In general social, educational, and economic resources influence whether individuals with mental problems enter a mental hospital (Gove and Howell, 1974). On the one hand, people with more social and economic resources are better able to mobilize medical and legal assistance to fight hospitalization. On the other hand, these resources also improve the chance that somebody in emotional need get the proper psychiatric treatment. At the same time do these resources influence discharge from mental hospitals. Thus, it is very likely that both the socioeconomic status and the education level of the individual influence mental hospital experience (Aro et al., 1995). The association between mental health problems and mortality may, therefore, be partly explained by the increased incidence of mental problems of the low educated.

An important issue is, however, that education attainment, mental hospitalization and mortality may all depend on the same observed and unobserved individual factors. Such confounding renders education and mental hospitalization endogenous in the mortality analysis. We obtain the causal impact of mental health problems (measured by mental hospitalization), a direct effect and an effect running through education, and the causal effect of education, on mortality by accounting for both the selection into the mental hospitalization process (both admittance and discharge) and the selection into education.

Our main outcome, the age at death is a duration variable and the mortality hazard rate, the instantaneous probability that an individual dies at a certain age conditional on surviving up to that age, is modelled. Accounting for right-censoring, when the individual is only known to have survived up to the end of the observation window, and left-truncation, when only those individuals are observed who were alive at a certain time, are easy to handle in hazard models (Van den Berg, 2001). A common way to accommodate the presence of observed characteristics is to specify a proportional hazard model, in which the hazard is the product of the baseline hazard, the age dependence, and a log-linear function of covariates. Neglecting confounding in inherently non-linear models, such as proportional hazard models, leads to biased inference. One approach is to explicitly model the individual-specific effects using unobserved heterogeneity that enter the hazard multiplicatively, a mixed proportional hazard model (MPH).

The richness of our data enables us to go beyond standard modelling of mortality rate, and to tackle the complex task of examining jointly the mental hospitalization and mortality processes using a mixed proportional hazards framework, with correlated unobserved heterogenity. In particular, we estimate the effects of the mental hospitalization process on the mortality rate using the "timing-of-events" - method (Abbring and van den Berg, 2003), which controls for correlated effects that arise from correlation between unobservables in the mental hospitalization and mortality processes.

To account for the endogeneity of the education attainment we use a propensity score method. Propensity score methods are increasingly used to take account of confounding in observational studies, (Caliendo and Kopeinig, 2008). The advantage of the propensity score is that it enables us to summarize the many possible confounding covariates as a single score. Propensity score weighting methods for hazard models, such as the mortality hazard, that account for censoring, truncation and dynamic selection issues have been introduced recently (Austin, 2014, Cole and Hernán, 2004). We apply inverse probability weighting (IPW) methods using the propensity score (Bijwaard and Jones, 2018, Hirano et al., 2003).

The overlap assumption and the unconfoundedness assumption are two critical assumptions for the application of propensity score methods. The overlap assumption requires that the propensity score is bounded away from zero and one. By comparing only adjacent education levels we remove the overlap problems. The unconfoundedness assumption, or no selection on unobservables, requires that all variables that affect, mental hospitalization, the mortality rate and the education choice are all observed. Recent research (Bijwaard and Jones, 2018) has shown that intelligence can be considered a principal source of education selection and, that accounting for intelligence is sufficient to rule selection on unobservables when estimating the impact of education on mortality. We postulate that, after controlling for correlated unobservables between the mental hospitalization and mortality process in the timing-of-events model, accounting for intelligence together with parental socio-economic situation and parental education in the probability to attain higher education is also sufficient for the unconfoundedness assumption to hold.

Data from the Swedish Military Conscription Data (1951-1960), linked to administrative Swedish registers, offers the opportunity to investigate the impact of mental hospitalization and 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. From the Swedish National Hospital Discharge Register we observe in-patient psychiatric care from 1964 till the end of 2012. These data include recording of demographic and socioeconomic characteristics such as education, parental (both fathers and mothers) socioeconomic status, parental education, area of residence along with anthropometric measures, an intelligence test and a psychiatric assessment. Educational level was classified in five categories: primary education; secondary education (2 years); full secondary education (3 years); post-secondary education and higher education.

The empirical analyses show that ignoring the endogeneity of the mental hospitalization process would induce an overestimation of the impact of mental health problems on mortality. Accounting for education endogeneity also affects the estimated effects of mental health problems. We find that mortality is higher for those in mental hospital (1.7 to 4 times higher) and for those who have been in mental hospital (1.5 to 2.1 times higher). For all educational groups (two adjacent education levels) we find a significant impact of improving education on the mortality rate, even after accounting for the endogeneity of education through inverse propensity weighting. The educational impact is the largest for the lowest education group, with a 40% lower mortality when improving education from primary education to 2 years of secondary education. Only for this group improving education also significantly moderates the impact of mental health problems on mortality while in a mental hospital. We do not find any significant moderating influence of education on the impact of post mental hospitalization on mortality. Higher education reduces the hazard into (first) hospitalization and re-admittance. But if an individual improves his education from 2 to 3 years of education the re-admittance hazard increases. Such an educational improvement would also increase the expected time spend in a mental hospital (the discharge hazard increases).

We also investigated the impact of mental health problems and education on cause-specific mortality rates, distinguishing six different causes of death: (1) Cancer; (2) Cardiovascular diseases (CVD); (3) Traffic accidents; (4) Suicide; (5) (other) External causes, and (6) Other causes of death. We estimate an extension of the timing-of-events model with IPW. The empirical results reveal that death due to external causes is affected the most by mental health problems. Mental health problems also severely affects death due to suicide, traffic accidents, cardiovascular diseases and due to other natural causes. Mortality due to cancer is only slightly affected by mental health problems. Still, after having experienced mental hospitalization death due to cancer also increases.

The influence of education on the cause-specific mortality rates is rather ambiguous. Only for death due to other natural causes we find a significant direct effect of improving education in all education groups. For the other causes of death improving education only influences the hazard in some educational groups. For many causes of death education also moderates the impact of mental hospitalization on the cause-specific mortality rates, both negatively and positively.

2 Method

We seek to find the causal impact of mental health problems (with mental hospitalization as a proxy) on mortality and how it is moderated by the education level of the individual. However, hospitalization and mortality may be influenced by the same individual factors and these factors may also determine the educational attainment. This will render both educational attainment and hospitalization endogenous to mortality later in life.

A common approach in mortality analysis is to estimate a (mixed) proportional hazard model for the mortality hazard using a Gompertz baseline hazard, which assumes an exponential increase in the mortality by age. A Gompertz mortality rate is known to provide accurate mortality rates for middle aged individuals (Gavrilov and Gavrilova, 1991). However, viewing the educational level and the mental hospitalization as ordinary (exogenous) variables may lead to biased inference of the effect of these variables on the morality hazard.

A major methodological concern with the empirical analysis of the impact of mental health problems on mortality is that the admittance and discharge processes to mental hospitals depend on individual characteristics, both observed and unobserved factors. This implies that any observed relationship between admittance to (or discharge from) mental hospital and mortality may be caused by unobserved factors that influence both the hospitalization and mortality. For example, a finding that men with higher intelligence live longer may not necessarily imply that low intelligence causes to die sooner. Rather, it may be induced by the higher mental hospitalization of low intelligent men. To account for the interdependence of the hospitalization process we model the first admittance-, discharge- and re-admittance hazard of this process simultaneously with the mortality hazard. This is a multistate model with correlated hazards, also called a 'timing-of-events model' (Abbring and van den Berg, 2003), which explicitly controls for the correlation between the mental hospitalization process and mortality, to account for this interdependence.

2.1 Timing-of-events method

Let T^m denote the time till death (mortality), T^h the time till the start of the first mental hospital spell, T^d the time till hospital discharge and, T^r the time till hospital re-admittance (after discharge). The durations of the hospital stay and time after hospitalization are denoted by $d^h = T^d - T^h$ and $d^r = T^r - T^d$.

We model the first admittance to mental hospital using a Mixed Proportional Hazard (MPH) model

$$\theta_h(t|x, v) = v_h \lambda_{h0}(t) \exp\Big(x\beta_x^h + e\beta_e^h\Big) \tag{1}$$

with a baseline hazard λ_{h0}, unobserved time-invariant characteristics v_h, and observed time-invariate characteristics x and education level e. We assume a piecewise constant baseline hazard in the age of the individual, i.e. $\lambda_{h0}(t) = \sum_{r=1}^{R} e^{\alpha_r} I_r(t)$ with $I_r(t) = I(t_{r-1} \leq t < t_r)$ and $t_0 = 0$, $t_R = \infty$. Here R is the total number of intervals considered. Any duration dependence can be approximated arbitrarily closely by increasing the number of intervals. β_x^h captures the impact of exogenous individual characteristics, x on the hospitalization hazard and β_e^h captures the impact of (possibly endogenous) individual education, e on the hospitalization hazard. For identification, we assume that the baseline hazard is one in the first interval, i.e. $\alpha_1 = 0$.[1]

As the individual is either in hospital or not, the hospitalization is alternating, and has three possible transitions: admittance, discharge and, (the absorbing state) death. The conditional hazards for the discharge and re-admittance spells also follow MPH models:

$$\theta_d\big(d^h\big|x, v_d\big) = v_d\lambda_{d0}(d)\exp\Big(x\beta_x^d + e\beta_e^d\Big) \tag{2}$$

$$\theta_r\big(d^r\big|x, v_r\big) = v_r\lambda_{r0}(d)\exp\Big(x\beta_x^r + e\beta_e^r\Big), \tag{3}$$

with transition specific piecewise constant baseline hazards λ_k, unobserved time-invariant characteristics v_k, and observed individual characteristics x where $k \in \{d, r\}$ denotes the hospitalization state. Again we assume, for both the discharge and the re-admittance hazard, a piecewise constant baseline hazard (in weeks for the discharge hazard and in years for the re-admittance hazard). In order to keep track of hospitalization events, we also define the associated time-varying indicators: the indicator $I^h(t)$ takes value one if the individual is in hospital at time t, and $I^o(t)$ indicates that the individual is out of hospital after a period of hospitalization.

The mortality hazard is also of the MPH form. We allow T^m, T^h, T^d and, T^r to be correlated through unobservable heterogeneity terms and through a possible direct effect of the hospitalization dynamics on the mortality hazard. The latter is the effect to which we now turn. We consider both the incidence of the hospitalization admittance and discharge event and allow the impact to vary systematically with education. Thus the extended MPH model for the mortality hazard is

$$\theta_m(t|t_h, t_d, t_r, x, e, v_m) = v_m\lambda_{m0}(t)\exp\Big(x\beta_x^m + e\beta_e^m + I^h(t)\big(\gamma_h + e\phi_h\big) + I^o(t)\big(\gamma_o + e\phi_o\big)\Big). \tag{4}$$

The duration dependence of the mortality hazard is assumed Gompertz. The Gompertz hazard, which assumes that the hazard increases exponentially with age, $\lambda_{m0}(t) = e^{\alpha_0+\alpha_1 t}$, is known to provide accurate mortality hazards (Gavrilov and Gavrilova, 1991).

It is well known that, due to dynamic sorting effects, the distribution of v_h among those who are admitted to hospital at t_a will differ from its population distribution. In particular, individuals with high v_h will tend to enter hospital earlier than individuals with low v_h. If v_h and v_m are dependent, then the distribution v_m for individual in hospital at a given age will differ from the distribution of v_m for individuals who have not been admitted. Similarly, if v_m and v_d are not independent, then the distribution of v_m among those who are discharged will differ from its population distribution. Therefore, one cannot infer the causal effect of mental hospitalization on mortality from a comparison of the realised durations of those who have been admitted at t_a with the rest of the population, because one would then mix the causal effect of admittance on the duration with the difference in the distribution of v_m between these individuals. In this case $I_h(t)$ and $I_o(t)$ will be endogenous, and T_h, T_d, T_r and T_m should be modelled jointly to account for dependence of the unobserved heterogeneity terms. Therefore, we allow v_h, v_d, v_r and v_m to be correlated. For the sake of parsimoniousness, we assume that each of the unobserved heterogeneity terms remains the same for recurrent durations of the

[1] In principle we could also achieve identification by restricting the expected value of the unobserved heterogeneity to one.

same type, and we adopt a discrete distribution, i.e. v has discrete support $(V_1,\ldots,V_K)$, with $V_k = \big(v_{h,k},\ldots,v_{m,k}\big)$ and $p_k = \Pr(V = V_k)$.[2]

The "timing-of-events" method of Abbring and van den Berg (2003) implies that the full effects of mental hospitalization on the mortality rate, γ_h and γ_o in our framework, have a causal interpretation. This requires that all transition rates are modelled parametrically as mixed proportional hazards, as we have. Identification of the causal effect additionally requires that the so-called "no-anticipation"-assumption holds. The (untestable) no-anticipation assumption requires that individuals do not anticipate entering mental hospital by dying before the anticipated event would occur. Although it can be argued the the no-anticipation assumption is valid, we are cautious in using a casual interpretation of the our effects. Still, even if the no-anticipation assumption does not hold the timing-of-events method corrects for possible endogeneity of the mental hospitalization processes.

