Educational differences in mortality and hospitalization for Cardiovascular diseases*

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September 30, 2020

Abstract

High educated individuals are less frequently admitted to hospital for cardiovascular diseases and live longer than the lower educated. An important issue is that education attainment, hospitalization and mortality may all depend on the same observed and unobserved individual factors. Such confounding renders education and hospitalization endogenous in mortality analysis.

We use Swedish Military Conscription Data (1951-1960) linked to administrative Swedish registers. Information on hospitalization for Cardiovascular Diseases (timing of admittance and discharge) are derived from the Inpatient register. We account for both the selection into hospitalization, by using a correlated multistate model for the hospitalization processes (both admittance an discharge) and mortality and, for the selection into education, by using a re-weighting technique (inverse propensity weighting) based on the probability to attain higher education. Our empirical results indicate a strong effect of hospitalization on mortality. The implied educational gain in number of months lost is, however, manly due to other factors than CVD hospitalization. Extending the analysis to cause specific mortality reveals that the largest educational differences exists in death due to external causes.

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

*Acknowledgements. I thank Mikko Myrskylä, Per Tynelius, attendants at the Nordic Demographic Symposium in Reykjavik for their helpful comments.

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1 Introduction

An association between higher educational attainment and better health outcomes, including less and later hospitalization, has been repeatedly reported in the literature (Mazumder, 2008, Clark and Royer, 2013, Fletcher, 2015, McCartney et al., 2013). Although the strength of these relationships varies, such associations have been observed in many countries and time periods. However, the extent to which education causes better health and later mortality is widely debated.

Allocative and productive efficiency models generate causality from education to health. In the former model, the more educated are assumed to pick a different input mix to produce health than the less educated (Rosenzweig and Schultz, 1981, Muurinen, 1982). That mix gives them more output than the mix selected by the less educated. In the latter model, the more educated are assumed to obtain more health output from given amounts of medical care and other inputs (Grossman, 1972, Michael and Becker, 1973). While there is empirical evidence that higher educated individuals are more efficient users of health investment in terms of both productive and allocative efficiency (Gilleskie and Harrison, 1998, Grossman, 2006), it is not established whether this is actually the result of education per se.

Higher education may have countervailing effects on hospitalization if it reduces the probability of negative health conditions that might lead to hospitalization yet increases the probability of hospitalization (e.g., through greater income, more knowledge, or better connections) for given health conditions. Likewise, higher education may have countervailing effects on mortality if it increases income and access to health-system care but also increases higher-risk behaviors and selection into more stressful occupations. Of course, which opposing effect dominates depends on preferences, resources, technologies, markets, and policies that prevail in the context being studied. Educational gains through increasing access to health services through higher income, for example, a priori would seem to be less important in the context of the Swedish health care system, with its broad coverage and access, than in a health-care system such as that in the United States, in which many individuals are not covered by health insurance.

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 hospital for cardiovascular diseases, i.e. the time till admittance and the time spent in hospital for CVD. An important issue is, however, that hospitalization and mortality may both depend on the same observed and unobserved individual factors. Such confounding renders hospitalization endogenous in the mortality analysis. To obtain causal educational gains on mortality and how this is affected by CVD hospitalization both the endogeneity of the hospitalization and the education choice should be accounted for.

In the literature three different approaches have been employed to examine the causal effects of education on health and mortality. The first approach exploits changes in compulsory schooling policies, usually increases in the minimum age or the legally permitted grade to leave school, as instrumental variables for educational attainment to control for endogeneity, i.e. an uncontrolled confounder affects both the education attained and the mortality. The estimates based on these studies point towards a small effect (Lleras-Muney, 2005, Van Kippersluis et al., 2011, Meghir et al., 2018), or even entirely absent (Arendt, 2005, Albouy and Lequien, 2009, Clark and Royer, 2013) causal effect of education on health outcomes. However, a major limitation of using changes in compulsory schooling to detect educational effects on health outcomes, and in particular mortality, is that often only a relatively small part of the population is affected by the laws (Mazumder, 2008, Fletcher, 2015). Another issue with the instrumental variable methods applied in these studies is that they implicitly assume that the compulsory schooling reforms only affect long-term health through their effect on education, ignoring any other contemporary policy changes that may accompany these reforms.

Another identification strategy is to use variation in education among siblings, often identical (monozygotic) twins, to distinguish the unobserved factors shared by these siblings. These studies obtain estimates of the impacts of the differences in schooling within a pair of identical twins on their health differences at various schooling levels. Results from such studies indicate that part of the educational differences in cause-specific mortality disappears when accounting for shared family background (Behrman et al., 2011, Lundborg, 2013, Næss et al., 2012, Amin et al., 2015). Although by using twins it is possible to control for both shared environmental and shared genetic factors, a major shortcoming of twin studies is that they only analyse twins, yet twins are usually not representative of the whole population. Using twins will substantially reduce the statistical power, because only twins with different education levels are analysed. Not only is it rare that twins would have the same cognitive

ability, they also experience a large number of non-shared events throughout life, events that may be unobserved and influence both education and mortality (e.g. accidents).

A third approach to account for confounding factors is to include them directly into the model. Results from such models for health-outcomes (Conti and Heckman, 2010, Conti et al., 2010) or for mortality (Bijwaard et al., 2015a,b) and cause-specific mortality (Bijwaard et al., 2019) show that at least half of the health disparities across educational groups is due to the selection of healthier, more able individuals in higher education. A disadvantage of these models is that they impose a rather stringent structure on the relation between education, mortality and the influence of confounding factors. Another limitation is that estimation of these structural models can be very computer intensive if a large data set is available.

The propensity score method (Hirano et al., 2003, Caliendo and Kopeinig, 2008) we employ in this paper also accounts for possible confounding factors, however, without making any structural assumptions on the relation between the confounding factors and hospitalization or mortality. It is based on the assumption that all variables that affect mortality, hospitalization and education attainment are observed. This is a stringent assumption, but our data contain important factors as detailed family socioeconomic background (including paternal- and maternal socioeconomic status at birth and education level), cognitive skills (IQ-test) and non-cognitive skills (psychological test). Recent research (Bijwaard and Jones, 2019) has shown that intelligence can be considered a principal source of education selection and, that accounting for intelligence (as we do) is sufficient to rule selection on unobservables when estimating the impact of education on mortality. We use an extension of the sensitivity method to the timing-of-events model of Imbens (2003) to test possible violation of the unconfoundedness assumption.

Only a few studies have attempted to identify the causal effect of education on mortality rates, using a regression discontinuity approach based on a reform in compulsory schooling (Meghir et al., 2018), an inverse propensity weighting method (Bijwaard et al., 2017, Bijwaard and Jones, 2019) or a structural modelling approach (Bijwaard et al., 2015a,b, 2019). Meghir et al. (2018) also investigated the impact of education on hospitalization (total number of days in hospital care or having hospitalization experience for, amongst other diseases, circulatory diseases) using Difference-in-difference regressions in the time from a compulsory schooling reform in Sweden. Tansel and Keskin (2017) considered the impact of education on the

number of days hospitalized and used a IV-Tobit approach (with a compulsory schooling law change as instrument) to estimate this relation for Turkey.

Yet, none of these studies accounted for selective hospitalization (nor the timing of hospitalization) and how this affects mortality. We rely on a Timing-of-Events model (Abbring and van den Berg, 2003)) to account for the endogeneity of the hospitalization process in the analysis of the mortality rate and an inverse propensity weighting (IPW) method to address the endogeneity of educational attainment. A timing-of-events model assumes a correlated mixed proportional hazards structure for the mortality and hospitalization hazards (first entry, discharge and re-admittance). It controls for correlated effects that arise from correlation between unobservables in the hospitalization and mortality processes.

Evidence suggests differential impact of education on various diseases accumulating in different educational cause-specific mortality gradients (Galobardes et al., 2004, Bijwaard et al., 2017, 2019). As the socioeconomic association seems the largest for cardiovascular diseases most studies have focussed on socioeconomic differences in mortality on these type of diseases. Some have indeed found that the incidence of cardiovascular disease is higher for individuals with low socioeconomic status (Mackenbach et al., 2008, Kulhánová et al., 2014). However, Bijwaard et al. (2017, 2019) found that most of the educational gains in mortality up till age 63 (the same maximum age we are using) are attributable to the reduction in mortality due to external causes and that the reduction in death due to CVDs with improving education is rather small.

To investigate whether education and hospitalization for CVD affects different causes of death differently we also estimate a model with cause-specific mortality rates, distinguishing five different causes of death : 1) Ischemic Heart Disease (IHD); (2) Stroke; (3) other cardiovascular causes; (4) External causes, and (5) Other (natural) causes of death. The model is an extension of the timing-of-events model with IPW.

Data from the Swedish Military Conscription Data (1951-1960), linked to administrative Swedish registers, offers the opportunity to investigate the impact of 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 CVD hospital 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; some secondary education (2 years); full secondary education (3 years); post-secondary education and higher education.

The empirical analyses show that both education and hospitalization for CVD are important factors explaining mortality. We find a clear educational gradient in the mortality, even after accounting for the endogeneity of education through inverse propensity weighting. We also find that mortality is much higher for those in hospital for CVD (39-68 times higher) and for those who have been in hospital (2.1 to 4.7 times higher). These hospitalization effects also exhibit a educational gradient, with a decreasing impact of hospitalization the higher the education level.

Based on the estimated model we calculate the educational gain of improving education in both the survival probability till age 63 (the highest age observed) and in the number of years lost till age 63. We also decompose these educational gains into a indirect effect, running through changes in the hospitalization process, and a direct effect due to other factors. We find that men with only primary education would gain the most (about 9 months from age 18 to 63) if they had a higher education level. Only a small part of this educational gain is running through a change in hospitalization for CVD. Although men with post-secondary education would only gain 2.3 months if they had higher education most of this educational gain (1.6 months) is attributable to changes in the CVD hospitalization for the higher educated.

We address the robustness of our model by comparing the estimation results with the results from a model without the IQ or psychological assessment in the propensity score and with the results from a doubly robust model. Neither of these models give substantial changes in the educational or hospitalization impact on mortality. The issue of possible violations of the unconfoundedness assumption is addressed with a sensitivity analysis that indicates that the impact of hospitalization on mortality would slightly increase with a discrete unobserved factor influencing hospitalization, mortality and the education choice.

The empirical results for the cause-specific mortality analysis reveal that all causes of death show a clear educational gradient, with the largest educational differences for external causes of death. They also reveal that, not surprisingly, death due to CVD (IHD, stroke and

other CVD) is affected the most by hospitalization for CVD. However, hospitalization also severely affects death due to other natural causes. Death due to external causes is elevated when the men are in hospital, but after discharge from hospital the death due to external causes is lower for the high educated (although still elevated for the other education levels). The implied educational gains in years lost by cause of death are only significant for men with only primary education for external causes or other natural causes. They do not indicate that hospitalization (indirect effect) play an important role in explaining the educational gain.

2 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 hospitalization for Cardiovascular Diseases (CVD)[1] is derived from the Inpatient register. Coverage runs from 1964 to December 31st 2012. 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 (University and PhD). A more detailed information of the data can be found in Bijwaard et al. (2017).

About 80 thousand (of the 518 thousand) men have experienced CVD hospitalization. Table 1 presents the distribution of this hospitalization by education attainment.[2]. The

[1] ICD 8 and 9: 390-459 ICD 10: I.

[2] Full demographic and childhood family characteristics at the time of military examinations by education level are presented in Table B.1, for men without hospitalization for CVD and in Table B.2, for men with hospitalization for CVD in Appendix B

hospitalization experience is lower for the high educated and so is average number of days spent in hospital. For those without hospitalization experience the low educated have died four times more often than the high educated. Hospitalization experience clearly increases mortality.