2.2 Likelihood function

We have data for $i = 1,\ldots,n$ male recruits in our observation window. Let K_{id} and K_{ir} denote the number of the discharges and re-admittances out/in a mental hospital of individual i. Note that for some individuals $K_{id} = 0$ and $K_{ir} = 0$, i.e an individual who either never entered a mental hospital or who died in hospital. An important feature of duration data is that for some individuals we only know that he or she survived up to a certain time (often the end of the observation window). In this case an individual is (right) censored and we use the survival function instead of the hazard in the likelihood function. The three indicators $\Delta^d_{ik}, \Delta^r_{ik}$ and Δ^m_i signal that k^{th} mental hospitalization discharge/re-entry or the mortality spell is uncensored. Δ^h_i indicates that the first mental hospitalization spell is uncensored. Thus the likelihood contribution of individual i conditional on the unobserved heterogeneity $v = (v_h, v_r, , v_d, v_m)$ is (suppressing dependence on observed characteristics x and education e), in the light of the preceding discussions:

$$
\begin{aligned}
L_i(v) \quad = \quad & \theta_h\big(t^h_i\big)|\cdot, v_h\big)^{\Delta^h_i} \exp\Big(-\int_0^{t^h_i} \theta_h(\tau|\cdot, v_h)\, d\tau\Big) \\
& \times \prod_{k=1}^{K_{id}} \Big[\theta_d\big(d^h_{ik}|\cdot, v_d\big)^{\Delta^d_{ik}} \exp\Big(-\int_0^{d^h_{ik}} \theta_d(\tau|\cdot, v_d)\, d\tau\Big)\Big]^{I^h(t^-_{ik})} \\
\times \prod_{j=1}^{K_{ir}} & \Big[\theta_r\big(d^r_{ij}|\cdot, v_r\big)^{\Delta^r_{ij}} \exp\Big(-\int_0^{d^r_{ij}} \theta_e(\tau|\cdot, v_r)\, d\tau\Big)\Big]^{I_o(t^-_{ij})} \\
\times\, & \theta_m(t_i|\cdot, v_m)^{\Delta^m_i} \exp\Big(-\int_0^{t_i} \theta_m(\tau|\cdot, v_m)\, d\tau\Big)
\end{aligned}
\tag{5}
$$

This likelihood naturally separates admittance, discharge, re-admittance and mortality spells, and for each spell allows for censoring. $I^h(t^-_{ik})$ indicates that the individual is in mental hospital just before t_{ik} and similarly for $I^o(t^-_{il})$. When $K_{id} = 0$ or $K_{ir} = 0$ the relevant term becomes 1. Note that the last, and only the last, mental hospitalization spell is censored. This is either because the individual is still alive at the end of the observation period, or has died.

[2] To assure that the probability is between zero and one we estimate q_k with $p_k = e^{q_k}/(1+\sum e^{q_j})$.

Another feature of duration data is that only individuals are observed having survived up to a certain age. In our case, mortality follow-up is only available from the conscription date, around age 18, onwards. In this case the individuals are left-truncated, and we need to condition on survival up to the age of first observation, $t_0 = 18$. With left-truncated data the distribution of unobserved heterogeneity among the survivors (up to the left-truncation time) changes. When only individuals are observed that have survived until age t_0 the likelihood contribution is

$$L_i = \int L_i(v) \exp\Big(\int_0^{t_0} \theta_m(\tau|\cdot, v_m)\, d\tau\Big)\, dG(v|T > t_0)$$

with the distribution of the unobserved heterogeniety conditional on survival up to t_0

$$dG(v|T > t_0) = \frac{\exp\Big(-\int_0^{t_0}\theta_m(\tau|\cdot, v_m)\, d\tau\Big) dG(v_m, v_h, v_d, v_r)}{\int \exp\Big(-\int_0^{t_0}\theta_m(\tau|\cdot, v_m)\, d\tau\Big)\, dG(v_m, v_h, v_d, v_r)} \tag{6}$$

with $G(v_e, v_u, v_m)$ is the joint distribution of the unobserved heterogeneity terms implied by the discussion of v_k.

2.3 Accounting for selective educational attainment

The timing-of-events method still fails to correct for possible enodogeity of education attainment. We follow a propensity score method to account for this endogeneity. Propensity score methods are increasingly used to estimate causal effects in observational studies. These methods aim to adjust for confounding factors between the treatment groups, in our case different education levels. The advantage of the propensity score is that it enables us to summarize the many possible confounding covariates as a single score. Propensity score methods include matching, stratification on the propensity score and inverse probability weighting (IPW) using the propensity score. The methods we apply are based on IPW-methods Hirano et al. (2003).

To this end we re-estimate the Timing-of-events models using a re-weighted pseudo-population based on inverse propensity score weighting (IPW), see Bijwaard and Jones (2018) for a (M)PH mortality model. To calculate the propensity score we could, in principle, estimate an ordered probit or ordered logit propensity score for our five ordered education levels, see Imai and van Dyk (2004) and Feng et al. (2012). However, the men in the lowest and highest education group differ too much in their observed background characteristics, which causes severe overlap problems. We therefore estimate separate logit propensity scores of attaining a higher education level through pairwise comparisons Lechner (2002) of adjacent education levels. We include variables that influence both the probability to obtain a higher education level and the probability to die.

Common assumptions in the literature using propensity score methods to identify the 'treatment effects' are the *Unconfoundedness* and the *common support* assumptions. The unconfoundedness assumption asserts that, conditional on observed individual characteristics education attainment is independent of the *potential* outcomes (transition hazards). This implies that (conditional on observed characteristics) the difference in the *potential* outcome if the individual had had low education and the *potential* outcome if the individual had had high education is only caused by education. This assumption requires that all variables that affect hospitalization, mortality and education attainment are observed. Note that this does not imply that we assume all relevant covariates are observed. Any missing factor is allowed to influence either the mental hospitalization process, mortality or educational attainment, not jointly. Although this is not testable and clearly a strong assumption, it may be a reasonable approximation. Bijwaard and Jones (2018) have shown that intelligence, as measured by an IQ-test, is a principal source of education selection and including this information in the propensity score is robust to possible unconfoundedness violation. Any alternative, that does not rely on unconfoundedness while allowing for consistent estimation of the educational impact, will have to make alternative untestable assumptions. The overlap, or common support, assumption requires that the propensity score, the conditional probability to attain higher education given observed individual characteristics, is bounded away from zero and one. This assumption is in principle testable. If there are values of the included covariates for which the probability of observing a higher education level is zero or one, we cannot compare these individuals between a high and a low education level. In that case we have to limit comparisons to sets of values where there is sufficient control in the propensity score among both low- and high educated. By comparing only adjacent education levels we remove the overlap problems.

If unconfoundedness holds, all biases due to observable covariates can be removed by conditioning on the propensity score. The educational impact can be estimated by weighting on the propensity score. Within each education group (of two consecutive education levels) we weight the men with the higher education by the inverse of the propensity score and those with the lower education by the inverse of one minus the propensity score. Such inverse probability weighting based on the propensity score creates a synthetic sample in which the educational attainment is independent of the included covariates. The synthetic sample is the result of assigning to each individual a weight that is proportional to the inverse of their propensity score.

Misspecification of the propensity score will generally produce bias. However, we use a doubly robust estimator, which also includes a regression adjustment. Rotnitzky and Robins (1995) point out that if either the regression adjustment or the propensity score is correctly specified the resulting estimator will be consistent.

3 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 and a psychological assessment. These data are linked to information on the parental socioeconomic situation at birth, the parental education, the education of the individual himself and date of death (up till 2012). The information (timing of admittance and discharge) on mental[3] hospitalization is derived from the Inpatient register. The data consist of the population of men born between 1950 and 1960, who were enlisted in the year they turned 18-20. We selected only those men for whom at least one parent is known. We also removed men without a known conscription date.

We aggregated the observed education into five classes: (*i*) Less than 10 years of education (only primary schooling); (*ii*) Some secondary education (2 years); (*iii*) Full secondary education (3 years); (*iv*) Post-secondary education (less than 3 years) and (*v*) Higher education

[3]Mental is defined by in ICD 8 and 9: code 290-319 in ICD 10 by F.

(University and PhD). A more detailed information of the data can be found in Bijwaard et al. (2017).

The Swedish National Hospital Discharge Registerfounded in 1964 has data on in-patient psychiatric care; coverage has been virtually complete since 1973. Admissions were coded according to the Swedish version of the ICD versions 8, 9 or 10. We extracted data on admissions from 1964 to December 31st 2012.

Selected demographic and childhood family characteristics at the time of military examinations by education level are presented in Table 1, for men without mental hospitalization and in Table 2, for men with mental hospitalization. We see a clear positive relation between the parental socioeconomic status, the parental 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. Not surprisingly, men with the highest education tend to do best on the IQ test.

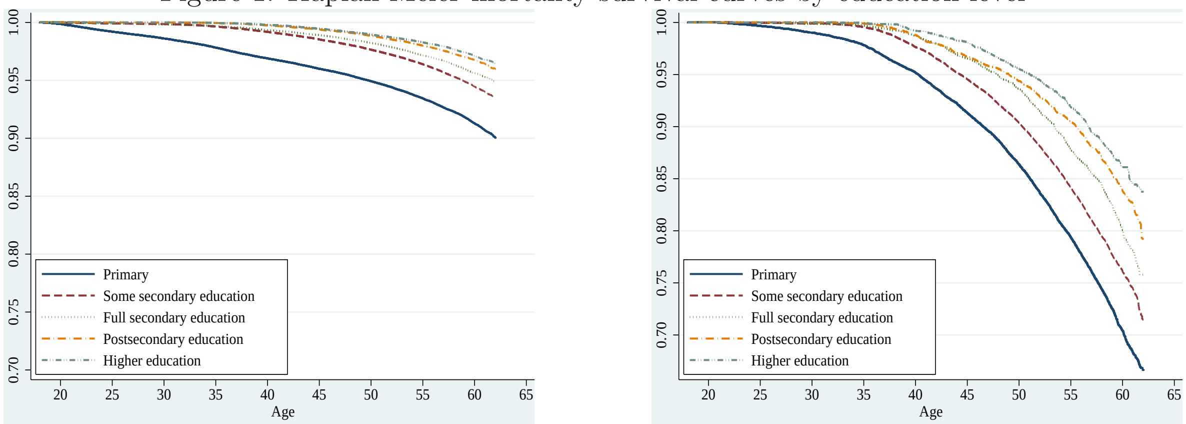
Men who have experienced some time in a mental hospital have lower IQ and a lower psychological assessment. We also find a clear educational gradient in the hospitalization prevalence and average number of days spent in hospital. Our principal measure of health is mortality with ages of death ranging from 18 up to 52–62. The lowest education group has a 2.5 (with mental hospitalization) to 3.4 (without mental hospitalization) times higher mortality. Mental hospitalization also seems to induce a much higher mortality.

The Kaplan-Meier mortality survival curves for the five education categories are shown in Figure 1 and reflect these mortality differences. Survival increases with the education level and the differences between the education levels increase with age. Compering the survival curves between without hospitalization (left panel) and with hospitalization (right panel) reflect the impact of mental health problems on mortality.

The Kaplan-Meier survival curves for the first admittance to a mental hospital, discharge a mental hospital or re-admittance to a mental hospital by education level in Figure 2 show a clear educational gradient (except for time spent in hospital).

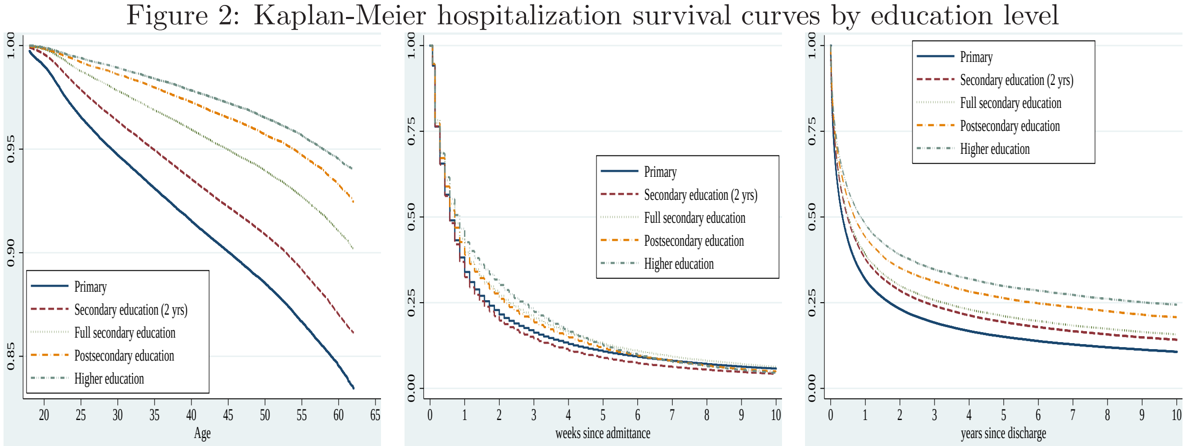
However, these mortality differences, both by education and by mental hospitalization experiences do not necessarily reflect the impact of mental health problems on mortality or education on mortality and mental hospitalization. It could be that the higher intelligence or higher socio-economic affecting both the mental hospitalization process and education causes the difference.

Figure 1: Kaplan-Meier mortality survival curves by education level



Without hospitalization **After hospitalization**

Figure 2: Kaplan-Meier hospitalization survival curves by education level



First hospitalization **Time in hospital** **Re-admittance**

Table 1: Descriptive statistics men never in mental hospital ($N = 468,424$)

	Primary	Secondary education some	Secondary education full	Post-secondary (< 3 years)	Higher
			SES mother at birth		
non-manual (high)	1%	1%	4%	4%	8%
non-manual (intermediate)	2%	3%	5%	6%	10%
non-manual (low)	14%	19%	30%	34%	42%
Farmers	19%	15%	13%	12%	9%
Skilled workers	48%	47%	36%	33%	22%
Unskilled workers	10%	9%	8%	7%	5%
Not classified	5%	4%	3%	3%	3%
Unknown	2%	1%	1%	1%	1%
			Education mother		
Primary (< 9 yrs)	70%	62%	51%	47%	33%
Primary (9–10 yrs)	6%	7%	10%	10%	12%
Secondary education (2 yrs)	16%	22%	24%	26%	25%
Secondary education (3 yrs)	1%	2%	3%	3%	5%
Post-secondary	1%	2%	4%	6%	10%
Higher	1%	1%	4%	5%	12%
Unknown	5%	4%	4%	3%	3%
			SES father at birth		
non-manual (high)	2%	2%	6%	6%	14%
non-manual (intermediate)	7%	10%	17%	22%	29%
non-manual (low)	7%	8%	12%	13%	14%
Farmers	12%	9%	8%	7%	5%
Skilled workers	26%	27%	23%	22%	15%
Unskilled workers	39%	36%	28%	24%	17%
Not classified	2%	2%	2%	2%	2%
Unknown	6%	4%	4%	3%	3%
			Education father		
Primary (< 9 yrs)	63%	57%	45%	40%	27%
Primary (9–10 yrs)	3%	3%	4%	4%	4%
Secondary education (2 yrs)	11%	15%	17%	17%	16%
Secondary education (3 yrs)	5%	8%	12%	15%	16%
Post-secondary	1%	2%	4%	5%	7%
Higher	1%	2%	6%	8%	21%
Unknown	15%	12%	12%	10%	10%
mother < 20 at birth	9%	9%	7%	5%	4%
father > 40 at birth	15%	13%	12%	11%	11%
birth order	3.3	3.1	3.0	2.9	2.8
global IQ[a]	4.1	4.7	5.7	6.2	6.8
Psychological assessment[a]	4.5	4.9	5.4	5.7	5.9
missing IQ	13%	14%	11%	11%	11%
missing Psychological assessment	14%	14%	12%	12%	12%
% died	7.5%	4.3%	3.5%	2.5%	2.2%
# of individuals	98,396	165,866	58,061	67,443	78,658
	21 %	35%	12%	14%	17%

[a] stanine score 1-9 running from low to high.