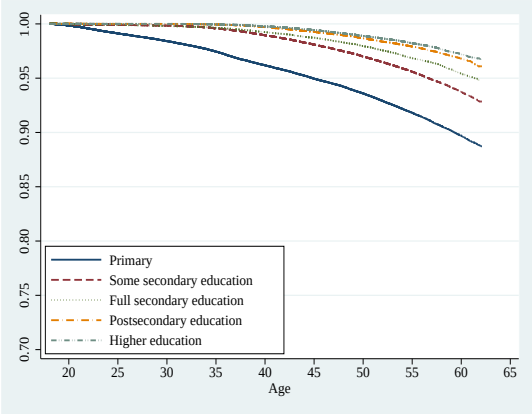
Table 1: Descriptive statistics on hospitalization and mortality

	Primary	Secondary education		Post-secondary	Higher
		some	full	(< 3 years)	
% with hospitalization	18.2%	16.4%	14.9%	13.6%	11.7%
Av.# of days in hospital	7.3	5.9	4.9	4.0	3.1
% died without hospitalization	9.1%	5.0%	3.7%	2.5%	2.2%
% died with hospitalization	14.4%	11.4%	9.5%	7.0%	6.1%

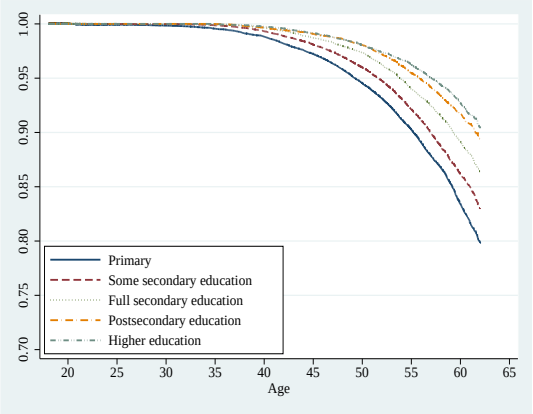
Next we calculate a simple non-parametric analysis of the timing of death, the Kaplan-Meier survival curves. These survival curves for the five education categories are shown in Figure 1 and reflect the mortality differences by education and by hospitalization experience. Survival increases with the education level and the differences between the education levels increase with age. Comparing the survival curves without hospitalization (left panel) and with hospitalization (right panel) reflect the impact of hospitalization on mortality. The Kaplan-Meier survival curves for the first admittance to hospital, discharge from hospital or re-admittance to hospital by education level in given in Figure 2 also show a clear educational gradient (except for time till discharge).

However, these mortality differences, both by education and by hospitalization experiences do not necessarily reflect the impact of education and/or hospitalization on mortality per se. It could be that the IQ or higher socio-economic background of high educated people causes the difference. For example, understanding a doctor's advice and adhering to complex treatments after hospitalization may be driven by intelligence rather than education. In the next section we explain how we account for this.

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

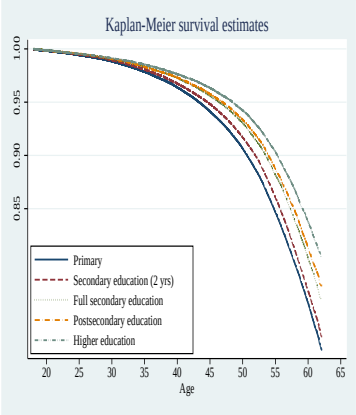


Without hospitalization

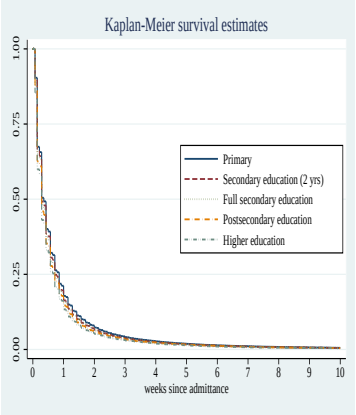


After CVD hospitalization

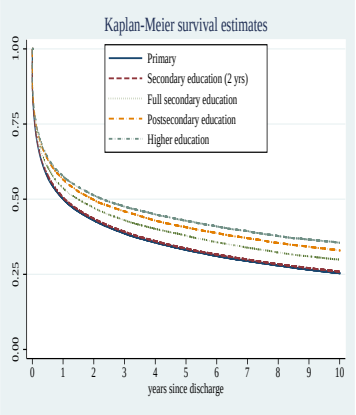
Figure 2: Kaplan-Meier hospitalization survival curves by education level



first hospitalization



discharge



re-admission

3 Method

A major methodological concern with the empirical analysis of the impact of hospitalization on mortality is that the admittance and discharge processes to hospitals depend on individual characteristics, both observed and unobserved. This implies that any observed relationship between admittance to (or discharge from) hospital and mortality may be caused by unobserved factors that influence both the hospitalization and mortality. For example, a finding that men with high educated fathers live longer may not necessarily imply that low socioeconomic background (low educated father) causes higher mortality. Rather, it may be induced by the higher hospitalization of men from low socio-economic background. 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 hospitalization process and mortality, to account for this interdependence.

3.1 Timing-of-events method

Let T^m denote the time till death (mortality), T^h the time till the start of the first 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 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 Gompertz baseline hazard in the age of the individual, i.e. exponentially increasing with age. 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.

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:

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

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

with transition specific Weibull baseline hazards $\lambda_{k0}(d) = \alpha_k d^{\alpha_k - 1}$, unobserved time-invariant characteristics v_k, and observed individual characteristics x where $k \in \{d, r\}$ denotes the hospitalization state. 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, our main outcome, is also of the MPH form. We allow the mortality hazard to depend on the timing of hospitalization process through a direct effect of hospitalization (captured by $I^h(t)$ and $I^o(t)$)or through correlated , unobservable heterogeneity terms:

$$\theta_m(t|t_h, t_d, t_r, x, e, v_m) = v_m\lambda_{m0}(t)\exp\Big(x\beta_x^m + e\big(\beta_e^m + \gamma_{he}I^h(t) + \phi_{oe}I^o(t)\big)\Big). \quad (4)$$

The age dependence of the mortality hazard is assumed Gompertz. The Gompertz hazard, which assumes that the hazard increases exponentially with age, $\lambda_{m0}(t) = e^{\alpha_m t}$, is known to provide accurate mortality hazards (Gavrilov and Gavrilova, 1991). Our parameters of interests are β_e^m, the effect of the individual education level ($e = 1, \ldots, 5$ with primary education, $e = 1$, as the reference category) on the mortality hazard and the impact of CVD hospitalization on mortality. The effects of staying in a hospital, γ_{he}, and hospital experience, ϕ_{oe}, on the mortality hazard also depend on the education level of the individual.

For the sake of parsimoniousness, we assume that each of the unobserved heterogeneity terms remains the same for recurrent durations of the 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 $p_k = \Pr(V = V_k)$.[3] The likelihood function is given in Appendix A.

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

It is important to note that the "timing-of-events" model allows us to estimate the causal effect of CVD hospitalization (by education level e) on the mortality rate, γ_{he} and ϕ_{oe}. To identify the model we rely on the assumption of "no anticipation" (Abbring and van den Berg, 2003). In other words, we assume that individuals do not anticipate entering hospital for CVD by dying before the anticipated event would occur. This assumption does not hold if individuals would die because they know they will enter a hospital for CVD. Although we think this is rather unlikely (but untestable with our data) we are cautious in using a causal interpretation of the obtained CVD hospitalization effects. Still, even if the no-anticipation assumption does not hold the timing-of-events method corrects for possible endogeneity of the hospitalization processes.

3.2 Accounting for selective educational attainment

The associations between hospitalization, mortality and education may partly be explained by confounding factors such as intelligence and parental background that affect both educational options and health. The timing-of-events method still fails to correct for possible enodogeity of educational attainment. We follow a inverse propensity weighting method to account for this endogeneity (Hirano et al., 2003). Inverse probability weighting based on the propensity score, or inverse propensity weighting (IPW), 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.

To this end we re-estimate the Timing-of-events models using a re-weighted pseudo-population based on inverse generalized propensity score weighting (IPW) (Frölich, 2004, Feng et al., 2012), see Bijwaard and Jones (2019) for an application of (a single valued) IPW method for a Mixed Proportional Hazard mortality model. We base our propensity scores on a multistage sequential model of educational choice developed by Cameron and Heckman (2001) with $e = 1, \ldots 5$ (see also (Heckman et al., 2018b,a)).

People begin in primary school ($e = 1$) and choose if they wish to finish some secondary school ($e = 2$). Importantly, the set of future choices available to them depends on their earlier educational choices. If people choose to finish some secondary school, they have the

choice to graduate secondary school ($e = 3$), if they graduate they have the choice to enroll in post-secondary schooling ($e = 4$), if they enroll, they have the choice to graduate from post-secondary schooling, if they graduate post-secondary schooling they have the choice to enroll in higher education ($e = 5$) and, if they enroll they have the choice to graduate from higher education.

We assume a Probit model for the probability of attaining a higher education level conditional on having obtained the (previous) lower level. We include in the propensity scores variables that influence both the probability to obtain a higher education level and the probability to die, such as parental background, IQ-level and psychological assessment (all obtained at the military examination). The propensity score of choosing education level e using the sequential probit assumption is:

$$\Pr(E = e) = \Phi(-\xi_{e+1}X)^{I(e<5)} \prod_{1<j\leq e} \Phi(\xi_j X) \tag{5}$$

with $\Phi(\cdot)$ is the standard Normal cumulative distribution.

We check if the propensity score is able to balance the distribution of all included variables in all education groups by calculating the standardized bias, or normalised difference in means, see Table B.3 in Appendix B.

Common assumptions in the literature using propensity score methods to identify the 'treatment effects' are the *Unconfoundedness* and the *overlap* assumptions. The overlap, or common support, assumption requires that the propensity score is bounded away from zero and one. Figures D.1 to D.5 in Appendix D show that we have sufficient overlap.

The unconfoundedness assumption (also known as selection on observables or the conditional independence assumption) asserts that, conditional on observed individual characteristics educational 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 one level of education and the *potential* outcome if the individual had had another level of education is only caused by education. If unconfoundedness holds, all biases due to observable covariates can be removed by weighting on the propensity score. The unconfoundedness 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.

Misspecification of the propensity score will generally produce bias. 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. To account for this we also use a doubly robust estimator, that includes the covariates in the propensity score and in a regression adjustment.

Although the unconfoundedness assumption is not directly testable and clearly a strong assumption, it may be a reasonable approximation. Bijwaard and Jones (2019) 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. The literature has developed a few ways to address violation of the unconfoundedness assumption, e.g. Imbens (2003), Nannicini (2007), Ichino et al. (2008). We estimate a model based on an extension of the sensitivity analysis of Imbens (2003) to quantify the robustness of our empirical findings to violation of this assumption. This approach is based on the assumption that the unconfoundedness assumption is satisfied only conditional on an additional unobserved covariate. By exploiting the parametric multistate model we assume for the hospitalization transitions and mortality and by assuming that the unobserved covariate follows a binomial distribution we are able to assess the sensitivity of our results to the unconfoundedeness assumption. In Section 4.1.1 we explain the details of this method.

4 Results

First, we estimate the 'Timing-of-events'-model (ToE-model) that only accounts for possible correlation of the hospitalization process and mortality through observed and unobserved factors. Second, we account for possible confounding of the education attained by applying a inverse propensity score weighting (IPW) in the Timing-of-events model ('ToE-model (IPW)'). In the propensity score we control for maternal socio-economic status, paternal education, maternal and paternal age at birth, birth order, IQ and psychological assessment at the military examination, see Table C.6 in **??**.

The results reported in Table 2 demonstrate the importance of both education and hos-

pitalization on mortality. We observe a clear educational gradient. For all education levels we find that mortality is higher for those in hospital and for those who have experienced hospitalization. Accounting for education endogeneity through IPW, reported in the second panel of the table, only slightly affects the estimated coefficients of education on the mortality rate. Using an IPW correction reduces the educational gradient in mortality. It also decreases the estimated impact of hospitalization experience on mortality, but hardly changing the educational gradient of this experience.

Table 2: Impact of hospitalization and education on mortality hazard

		Education level[a]				
		(1)	(2)	(3)	(4)	(5)
ToE-model	education	–	-0.587^{**}	-0.928^{**}	-1.300^{**}	-1.443^{**}
			(0.016)	(0.025)	(0.028)	(0.027)
	in hospital	4.213^{**}	4.016^{**}	3.854^{**}	3.642^{**}	3.546^{**}
		(0.055)	(0.053)	(0.085)	(0.096)	(0.106)
	hospital experience	1.830^{**}	1.620^{**}	1.400^{**}	1.096^{**}	0.928^{**}
		(0.108)	(0.108)	(0.114)	(0.116)	(0.117)
ToE-model (IPW)	education	–	-0.585^{**}	-0.863^{**}	-1.216^{**}	-1.303^{**}
			(0.016)	(0.025)	(0.027)	(0.027)
	in hospital	4.221^{**}	4.038^{**}	3.966^{**}	3.718^{**}	3.660^{**}
		(0.060)	(0.055)	(0.084)	(0.090)	(0.094)
	hospital experience	1.546^{**}	1.370^{**}	1.236^{**}	0.837^{**}	0.730^{**}
		(0.110)	(0.109)	(0.115)	(0.117)	(0.118)

[a] (1) primary education; (2) Some Secondary education; (3) Full secondary education; (4) Post-secondary education; (5) University or PhD. $^{+}p < 0.05$, $^{**}p < 0.01$.

4.1 Robustness

First, we investigate whether removing the possibility of reverse causation changes the estimated impact of education (and hospitalization) on mortality. Reverse causation might occur as education influences both psychological fitness and intelligence measured at the military examination. A couple of studies have shown that additional education improves intelligence (Falch and Sandgren Massih, 2011, Banks and Mazzonna, 2012, Schneeweis et al., 2014, Carlsson et al., 2015, Dahmann, 2017). In that case, intelligence is a mediator in the causal path from education to health (Bijwaard and Jones, 2019). Ideally, we would have continuous measurement of the (development) of intelligence over the life cycle, to account for both the selection and mediation of intelligence in the causal path from education to mortality. However, in our data, we only observe intelligence at late adolescence (the military examination) when measured IQ can be either the result of the attained education or a proxy of early childhood intelligence which influences education choice. Similar reasoning holds for psychological fitness. To account for this possible reverse causation we also estimate models without psychological assessment or IQ measurement in the propensity score. The results in the first panel of Table 3 reveal that leaving out these measurements form the propensity score only have a small effect on the estimated coefficients of education and hospitalization for CVD in the mortality hazard.

Second, throughout we have assumed that the propensity scores are estimated consistently. Misspecification of the propensity score will generally produce bias. 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. Thus, to improve the robustness of the proposed methodology we also estimate a doubly robust estimator of the model, which also includes a regression adjustment (using the same control variables as included in the propensity score). The results in the second panel of Table 3 indicate that these doubly robust estimation are very similar to the original estimates, reported in the second panel of Table 2.

Table 3: Impact of hospitalization and education on mortality hazard IPW, robustness

	Education level[a]				
	(1)	(2)	(3)	(4)	(5)
	without IQ or psychological assessment				
education	–	-0.597^{**}	-0.965^{**}	-1.297^{**}	-1.453^{**}
		(0.016)	(0.025)	(0.027)	(0.028)
in hospital	4.221^{**}	3.969^{**}	3.793^{**}	3.668^{**}	3.327^{**}
	(0.055)	(0.053)	(0.086)	(0.094)	(0.108)
hospital experience	1.966^{**}	1.713^{**}	1.485^{**}	1.159^{**}	1.045^{**}
	(0.107)	(0.107)	(0.113)	(0.115)	(0.116)
	doubly robust				
education	–	-0.597^{**}	-0.873^{**}	-1.238^{**}	-1.325^{**}
		(0.016)	(0.025)	(0.027)	(0.027)
in hospital	4.227^{**}	4.002^{**}	4.023^{**}	3.692^{**}	3.614^{**}
	(0.057)	(0.052)	(0.082)	(0.089)	(0.093)
hospital experience	1.637^{**}	1.423^{**}	1.321^{**}	0.915^{**}	0.796^{**}
	(0.108)	(0.107)	(0.113)	(0.115)	(0.116)

[a] (1) primary education; (2) Some Secondary education; (3) Full secondary education; (4) Post-secondary education; (5) University or PhD. $^{+}p < 0.05, ^{**}p < 0.01$.

4.1.1 Sensitivity

The critical assumption in propensity score weighting is that of no selection on unobservables. To test the sensitivity of the estimates to the unconfoundedness assumption we build on the sensitivity analyses of Imbens (2003).

Following Imbens (2003) we introduce an unobserved covariate U with marginal distribution $\Pr(U = 1) = \Pr(U = 0) = \frac{1}{2}$. This covariate is allowed to influence the education choice at each education decision node, $p_e = \Phi(\xi_e X + \alpha_e U)$ and the hospitalization and mortality hazards, $\theta_j(t|x, v, U) = \theta_j(t|x, v)\exp(\beta_j U)$ for $j = \{h, d, r, m\}$. With our assumed functional forms for the hazard rates (and the propensity scores) we can estimate all parameters of the model using a maximum likelihood approach, which is the sum of the likelihood for $U = 0$ (the 'standard' likelihood) times the propensity score for $U = 0$ plus the likelihood for $U = 1$ times the propensity score for $U = 1$. See Appendix A.1 for more details.

The estimation result for this sensitivity analysis reveals that although U influences the hazard rates it hardly influences the education choice (only to continue to secondary education), see Table C.7 and Table C.8 in Appendix C. This does not lead to substantial changes in the impact of education (without hospitalization) on mortality. But, the estimated impact

of hospitalization and hospital experience (by education level) on the mortality rate increases, see Table 4.

Table 4: Impact of hospitalization on mortality hazard, Timing-of-event with IPW and with Imbens correction for unconfoundedness

	Education level[a]				
	(1)	(2)	(3)	(4)	(5)
education	–	-0.482^{**}	-0.814^{**}	-1.145^{**}	-1.350^{**}
		(0.020)	(0.030)	(0.033)	(0.034)
in hospital	4.916^{**}	4.764^{**}	4.622^{**}	4.453^{**}	4.269^{**}
	(0.049)	(0.047)	(0.083)	(0.094)	(0.105)
hospital experience	2.911^{**}	2.772^{**}	2.584^{**}	2.336^{**}	2.104^{**}
	(0.110)	(0.109)	(0.116)	(0.118)	(0.120)

[a] (1) primary education; (2) Some Secondary education; (3) Full secondary education; (4) Post-secondary education; (5) University or PhD. $^{+}p < 0.05, ^{**}p < 0.01$.

4.2 Implied Educational gain

The reported coefficients of education and hospitalization in Table 2 are rather difficult to interpret and hide the dynamics over the life of an individual, through the impact of education on hospitalization, on the mortality. Admission to and discharge from hospital also show a clear educational gradient, see Table C.1 to Table C.3 in Appendix C. In this section we use counterfactual simulations to assess the educational gain in the probability to survive up till age 63, the end of the observation window, and the educational gain in the number of months lost till that age. For both outcomes we decompose the total educational gains into a *direct effect*, the educational gain not running through CVD hospitalization, and an *indirect effect*, the educational gain running through changes in CVD hospitalization.

This simulation is based on a synthetic cohort of individuals, all entering at age 18. The synthetic cohort consists of 10,000 men not in hospital, for which the distribution of the start population of men equals the observed distribution at the military examination (ignoring the educational distribution). For each simulation round (of 100 rounds), we draw a vector of parameter estimates assuming that the estimated coefficients are normally distributed around the point estimates with a variance-covariance matrix equal to the estimated one (which is the standard assumption). Then, on a monthly basis, we simulate the transitions for each member of the synthetic cohort using the implied transition intensities. Originally, the men

can only enter hospital for CVD or die and we are using the (first) hospitalization and mortality hazards to simulate these events. If a simulated man enters hospital for CVD, we use the discharge hazard from hospital (and adjust the mortality hazard), and similarly for a man with simulated CVD hospital experience we simulate possible re-admission (and adjust the mortality hazard). The simulated survival outcome is the average percentage of simulated men that survives till age 63. The simulated months lost outcome is the average month lost (months before age 63) for each simulated man. Note that when the survival is censored by age 63, no months are lost.

For the counterfactual simulations we impose a given education level for the hospitalization hazards and the mortality hazards. Let $Y(e_1, e_2)$ be the simulated average outcome (survival probability or months lost) for men with a mortality rate given education level e_1 and hospitalization hazards given education level e_2, then the educational gain for improving education from e to $e+1$ is:

$$\begin{aligned} G(e, e+1) &= Y(e+1, e+1) - Y(e, e) && (6) \\ &= \Big[Y(e+1, e+1) - Y(e, e+1)\Big] + \Big[Y(e, e+1) - Y(e, e)\Big] && (7) \end{aligned}$$

with the direct effect, the educational gain not running through CVD hospitalization, in the first term in brackets of (6) and the indirect effect, the educational gain running through changes in CVD hospitalization, in the second term in brackets.

Table 5 reports the educational gains in the survival probability and in years lost. Improving education would lead to 2% to 5.5%-point increase in the survival probability from age 18 to age 63 and 2 to 9 months longer expected life (till age 63). For some educational improvement the direct effect of education (not running through CVD hospitalization) plays a larger role in explaining the gain, while for other educational improvements the importance of CVD hospitalization is larger. For men with primary or with full-secondary education the survival gains are mainly (90%) due to changes in factors not related to CVD hospitalization and for men with some secondary or post-secondary education differences in CVD hospitalization are more important in explaining the survival gains. For the educational gains in years lost till age 63 only the direct effects of education are significant (not for the post-secondary to higher education). This implies that the additional months alive if a man would have had

one level higher education are not driven by changes in the CVD hospitalization rate, but by other factors influenced by education.

Table 5: Implied educational gain and its decomposition into a direct and an indirect effect

	Education level[a]			
	(2)	(3)	(4)	(5)
	survival probability till age 63			
Total effect	0.055**	0.031**	0.030**	0.019**
	(0.007)	(0.007)	(0.007)	(0.007)
Direct effect[b]	0.049**	0.017+	0.026**	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Indirect effect[b]	0.005	0.014**	0.004	0.013**
	(0.007)	(0.005)	(0.005)	(0.005)
	months lost 18–63			
Total effect	9.08**	4.33**	4.00**	2.02+
	(1.19)	(0.98)	(0.97)	(0.89)
Direct effect[b]	8.53**	2.75+	3.56**	0.74
	(1.14)	(1.08)	(1.04)	(0.89)
Indirect effect[b]	0.54	1.58	0.43	1.27
	(1.02)	(0.86)	(0.80)	(0.78)

[a] (2) primary education to Some Secondary education; (3) Some Secondary education to Full secondary education; (4) Full secondary education to Post-secondary education; (5) Post-secondary education to University or PhD. $^{+}p < 0.05$, $^{**}p < 0.01$.

[b] Indirect effect: effect of education running through CVD hospitalization; Direct effect: effect of education running through other (not CVD hospitalization) factors

5 Cause of death

In the previous section we have shown that hospitalization increases and education decreases mortality. Bijwaard et al. (2017, 2019) 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 education and hospitalization on cause-specific mortality and how the impact of hospitalization differs by education.

We aggregated the causes of death into five (the first three reflect death due to CVD) categories: (1) Ischemic Heart Disease ; (2) Stroke; (3) other cardiovascular causes; (4) external (suicide, traffic accidents and homicide) causes of death, and (5) Other causes of death. Table 6 reports the percentage of individuals that died from a particular cause before the end of the observation window.

Table 6: Percentage who died by education level and hospitalization experience

	Primary	Secondary education		Post-secondary	Higher
		Some	Full	(< 3 years)	
			All		
Ischemic Heart Disease	1.1%	0.8%	0.6%	0.4%	0.3%
Stroke	0.3%	0.2%	0.1%	0.1%	0.1%
Other CVD	0.6%	0.4%	0.3%	0.2%	0.2%
external causes	3.3%	1.7%	1.2%	0.7%	0.6%
Other causes	4.6%	3.0%	2.4%	1.7%	1.5%
Total # of death	11,427	11,396	2,894	2,258	2,166
			Never in hospital for CVD		
Ischemic Heart Disease	0.9%	0.5%	0.4%	0.3%	0.2%
Stroke	0.1%	0.1%	0.1%	0.0%	0.0%
Other CVD	0.6%	0.4%	0.3%	0.2%	0.2%
external causes	3.7%	1.8%	1.2%	0.7%	0.6%
Other causes	3.9%	2.4%	1.8%	1.3%	1.2%
# of death	8,446	7,881	2,005	1,572	1,575
			After CVD hospitalization experience		
Ischemic Heart Disease	2.4%	1.9%	1.5%	1.0%	0.8%
Stroke	0.9%	0.8%	0.6%	0.4%	0.5%
Other CVD	1.6%	1.3%	1.0%	0.8%	0.6%
external causes	1.6%	1.1%	0.9%	0.7%	0.4%
Other causes	7.8%	6.2%	5.4%	4.1%	3.8%
# of death	2,981	3,515	889	686	591

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 hospitalization. The (non-parametric) Aalen–Johansen cumulative incidence func-

tions Aalen and Johansen (1978) depicted in Figure D.6 in Appendix D for CVD related causes of death and Figure D.7 in Appendix D for external or other natural causes of death, show again a clear educational gradient in the probability to die from each of the five causes of death. Comparing the cumulative incidence curves with and without hospitalizations we notice two things. First, the shape of the cumulative incidence curves for external causes (including suicide, traffic accidents and homicide) without hospitalization differs substantially from the cumulative incidence curves for other causes of death without hospitalization and, second, only the probability to die from cardiovascular diseases increases after hospitalization for CVD. Of course, some caution in interpreting these figures is that the probability somebody has been in hospital for CVD also increases with age and depends on observed and unobserved individual factors and this is not accounted for in the cumulative incidence functions. We account for such dynamic selection in our timing-of-events model.

We use an extension of the timing-of-events model to cause-specific mortality. Instead of one mortality hazard we have five 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 sequential probit estimation of improving education, see Table C.6 in Appendix C).

The results in Table 7 indicate that all causes of death show a clear educational gradient (except for stroke or other natural causes of death between post-secondary and university/PhD), with the largest educational differences for external causes of death. The results also indicate that death due to other CVD is affected the most by hospitalization for CVD. However, such hospitalization also affects the mortality due to other natural causes and due to external causes. The educational gradient (decreasing impact of hospitalization with increasing education) is not always present. Note that for the men with the highest education level experience of hospitalization for CVD decreases mortality due to external causes.