Table 2: Descriptive statistics men who experienced mental hospitalization ($N = 49,419$)

	Primary	Secondary education some	Secondary education full	Post-secondary (< 3 years)	Higher
			SES mother at birth		
non-manual (high)	1%	2%	4%	4%	8%
non-manual (intermediate)	2%	3%	5%	6%	9%
non-manual (low)	15%	18%	30%	34%	41%
Farmers	13%	10%	11%	10%	8%
Skilled workers	49%	49%	37%	34%	23%
Unskilled workers	11%	11%	8%	7%	6%
Not classified	6%	6%	4%	4%	3%
Unknown	1%	1%	1%	1%	1%
			Education mother		
Primary (< 9 yrs)	68%	62%	51%	48%	35%
Primary (9–10 yrs)	6%	7%	10%	10%	12%
Secondary education (2 yrs)	16%	21%	23%	24%	26%
Secondary education (3 yrs)	1%	2%	3%	3%	5%
Post-secondary	2%	2%	4%	6%	9%
Higher	1%	1%	4%	5%	10%
Unknown	5%	5%	5%	4%	4%
			SES father at birth		
non-manual (high)	2%	2%	6%	7%	14%
non-manual (intermediate)	8%	10%	19%	22%	29%
non-manual (low)	8%	9%	12%	13%	13%
Farmers	7%	5%	6%	5%	4%
Skilled workers	27%	29%	24%	23%	16%
Unskilled workers	41%	39%	28%	27%	18%
Not classified	5%	4%	4%	3%	3%
Unknown	2%	2%	2%	2%	2%
			Education father		
Primary (< 9 yrs)	61%	56%	43%	40%	28%
Primary (9–10 yrs)	3%	3%	4%	4%	4%
Secondary education (2 yrs)	12%	15%	17%	16%	16%
Secondary education (3 yrs)	6%	8%	11%	15%	15%
Post-secondary	2%	2%	4%	6%	6%
Higher	2%	2%	7%	8%	20%
Unknown	14%	13%	13%	11%	11%
mother < 20 at birth	10%	10%	7%	6%	5%
father > 40 at birth	11%	10%	11%	10%	10%
birth order	3.3	3.2	3.0	2.9	2.8
global IQ[a]	3.6	4.1	5.3	5.8	6.3
Psychological assessment[a]	3.5	3.9	4.7	5.1	5.3
missing IQ	17%	7%	5%	4%	4%
missing Psychological assessment	18%	8%	5%	5%	4%
% died	25.6%	20.0%	16.9%	13.2%	11.2%
% with hospitalization	14%	11%	8%	6%	5%
Av.# of days in hospital	68	31	27	12	8
# of individuals	113,911	186,860	63,012	71,550	82,510
	31 %	42%	10%	8%	8%

[a] stanine score 1-9 running from low to high.

4 Results

The full model, given by the correlated MPH hazards (1) to (4), nests the conventional (M)PH models for the mortality hazard. The PH model ignores unobservable heterogeneity altogether, $\theta_m^{PH}(t|t_h, t_d, t_r, x, e, v_m) = \lambda_{m0}(t)\exp\Big(x\beta_x^m + e\beta_e^m + I^h(t)\big(\gamma_h + e\phi_h\big) + I^o(t)\big(\gamma_o + e\phi_o\big)\Big)$, whereas the MPH model, $\theta_m^{MPH}(t|t_h, t_d, t_r, x, e, v_m) = v_m\theta_m^{PH}(t|t_h, t_d, t_r, x, e, v_m)$ ignores the correlation between θ_m and the hospitalization hazards. To illustrate the consequences of ignoring the endogeneity induced by the correlations between the unobservable heterogeneity terms we report in Table 3 the estimated effects of mental health problems for the PH, MPH and the full model. To illustrate the consequence of ignoring the endogeneity of education on the impact of mental health problems we also report the full timing-of-events model with inverse propensity weighting based on the propensity scores of improving the education level (within an education group). Note that, to exclude any overlap problems in the propensity score method, we only use the observation of individuals with two adjacent education levels for each model estimation: Primary education and some secondary education; some secondary education and full secondary education, etc.

First, we estimate a Gompertz proportional hazard ('PH-model') assuming both the indicator of being in hospital ('in hospital'), the indicator of previously been admitted to hospital ('out of hospital') and the education level are all exogenous. Next we account for unobserved factors that influence the mortality hazard (but are independent of the mental hospitalization hazard: 'MPH-model'). When estimating the 'Timing-of-events-model' we account for possible correlation of the hospitalization process and mortality through observed and unobserved factors. Finally, we account for possible confounding of the education attained by applying a inverse propensity score weighting (IPW) in the Timing-of-events model ('Timing-of-events-model (IPW)). For all estimations we also control for maternal and paternal socio-economic status, maternal and paternal education, maternal and paternal age at birth, birth order, IQ and psychological assessment at the military examination.[4]

The simple PH model already demonstrates the importance of mental health problems on mortality. For all education levels we find that mortality is higher for those in mental hospital and for those who have been in mental hospital. Extending this model to incorporate (uncorrelated) unobserved heterogeneity increases the estimated effects of mental health problems.

Taking into account the correlated unobserved heterogeneity in the timing-of-events model substantially decreases the estimates. We conclude that ignoring the endogeneity issue would result in substantial selectivity biases. Accounting for education endogeneity through IPW also affects the estimated effects of mental health problems. This decreases the estimated survival after mental hospitalization (out-of-hospital). The impact of including IPW on mortality when residing in a hospital is more ambiguous: for the high educated and for those with secondary education the IPW models reduces the impact of residing in a mental hospital on mortality, while for the low educated and the full secondary and post secondary education this (slightly) increases the impact.

Table 4 reports the impact of education on the different hazards in the final 'Timing-of-events-model (IPW) model, both the direct effect, direct', and, only for the mortality hazard,

[4]The full tables of the estimated coefficients of the Timing-of-events-model (IPW) for the mortality hazard are given in Table B.1 and for the other hazards in Table B.2 to Table B.4 in Appendix B.

Table 3: Impact of mental health problems on mortality hazard

		Education level[a]			
		(1)	(2)	(3)	(4)
PH-model	in hospital	1.397**	1.637**	1.704**	1.857**
		(0.023)	(0.023)	(0.048)	(0.056)
	out of hospital	0.482**	0.465**	0.347**	0.239+
		(0.038)	(0.037)	(0.085)	(0.107)
MPH-model	in hospital	1.684**	1.899**	2.100**	2.629**
		(0.031)	(0.032)	(0.089)	(0.097)
	out of hospital	0.732**	0.759**	0.576**	0.351**
		(0.047)	(0.050)	(0.125)	(0.130)
ToE-model	in hospital	0.688**	1.343**	1.360**	0.913**
		(0.033)	(0.033)	(0.064)	(0.134)
	out of hospital	0.384**	0.273**	0.205**	0.585**
		(0.039)	(0.042)	(0.096)	(0.123)
ToE-model (IPW)	in hospital	0.762**	0.544**	1.391**	0.546**
		(0.032)	(0.040)	(0.056)	(0.117)
	out of hospital	0.425**	0.698**	0.432**	0.744**
		(0.039)	(0.041)	(0.086)	(0.118)

[a] (1) Some Secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
$^{+}p < 0.05, ^{**}p < 0.01$.

through hospitalization (either when in hospital or after hospitalization).[5] For all educational groups (two adjacent education levels) we find a significant impact of improving education, even after accounting for the endogeneity of education through inverse propensity weighting. The educational impact is the largest for the lowest education group, with a $40\% = e^{-0.526}$ lower mortality when improving education from primary education to 2 years of secondary education. Only for this group improving education also significantly moderates the mortality while in a mental hospital. Those with 2 years of secondary education are more affected by mental hospitalization than those with primary education. We do not find any significant moderating influence of education on the impact of post mental hospitalization on mortality. Higher education reduces the hazard into (first) hospitalization and re-admittance. But if an individual improves his education form 2 to 3 years of education the re-admittance hazard increases. Such an educational improvement would also increase the expected time spend in a mental hospital (the discharge hazard increases).

[5]The full table of the estimated coefficients logit propensity score is given in Table B.5 in Appendix B. The comparison of the estimated educational effects by estimation method are reported in Table A.1 for the mortality hazard and in Table A.2 for the other hazards in Appendix A.

Table 4: Impact of education on mortality hazard, IPW Timing-of-events model)

	Education level[a]			
	(1)	(2)	(3)	(4)
	Mortality hazard			
direct	-0.526^{**}	-0.218^{**}	-0.316^{**}	-0.141^{**}
	(0.016)	(0.025)	(0.033)	(0.035)
in hospital	0.294^{**}	0.022	0.104	−0.001
	(0.031)	(0.050)	(0.074)	(0.083)
out of hospital	−0.025	−0.113	0.046	−0.120
	(0.054)	(0.088)	(0.131)	(0.164)
	First hospitalization			
direct	-0.125^{**}	-0.219^{**}	-0.257^{**}	-0.145^{**}
	(0.012)	(0.017)	(0.022)	(0.024)
	Discharge			
direct	−0.000	-0.039^{**}	0.031	0.002
	(0.009)	(0.014)	(0.019)	(0.025)
	Re-admittance			
direct	-0.121^{**}	0.059^{**}	-0.152^{**}	-0.104^{**}
	(0.008)	(0.011)	(0.018)	(0.018)

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
$^{+}p < 0.05,^{**} p < 0.01$.

5 Cause of death

In the previous section we have shown that mental health problems increases and education decreases mortality. Bijwaard et al. (2018, 2017) have shown that, even after accounting for selective education choice, education is negatively associated with most major causes of death. Here, we investigate the impact of mental health problems and education on cause-specific mortality and how the impact of mental health problems is moderated by education. Previous research has already indicated that the excess mortality due to mental disorders is not solely explained by increased risk of suicide and other external causes of death. While suicide rates are much higher for individuals with mental disorders, the total number of deaths due to suicide are small compared to other causes of death. Joukamaa et al. (2001) and Nordentoft et al. (2013) have shown that mortality from cardiovascular diseases and cancers are also higher for men with mental disorders.

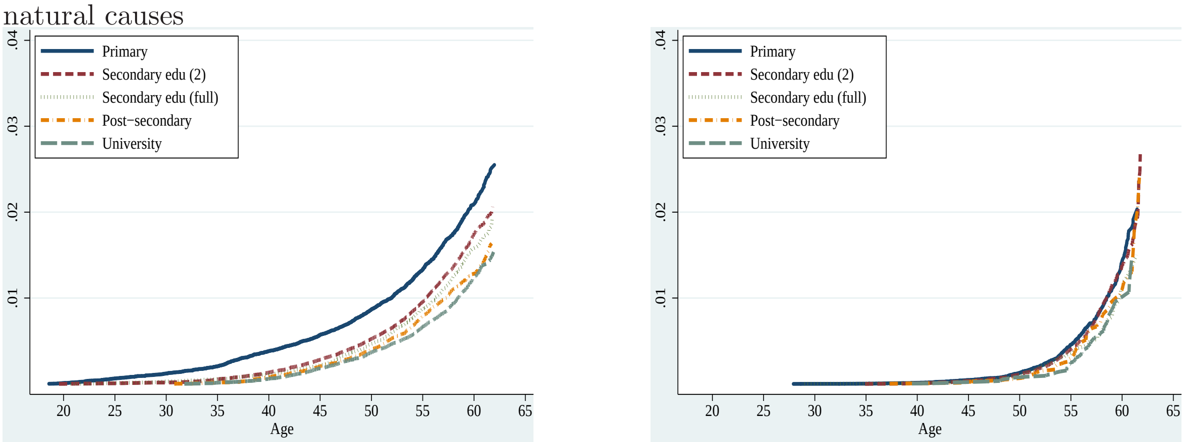
We aggregated the causes of death into six categories: (1) Cancer, all kind of cancers; (2) Cardiovascular diseases (CVD); (3) Traffic accidents; (4) Suicide; (5) (other) External causes, and finally (6) Other causes of death. Table 5 reports the percentage of individuals that died from a particular cause before the end of the observation window. We observe a clear increase in death for all causes of death after mental hospitalization, especially for other natural causes of death. We also observe an educational gradient, both with and without mental hospitalization.