Table 7: Impact of CVD hospitalization and education on Cause-specific mortality hazard (IPW)

		Education level[a]				
		(1)	(2)	(3)	(4)	(5)
IHD	education	–	−0.242**	−0.365**	−0.664**	−0.813**
			(0.044)	(0.065)	(0.071)	(0.073)
	in hospital	5.789**	5.831**	5.554**	5.399**	5.927**
		(0.043)	(0.041)	(0.054)	(0.056)	(0.060)
	hospital experience	1.975**	2.083**	1.836**	1.957**	1.752**
		(0.112)	(0.110)	(0.117)	(0.119)	(0.123)
stroke	education	–	−0.210**	−0.582**	−1.069**	−0.833**
			(0.076)	(0.123)	(0.148)	(0.129)
	in hospital	5.755**	5.745**	5.850**	5.271**	5.664**
		(0.081)	(0.076)	(0.095)	(0.113)	(0.127)
	hospital experience	2.053**	2.132**	2.326**	1.960**	1.609**
		(0.219)	(0.217)	(0.227)	(0.237)	(0.251)
other CVD	education	–	−0.149**	−0.342**	−0.609**	−0.768**
			(0.055)	(0.084)	(0.092)	(0.094)
	in hospital	6.464**	6.332**	6.185**	6.098**	5.989**
		(0.053)	(0.051)	(0.064)	(0.065)	(0.085)
	hospital experience	2.467**	2.389**	2.296**	2.489**	1.593**
		(0.118)	(0.118)	(0.125)	(0.126)	(0.141)
other natural	education	–	−0.433**	−0.702**	−1.025**	−1.012**
			(0.023)	(0.036)	(0.039)	(0.036)
	in hospital	5.115**	5.007**	5.063**	4.866**	4.842**
		(0.066)	(0.055)	(0.095)	(0.103)	(0.104)
	hospital experience	2.814**	2.638**	2.484**	2.074**	1.976**
		(0.147)	(0.147)	(0.153)	(0.156)	(0.157)
external	education	–	−0.716**	−0.969**	−1.268**	−1.603**
			(0.025)	(0.041)	(0.046)	(0.050)
	in hospital	5.387**	5.088**	5.281**	5.029**	4.337**
		(0.041)	(0.039)	(0.061)	(0.069)	(0.134)
	hospital experience	0.756**	0.475**	0.676**	0.516**	−0.816**
		(0.040)	(0.038)	(0.061)	(0.069)	(0.135)

[a] (1) primary education; (2) Some Secondary education; (3) Full secondary education; (4) Post-secondary education; (5) University or PhD. $^{+}p < 0.05$, $^{**}p < 0.01$.

5.1 Implied Educational gain

The coefficients in a competing risks model are even more difficult to interpret. We therefore derive the implied educational gains, similar to the analysis in Section 4.2 based on the estimated model for the cause-specific mortality. In a competing risk setting for cause specific mortality we can derive the implied educational gain in months lost for each specific cause of

death. If a simulated man dies from a specific cause of death, say ischemic heart diseases, the simulated months lost due to this cause for this man is the number of months this man had died before age 63 and no month lost for the other causes of death.

Table 8 reports the estimated months lost for each cause of death, decomposed into a direct effect, the educational gain not running through CVD hospitalization, and the indirect effect, the educational gain running through CVD hospitalization. Only for the men with only primary education we find significant education gains when improving education with one level. These men would have gained 4.1 months alive till age 63 due to lower mortality due to external causes and 2.3 months due to lower mortality due to other natural causes of death. For both causes the educational gain is almost exclusively a direct effect of education (not running through changes in the CVD hospitalization). For the high educated we also find a significant direct effect of improving education, from post-secondary to higher education, on the number of months lost due to external causes of death. Note for that for none of the causes of death directly related to CVD hospitalization (Ischemic heart disease, stroke, or other CVD) we find a significant educational gain (total, direct nor indirect) in the number of months lost for any of the education levels.

Table 8: Implied educational gain in months lost 18-63 by Cause of death

	Education level[a]			
	(2)	(3)	(4)	(5)
	Ischemic heart disease			
Total effect	−0.04	0.11	0.10	−0.25
	(0.34)	(0.31)	(0.25)	(0.32)
Direct effect[b]	−0.08	0.13	0.13	−0.26
	(0.34)	(0.32)	(0.29)	(0.34)
Indirect effect[b]	0.05	−0.02	−0.04	0.01
	(0.32)	(0.28)	(0.24)	(0.30)
	stroke			
Total effect	−0.00	0.04	0.11	−0.11
	(0.16)	(0.14)	(0.13)	(0.17)
Direct effect[b]	−0.00	0.04	0.10	−0.11
	(0.16)	(0.14)	(0.14)	(0.14)
Indirect effect[b]	−0.01	−0.00	0.01	0.00
	(0.01)	(0.14)	(0.12)	(0.14)
	other CVD			
Total effect	−0.11	0.02	−0.05	0.04
	(0.28)	(0.24)	(0.25)	(0.29)
Direct effect[b]	−0.12	−0.05	−0.06	0.05
	(0.29)	(0.30)	(0.24)	(0.26)
Indirect effect[b]	0.01	0.07	0.01	−0.01
	(0.28)	(0.25)	(0.24)	(0.26)
	external			
Total effect	4.07**	0.71	0.89	1.00
	(0.77)	(0.60)	(0.55)	(0.59)
Direct effect[b]	3.97**	0.61	0.79	1.04+
	(0.80)	(0.64)	(0.58)	(0.52)
Indirect effect[b]	0.10	0.10	0.08	−0.05
	(0.60)	(0.52)	(0.52)	(0.42)
	other natural			
Total effect	2.32**	1.25	1.07	−0.05
	(0.82)	(0.68)	(0.60)	(0.67)
Direct effect[b]	2.35**	1.24	1.02	−0.19
	(0.74)	(0.71)	(0.70)	(0.64)
Indirect effect[b]	−0.04	0.00	0.05	0.14
	(0.68)	(0.70)	(0.65)	(0.64)

[a] (2) primary education to Some Secondary education; (3) Some Secondary education to Full secondary education; (4) Full secondary education to Post-secondary education; (5) Post-secondary education to University or PhD. $^{+}p < 0.05, ^{**}p < 0.01$.

[b] Indirect effect: effect of education running through CVD hospitalization; Direct effect: effect of education running through other (not CVD hospitalization) factors

6 Conclusion and discussion

Higher educated individuals are less frequently admitted to hospital for cardiovascular diseases (CVD) and live longer than their lower educated peers. A common approach to obtain the impact of both education and CVD hospitalization is to estimate a (mixed) proportional hazard model for the mortality hazard. However, viewing the educational level and the hospitalization as ordinary (exogenous) variables may lead to biased inference of the effect of these variables on the mortality hazard. Any observed relationship between admittance to (or discharge from) 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 hospitalization endogenous in the mortality analysis. We obtain the causal impact of education and hospitalization by education on mortality by accounting for both the selection into the hospitalization process (both admittance and discharge) and the selection into education.

In particular, we estimate the effects of the 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 hospitalization and mortality processes. To account for the endogeneity of the education attainment we apply inverse probability weighting (IPW) methods using the propensity score.

In the empirical analysis we use Swedish Military Conscription Data (1951-1960), linked to administrative Swedish registers including information on hospitalization and death in which we identified five education groups. Using the timing-of-events IPW methods we estimate the impact of hospitalization on the mortality risk and this differs by education.

We investigate the robustness of our estimates to reverse causality of intelligence and psychological assessment and by accounting for misspecification of the propensity score by using a doubly robust estimation procedure. The results of these alternative specifications hardly differ from the main specification. We carry out a sensitivity analysis to quantify the robustness of our empirical findings to violation of the unconfoundedness assumption of the propensity score (no unobserved factors influencing both the propensity score and the transition rates) based on an extension of the sensitivity analysis of Imbens (2003) and only find a small change in the impact (and its educational gradient) of hospital experience on the

mortality rate.

We also investigate the impact of education and hospitalization for CVD on cause-specific mortality rates, distinguishing five different causes of death. Using an extension of the timing-of-events model with IPW we find that all causes of death show a clear educational gradient (except between post-secondary and university/PhD), with the largest educational differences for external causes of death. We also find that death due to other CVD is affected the most by hospitalization. However, hospitalization for CVD also affects the mortality due to other natural causes and due to external causes.

Our study has four distinct strengths compared to previous research. First, a clear advantage of the study is our very large sample size (700,000), which allows for the estimation of a advanced timing-of-events model for five sequential educational levels. Second, the data are population-based and are not prone to self selection issues, because military conscription was mandatory in Sweden during the study period. Third, the statistical method we use, timing-of-events model with inverse propensity score weighting, accounts for confounding effects of both hospitalization and education. This approach enables us to draw more accurate causal conclusions, without encountering the generalization issues inherent in relying on compulsory schooling reforms to account for confounding.

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 chronic diseases at age 18 and are, therefore, likely an underestimate of the impact of CVD hospitalization on mortality. Another limitation is that we only observe mortality before the age of 63. In the future, when these men have been followed for a longer period, the educational differences in mortality and the relevance of CVD hospitalization in explaining this may change as mortality due to CVD plays a larger role. Finally, the issue of reverse causality that early childhood health affects educational attainment might distort our analyses. However, 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.

During the observation period, Sweden had an advanced public health care system provid-

ing services independently of individual income. This may limit the role of financial resources explaining the impact of improved education on hospitalization and mortality. However, the role of education in allowing better access to and understanding of information and in changing health behaviour is still potentially present. This study provides better insight in the role of hospitalization for CVD in explaining the educational difference in mortality. Of course, this is only one of the many possible channels that explain this difference.

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Appendix A 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:

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

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.

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 heterogeneity conditional on survival up to t_0

$$dG(v|T > t_0) = \frac{\exp\Big(- \int_0^{t_0} \theta_m(\tau|\cdot, v_m)\, d\tau \Big) dG(v_m, v_h, v_d, v_r)}{\int \exp\Big(- \int_0^{t_0} \theta_m(\tau|\cdot, v_m)\, d\tau \Big)\, dG(v_m, v_h, v_d, v_r)} \tag{A.2}$$

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

Appendix A.1 Likelihood for Timing-of-events model with Imbens (2003) unmeasured confounding

Following Imbens (2003) we introduce an unobserved covariate U with marginal distribution $\Pr(U = 1) = \Pr(U = 0) = \frac{1}{2}$. This covariate is allowed to influence the education choice at each education decision node, $p_e = \Phi(\xi_e X + \xi_e^u U)$ and the hospitalization and mortality hazards, $\theta_j(t|x, v, U) = \theta_j(t|x, v) \exp(\gamma_j U)$ for $j = \{h, d, r, m\}$.

The likelihood contribution of individual i conditional on the unobserved heterogeneity $v = (v_h, v_r, , v_d, v_m)$ and the unobserved covariate u is (suppressing dependence on observed

characteristics x) is:

$$
\begin{aligned}
L_i(v) \;=\; & \prod_{e=1}^{5} \Pr(E=e)\Big[\theta_h\big(t_i^h\big)\big|\cdot,e,v_h\big)^{\Delta_i^h} \exp\Big(-\int_0^{t_i^h}\theta_h(\tau|\cdot,e,v_h)\,d\tau\Big) \\
& \times \prod_{k=1}^{K_{id}}\Big[\theta_d\big(d_{ik}^h\big|\cdot,e,v_d\big)^{\Delta_{ik}^d} \exp\Big(-\int_0^{d_{ik}^h}\theta_d(\tau|\cdot,v_d)\,d\tau\Big)\Big]^{I^h(t_{ik}^-)} \\
& \times \prod_{j=1}^{K_{ir}}\Big[\theta_r\big(d_{ij}^r\big|\cdot,e,v_r\big)^{\Delta_{ij}^r} \exp\Big(-\int_0^{d_{ij}^r}\theta_r(\tau|\cdot,v_r)\,d\tau\Big)\Big]^{I_o(t_{ij}^-)} \\
& \times \theta_m(t_i|\cdot,ev_m)^{\Delta_i^m} \exp\Big(-\int_0^{t_i}\theta_m(\tau|\cdot,e,v_m)\,d\tau\Big)\Big] \qquad (A.3) \\
& + \prod_{e=1}^{5} \Pr(E=e|U)\Big[\Big(\theta_h\big(t_i^h\big)\big|\cdot,e,v_h\big)e^{\gamma_h}\Big)^{\Delta_i^h} \exp\Big(-\int_0^{t_i^h}\theta_h(\tau|\cdot,e,v_h)e^{\gamma_h}\,d\tau\Big) \\
& \times \prod_{k=1}^{K_{id}}\Big[\Big(\theta_d\big(d_{ik}^h\big|\cdot,e,v_d\big)e^{\gamma_d}\Big)^{\Delta_{ik}^d} \exp\Big(-\int_0^{d_{ik}^h}\theta_d(\tau|\cdot,v_d)e^{\gamma_d}\,d\tau\Big)\Big]^{I^h(t_{ik}^-)} \\
& \times \prod_{j=1}^{K_{ir}}\Big[\Big(\theta_r\big(d_{ij}^r\big|\cdot,e,v_r\big)e^{\gamma_r}\Big)^{\Delta_{ij}^r} \exp\Big(-\int_0^{d_{ij}^r}\theta_r(\tau|\cdot,v_r)e^{\gamma_r}\,d\tau\Big)\Big]^{I_o(t_{ij}^-)} \\
& \times \Big(\theta_m(t_i|\cdot,ev_m)e^{\gamma_m}\Big)^{\Delta_i^m} \exp\Big(-\int_0^{t_i}\theta_m(\tau|\cdot,e,v_m)e^{\gamma_m}\,d\tau\Big)\Big]
\end{aligned}
$$

where $\Pr(E=e)$ is given in (5) and

$$
\Pr(E=e|U) = \Phi\big(-\xi_{e+1}X - \xi_e^u\big)^{I(e<5)} \prod_{1<j\le e} \Phi\big(\xi_j X + \xi_e^u\big)
$$

The (unconditional) likelihood contribution is (again) obtained by integrating out over $G(v|T > t_0)$, the distribution of the unobserved heterogeneity conditional on survival up to t_0.

Appendix B Additional tables

For an IPW method to hold we need to check if the propensity score is able to balance the distribution of all included variables in all education groups. One suitable way to check whether there are still differences is by calculating the standardized bias, or normalised difference in means:

$$
100 \cdot \frac{\bar{x}_e - \bar{x}_p}{\sqrt{\mathrm{Var}(x)_p}} \qquad (B.1)
$$

Table B.1: Descriptive statistics men never in hospital for CVD ($N = 437,614$)

	Primary	Secondary education some	full	Post-secondary (< 3 years)	Higher
			SES mother at birth		
non-manual (high)	1%	1%	3%	4%	7%
non-manual (intermediate)	2%	2%	4%	5%	9%
non-manual (low)	13%	19%	29%	33%	41%
Farmers	18%	14%	13%	12%	9%
Skilled workers	50%	48%	39%	35%	24%
Unskilled workers	10%	10%	8%	7%	6%
Not classified	5%	5%	3%	3%	3%
Unknown	1%	1%	1%	1%	1%
			Education father		
Primary (< 9 yrs)	65%	59%	48%	43%	30%
Primary (9–10 yrs)	3%	3%	4%	4%	4%
Secondary education (2 yrs)	11%	15%	17%	17%	16%
Secondary education (3 yrs)	5%	7%	11%	14%	16%
Post-secondary	1%	2%	3%	5%	6%
Higher	1%	2%	5%	6%	18%
Unknown	14%	12%	12%	11%	11%
mother < 20 at birth	10%	9%	7%	5%	4%
father > 40 at birth	15%	13%	12%	12%	11%
birth order	2.3	2.1	2.0	1.9	1.8
global IQ[a]	4.1	4.6	5.7	6.2	6.8
Psychological assessment[a]	4.4	4.8	5.4	5.7	5.9
missing IQ	14%	14%	12%	12%	12%
missing Psychological assessment	15%	15%	12%	12%	12%
# of individuals	93,219	156,123	53,654	61,786	72,832

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

With $e = 1, \ldots, 5$ the education group and p is the whole sample population. Table B.3 shows the percentage bias measure before and after adjusting the data in our sample. They reveal substantial imbalances between those who attained adjacent education levels before accounting for selective education choice. The biases in columns labelled 'after' show that these imbalances disappear when we use the inverse propensity weights.

Table B.2: Descriptive statistics men who experienced CVD hospitalization ($N = 80,229$)

	Primary	Secondary education some	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	18%	14%	13%	12%	9%
Skilled workers	48%	47%	36%	33%	22%
Unskilled workers	10%	9%	8%	6%	5%
Not classified	5%	5%	3%	3%	3%
Unknown	2%	1%	1%	1%	1%
			Education father		
Primary (< 9 yrs)	62%	57%	44%	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%	15%
Post-secondary	1%	2%	4%	6%	7%
Higher	2%	2%	6%	8%	21%
Unknown	15%	12%	12%	10%	10%
mother < 20 at birth	9%	9%	7%	5%	4%
father > 40 at birth	11%	11%	10%	10%	10%
birth order	2.4	2.2	2.0	1.9	1.8
global IQ[a]	3.9	4.5	5.6	6.1	6.7
Psychological assessment[a]	4.2	4.6	5.3	5.6	5.8
missing IQ	9%	5%	4%	3%	3%
missing Psychological assessment	10%	6%	4%	4%	4%
# of individuals	20,692	30,737	9,358	9,764	9,678

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

Table B.3: Standardized bias before and after matching, pairwise comparisons

	Educational levels[a]									
	(1)		(2)		(3)		(4)		(5)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mother's SES										
Unskilled workers	6.41	0.17	3.99	-0.08	-1.99	-0.19	-6.02	0.10	-11.15	0.39
Farmers	12.12	-1.62	1.18	-0.49	-1.89	-0.60	-4.93	-0.11	-13.68	0.73
Non-manual (low)	-25.12	0.91	-13.88	0.48	10.93	-0.82	20.54	-0.26	39.95	-1.00
Non-manual (medium)	-12.21	0.75	-8.49	0.75	2.44	0.09	8.87	-0.02	26.54	-0.06
Non-manual (high)	-10.36	1.97	-9.19	-0.27	4.52	-0.26	4.78	0.06	27.52	-0.30
not classified	3.97	0.30	3.17	-0.10	-3.24	0.25	-4.85	-0.21	-5.99	0.17
missing	1.57	-0.25	-0.47	-0.37	-0.15	-0.16	-1.16	-0.77	0.02	-1.33
Father's education										
less than 9 years	26.27	-1.89	14.54	-0.35	-10.16	0.71	-19.12	0.56	-44.87	2.05
9-10 years	-3.56	-0.18	-1.14	-0.19	3.22	-0.13	3.25	0.23	2.23	0.01
Full secondary	-15.85	0.20	-7.12	-0.48	6.10	-0.23	16.19	-0.64	19.32	-0.74
University $<$ 3 years	-11.29	0.52	-5.75	0.37	3.28	-0.14	10.86	0.08	16.68	-0.36
University $\geq$ 3 years	-18.55	3.54	-16.12	1.97	1.48	0.02	7.70	0.06	54.31	-0.32
PhD studies	-6.59	1.00	-6.50	2.11	-0.63	0.13	-0.46	0.07	24.69	-0.03
missing	8.60	-0.88	0.06	-0.79	-1.70	-0.90	-5.83	-0.33	-5.66	-2.12

[a] (1) primary education to Secondary education (max 2 years); (2) Secondary education (max 2 years) to Secondary education 3 year; (3) Secondary education 3 years to post-secondary education; (4) Post secondary education to University or PhD.

Table B.3: Standardized bias before and after matching (continued)

	Educational levels[a]									
	(1)		(2)		(3)		(4)		(5)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mother < 20 at birth	7.99	1.40	5.33	0.41	-2.91	0.55	-7.83	0.95	-14.10	3.73
Father > 40 at birth	5.78	-0.77	0.41	-0.67	-2.43	-0.71	-3.78	-0.19	-3.77	-1.84
family size 1	-6.02	0.08	-2.49	0.65	4.85	-0.17	4.62	-0.28	6.24	-0.46
family size 3	-2.94	-0.34	-0.61	-0.37	0.25	-0.21	1.81	-0.34	3.68	-0.17
family size 4	6.94	0.19	2.55	0.04	-3.92	0.41	-5.92	0.43	-7.23	0.16
family size ≥ 5	20.21	0.39	5.73	0.06	-10.28	0.78	-15.00	0.99	-20.02	0.42
birth order 2	-2.49	-0.15	0.18	-0.06	1.13	0.09	1.38	-0.19	0.96	-0.24
birth order 3	5.61	-0.31	1.92	-0.32	-2.94	0.30	-4.64	1.12	-5.83	0.71
birth order 4	8.08	-0.58	3.05	-0.21	-4.20	0.27	-6.88	-0.61	-8.89	0.04
birth order ≥ 5	12.84	-0.03	3.26	-0.25	-6.15	0.18	-8.78	0.35	-12.80	-2.26
Global IQ[b]										
1	25.10	-0.15	2.38	-0.06	-12.81	0.73	-15.81	0.70	-16.54	-1.50
2	24.61	-0.06	7.38	-0.04	-14.12	0.59	-19.56	1.01	-22.95	0.76
3	20.16	-0.20	9.86	-0.08	-10.82	0.57	-19.06	0.23	-25.38	1.56
4	12.75	-0.28	11.48	-0.04	-6.19	0.59	-14.88	0.33	-25.97	1.65
6	-14.77	-0.32	-1.55	-0.22	11.98	-0.26	12.57	0.02	3.83	-0.09
7	-21.50	0.75	-11.83	-0.04	12.95	-0.14	22.60	0.08	26.99	-0.50
8	-21.17	1.04	-17.25	0.97	8.19	-0.04	21.94	0.07	43.00	-0.50
9	-17.41	4.07	-16.83	1.78	1.23	0.20	12.09	-0.14	50.72	-0.41
missing	4.04	-2.40	2.09	-1.12	-4.64	-1.14	-3.80	-1.50	-3.48	-2.17
Psychological assessment[b]										
1	13.42	0.84	2.90	0.34	-7.32	1.14	-10.38	2.09	-10.52	3.67
2	15.82	1.22	4.44	0.15	-9.07	0.37	-13.19	0.55	-13.52	0.27
3	13.22	0.70	4.58	0.14	-6.06	0.23	-12.05	0.35	-13.54	0.08
4	6.54	0.33	4.63	-0.12	-2.16	-0.06	-7.46	-0.90	-11.39	0.66
6	-8.89	-0.43	-1.50	-0.13	6.29	-0.01	7.74	0.15	4.16	0.21
7	-14.19	-0.53	-7.07	0.21	7.81	-0.28	13.73	0.39	17.72	-1.01
8	-14.54	0.72	-9.80	0.90	6.08	-0.15	14.73	0.14	24.86	-0.65
9	-10.84	1.22	-8.90	1.55	2.86	0.11	10.30	0.21	24.00	-0.37
missing	4.67	-2.16	2.24	-1.08	-4.90	-1.12	-4.36	-1.16	-4.00	-2.04
birth year										
1951	3.92	0.91	-4.04	0.56	5.64	0.38	-1.18	0.78	0.45	1.34
1952	6.66	1.61	-4.13	-0.01	0.23	0.10	-0.37	0.21	0.31	-0.36
1953	8.21	1.30	-4.20	0.56	-1.08	0.18	-0.36	0.84	-0.69	-0.24
1954	-2.08	-0.89	1.67	-0.26	-2.17	-0.28	0.65	-0.01	0.18	0.39
1955	-1.99	-0.45	2.17	-0.38	-2.78	-0.21	-0.29	-0.37	0.21	-0.44
1956	-2.25	-0.85	2.40	-0.12	-3.07	-0.07	-0.14	-0.23	0.14	0.46
1957	-3.73	-0.75	3.10	-0.38	-3.11	-0.04	1.06	0.17	-0.40	-0.56
1958	-5.49	-0.15	3.98	0.27	-3.01	0.13	1.03	-0.17	-0.03	0.99
1959	-7.94	0.76	4.93	-0.68	-1.64	-0.97	0.92	-1.22	0.24	-1.53

[a] (1) primary education; (2) Some Secondary education; (3) Full Secondary education 3 years; (4) post-secondary education; (5) Higher

[b] Running from low to high.