Table 5: Percentage who died by education level and mental hospitalization experience

	Primary	Secondary education Some	Full	Post-secondary (< 3 years)	Higher
			All		
cancer	1.9%	1.4%	1.3%	1.1%	0.9%
CVD	2.1%	1.4%	1.1%	0.7%	0.5%
Traffic accidents	1.1%	0.6%	0.4%	0.3%	0.2%
Suicide	1.3%	0.8%	0.6%	0.4%	0.4%
External causes	0.8%	0.3%	0.2%	0.1%	0.1%
Other natural	2.8%	1.6%	1.1%	0.6%	0.5%
Total # of death	11,410	11,381	2,891	2,256	2,165
			Never in mental hospital		
cancer	1.7%	1.2%	1.2%	1.0%	0.9%
CVD	1.6%	1.1%	0.9%	0.6%	0.5%
Traffic accidents	1.0%	0.4%	0.3%	0.2%	0.2%
Suicide	1.0%	0.5%	0.4%	0.3%	0.2%
External causes	0.6%	0.2%	0.1%	0.1%	0.0%
Other natural	1.6%	0.9%	0.7%	0.4%	0.4%
# of death	7,410	7,169	2,053	1,710	1,729
			After mental hospitalization		
cancer	2.9%	2.5%	2.3%	2.0%	1.6%
CVD	4.8%	3.8%	3.4%	2.5%	1.5%
Traffic accidents	2.2%	2.2%	1.4%	1.2%	0.8%
Suicide	3.4%	2.8%	2.9%	2.9%	3.1%
External causes	1.9%	1.3%	1.0%	0.8%	0.6%
Other natural	10.4%	7.6%	5.9%	3.8%	3.7%
# of death	3,105	3,241	643	407	313

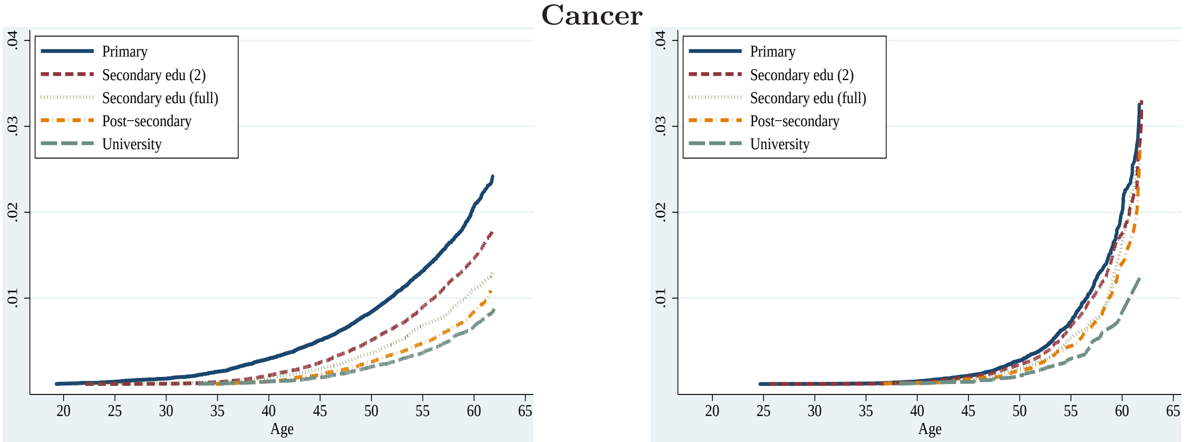
To take the timing of the deaths into account, we also calculated the cumulative incidence functions, the probability of dying from a specific cause of death before some age, with or without mental hospitalization. The (non-parametric) Aalen–Johansen cumulative incidence functions Aalen and Johansen (1978) depicted in Figure 3, for non-external causes of death and Figure 4, for external causes of death, show again a clear educational gradient in the probability to die from each of the six causes of death. Comparing the cumulative incidence curves with and without mental hospitalizations we notice two things. First, the shape of the cumulative incidence curves for external causes (including traffic accidents and suicide) are completely different with and without hospitalization and, second, the probability to die from cardiovascular diseases and other natural causes increases substantially after hospitalization. Of course, some caution in interpreting these figures is that the probability somebody has been in a mental hospital is also increases with age and this is not accounted for in the cumulative incidence functions. We do account for such dynamic selection in our timing-of-events model.

Figure 3: Cumulative incidence curves by cause of death, hospitalization and education level, natural causes



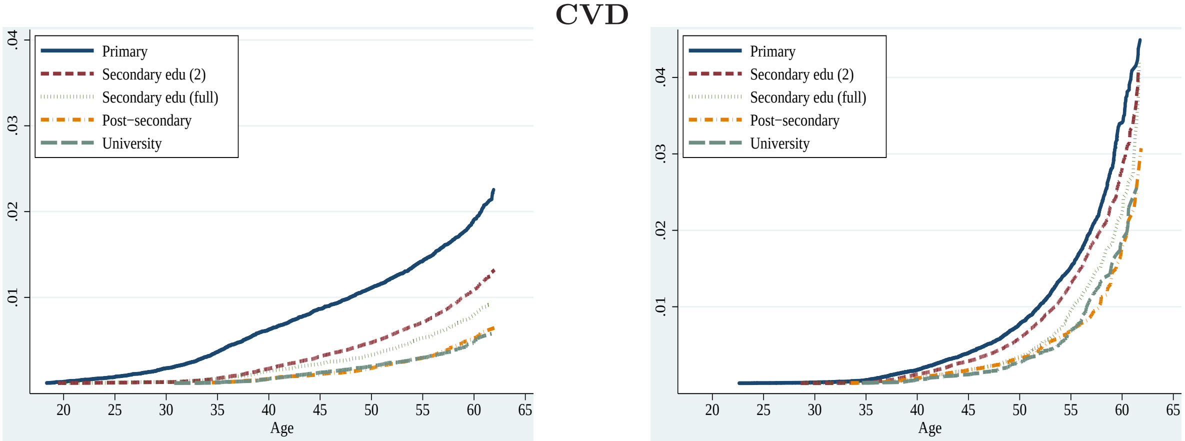
no hospitalization **after hospitalization**

Cancer



no hospitalization **after hospitalization**

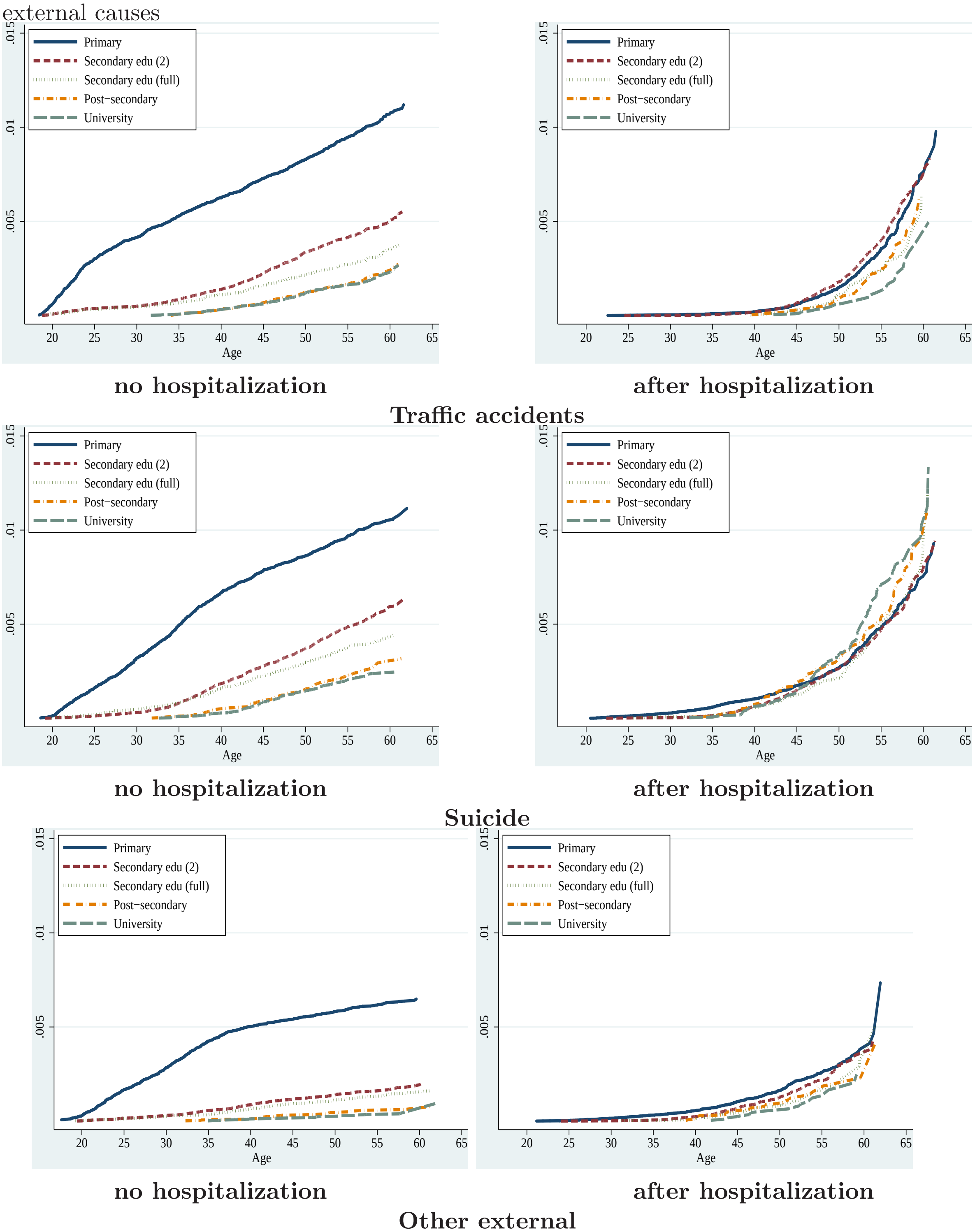
CVD



no hospitalization **after hospitalization**

Other natural

Figure 4: Cumulative incidence curves by cause of death, hospitalization and education level, external causes



Next we extend the timing-of-events model to cause-specific mortality. Instead of one mortality hazard we have six mortality hazards, one for each cause of death. Each of these hazards has an MPH form as in (4). To account for possible endogeneity of the hospitalization process the unobserved heterogeneity of each cause-specific hazard is possibly correlated with the hospitalization hazards in (1) to (3) and with the other cause-specific hazards. Just as for the analysis of total mortality we account for possible endogeneity of education by using an inverse propensity weighting (in fact the weights are exactly the same based on the same logit estimation of improving education, see Table B.5 in Appendix B).

Table 6 presents the estimated impact of mental health problems on the cause-specific mortality rates for the timing-of-events model with IPW.[6] Death due to external causes is, for all education groups, affected the most by mental health problems. For the highest education group the mortality rate due to external causes is more than ten times higher when in a mental hospital. Mental health problems also severely affects death due to suicide and traffic accidents, also non-natural causes, and death due to cardiovascular diseases and other natural causes. Mortality due to cancer is only slightly affected by mental health problems: for the highest education group mental hospitalization decreases cancer mortality and for the one-below-highest education group mental hospitalization does not have a significant impact on cancer mortality. Still, after having experienced mental hospitalization death due to cancer also increases.

Table 7 reports the estimated impact of education on the cause-specific mortality rates and how education moderates the impact of mental health problems for the timing-of-events model with IPW. Both the direct effect of education, 'direct', and the effect running through mental health problems (either in hospital or after having experienced hospitalization) are reported. We get rather mixed results. Only for death due to other natural causes we find a significant direct effect of improving education in all education groups. For all but the highest education group, improving education decreases the hazard of dying from other natural causes. Improving education also decreases the hazard of dying from traffic accidents (only the two low education groups), to die from external causes (not significant for the highest education group), to commit suicide (only significant if attainting one more year of secondary education) and, to die from cardiovascular diseases (only the lowest and the highest education groups). Higher education increases the hazard of dying from cancer for the middle education groups. For many causes of death education also moderates the impact of mental health problems on the cause-specific mortality rates, both negatively and positively.

[6] The full tables of the estimated coefficients of the cause-specific timing-of-events IPW for all the cause-specific mortality hazards are given in Table C.1 to C.6 in Appendix C.

Table 6: Impact of mental health problems on Cause-specific mortality hazard

		Education level[a]			
		(1)	(2)	(3)	(4)
Cancer	in hospital	0.409**	0.140**	0.078	−0.126**
		(0.022)	(0.019)	(0.040)	(0.050)
	out of hospital	1.550**	1.294**	1.443**	1.908**
		(0.027)	(0.025)	(0.051)	(0.062)
CVD	in hospital	0.875**	0.515**	0.749**	1.049**
		(0.018)	(0.017)	(0.036)	(0.040)
	out of hospital	1.673**	1.624**	1.371**	0.974**
		(0.020)	(0.020)	(0.045)	(0.062)
Traffic accidents	in hospital	0.338**	1.152**	1.184**	1.387**
		(0.027)	(0.025)	(0.061)	(0.064)
	out of hospital	1.924**	1.528**	1.453**	1.570**
		(0.028)	(0.027)	(0.071)	(0.077)
Suicide	in hospital	0.826**	1.099**	1.340**	1.653**
		(0.024)	(0.024)	(0.049)	(0.053)
	out of hospital	1.600**	1.735**	1.449**	1.675**
		(0.027)	(0.025)	(0.056)	(0.062)
External	in hospital	1.537**	1.651**	1.469**	2.347**
		(0.034)	(0.037)	(0.082)	(0.096)
	out of hospital	1.816**	1.683**	1.865**	1.731**
		(0.034)	(0.034)	(0.084)	(0.099)
Other natural	in hospital	0.840**	1.250**	1.346**	1.171**
		(0.015)	(0.015)	(0.033)	(0.045)
	out of hospital	1.755**	1.805**	1.737**	2.338**
		(0.015)	(0.015)	(0.035)	(0.048)

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.