Appendix C Full tables with parameter estimates

Table C.1: Parameters of (first) CVD hospitalization hazard (Gompertz)

	Model[a]			
	ToE	Toe IPW	Toe IPW rob	ToE Imbens
primary education	–	–	–	–
Some Secondary education	-0.084^{**}	-0.043^{**}	-0.040^{**}	-0.032
	(0.009)	(0.009)	(0.009)	(0.017)
Full Secondary education	-0.248^{**}	-0.150^{**}	-0.153^{**}	-0.120^{**}
	(0.012)	(0.012)	(0.012)	(0.024)
Post-secondary education	-0.308^{**}	-0.178^{**}	-0.180^{**}	-0.167^{**}
	(0.012)	(0.012)	(0.012)	(0.024)
University or PhD	-0.457^{**}	-0.311^{**}	-0.318^{**}	-0.255^{**}
	(0.012)	(0.012)	(0.012)	(0.027)
γ	0.099^{**}	0.098^{**}	0.095^{**}	0.100^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
v_1	-9.517^{**}	-9.511^{**}	-9.410^{**}	-10.749^{**}
	(0.025)	(0.025)	(0.032)	(0.038)
v_2	-9.436^{**}	-9.571^{**}	-9.429^{**}	-11.295^{**}
	(0.084)	(0.094)	(0.103)	(0.058)

[a] ToE: Timing-of-events; ToE IPW; Timing-of-events with Inverse propensity weighting; ToE IPW rob; Robust Timing-of-events with Inverse propensity weighting; ToE Imbens: Timing-of-events with Imbens unmeasured confounding

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

Table C.2: Parameters of CVD hospitalization discharge hazard (Weibull)

	Model[a]			
	ToE	Toe IPW	Toe IPW rob	ToE Imbens
primary education	–	–	–	–
Some Secondary education	0.078**	0.035**	0.046**	0.032**
	(0.007)	(0.007)	(0.007)	(0.008)
Full Secondary education	0.089**	0.026**	0.026**	0.058**
	(0.010)	(0.010)	(0.010)	(0.012)
Post-secondary education	0.149**	0.031**	0.065**	0.095**
	(0.010)	(0.010)	(0.010)	(0.012)
University or PhD	0.206**	0.096**	0.108**	0.178**
	(0.010)	(0.010)	(0.010)	(0.014)
α	0.991	0.966**	0.975**	1.007**
	(0.010)	(0.002)	(0.002)	(0.016)
v_1	0.753**	0.765**	0.671**	−0.843**
	(0.006)	(0.006)	(0.016)	(0.017)
v_2	−0.608**	−0.631**	−0.742**	−0.751**
	(0.008)	(0.009)	(0.018)	(0.019)

[a] ToE: Timing-of-events; ToE IPW; Timing-of-events with Inverse propensity weighting; ToE IPW rob; Robust Timing-of-events with Inverse propensity weighting; ToE Imbens: Timing-of-events with Imbens unmeasured confounding

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

Table C.3: Parameters of CVD re-hospitalization hazard (Weibull)

	Model[a]			
	ToE	Toe IPW	Toe IPW rob	ToE Imbens
primary education	–	–	–	–
Some Secondary education	-0.024^{**}	0.004	0.004	0.000
	(0.007)	(0.007)	(0.007)	(0.009)
Full Secondary education	-0.117^{**}	-0.073^{**}	-0.069^{**}	-0.080^{**}
	(0.010)	(0.010)	(0.010)	(0.014)
Post-secondary education	-0.205^{**}	-0.137^{**}	-0.142^{**}	-0.131^{**}
	(0.010)	(0.010)	(0.010)	(0.014)
University or PhD	-0.254^{**}	-0.154^{**}	-0.155^{**}	-0.177^{**}
	(0.010)	(0.010)	(0.010)	(0.016)
α	0.348	0.348^{**}	0.348^{**}	0.388^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
v_1	-0.603^{**}	-0.624^{**}	-0.571^{**}	-0.607^{**}
	(0.006)	(0.006)	(0.015)	(0.026)
v_2	0.148^{**}	0.130^{**}	0.135^{**}	0.685^{**}
	(0.008)	(0.008)	(0.016)	(0.024)

[a] ToE: Timing-of-events; ToE IPW; Timing-of-events with Inverse propensity weighting; ToE IPW rob; Robust Timing-of-events with Inverse propensity weighting; ToE Imbens: Timing-of-events with Imbens unmeasured confounding

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

Table C.4: Parameters of mortality hazard

	Model[a]			
	ToE	Toe IPW	Toe IPW rob	ToE Imbens
primary education	–	–	–	–
in hospital	4.213**	4.221**	4.227**	4.916**
	(0.055)	(0.060)	(0.057)	(0.049)
hospital experience	1.830**	1.546**	1.637**	2.911**
	(0.108)	(0.110)	(0.108)	(0.110)
Some Secondary education	−0.587**	−0.585**	−0.597**	−0.482**
	(0.016)	(0.016)	(0.016)	(0.020)
in hospital	4.016**	4.038**	4.002**	4.764**
	(0.053)	(0.055)	(0.052)	(0.047)
hospital experience	1.620**	1.370**	1.423**	2.772**
	(0.108)	(0.109)	(0.107)	(0.109)
Full Secondary education	−0.928**	−0.863**	−0.873**	−0.814**
	(0.025)	(0.025)	(0.025)	(0.030)
in hospital	3.854**	3.966**	4.023**	4.622**
	(0.085)	(0.084)	(0.082)	(0.083)
hospital experience	1.400**	1.236**	1.321**	2.584**
	(0.114)	(0.115)	(0.113)	(0.116)
Post-secondary education	−1.300**	−1.216**	−1.238**	−1.145**
	(0.028)	(0.027)	(0.027)	(0.033)
in hospital	3.642**	3.718**	3.692**	4.453**
	(0.096)	(0.090)	(0.089)	(0.094)
hospital experience	1.096**	0.837**	0.915**	2.336**
	(0.116)	(0.117)	(0.115)	(0.118)
University or PhD	−1.443**	−1.303**	−1.325**	−1.350**
	(0.027)	(0.027)	(0.027)	(0.034)
in hospital	3.546**	3.660**	3.614**	4.269**
	(0.106)	(0.094)	(0.093)	(0.105)
hospital experience	0.928**	0.730**	0.796**	2.104**
	(0.117)	(0.118)	(0.116)	(0.120)
γ hospital experience	−0.017**	−0.010**	−0.013**	−0.020**
	(0.002)	(0.002)	(0.002)	(0.002)
γ constant	0.072**	0.067**	0.065**	0.068**
	(0.001)	(0.001)	(0.001)	(0.001)
v_1	−9.569**	−9.398**	−9.378**	−9.407**
	(0.045)	(0.046)	(0.057)	(0.058)
v_2	−7.834**	−7.682**	−7.841**	−8.061**
	(0.042)	(0.043)	(0.054)	(0.053)
p_1	0.860**	0.859**	0.864**	0.641**
	(0.010)	(0.010)	(0.012)	(0.013)

[a] ToE: Timing-of-events; ToE IPW; Timing-of-events with Inverse propensity weighting; ToE IPW rob; Robust Timing-of-events with Inverse propensity weighting; ToE Imbens: Timing-of-events with Imbens unmeasured confounding

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

Table C.5: Parameters control variables in Robust Timing-of-events with Inverse propensity weighting

	Hazard[a]			
	Mortality	First	Discharge	Re-admit
SES mother at birth				
not classified	0.015	0.062^{**}	0.063^{**}	-0.020
Unskilled workers	0.110^{**}	0.020	0.041^{**}	0.039^{**}
Farmers	-0.191^{**}	-0.099^{**}	-0.001	-0.046^{**}
non-manual (low)	0.078^{**}	-0.017	-0.012	-0.041^{**}
non-manual (intermediate)	0.144^{**}	-0.091^{**}	0.034^{+}	-0.029
non-manual (high)	0.129^{**}	-0.055^{+}	0.031	-0.034
missing	0.738^{**}	-0.275^{**}	0.045	-0.009
father's education				
less than 9 years	-0.055^{**}	0.000	0.003	-0.032^{**}
9-10 years	-0.001	-0.030	-0.005	-0.067^{**}
Full secondary education	0.024	-0.002	-0.016	-0.026^{+}
university ($<$ 3 years)	0.150^{**}	-0.007	0.013	-0.014
university ($\geq$ 3 years)	0.187^{**}	-0.137^{**}	-0.076^{**}	-0.159^{**}
PhD	0.199^{**}	0.203^{**}	0.296^{**}	0.240^{**}
missing	0.232^{**}	-0.048^{**}	-0.021	-0.002
IQ measurement				
1	0.025	0.146^{**}	-0.233^{**}	0.168^{**}
2	0.030	0.140^{**}	0.043^{**}	0.075^{**}
3	0.090^{**}	0.089^{**}	0.005	-0.032^{**}
4	0.027	0.017	-0.005	0.003
6	-0.020	-0.020	0.009	-0.020^{+}
7	0.064^{**}	-0.059^{**}	0.072^{**}	-0.064^{**}
8	0.089^{**}	-0.118^{**}	-0.001	-0.038^{**}
9	0.253^{**}	-0.102^{**}	0.049^{**}	0.100^{**}
missing	0.233^{**}	-0.401^{**}	-0.269^{**}	0.188^{**}

[a] Mortality: mortality hazard; First: first CVD hospitalization hazard; discharge: CVD hospitalization discharge hazard; re-admit: CVD re-hospitalization hazard.
Reference category: mother skilled worker and secondary education (max 2 years) and IQ level 5. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.5: Parameters control variables in Robust Timing-of-events with Inverse propensity weighting (continued)

	Hazard[a]			
	Mortality	First	Discharge	Re-admit
Psychological assessment				
1	0.843^{**}	0.151^{**}	-0.062^{**}	0.186^{**}
2	0.460^{**}	0.186^{**}	-0.092^{**}	0.046^{**}
3	0.239^{**}	0.112^{**}	-0.096^{**}	0.074^{**}
4	0.098^{**}	0.043^{**}	-0.033^{**}	-0.009
6	-0.116^{**}	0.014	0.016	-0.014
7	-0.107^{**}	0.018	0.013	-0.026^{+}
8	-0.059^{+}	0.059^{**}	0.107^{**}	0.028^{+}
9	-0.087	0.023	0.005	-0.071^{**}
missing	0.707^{**}	0.326^{**}	-0.065^{+}	0.163^{**}
birth year				
1951	0.084^{**}	0.012	0.035^{**}	-0.005
1952	0.064^{**}	-0.002	0.045^{**}	-0.026^{**}
1953	0.009	0.042^{**}	0.076^{**}	-0.094^{**}
1954	-0.262^{**}	0.036^{+}	0.119^{**}	-0.072^{**}
1955	-0.220^{**}	0.074^{**}	0.088^{**}	-0.117^{**}
1956	-0.301^{**}	0.015	0.105^{**}	-0.143^{**}
1957	-0.273^{**}	0.046^{**}	0.125^{**}	-0.156^{**}
1958	-0.315^{**}	0.080^{**}	0.103^{**}	-0.160^{**}
1959	-0.711^{**}	-1.517^{**}	0.219^{**}	-0.086^{**}
birth info				
mother $<$ 20 at birth	0.123^{**}	0.055^{**}	0.023^{+}	0.034^{**}
father $>$ 40 at birth	0.206^{**}	-0.245^{**}	-0.010	-0.017
family size 1	0.051^{+}	0.041^{**}	0.003	0.048^{**}
family size 3	-0.020	-0.033^{**}	0.031^{**}	0.017^{+}
family size 4	0.037	-0.030^{+}	0.048^{**}	0.038^{**}
family size 5 or higher	0.056^{+}	-0.051^{**}	-0.014	0.043^{**}
birth order 2	-0.035^{+}	0.030^{**}	0.038^{**}	0.011
birth order 3	-0.074^{**}	0.112^{**}	0.051^{**}	0.031^{**}
birth order 4	-0.155^{**}	0.128^{**}	0.027^{+}	0.014
birth order 5 or higher	0.001	0.176^{**}	0.100^{**}	-0.052^{**}

[a] Mortality: mortality hazard; First: first CVD hospitalization hazard; discharge: CVD hospitalization discharge hazard; re-admit: CVD re-hospitalization hazard. Reference category: 1950, psychological assessment 5. $^{+}p < 0.05$,$^{**}p < 0.01$.