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

Table 7: Impact of education on Cause-specific mortality hazard

		Education level[a]			
		(1)	(2)	(3)	(4)
Cancer		0.011	0.119^{**}	0.087^{**}	−0.014
		(0.012)	(0.016)	(0.020)	(0.019)
	in hospital	−0.016	-0.137^{**}	0.072	0.360^{**}
		(0.028)	(0.041)	(0.059)	(0.067)
	out of hospital	0.005	0.335^{**}	-0.395^{**}	-0.613^{**}
		(0.036)	(0.054)	(0.085)	(0.094)
CVD		-0.029^{+}	−0.021	0.006	-0.055^{+}
		(0.012)	(0.017)	(0.024)	(0.025)
	in hospital	0.030	0.165^{**}	0.053	-0.330^{**}
		(0.024)	(0.036)	(0.054)	(0.064)
	out of hospital	-0.150^{**}	0.002	0.357^{**}	0.119
		(0.028)	(0.044)	(0.068)	(0.099)
Traffic accidents		-0.139^{**}	-0.281^{**}	0.004	−0.005
		(0.021)	(0.034)	(0.045)	(0.044)
	in hospital	0.432^{**}	−0.038	0.250^{**}	-0.391^{**}
		(0.034)	(0.061)	(0.087)	(0.100)
	out of hospital	-0.376^{**}	-0.354^{**}	0.027	0.474^{**}
		(0.039)	(0.079)	(0.108)	(0.122)
Suicide		−0.030	-0.063^{+}	−0.003	0.054
		(0.019)	(0.027)	(0.037)	(0.039)
	in hospital	−0.030	0.108^{+}	0.489^{**}	−0.077
		(0.032)	(0.050)	(0.066)	(0.076)
	out of hospital	−0.028	0.615^{**}	−0.115	0.739^{**}
		(0.036)	(0.052)	(0.080)	(0.086)
External		-0.580^{**}	0.241^{**}	-0.347^{**}	−0.159
		(0.030)	(0.047)	(0.075)	(0.093)
	in hospital	0.434^{**}	-0.234^{**}	0.533^{**}	−0.208
		(0.047)	(0.075)	(0.123)	(0.145)
	out of hospital	0.065	−0.029	0.220	0.087
		(0.047)	(0.083)	(0.125)	(0.159)
Other natural		-0.130^{**}	-0.134^{**}	-0.186^{**}	0.065^{+}
		(0.013)	(0.020)	(0.028)	(0.030)
	in hospital	0.074^{**}	0.117^{**}	0.093	0.479^{**}
		(0.020)	(0.033)	(0.051)	(0.059)
	out of hospital	0.039	-0.175^{**}	−0.044	-0.795^{**}
		(0.020)	(0.037)	(0.059)	(0.069)

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.

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

6 Conclusion and discussion

Higher mortality risks for people with mental disorders are well recognized. Poor mental health is associated with low education, which is also associated with poor health and higher mortality. The association between mental health and mortality may, therefore, be partly explained by the increased incidence of mental problems of the low educated. In this paper we investigate the impact of poor mental health and education on mortality and how education shapes the impact of poor mental health on mortality.

A common approach is to estimate a (mixed) proportional hazard model for the mortality hazard using a Gompertz baseline hazard, which assumes an exponential increase in the mortality by age. However, viewing the educational level and the mental health problems as ordinary (exogenous) variables may lead to biased inference of the effect of these variables on the mortality hazard. A major issue with the empirical analysis of the impact of mental health problems (as measured by mental hospitalization) on mortality is that the admittance and discharge processes may depend on both observed and unobserved individual characteristics. This implies that any observed relationship between admittance to (or discharge from) mental hospital and mortality may be caused by unobserved factors that influence both the hospitalization and mortality. Educational attainment is also very likely to depend on the same observed factors. Such confounding renders education and mental hospitalization endogenous in the mortality analysis. We obtain the causal impact of mental health problems, a direct effect and an effect running through education, and the causal effect of education, on mortality by accounting for both the selection into mental hospitalization process (both admittance and discharge) and the selection into education.

In particular, we estimate the effects of the mental hospitalization process on the mortality rate using the "timing-of-events" - method (Abbring and van den Berg, 2003). We control for correlated effects that arise from correlation between unobservables in the mental hospitalization and mortality processes. To account for the endogeneity of the education attainment we apply inverse probability weighting (IPW) methods using the propensity score.

We use Swedish Military Conscription Data (1951-1960), linked to administrative Swedish registers including information on mental hospitalization and death in which we identified five education groups. Using the timing-of-events IPW methods we, for each adjacent education group, estimate the impact of mental health problems and improving education on the mortality risk and how education shapes the impact of mental health problems on the mortality risk.

The empirical analyses reveal that ignoring the endogeneity of the mental hospitalization process would lead to an overestimation of the impact of mental health problems on mortality. Accounting for education endogeneity decreases the estimated effects of mental health problems. For all education levels we find that mortality is higher for those in mental hospital and for those who have experienced mental hospitalization. For all educational groups (two adjacent education levels) we find a significant impact of increasing education, even after accounting for the endogeneity of education through inverse propensity weighting. The educational impact is the largest for the lowest education group. Only for this group improving education also significantly moderates the impact of mental health problems on mortality while in a mental hospital.

We also investigated the impact of mental health problems and education on cause-specific mortality rates, distinguishing six different causes of death. Using an extension of the timing-of-events model with IPW we find that most causes of death, except for cancer, are affected by being in a mental hospital. Still, after having experienced mental hospitalization death due to cancer also increases. The influence of education on the cause-specific mortality rates is rather ambiguous. For many causes of death education also moderates the impact of mental health problems on the cause-specific mortality rates, both negatively and positively.

A limitation of our data, based on military entrance examination, is that we only observe men and no information on women is available. Another limitation is that, 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 and are, therefore, likely an underestimate of the impact of mental hospitalization on mortality.

Another issue is that mental hospitalization could also signify other meanings than poor mental health. First, it could indicate the demand for mental health care, which implies that hospitalization is a measure of health input. How much of this health input is used depends on the individual demand for mental health, health endowment and access to substitute health inputs. Second, it could reflect the supply of mental hospitals and their accessibility. This has also implications for the effect of education on mental hospitalization. More education may have countervailing effects on hospitalization if, on the one hand, it reduces the hospitalization incidence, through better health conditions, while, on the other hand, it increases hospitalization for a given mental health condition, through greater income, more knowledge, or better preventions. Most previous studies addressing inequalities in mental care have assumed that a fair distribution of care is achieved when individuals of equal ill health status use the same quantity of care, disregarding differences in quality of care and disparities in outcome. As far as mental health is concerned, however, there is some evidence of unequal quality and outcome of care. Lower socioeconomic groups use less specialized care, while medication use and dosage are also less appropriate in such groups. In addition, some population studies have shown that poverty and low socioeconomic status (SES) increase the duration of episodes for a given baseline clinical status. However, we postulate that in the Swedish situation, with universal health insurance and access, mental hospitalization as an indicator of poor mental health would prevail.

Finally, the issue of reverse causality that early childhood health affects educational attainment might distort our analyses. We do not have sufficient information about childhood health status, which prevents us from investigating the possibility of reverse causality from health to education in our sample.

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Appendix A Additional tables

Table A.1: Impact of education on mortality hazard by estimation model

		Education level[a]			
		(1)	(2)	(3)	(4)
PH-model		-0.526^{**}	-0.202^{**}	-0.319^{**}	-0.125^{**}
		(0.017)	(0.025)	(0.033)	(0.035)
	in hospital	0.351^{**}	0.052	0.159^{**}	-0.107
		(0.031)	(0.052)	(0.073)	(0.083)
	out of hospital	-0.031	0.014	0.051	0.213
		(0.053)	(0.091)	(0.133)	(0.155)
MPH-model		-0.609^{**}	-0.213^{**}	-0.355^{**}	-0.152^{**}
		(0.019)	(0.027)	(0.037)	(0.041)
	in hospital	0.312^{**}	0.040	0.158	-0.114
		(0.040)	(0.064)	(0.099)	(0.121)
	out of hospital	-0.046	0.043	0.019	0.216
		(0.066)	(0.118)	(0.164)	(0.188)
Timing-of-events-model		-0.544^{**}	-0.208^{**}	-0.322^{**}	-0.134^{**}
		(0.017)	(0.026)	(0.033)	(0.036)
	in hospital	0.377^{**}	0.085	0.113	-0.075
		(0.032)	(0.052)	(0.075)	(0.085)
	out of hospital	-0.050	-0.034	0.128	0.137
		(0.054)	(0.092)	(0.133)	(0.163)
Timing-of-events-model (IPW)		-0.526^{**}	-0.218^{**}	-0.316^{**}	-0.141^{**}
		(0.016)	(0.025)	(0.033)	(0.035)
	in hospital	0.294^{**}	0.022	0.104	-0.001
		(0.031)	(0.050)	(0.074)	(0.083)
	out of hospital	-0.025	-0.113	0.046	-0.120
		(0.054)	(0.088)	(0.131)	(0.164)

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
$^{+}p < 0.05, ^{**}p < 0.01$.

Table A.2: Impact of education on mental health problems Swedish Conscripts by estimation model

	Education level[a]			
	(1)	(2)	(3)	(4)
	First hospitalization			
PH-model	-0.082^{**}	-0.205^{**}	-0.240^{**}	-0.132^{**}
	(0.011)	(0.017)	(0.021)	(0.023)
MPH-model	-0.141^{**}	-0.231^{**}	-0.318^{**}	-0.161^{**}
	(0.014)	(0.020)	(0.028)	(0.030)
Timing-of-events-model	-0.117^{**}	-0.206^{**}	-0.258^{**}	-0.138^{**}
	(0.012)	(0.017)	(0.022)	(0.024)
Timing-of-events-model (IPW)	-0.125^{**}	-0.219^{**}	-0.257^{**}	-0.145^{**}
	(0.012)	(0.017)	(0.022)	(0.024)
	Discharge			
PH-model	0.005	-0.024	0.064^{**}	0.034
	(0.008)	(0.013)	(0.018)	(0.021)
MPH-model	-0.021^{+}	-0.024	0.045^{+}	-0.008
	(0.009)	(0.016)	(0.021)	(0.025)
Timing-of-events-model	-0.003	-0.059^{**}	-0.007	-0.032
	(0.009)	(0.016)	(0.021)	(0.025)
Timing-of-events-model (IPW)	-0.000	-0.039^{**}	0.031	0.002
	(0.009)	(0.014)	(0.019)	(0.025)
	Re-admittance			
PH-model	-0.109^{**}	0.005	-0.136^{**}	-0.102^{**}
	(0.004)	(0.008)	(0.011)	(0.013)
MPH-model	-0.111^{**}	0.020	-0.135^{**}	-0.091^{**}
	(0.007)	(0.013)	(0.016)	(0.021)
Timing-of-events-model	-0.099^{**}	0.032^{**}	-0.151^{**}	-0.084^{**}
	(0.009)	(0.012)	(0.018)	(0.018)
Timing-of-events-model (IPW)	-0.121^{**}	0.059^{**}	-0.152^{**}	-0.104^{**}
	(0.008)	(0.011)	(0.018)	(0.018)

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
$^{+}p < 0.05,^{**}p < 0.01$.

Appendix B Full tables with parameter estimates IPW timing of events model mortality

Table B.1: Parameter estimates mortality rate, IPW Timing-of-events model

	Education level[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
non-manual (high)	0.078	−0.045	−0.028	0.031
non-manual (intermediate)	0.060	0.104	0.083	0.053
non-manual (low)	0.078**	−0.011	−0.011	0.005
Farmers	−0.032	−0.019	0.035	0.007
Unskilled workers	0.067**	0.064+	0.121+	0.210**
Not classified	−0.192**	−0.087	−0.035	−0.024
Unknown	0.576**	0.350**	0.215	0.145
SES father at birth				
non-manual (high)	0.015	−0.016	−0.038	−0.076
non-manual (intermediate)	0.027	0.024	0.035	−0.003
non-manual (low)	0.052	0.052	−0.076	−0.062
Farmers	−0.244**	−0.180**	−0.226**	−0.149
Unskilled workers	0.040+	0.045	−0.019	0.018
Not classified	0.060	0.095	−0.056	−0.095
Unknown	0.996**	0.579**	0.441**	0.115
mother's education				
Primary (< 9 yrs)	−0.038+	−0.036	−0.019	−0.004
Primary (9–10 yrs)	−0.010	0.018	0.013	−0.023
Secondary education (3 yrs)	0.039	−0.036	0.151	0.063
Post-secondary	−0.068	−0.151+	−0.150	−0.063
Higher	0.118	−0.020	0.004	−0.092
PhD	−1.683	−0.831	0.408	0.521
Unknown	0.137**	0.094+	−0.070	−0.200+
father's education				
Primary (< 9 yrs)	−0.012	−0.010	−0.060	0.019
Primary (9–10 yrs)	−0.080	0.049	0.099	0.225**
Secondary education (3 yrs)	0.001	−0.016	−0.071	0.047
Post-secondary	0.161**	0.123+	−0.050	0.031
Higher	0.099	0.042	−0.090	−0.008
PhD	0.424**	0.160	0.135	0.088
Unknown	0.066+	0.113**	0.087	0.275**