Table C.6: Parameters education choice, sequential probit model

	Education choice[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
not classified	0.020	0.009	0.020	0.077**
Unskilled workers	−0.016+	0.003	−0.004	0.065**
Farmers	−0.120**	0.046**	−0.003	0.039**
non-manual (low)	0.178**	0.288**	0.114**	0.187**
non-manual (intermediate)	0.228**	0.372**	0.187**	0.247**
non-manual (high)	0.230**	0.521**	0.146**	0.369**
missing	0.013	0.130**	0.059+	0.178**
father's education				
less than 9 years	−0.229**	−0.174**	−0.065**	−0.098**
9-10 years	−0.080**	0.014	−0.006	0.007
Full secondary education	0.083**	0.168**	0.115**	0.033**
university ($<$ 3 years)	0.169**	0.243**	0.165**	0.090**
university ($\geq$ 3 years)	0.303**	0.635**	0.318**	0.462**
PhD	0.409**	0.955**	0.436**	0.775**
missing	−0.195**	−0.101**	−0.008	0.038+
IQ measurement				
1	−0.637**	−0.848**	−0.526**	−0.151+
2	−0.463**	−0.657**	−0.400**	−0.311**
3	−0.324**	−0.437**	−0.265**	−0.164**
4	−0.183**	−0.258**	−0.135**	−0.120**
6	0.224**	0.248**	0.117**	0.094**
7	0.441**	0.563**	0.265**	0.216**
8	0.651**	0.921**	0.413**	0.352**
9	0.841**	1.332**	0.585**	0.571**
missing	−0.264**	0.136**	0.166**	0.169**

[a] (1) some secondary education over primary education; (2) full secondary education over some secondary; (3) post-secondary over full secondary education; (4) higher over post-secondary education.
$^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.6: (continued)

	Education choice[a]			
	(1)	(2)	(3)	(4)
Psychological assessment				
1	-0.240^{**}	-0.268^{**}	-0.038	0.173^{**}
2	-0.196^{**}	-0.198^{**}	-0.012	0.139^{**}
3	-0.145^{**}	-0.111^{**}	-0.042^{**}	0.088^{**}
4	-0.081^{**}	-0.063^{**}	-0.037^{**}	0.032^{**}
6	0.074^{**}	0.094^{**}	0.034^{**}	0.025^{+}
7	0.155^{**}	0.226^{**}	0.097^{**}	0.080^{**}
8	0.233^{**}	0.357^{**}	0.151^{**}	0.119^{**}
9	0.292^{**}	0.489^{**}	0.201^{**}	0.171^{**}
missing	-0.189^{**}	-0.058^{+}	0.014	0.113^{+}
birth year				
1951	-0.018^{+}	-0.065^{+}	0.081^{+}	0.022
1952	-0.042^{**}	-0.043^{**}	0.197^{**}	0.019
1953	-0.097^{**}	-0.080^{**}	0.195^{**}	-0.010
1954	0.138^{**}	-0.204^{**}	0.219^{**}	-0.028
1955	0.129^{**}	-0.230^{**}	0.216^{**}	-0.014
1956	0.137^{**}	-0.230^{**}	0.230^{**}	-0.012
1957	0.172^{**}	-0.238^{**}	0.232^{**}	-0.049^{**}
1958	0.210^{**}	-0.259^{**}	0.231^{**}	-0.047^{**}
1959	0.618^{**}	-0.184^{**}	0.203^{**}	-0.092^{**}
birth info				
mother $<$ 20 at birth	-0.164^{**}	-0.204^{**}	-0.172^{**}	-0.093^{**}
father $>$ 40 at birth	0.028^{**}	0.071^{**}	0.058^{**}	0.047^{**}
family size 1	0.014	0.024^{**}	-0.003	0.042
family size 3	-0.066^{**}	-0.061^{**}	-0.006	-0.023
family size 4	-0.140^{**}	-0.135^{**}	-0.034^{**}	-0.053^{**}
family size 5 or higher	-0.214^{**}	-0.243^{**}	-0.067^{**}	-0.059^{**}
birth order 2	-0.050^{**}	-0.066^{**}	-0.029^{**}	-0.008
birth order 3	-0.046^{**}	-0.050^{**}	-0.031^{**}	0.007
birth order 4	-0.024^{+}	-0.045^{**}	-0.041^{+}	0.016
birth order 5 or higher	-0.040^{**}	-0.011	-0.034	-0.043
constant	0.925^{**}	0.926^{**}		

[a] (1) some secondary education over primary education; (2) full secondary education over some secondary; (3) post-secondary over full secondary education; (4) higher over post-secondary education.
$^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.7: Parameters control variables in Imbens Timing-of-events

	Hazard[a]			
	Mortality	First	Discharge	Re-admit
SES mother at birth				
not classified	0.053	0.057^{**}	0.061^{**}	0.042^{+}
Unskilled workers	0.139^{**}	0.006	0.026^{**}	0.088^{**}
Farmers	-0.210^{**}	-0.092^{**}	0.009	-0.048^{**}
non-manual (low)	0.090^{**}	-0.032^{**}	0.032^{**}	-0.006
non-manual (intermediate)	0.122^{**}	-0.052^{+}	0.054^{**}	-0.045^{+}
non-manual (high)	0.050	-0.039	0.061^{**}	-0.015
missing	0.761^{**}	-0.311^{**}	0.022	0.055
father's education				
less than 9 years	-0.053^{**}	-0.001	0.016	-0.006
9-10 years	0.018	-0.003	0.008	-0.048^{+}
Full secondary education	0.009	-0.003	-0.011	-0.015
university ($<$ 3 years)	0.124^{**}	-0.032	-0.014	0.047^{+}
university ($\geq$ 3 years)	0.056	-0.115^{**}	-0.042^{+}	-0.057^{+}
PhD	0.220^{+}	-0.105	-0.189^{**}	0.016
missing	0.253^{**}	-0.062^{**}	0.021	0.037^{+}
IQ measurement				
1	0.017	0.191^{**}	-0.098^{**}	0.148^{**}
2	0.011	0.118^{**}	-0.005	0.063^{**}
3	0.015	0.092^{**}	0.030^{**}	-0.033^{+}
4	0.027	0.029^{+}	-0.010	0.007
6	-0.019	-0.028^{+}	0.016	-0.029^{+}
7	0.046	-0.064^{**}	0.032^{**}	-0.021
8	0.058	-0.139^{**}	0.018	-0.016
9	0.075	-0.132^{**}	0.020	0.011
missing	0.261^{**}	-0.376^{**}	-0.241^{**}	0.211^{**}

[a] Mortality: mortality hazard; First: first CVD hospitalization hazard; discharge: CVD hospitalization discharge hazard; re-admit: CVD re-hospitalization hazard.
Reference category: mother skilled worker and secondary education (max 2 years) and IQ level 5. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.7: Parameters control variables in Imbens Timing-of-events (continued)

	Hazard[a]			
	Mortality	First	Discharge	Re-admit
Psychological assessment				
1	0.936^{**}	0.223^{**}	-0.189^{**}	0.200^{**}
2	0.467^{**}	0.178^{**}	-0.058^{**}	0.083^{**}
3	0.278^{**}	0.100^{**}	-0.046^{**}	0.046^{**}
4	0.067^{**}	0.033^{**}	-0.013	-0.005
6	-0.102^{**}	-0.004	0.022^{+}	-0.028^{+}
7	-0.089^{**}	-0.010	0.046^{**}	-0.014
8	-0.112^{**}	0.041^{+}	0.055^{**}	0.041^{+}
9	-0.091	0.102^{**}	-0.021	-0.022
missing	0.779^{**}	0.352^{**}	-0.179^{**}	0.150^{**}
birth year				
1951	0.005	-0.004	0.061^{**}	-0.029^{+}
1952	-0.010	-0.013	0.068^{**}	-0.048^{**}
1953	0.011	0.020	0.095^{**}	-0.068^{**}
1954	-0.209^{**}	0.028	0.127^{**}	-0.118^{**}
1955	-0.187^{**}	0.053^{**}	0.124^{**}	-0.125^{**}
1956	-0.229^{**}	0.029	0.122^{**}	-0.131^{**}
1957	-0.217^{**}	0.045^{**}	0.119^{**}	-0.152^{**}
1958	-0.250^{**}	0.038^{+}	0.143^{**}	-0.165^{**}
1959	-0.753^{**}	-1.770^{**}	0.088^{**}	-0.161^{**}
birth info				
mother $<$ 20 at birth	0.079^{**}	0.031^{+}	0.027^{+}	0.021
father $>$ 40 at birth	0.219^{**}	-0.263^{**}	-0.008	0.012
family size 1	0.052^{+}	0.038^{**}	0.009	-0.002
family size 3	-0.001	-0.038^{**}	0.053^{**}	-0.000
family size 4	0.053^{+}	-0.028^{+}	0.032^{**}	-0.004
family size 5 or higher	0.075^{**}	-0.055^{**}	0.062^{**}	0.015
birth order 2	-0.010	0.024^{+}	0.024^{**}	-0.003
birth order 3	-0.071^{**}	0.099^{**}	-0.002	0.021
birth order 4	-0.187^{**}	0.141^{**}	0.042^{**}	-0.001
birth order 5 or higher	-0.032	0.181^{**}	0.030	-0.026
γ (effect of U)	-1.487^{**}	1.918^{**}	1.439^{**}	-0.631^{**}

[a] Mortality: mortality hazard; First: first CVD hospitalization hazard; discharge: CVD hospitalization discharge hazard; re-admit: CVD re-hospitalization hazard. Reference category: 1950, psychological assessment 5. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.8: Parameters education choice, sequential probit model with Imbens correction for unconfoundedness

	Education choice[a]			
	(1)	(2)	(3)	(4)
SES mother at birth				
not classified	0.020	0.009	0.020	0.077**
Unskilled workers	−0.016+	0.003	−0.004	0.065**
Farmers	−0.120**	0.045**	−0.004	0.039**
non-manual (low)	0.178**	0.288**	0.114**	0.187**
non-manual (intermediate)	0.228**	0.372**	0.187**	0.247**
non-manual (high)	0.230**	0.521**	0.146**	0.370**
missing	0.013	0.130**	0.059+	0.179**
father's education				
less than 9 years	−0.229**	−0.174**	−0.065**	−0.099**
9-10 years	−0.080**	0.014	−0.006	0.008
Full secondary education	0.083**	0.168**	0.115**	0.033**
university ($<$ 3 years)	0.169**	0.243**	0.165**	0.091**
university ($\geq$ 3 years)	0.303**	0.635**	0.318**	0.462**
PhD	0.409**	0.955**	0.436**	0.776**
missing	−0.195**	−0.101**	−0.008	0.038+
IQ measurement				
1	−0.637**	−0.848**	−0.526**	−0.153+
2	−0.463**	−0.658**	−0.400**	−0.311**
3	−0.324**	−0.438**	−0.265**	−0.164**
4	−0.183**	−0.259**	−0.135**	−0.120**
6	0.224**	0.248**	0.117**	0.094**
7	0.441**	0.563**	0.265**	0.216**
8	0.651**	0.921**	0.413**	0.352**
9	0.841**	1.332**	0.585**	0.572**
missing	−0.264**	0.134**	0.164**	0.165**

[a] (1) some secondary education over primary education; (2) full secondary education over some secondary; (3) post-secondary over full secondary education; (4) higher over post-secondary education.
$^{+}p < 0.05$, $^{**}p < 0.01$.

Table C.8: (continued)

	Education choice[a]			
	(1)	(2)	(3)	(4)
Psychological assessment				
1	-0.240^{**}	-0.268^{**}	-0.038	0.172^{**}
2	-0.196^{**}	-0.198^{**}	-0.012	0.139^{**}
3	-0.145^{**}	-0.111^{**}	-0.042^{**}	0.088^{**}
4	-0.081^{**}	-0.063^{**}	-0.037^{**}	0.032^{+}
6	0.074^{**}	0.094^{**}	0.034^{**}	0.025^{+}
7	0.155^{**}	0.226^{**}	0.097^{**}	0.080^{**}
8	0.233^{**}	0.357^{**}	0.151^{**}	0.119^{**}
9	0.292^{**}	0.489^{**}	0.201^{**}	0.171^{**}
missing	-0.188^{**}	-0.056^{+}	0.015	0.116^{+}
birth year				
1951	-0.018^{+}	-0.065^{**}	0.081^{**}	0.022
1952	-0.042^{**}	-0.043^{**}	0.196^{**}	0.019
1953	-0.097^{**}	-0.080^{**}	0.195^{**}	-0.010
1954	0.138^{**}	-0.205^{**}	0.219^{**}	-0.028
1955	0.129^{**}	-0.230^{**}	0.216^{**}	-0.014
1956	0.137^{**}	-0.230^{**}	0.230^{**}	-0.013
1957	0.172^{**}	-0.239^{**}	0.232^{**}	-0.050^{**}
1958	0.210^{**}	-0.259^{**}	0.230^{**}	-0.047^{**}
1959	0.618^{**}	-0.184^{**}	0.203^{**}	-0.091^{**}
birth info				
mother < 20 at birth	-0.164^{**}	-0.205^{**}	-0.172^{**}	-0.093^{**}
father > 40 at birth	0.028^{**}	0.071^{**}	0.058^{**}	0.047^{**}
family size 1	0.014	0.024^{**}	-0.003	0.042^{**}
family size 3	-0.066^{**}	-0.061^{**}	-0.006	-0.024^{**}
family size 4	-0.140^{**}	-0.135^{**}	-0.034^{**}	-0.053^{**}
family size 5 or higher	-0.214^{**}	-0.244^{**}	-0.067^{**}	-0.059^{**}
birth order 2	-0.050^{**}	-0.066^{**}	-0.029^{**}	-0.009
birth order 3	-0.047^{**}	-0.050^{**}	-0.031^{**}	0.007
birth order 4	-0.024^{+}	-0.045^{**}	-0.041^{+}	0.015
birth order 5 or higher	-0.040^{**}	-0.011	-0.034	-0.043
constant	0.926^{**}	0.091^{**}	0.128^{**}	-0.265^{**}
ξ^u (effect of U)	-0.002	-0.050^{+}	-0.004	-0.056

[a] (1) some secondary education over primary education; (2) full secondary education over some secondary; (3) post-secondary over full secondary education; (4) higher over post-secondary education.
$^{+}p < 0.05$, $^{**}p < 0.01$.