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Gompertz age dependence and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table B.1: Parameter estimates mortality rate, IPW Timing-of-events model (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
IQ measurement				
1	0.035	0.131^{**}	−0.218	−0.245
2	0.022	0.135^{**}	−0.065	−0.347
3	0.051^{+}	0.080^{+}	−0.051	0.021
4	0.047	0.064^{+}	−0.068	-0.156^{+}
6	0.012	−0.011	−0.065	-0.126^{+}
7	0.082^{+}	0.003	−0.001	−0.058
8	0.183^{**}	−0.039	0.037	−0.074
9	0.353^{**}	0.016	0.066	-0.199^{**}
10	0.062	−0.113	0.006	0.063
Psychological assessment				
1	0.631^{**}	0.602^{**}	0.260^{**}	0.302^{+}
2	0.351^{**}	0.356^{**}	0.314^{**}	0.233^{**}
3	0.259^{**}	0.246^{**}	0.010	0.044
4	0.072^{**}	0.061	−0.031	−0.021
6	-0.062^{+}	-0.095^{**}	−0.080	−0.063
7	−0.049	−0.069	-0.118^{+}	−0.100
8	0.009	−0.074	-0.143^{+}	-0.146^{+}
9	0.038	−0.062	−0.114	−0.153
10	0.607^{**}	0.766^{**}	0.452^{**}	0.319
birth info				
mother $<$ 20 at birth	0.016	0.085^{**}	−0.027	−0.036
father $>$ 40 at birth	0.159^{**}	0.003	−0.008	−0.042
birth order 2	0.019	0.019	−0.020	-0.096^{**}
birth order 3	−0.013	−0.032	-0.099^{+}	−0.061
birth order 4	-0.085^{**}	−0.026	−0.041	−0.100
birth order ≥ 5	0.142^{**}	0.071	0.027	−0.048
gamma	0.072^{**}	0.100^{**}	0.102^{**}	0.120^{**}

[a] (1) Some secondary education; (2) Full secondary education; (3) Post-secondary education; (4) University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Gompertz age dependence and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.2: Parameter estimates first hospitalization rate, IPW Timing-of-events model

	Education level[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
non-manual (high)	0.148**	0.052	0.047	0.111
non-manual (intermediate)	0.103+	0.058	0.083	0.005
non-manual (low)	0.069**	−0.001	0.070	0.081
Farmers	−0.092**	−0.114**	−0.035	−0.021
Unskilled workers	0.158**	0.123**	0.026	0.142**
Not classified	0.244**	0.227**	0.214**	0.271**
Unknown	−0.102	−0.103	−0.002	0.018
SES father at birth				
non-manual (high)	0.009	0.048	−0.003	0.028
non-manual (intermediate)	0.021	0.009	−0.046	−0.021
non-manual (low)	0.034	0.042	−0.034	−0.055
Farmers	−0.444**	−0.423**	−0.320**	−0.276**
Unskilled workers	−0.015	−0.023	0.002	0.034
Not classified	0.167**	0.188**	0.144	0.010
Unknown	−0.937**	−0.909**	−0.858**	−0.637**
mother's education				
Primary (< 9 yrs)	−0.039+	−0.043+	−0.018	−0.002
Primary (9–10 yrs)	0.048	0.044	0.031	0.043
Secondary education (3 yrs)	0.059	−0.053	0.079	−0.029
Post-secondary	0.102+	0.044	0.000	0.026
Higher	0.131+	0.103	−0.015	0.032
PhD	0.985**	0.642	0.700+	1.099**
Unknown	0.078+	0.137**	0.041	0.038
father's education				
Primary (< 9 yrs)	−0.061**	−0.055**	−0.052	−0.025
Primary (9–10 yrs)	−0.016	0.030	−0.005	−0.061
Secondary education (3 yrs)	0.042	0.025	0.040	0.061
Post-secondary	0.069	0.008	0.081	0.040
Higher	0.151**	0.164**	0.182**	0.068
PhD	0.004	0.377**	0.354**	0.032
Unknown	0.249**	0.283**	0.274**	0.224**

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant age dependence and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.2: Parameter estimates first hospitalization rate, IPW Timing-of-events model

	Education level[a]			
	(1)	(2)	(3)	(4)
IQ measurement				
1	0.386**	0.413**	0.280**	0.314
2	0.361**	0.419**	0.370**	0.419**
3	0.244**	0.306**	0.294**	0.346**
4	0.165**	0.170**	0.186**	0.249**
6	−0.098**	−0.121**	−0.055	−0.062
7	−0.152**	−0.177**	−0.194**	−0.169**
8	−0.237**	−0.243**	−0.217**	−0.338**
9	−0.257**	−0.213**	−0.294**	−0.519**
10	−0.850**	−1.355**	−1.380**	−1.473**
Psychological assessment				
1	1.572**	1.650**	1.200**	1.271**
2	1.009**	1.010**	0.796**	0.782**
3	0.592**	0.596**	0.402**	0.432**
4	0.246**	0.277**	0.193**	0.200**
6	−0.139**	−0.133**	−0.142**	−0.099+
7	−0.189**	−0.207**	−0.211**	−0.171**
8	−0.205**	−0.260**	−0.349**	−0.254**
9	−0.185+	−0.163+	−0.228**	−0.230**
10	1.073**	0.910**	0.470**	0.314+
birth info				
mother $<$ 20 at birth	0.115**	0.209**	0.148**	0.154**
father $>$ 40 at birth	−0.357**	−0.342**	−0.252**	−0.239**
birth order 2	0.056**	0.060**	0.048	0.012
birth order 3	0.099**	0.120**	0.046	0.014
birth order 4	0.164**	0.175**	0.100+	0.056
birth order ≥ 5	0.145**	0.158**	−0.027	−0.024

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant age dependence and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05$,$^{**}\, p < 0.01$.

Table B.3: Parameter estimates discharge rate, IPW Timing-of-events model

	Education level[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
non-manual (high)	0.008	−0.153**	0.011	0.018
non-manual (intermediate)	0.004	−0.049	−0.008	0.013
non-manual (low)	−0.001	0.002	−0.050	0.018
Farmers	0.025	0.047	0.016	0.033
Unskilled workers	0.000	0.013	0.074	0.130+
Not classified	−0.014	−0.044	−0.072	0.149
Unknown	−0.067	−0.028	0.101	0.044
SES father at birth				
non-manual (high)	−0.030	0.023	0.070	−0.066
non-manual (intermediate)	0.030	0.023	0.013	−0.022
non-manual (low)	−0.011	−0.066**	0.053	−0.049
Farmers	0.025	−0.012	−0.011	−0.028
Unskilled workers	0.016	0.040**	−0.004	−0.025
Not classified	0.023	0.000	0.007	−0.186+
Unknown	−0.002	0.050	−0.106	−0.346**
mother's education				
Primary (< 9 yrs)	−0.007	−0.007	0.031	0.020
Primary (9–10 yrs)	−0.028	0.033	−0.016	0.017
Secondary education (3 yrs)	−0.074+	−0.077	−0.038	0.176+
Post-secondary	−0.076+	0.066	−0.047	0.019
Higher	−0.003	0.130**	0.022	−0.081
PhD	0.132	0.259	0.656	−1.681**
Unknown	−0.013	−0.004	−0.042	−0.120
mother's education				
Primary (< 9 yrs)	−0.003	0.029	−0.050	0.029
Primary (9–10 yrs)	−0.018	−0.042	0.053	0.037
Secondary education (3 yrs)	−0.059**	−0.012	−0.021	0.040
Post-secondary	−0.022	0.009	−0.037	−0.010
Higher	−0.034	−0.082+	−0.071	−0.006
PhD	−0.097	−0.076	−0.170	0.161
Unknown	−0.056**	−0.050+	0.015	0.139+

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant duration dependence in weeks and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table B.3: Parameter estimates discharge rate, IPW Timing-of-events model (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
IQ measurement				
1	-0.041^{+}	-0.057^{+}	-0.116	-0.025
2	-0.056^{**}	-0.097^{**}	-0.139^{+}	-0.017
3	-0.005	-0.035	-0.055	0.021
4	-0.003	-0.026	0.039	0.000
6	0.034	0.025	-0.035	0.018
7	-0.015	0.070^{**}	-0.042	-0.015
8	0.067	0.066	-0.052	0.050
9	-0.067	-0.162^{+}	-0.015	-0.105
10	-0.046	-0.036	-0.107	-0.075
Psychological assessment				
1	-0.151^{**}	-0.280^{**}	-0.073	-0.121
2	-0.102^{**}	-0.180^{**}	0.015	-0.038
3	-0.038^{+}	-0.082^{**}	-0.077^{+}	0.023
4	-0.013	-0.072^{**}	-0.030	0.045
6	0.023	0.055^{+}	0.054	0.107^{+}
7	0.070^{**}	0.051	0.073	0.104^{+}
8	0.028	-0.045	-0.026	0.100
9	0.206^{**}	0.053	-0.051	0.122
10	-0.129^{**}	-0.222^{**}	0.007	0.048
birth info				
mother $<$ 20 at birth	0.003	0.043^{+}	-0.014	-0.050
father $>$ 40 at birth	0.009	0.072^{**}	-0.049	-0.054
birth order 2	0.005	0.012	-0.038	-0.000
birth order 3	-0.003	0.034	-0.001	0.038
birth order 4	-0.008	0.078^{**}	-0.001	-0.071
birth order ≥ 5	0.008	0.008	-0.004	-0.037

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant duration dependence in weeks and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.4: Parameter estimates re-admittance rate, IPW Timing-of-events model

	Education level[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
non-manual (high)	0.007	0.129**	0.303**	0.248**
non-manual (intermediate)	−0.042	0.023	0.098+	0.188**
non-manual (low)	0.002	−0.012	0.095**	0.017
Farmers	−0.069**	−0.024	0.089+	0.210**
Unskilled workers	0.045**	−0.034+	0.061	0.037
Not classified	0.053**	0.089**	0.199**	0.089
Unknown	−0.035	−0.081+	0.096	0.034
SES father at birth				
non-manual (high)	0.026	0.095**	−0.214**	−0.067
non-manual (intermediate)	0.081**	−0.002	−0.130**	−0.025
non-manual (low)	0.089**	0.053**	−0.131**	0.030
Farmers	−0.164**	−0.093**	−0.247**	−0.329**
Unskilled workers	−0.004	−0.077**	−0.147**	0.010
Not classified	−0.011	0.010	−0.336**	−0.286**
Unknown	−0.052+	−0.063	−0.245**	−0.138+
mother's education				
Primary (< 9 yrs)	−0.083**	−0.065**	−0.024	−0.012
Primary (9–10 yrs)	−0.045+	−0.089**	−0.015	−0.088**
Secondary education (3 yrs)	−0.030	−0.021	0.160**	0.255**
Post-secondary	0.016	−0.239**	−0.012	−0.025
Higher	0.043	−0.146**	0.223**	−0.157**
PhD	−0.017	−0.714**	0.131	1.091**
Unknown	−0.018	0.034	−0.187**	−0.223**
mother's education				
Primary (< 9 yrs)	−0.043**	−0.041**	−0.115**	−0.076**
Primary (9–10 yrs)	−0.108**	0.011	0.033	0.252**
Secondary education (3 yrs)	0.056**	−0.019	−0.195**	0.022
Post-secondary	0.022	−0.036	−0.165+	−0.062
Higher	0.023	−0.032	0.153**	0.079+
PhD	−0.136	0.330**	0.240**	−0.228**
Unknown	0.085**	0.091**	0.125**	0.105**

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant duration dependence in years and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.4: Parameter estimates re-admittance rate, IPW Timing-of-events model (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
IQ measurement				
1	0.117**	0.103**	0.075	0.281**
2	0.113**	0.170**	0.198**	0.096
3	0.063**	0.058**	−0.021	0.207**
4	0.012	0.076**	0.107**	0.017
6	−0.060**	−0.074**	−0.040	0.010
7	−0.102**	−0.032	0.046	0.031
8	−0.265**	−0.193**	−0.002	−0.006
9	−0.437**	−0.152**	0.024	−0.039
10	0.033	−0.125**	−0.074	0.238+
Psychological assessment				
1	0.367**	0.318**	0.174**	0.071
2	0.240**	0.166**	0.100**	0.090**
3	0.117**	0.083**	−0.012	−0.033
4	0.064**	0.035+	0.048	0.002
6	−0.022	−0.030	−0.043	0.031
7	−0.018	0.007	0.012	−0.022
8	0.039	0.113**	−0.161**	−0.037
9	−0.020	−0.110+	−0.136**	0.254**
10	0.259**	0.385**	0.229**	−0.049
birth info				
mother $<$ 20 at birth	−0.010	0.058**	−0.005	−0.107**
father $>$ 40 at birth	−0.096**	−0.150**	−0.219**	−0.112**
birth order 2	0.054**	0.010	0.019	−0.008
birth order 3	0.067**	−0.019	0.025	−0.039
birth order 4	0.053**	−0.004	0.068	0.044
birth order $\geq$ 5	0.043+	0.096**	0.133**	0.094

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. Piecewise constant duration dependence in years and discrete unobserved (correlated) heterogeneity with 3 points of support are also included. $^{+}p < 0.05, ^{**}p < 0.01$.

Table B.5: Parameter estimates logit propensity score

	Education level[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
non-manual (high)	-0.063	0.473^{**}	-0.151^{**}	0.318^{**}
non-manual (intermediate)	0.055	0.169^{**}	0.014	0.138^{**}
non-manual (low)	0.105^{**}	0.199^{**}	0.032	0.136^{**}
Farmers	-0.232^{**}	0.050^{+}	-0.024	0.056^{+}
Unskilled workers	-0.032^{+}	0.024	-0.066^{**}	0.083^{**}
Not classified	0.100^{**}	-0.087^{**}	0.008	0.051
Unknown	-0.021	0.108^{+}	-0.014	0.214^{**}
SES father at birth				
non-manual (high)	-0.186^{**}	0.353^{**}	-0.036	0.372^{**}
non-manual (intermediate)	-0.061^{**}	0.156^{**}	0.046	0.161^{**}
non-manual (low)	-0.056^{**}	0.234^{**}	-0.081^{**}	0.188^{**}
Farmers	-0.087^{**}	-0.043	-0.077^{+}	-0.107^{**}
Unskilled workers	-0.078^{**}	-0.052^{**}	-0.064^{**}	-0.005
Not classified	-0.080^{**}	0.060	-0.045	0.017
Unknown	-0.218^{**}	0.010	-0.142^{**}	0.037
mother's education				
Primary (< 9 yrs)	-0.279^{**}	-0.062^{**}	-0.085^{**}	-0.128^{**}
Primary (9–10 yrs)	-0.147^{**}	0.139^{**}	-0.066^{**}	0.024
Secondary education (3 yrs)	-0.141^{**}	0.256^{**}	-0.055	0.172^{**}
Post-secondary	0.105^{**}	0.174^{**}	0.188^{**}	0.175^{**}
Higher	-0.057	0.353^{**}	0.155^{**}	0.333^{**}
PhD	-0.999^{**}	0.602	-0.071	0.587^{**}
Unknown	-0.415^{**}	0.103^{**}	-0.158^{**}	-0.041
father's education				
Primary (< 9 yrs)	-0.261^{**}	-0.151^{**}	-0.027	-0.092^{**}
Primary (9–10 yrs)	-0.151^{**}	-0.017	-0.006	-0.002
Secondary education (3 yrs)	0.031	0.093^{**}	0.149^{**}	0.006
Post-secondary	0.115^{**}	0.103^{**}	0.200^{**}	0.074^{**}
Higher	-0.117^{**}	0.445^{**}	0.028	0.539^{**}
PhD	-0.420^{**}	0.698^{**}	-0.183^{+}	0.919^{**}
Unknown	-0.350^{**}	-0.016	-0.087^{**}	0.081^{**}

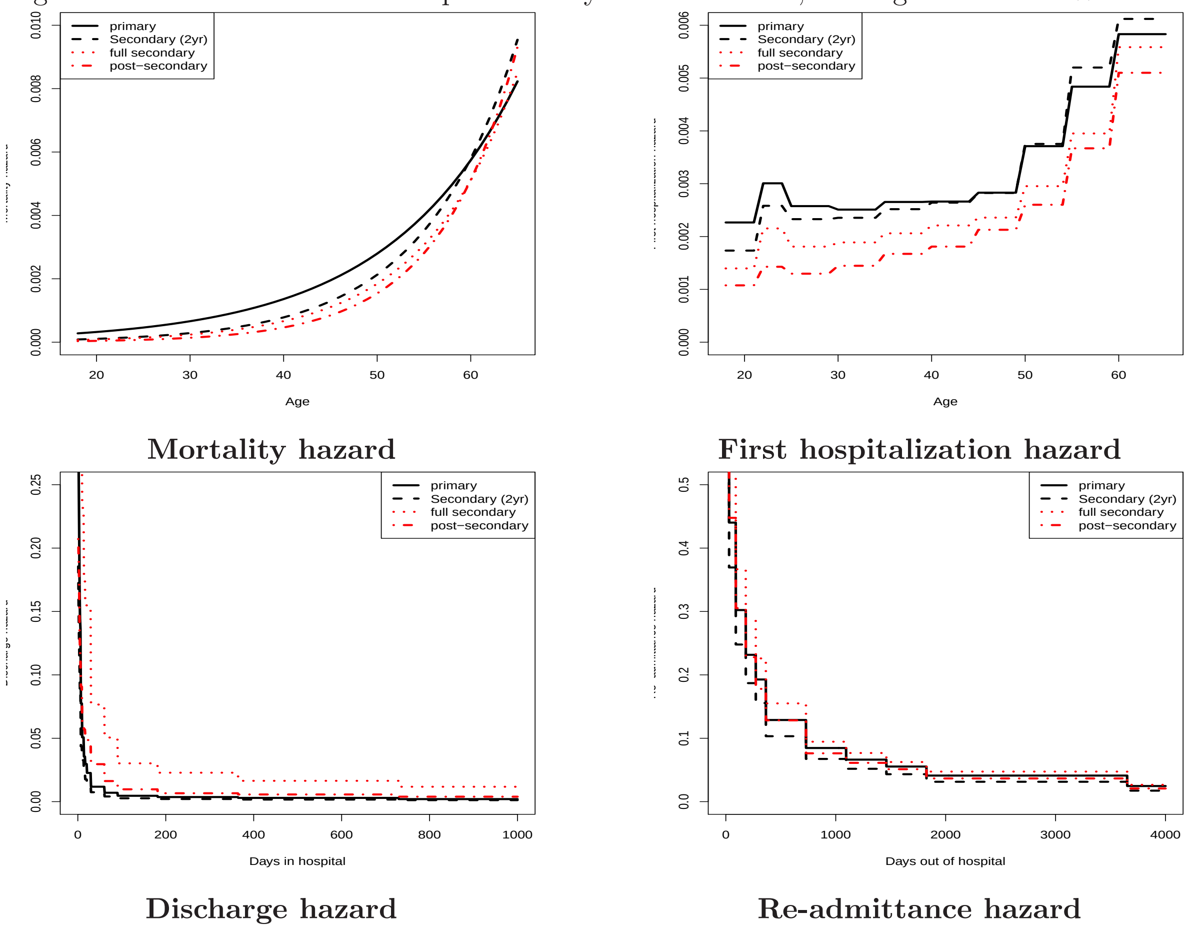
[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05$,$^{**}p < 0.01$.

Table B.5: Parameter estimates logit propensity score (continued)

	Education level[a]			
	(1)	(2)	(3)	(4)
IQ measurement				
1	-0.713^{**}	-1.059^{**}	-0.768^{**}	-0.221
2	-0.458^{**}	-0.793^{**}	-0.446^{**}	-0.511^{**}
3	-0.308^{**}	-0.493^{**}	-0.314^{**}	-0.265^{**}
4	-0.152^{**}	-0.293^{**}	-0.144^{**}	-0.187^{**}
6	0.190^{**}	0.286^{**}	0.116^{**}	0.153^{**}
7	0.270^{**}	0.635^{**}	0.265^{**}	0.345^{**}
8	0.196^{**}	1.076^{**}	0.385^{**}	0.558^{**}
9	-0.097	1.626^{**}	0.452^{**}	0.914^{**}
10	-0.095^{+}	0.015	0.202^{**}	0.187^{+}
Psychological assessment				
1	-0.315^{**}	-0.402^{**}	-0.223^{**}	0.288^{**}
2	-0.251^{**}	-0.306^{**}	-0.150^{**}	0.239^{**}
3	-0.196^{**}	-0.134^{**}	-0.154^{**}	0.149^{**}
4	-0.101^{**}	-0.069^{**}	-0.089^{**}	0.055^{**}
6	0.051^{**}	0.117^{**}	0.041^{+}	0.038^{+}
7	0.084^{**}	0.269^{**}	0.110^{**}	0.123^{**}
8	0.100^{**}	0.414^{**}	0.176^{**}	0.182^{**}
9	0.032	0.548^{**}	0.222^{**}	0.260^{**}
10	-0.179^{**}	-0.112	-0.073	0.156^{+}
birth info				
mother < 20 at birth	-0.176^{**}	-0.238^{**}	-0.204^{**}	-0.170^{**}
father > 40 at birth	0.122^{**}	0.031	0.117^{**}	0.085^{**}
birth order 2	-0.048^{**}	-0.115^{**}	-0.026^{+}	-0.034^{**}
birth order 3	-0.101^{**}	-0.173^{**}	-0.033	-0.032
birth order 4	-0.114^{**}	-0.243^{**}	-0.082^{**}	-0.051
birth order ≥ 5	-0.181^{**}	-0.282^{**}	-0.051	-0.134^{**}
constant	1.249^{**}	-1.141^{**}	0.083^{**}	-0.463^{**}

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05,^{**}p < 0.01$.

Figure B.1: estimated duration dependence by education level, Timing-of-events IPW model



Appendix C Full tables with parameter estimates IPW timing of events model cause-specific mortality

Table C.1: Parameter estimates Cancer Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	0.409^{**}	0.140^{**}	0.078	-0.126^{**}
out of hospital	1.550^{**}	1.294^{**}	1.443^{**}	1.908^{**}
Impact of education				
direct	0.011	0.119^{**}	0.087^{**}	-0.014
in hospital	-0.016	-0.137^{**}	0.072	0.360^{**}
out of hospital	0.005	0.335^{**}	-0.395^{**}	-0.613^{**}
SES mother at birth				
non-manual (high)	0.005	0.053	0.201^{**}	0.056
non-manual (intermediate)	-0.246^{**}	-0.055	-0.052	-0.089^{+}
non-manual (low)	-0.014	0.046^{**}	0.063^{+}	-0.073^{**}
Farmers	0.036^{+}	0.041^{+}	0.001	-0.104^{**}
Unskilled workers	-0.056^{**}	-0.049^{+}	0.260^{**}	0.132^{**}
Not classified	0.133^{**}	0.102^{**}	0.238^{**}	-0.029
Unknown	0.000	-0.114^{+}	0.085	-0.204^{+}
father's education				
Primary ($<$ 9 yrs)	-0.003	0.051^{**}	0.055^{+}	-0.016
Primary (9–10 yrs)	-0.104^{**}	0.124^{**}	0.277^{**}	0.010
Secondary education (3 yrs)	0.048	0.001	0.087^{**}	0.033
Higher	0.026	-0.037	-0.031	0.101^{**}
Missing	-0.138^{**}	-0.088^{**}	-0.113^{**}	-0.079
IQ measurement				
1	-0.265^{**}	-0.144^{**}	-0.238	-0.279
2	-0.182^{**}	-0.223^{**}	-0.672^{**}	-0.023
3	-0.072^{**}	-0.063^{**}	-0.164^{**}	0.028
4	-0.085^{**}	-0.098^{**}	0.008	-0.039
6	-0.022	0.056^{**}	0.085^{**}	0.066^{+}
7	0.011	0.055^{+}	0.071^{+}	0.111^{**}
8	0.011	-0.039	0.144^{**}	0.192^{**}
9	-0.259^{**}	-0.077	0.052	0.150^{**}
missing	-0.294^{**}	-0.419^{**}	0.128	0.084
Psychological assessment				
1	-0.116^{**}	-0.079^{**}	-0.176^{**}	-0.335^{**}
2	-0.084^{**}	-0.197^{**}	-0.264^{**}	-0.271^{**}
3	0.059^{**}	-0.043^{+}	-0.003	-0.094^{+}
4	0.002	0.020	0.018	-0.194^{**}
6	0.092^{**}	0.108^{**}	0.071^{+}	-0.050
7	0.050^{+}	0.079^{**}	0.001	0.024
8	0.162^{**}	0.101^{**}	0.093^{+}	-0.047
9	0.137^{+}	-0.070	0.014	-0.098^{+}
missing	-0.014	0.034	-0.292^{**}	-0.226^{+}
birth info				
mother $<$ 20 at birth	-0.023	-0.092^{**}	-0.151^{**}	-0.127^{**}
father $>$ 40 at birth	0.028	-0.027	-0.011	0.008
birth order 2	0.007	0.018	0.040	0.070^{**}
birth order 3	0.067^{**}	0.046^{+}	0.063^{+}	-0.059^{+}
birth order 4	-0.044^{+}	-0.011	0.083	0.122^{**}
birth order ≥ 5	-0.048^{+}	-0.029	0.139^{**}	0.112^{+}

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05$,** $p < 0.01$.

Table C.2: Parameter estimates CVD Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	0.875^{**}	0.515^{**}	0.749^{**}	1.049^{**}
out of hospital	1.673^{**}	1.624^{**}	1.371^{**}	0.974^{**}
Impact of education				
direct	-0.029^{+}	-0.021	0.006	-0.055^{+}
in hospital	0.030	0.165^{**}	0.053	-0.330^{**}
out of hospital	-0.150^{**}	0.002	0.357^{**}	0.119
SES mother at birth				
non-manual (high)	0.020	-0.123^{**}	-0.346^{**}	-0.320^{**}
non-manual (intermediate)	0.083^{**}	-0.143^{**}	-0.061	-0.222^{**}
non-manual (low)	-0.004	-0.003	-0.140^{**}	-0.122^{**}
Farmers	0.003	0.026	-0.191^{**}	-0.072
Unskilled workers	0.014	0.037	-0.112^{**}	-0.075
Not classified	-0.108^{**}	-0.002	-0.200^{**}	0.007
Unknown	0.039	-0.145^{**}	-0.463^{**}	-0.016
father's education				
Primary (< 9 yrs)	0.024	0.066^{**}	0.006	0.071^{+}
Primary (9–10 yrs)	-0.003	0.005	0.059	0.342^{**}
Secondary education (3 yrs)	-0.131^{**}	-0.069^{+}	-0.220^{**}	-0.036
Higher	-0.151^{**}	-0.013	0.086^{+}	0.001
Missing	0.016	0.007	-0.127^{**}	0.095
IQ measurement				
1	0.102^{**}	0.222^{**}	-0.075	0.219
2	0.062^{**}	0.126^{**}	0.246^{**}	0.052
3	0.040^{+}	0.000	0.050	0.171^{**}
4	-0.007	0.065^{**}	-0.012	-0.205^{**}
6	0.054^{**}	-0.117^{**}	-0.112^{**}	-0.101^{**}
7	-0.044	0.033	-0.021	-0.074
8	-0.006	0.141^{**}	0.046	0.090^{+}
9	0.266^{**}	0.082	-0.078	-0.041
missing	0.203^{**}	0.280^{**}	-0.353^{**}	-0.225
Psychological assessment				
1	-0.155^{**}	-0.257^{**}	-0.394^{**}	-0.328^{**}
2	-0.037^{+}	0.030	-0.068	-0.113^{+}
3	-0.019	-0.091^{**}	-0.231^{**}	-0.264^{**}
4	0.029	-0.075^{**}	-0.002	-0.014
6	0.019	-0.016	0.099^{**}	-0.030
7	0.094^{**}	0.164^{**}	0.152^{**}	-0.092^{+}
8	-0.134^{**}	0.163^{**}	0.171^{**}	-0.199^{**}
9	-0.015	-0.184^{**}	0.050	0.021
missing	-0.122^{**}	-0.300^{**}	0.442^{**}	0.203
birth info				
mother < 20 at birth	0.001	-0.175^{**}	0.024	-0.151^{**}
father > 40 at birth	0.071^{**}	0.064^{**}	0.051	0.043
birth order 2	-0.013	-0.112^{**}	-0.114^{**}	-0.047
birth order 3	-0.057^{**}	-0.122^{**}	-0.099^{**}	-0.119^{**}
birth order 4	-0.072^{**}	-0.013	0.038	-0.294^{**}
birth order ≥ 5	0.063^{**}	-0.029	-0.072	-0.169^{+}

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05, ^{**}p < 0.01$.

Table C.3: Parameter estimates Suicide Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	0.826**	1.099**	1.340**	1.653**
out of hospital	1.600**	1.735**	1.449**	1.675**
Impact of education				
direct	−0.030	−0.063+	−0.003	0.054
in hospital	−0.030	0.108+	0.489**	−0.077
out of hospital	−0.028	0.615**	−0.115	0.739**
SES mother at birth				
non-manual (high)	−0.334**	0.244**	0.200+	0.255**
non-manual (intermediate)	−0.090	0.199**	−0.050	0.366**
non-manual (low)	−0.099**	−0.050	−0.140**	0.134+
Farmers	0.214**	0.343**	0.191**	0.218**
Unskilled workers	−0.034	0.121**	−0.402**	−0.129
Not classified	−0.018	0.237**	0.132	0.813**
Unknown	0.252**	0.366**	0.395**	0.634**
father's education				
Primary (< 9 yrs)	−0.132**	−0.152**	−0.219**	−0.055
Primary (9–10 yrs)	−0.067	−0.265**	−0.077	0.132
Secondary education (3 yrs)	−0.069+	−0.109**	0.055	−0.075
Higher	0.096+	−0.087	0.131+	0.255**
Missing	−0.157**	−0.212**	−0.001	−0.195+
IQ measurement				
1	−0.105**	0.105+	−0.827+	−17.388
2	0.245**	0.243**	0.884**	−1.189**
3	0.038	0.077+	−0.534**	−0.268+
4	−0.028	−0.070+	−0.098	0.073
6	0.042	0.174**	0.192**	−0.025
7	0.340**	0.200**	−0.008	0.017
8	0.291**	0.396**	0.085	−0.160+
9	0.118	−0.573**	−0.128	0.253**
missing	−0.329**	0.780**	0.857**	0.574+
Psychological assessment				
1	−0.133**	−0.204**	−0.071	0.194
2	−0.056+	−0.055	−0.356**	−0.256**
3	−0.134**	−0.074+	0.072	−0.163+
4	0.023	0.020	0.012	−0.778**
6	−0.208**	−0.140**	0.150+	−0.258**
7	−0.035	−0.325**	0.189**	−0.010
8	−0.062	0.060	0.402**	0.456**
9	−0.318**	−0.588**	0.551**	0.405**
missing	0.153**	−0.625**	−0.604**	−0.698**
birth info				
mother < 20 at birth	0.065**	0.101**	0.259**	0.410**
father > 40 at birth	0.106**	−0.030	0.077	−0.019
birth order 2	−0.062**	−0.098**	−0.272**	−0.045
birth order 3	−0.127**	−0.244**	−0.046	−0.000
birth order 4	−0.278**	−0.266**	−0.978**	0.251**
birth order ≥ 5	0.052	0.246**	0.320**	0.121

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.4: Parameter estimates Traffic Accidents Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	0.338^{**}	1.152^{**}	1.184^{**}	1.387^{**}
out of hospital	1.924^{**}	1.528^{**}	1.453^{**}	1.570^{**}
Impact of education				
direct	-0.139^{**}	-0.281^{**}	0.004	-0.005
in hospital	0.432^{**}	-0.038	0.250^{**}	-0.391^{**}
out of hospital	-0.376^{**}	-0.354^{**}	0.027	0.474^{**}
SES mother at birth				
non-manual (high)	0.090	-0.217^{**}	-0.313^{**}	-0.107
non-manual (intermediate)	-0.094^{+}	-0.263^{**}	-0.101	0.434^{**}
non-manual (low)	0.074^{**}	0.021	-0.231^{**}	-0.049
Farmers	0.239^{**}	0.146^{**}	0.205^{**}	0.256^{**}
Unskilled workers	-0.125^{**}	-0.140^{**}	-0.099	-0.110
Not classified	0.026	-0.264^{**}	-0.570^{**}	0.051
Unknown	0.363^{**}	-0.059	-0.183	-0.897^{**}
father's education				
Primary (< 9 yrs)	0.071^{**}	-0.090^{**}	0.086^{+}	0.210^{**}
Primary (9–10 yrs)	0.020	0.111^{+}	0.061	0.386^{**}
Secondary education (3 yrs)	0.062	0.112^{**}	-0.076	0.053
Higher	-0.020	-0.023	0.308^{**}	0.064
Missing	0.116^{**}	-0.178^{**}	0.091	-0.215^{**}
IQ measurement				
1	-0.311^{**}	-0.418^{**}	-0.159	0.815^{**}
2	-0.175^{**}	-0.132^{**}	0.114	0.691^{**}
3	-0.030	0.034	0.038	-0.128
4	0.096^{**}	0.075^{**}	0.126^{**}	0.272^{**}
6	0.107^{**}	0.072^{**}	-0.060	0.121^{+}
7	0.151^{**}	-0.049	-0.063	0.207^{**}
8	0.188^{**}	0.105^{+}	-0.354^{**}	-0.104
9	0.881^{**}	0.087	-0.260^{**}	-0.053
missing	0.164^{+}	0.047	-0.194	0.377^{+}
Psychological assessment				
1	-0.575^{**}	-0.803^{**}	-0.349^{**}	-1.225^{**}
2	-0.486^{**}	-0.177^{**}	0.017	0.116
3	-0.271^{**}	-0.032	0.008	-0.038
4	-0.159^{**}	-0.013	-0.056	0.082
6	0.027	0.086^{**}	0.038	-0.028
7	0.011	-0.065	-0.015	0.127^{+}
8	-0.032	-0.050	0.095	0.087
9	-0.134	-0.201^{+}	-0.288^{**}	0.040
missing	-0.868^{**}	-0.276^{**}	0.034	-0.111
birth info				
mother < 20 at birth	-0.047	0.041	-0.029	0.134
father > 40 at birth	0.208^{**}	0.337^{**}	0.219^{**}	0.260^{**}
birth order 2	0.203^{**}	0.127^{**}	0.051	0.125^{**}
birth order 3	0.066^{**}	0.107^{**}	0.088^{+}	0.247^{**}
birth order 4	0.179^{**}	0.386^{**}	0.150^{+}	0.152^{+}
birth order ≥ 5	0.231^{**}	0.166^{**}	-0.026	0.334^{**}

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05, ^{**}p < 0.01$.

Table C.5: Parameter estimates External Causes Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	1.537^{**}	1.651^{**}	1.469^{**}	2.347^{**}
out of hospital	1.816^{**}	1.683^{**}	1.865^{**}	1.731^{**}
Impact of education				
direct	-0.580^{**}	0.241^{**}	-0.347^{**}	-0.159
in hospital	0.434^{**}	-0.234^{**}	0.533^{**}	-0.208
out of hospital	0.065	-0.029	0.220	0.087
SES mother at birth				
non-manual (high)	-0.327^{**}	0.252^{**}	-0.041	0.094
non-manual (intermediate)	0.129^{+}	0.035	-0.438^{**}	-0.312^{**}
non-manual (low)	0.086^{**}	0.028	-0.283^{**}	-0.655^{**}
Farmers	-0.075^{+}	-0.033	-0.236^{**}	-0.288^{**}
Unskilled workers	-0.051	-0.132^{**}	-0.333^{**}	-0.595^{**}
Not classified	-0.153^{**}	0.132^{+}	-0.284^{+}	-0.627^{**}
Unknown	0.699^{**}	0.368^{**}	-0.708^{**}	-18.264
father's education				
Primary (< 9 yrs)	-0.020	0.094^{+}	-0.176^{**}	0.189
Primary (9–10 yrs)	0.310^{**}	0.172^{+}	-0.350^{+}	0.163
Secondary education (3 yrs)	-0.022	0.297^{**}	0.085	0.197
Higher	0.316^{**}	0.306^{**}	-0.351^{**}	0.590^{**}
Missing	0.118^{**}	0.281^{**}	-0.387^{**}	0.371^{**}
IQ measurement				
1	-0.358^{**}	-0.067	1.527^{**}	1.789^{**}
2	0.052	0.215^{**}	0.094	-0.375
3	0.169^{**}	0.079	0.247^{**}	-1.153^{**}
4	0.063	0.125^{**}	0.184^{+}	-0.023
6	-0.017	-0.152^{**}	-0.392^{**}	-0.165
7	0.067	-0.323^{**}	-0.784^{**}	-0.386^{**}
8	0.126	-0.399^{**}	0.260^{**}	0.325^{**}
9	-0.252	-0.429^{**}	-0.526^{**}	-0.618^{**}
missing	0.204^{**}	0.557^{**}	0.991^{**}	0.640
Psychological assessment				
1	0.163^{**}	0.113^{+}	0.607^{**}	-0.222
2	0.144^{**}	-0.129^{**}	0.066	0.161
3	-0.003	-0.349^{**}	0.334^{**}	0.196
4	0.102^{**}	-0.338^{**}	0.087	0.643^{**}
6	-0.249^{**}	-0.404^{**}	0.544^{**}	0.390^{**}
7	-0.161^{**}	-0.139^{+}	0.285^{**}	0.395^{**}
8	-0.117	-0.121	0.252^{+}	0.100
9	0.193	0.394^{**}	0.228	-1.231^{**}
missing	-0.150^{+}	-0.428^{**}	-1.006^{**}	-0.313
birth info				
mother < 20 at birth	0.101^{**}	0.093^{+}	0.042	0.429^{**}
father > 40 at birth	0.308^{**}	0.073	0.493^{**}	0.401^{**}
birth order 2	-0.036	-0.160^{**}	-0.031	-0.245^{**}
birth order 3	-0.053	-0.078^{+}	-0.014	0.032
birth order 4	0.002	-0.077	0.051	0.412^{**}
birth order ≥ 5	0.040	0.099	-0.269	-1.304^{**}

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.6: Parameter estimates Other natural Causes Cause-specific Gompertz Proportional hazard, IPW Timing-of-events

	Education level[a]			
	(1)	(2)	(3)	(4)
Mental hospitalization				
in hospital	0.840^{**}	1.250^{**}	1.346^{**}	1.171^{**}
out of hospital	1.755^{**}	1.805^{**}	1.737^{**}	2.338^{**}
Impact of education				
direct	-0.130^{**}	-0.134^{**}	-0.186^{**}	0.065^{+}
in hospital	0.074^{**}	0.117^{**}	0.093	0.479^{**}
out of hospital	0.039	-0.175^{**}	-0.044	-0.795^{**}
SES mother at birth				
non-manual (high)	-0.104^{**}	-0.012	0.176^{**}	-0.208^{**}
non-manual (intermediate)	0.097^{**}	0.114^{**}	0.047	-0.254^{**}
non-manual (low)	0.010	-0.027	0.072^{**}	0.068^{+}
Farmers	-0.196^{**}	-0.288^{**}	0.112^{**}	-0.028
Unskilled workers	0.022	0.012	0.141^{**}	0.000
Not classified	-0.053^{**}	-0.155^{**}	-0.413^{**}	-0.062
Unknown	0.114^{**}	0.168^{**}	0.229^{**}	0.094
father's education				
Primary ($<$ 9 yrs)	-0.004	0.022	-0.020	-0.276^{**}
Primary (9–10 yrs)	-0.143^{**}	-0.077^{+}	-0.187^{**}	-0.465^{**}
Secondary education (3 yrs)	0.054^{**}	0.067^{**}	0.377^{**}	-0.086^{+}
Higher	0.080^{**}	0.059^{+}	0.032	-0.211^{**}
Missing	-0.031	0.007	0.040	-0.265^{**}
IQ measurement				
1	-0.011	-0.145^{**}	0.131	-0.030
2	-0.017	-0.074^{**}	-0.052	-0.325^{+}
3	0.012	-0.131^{**}	-0.180^{**}	-0.094
4	0.004	-0.123^{**}	0.033	0.129^{**}
6	0.042^{+}	-0.028	0.114^{**}	-0.076
7	-0.132^{**}	-0.159^{**}	0.157^{**}	0.003
8	-0.154^{**}	-0.087^{**}	-0.014	-0.144^{**}
9	-0.201^{**}	0.018	0.261^{**}	-0.042
missing	0.020	0.196^{**}	0.097	0.044
Psychological assessment				
1	-0.006	-0.007	-0.156^{**}	-0.128
2	-0.034^{+}	0.014	0.041	0.069
3	0.078^{**}	0.049^{+}	-0.095^{+}	0.170^{**}
4	-0.057^{**}	0.047^{+}	0.075^{+}	0.128^{**}
6	0.059^{**}	-0.011	-0.288^{**}	0.132^{**}
7	0.005	-0.084^{**}	0.010	-0.031
8	0.078^{+}	-0.063	-0.201^{**}	0.028
9	-0.113	0.332^{**}	-0.123	-0.198^{**}
missing	0.251^{**}	0.151^{**}	0.367^{**}	0.443^{**}
birth info				
mother $<$ 20 at birth	0.061^{**}	0.076^{**}	0.063	-0.015
father $>$ 40 at birth	0.190^{**}	0.249^{**}	0.199^{**}	0.243^{**}
birth order 2	0.007	0.012	0.102^{**}	-0.102^{**}
birth order 3	0.031^{+}	-0.108^{**}	-0.072^{+}	0.111^{**}
birth order 4	-0.076^{**}	-0.049^{+}	-0.308^{**}	-0.421^{**}
birth order ≥ 5	-0.120^{**}	-0.267^{**}	-0.174^{**}	0.053

[a] (1) Primary & Some secondary education; (2) Some secondary education & Full secondary education; (3) Full secondary education & Post-secondary education; (4) Post-secondary education & University or PhD.
Reference category: mother/father skilled worker and secondary education (max 2 years),IQ level and psychological assessment 5. $^{+}p < 0.05$, $^{**}p < 0.01$.