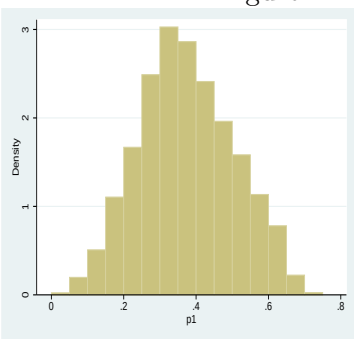
Table C.9: Parameters of Cause specific mortality hazard (IPW)

	Cause of death[a]				
	IHD	Stroke	other CVD	other natural	external
primary education	–	–	–	–	–
in hospital	5.789**	5.755**	6.464**	5.115**	5.387**
	(0.043)	(0.081)	(0.053)	(0.066)	(0.041)
hospital experience	1.975**	2.053**	2.467**	2.814**	0.756**
	(0.112)	(0.219)	(0.118)	(0.147)	(0.040)
Some Secondary education	−0.242**	−0.210**	−0.149**	−0.433**	−0.716**
	(0.044)	(0.076)	(0.055)	(0.023)	(0.025)
in hospital	5.831**	5.745**	6.332**	5.007**	5.088**
	(0.041)	(0.076)	(0.051)	(0.055)	(0.039)
hospital experience	2.083**	2.132**	2.389**	2.638**	0.475**
	(0.110)	(0.217)	(0.118)	(0.147)	(0.038)
Full Secondary education	−0.365**	−0.582**	−0.342**	−0.702**	−0.969**
	(0.065)	(0.123)	(0.084)	(0.036)	(0.041)
in hospital	5.554**	5.850**	6.185**	5.063**	5.281**
	(0.054)	(0.095)	(0.064)	(0.095)	(0.061)
hospital experience	1.836**	2.326**	2.296**	2.484**	0.676**
	(0.117)	(0.227)	(0.125)	(0.153)	(0.061)
Post-secondary education	−0.664**	−1.069**	−0.609**	−1.025**	−1.268**
	(0.071)	(0.148)	(0.092)	(0.039)	(0.046)
in hospital	5.399**	5.271**	6.098**	4.866**	5.029**
	(0.056)	(0.113)	(0.065)	(0.103)	(0.069)
hospital experience	1.957**	1.960**	2.489**	2.074**	0.516**
	(0.119)	(0.237)	(0.126)	(0.156)	(0.069)
University or PhD	−0.813**	−0.833**	−0.768**	−1.012**	−1.603**
	(0.073)	(0.129)	(0.094)	(0.036)	(0.050)
in hospital	5.927**	5.664**	5.989**	4.842**	4.337**
	(0.060)	(0.127)	(0.085)	(0.104)	(0.134)
hospital experience	1.752**	1.609**	1.593**	1.976**	−0.816**
	(0.123)	(0.251)	(0.141)	(0.157)	(0.135)
γ hospital experience	−0.012**	−0.018**	−0.009**	−0.032**	–
	(0.002)	(0.005)	(0.002)	(0.003)	
γ constant	0.086**	0.074**	0.056**	0.088**	–
	(0.001)	(0.002)	(0.001)	(0.001)	
v_1	−13.272**	−14.090**	−13.007**	−10.769**	−7.453**
	(0.076)	(0.144)	(0.094)	(0.051)	(0.020)
v_2	−6.912**	−7.647**	−6.224**	−27.890	−3.325**
	(0.061)	(0.110)	(0.068)	(380.010)	(0.023)
p_1	0.957**				
	(0.002)				

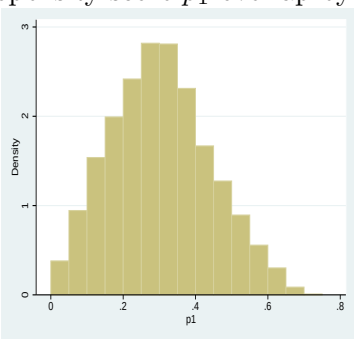
[a] IHD: Ischemic Heart Disease
$^{+}p < 0.05$, $^{**}p < 0.01$.

Appendix D Additional figures

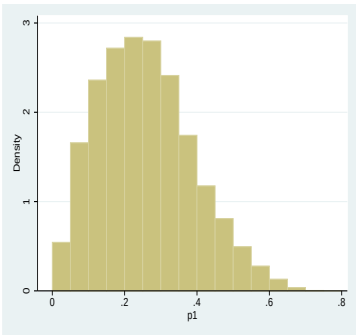
Figure D.1: Propensity score p_1 overlap by education level



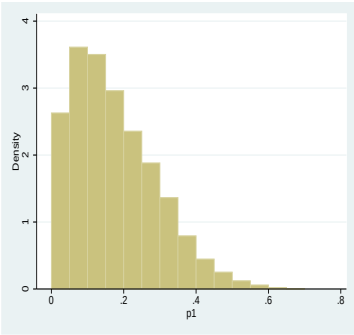
Primary



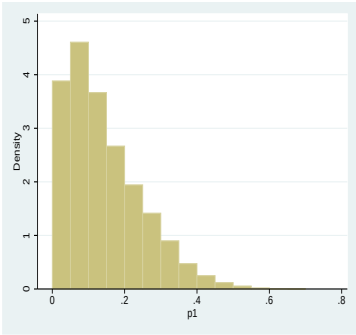
Some secondary



Full secondary

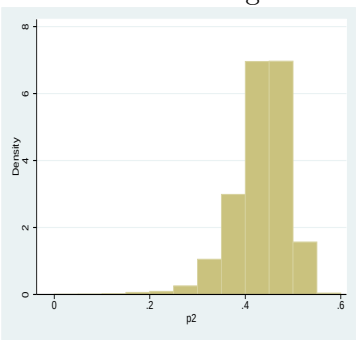


Post secondary

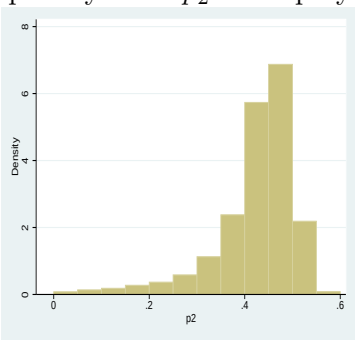


Higher

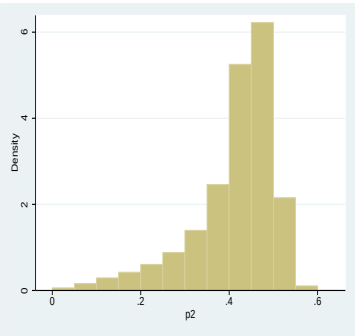
Figure D.2: Propensity score p_2 overlap by education level



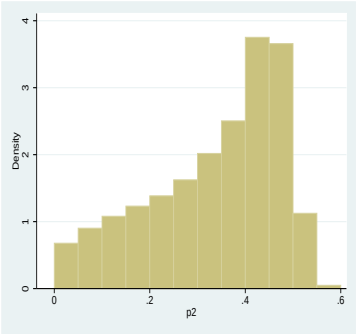
Primary



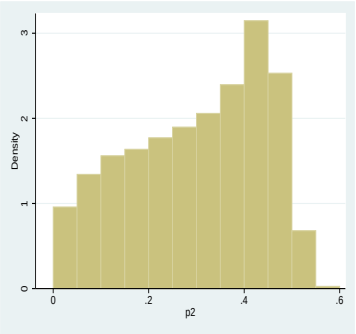
Some secondary



Full secondary

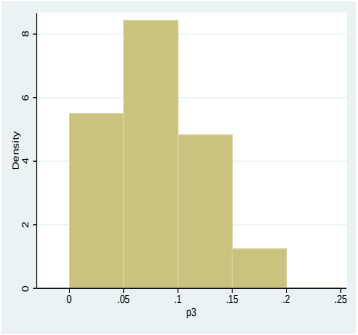


Post secondary

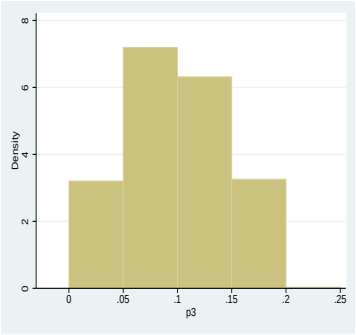


Higher

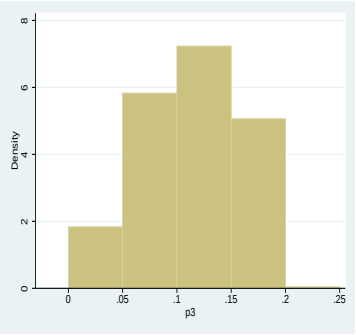
Figure D.3: Propensity score p_3 overlap by education level



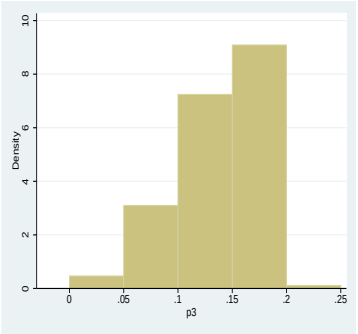
Primary



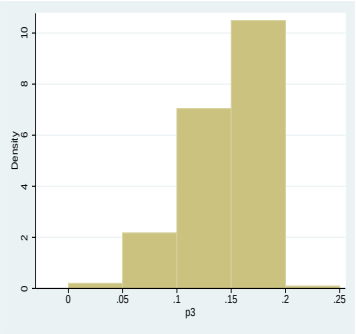
Some secondary



Full secondary

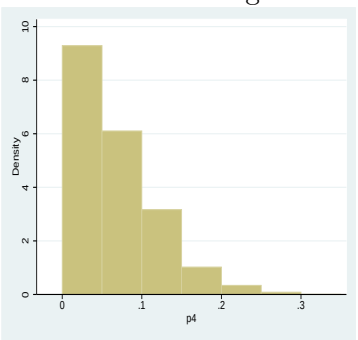


Post secondary

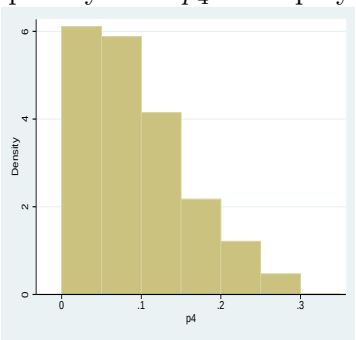


Higher

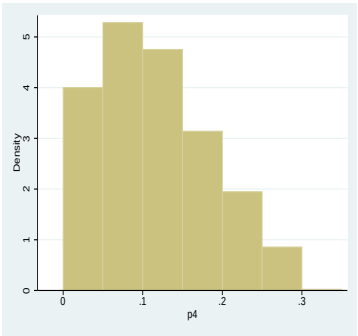
Figure D.4: Propensity score p_4 overlap by education level



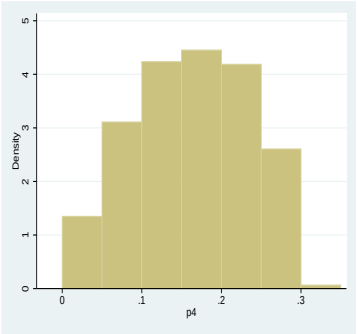
Primary



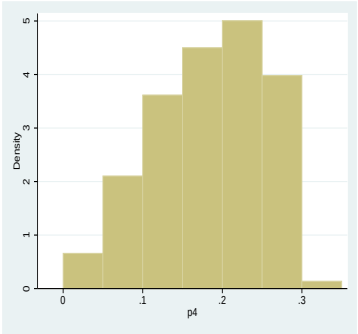
Some secondary



Full secondary

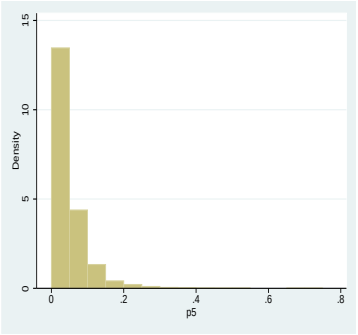


Post secondary

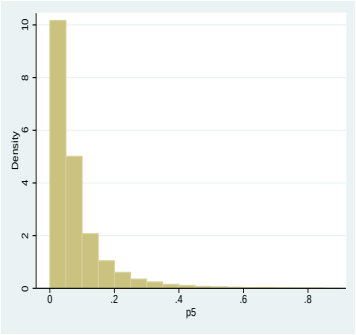


Higher

Figure D.5: Propensity score p_5 overlap by education level



Primary



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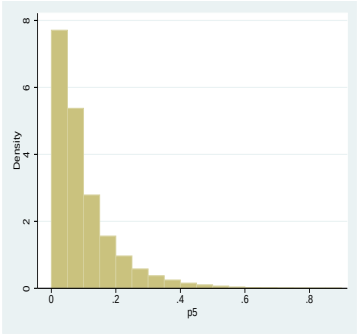
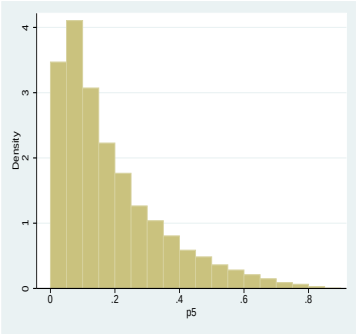
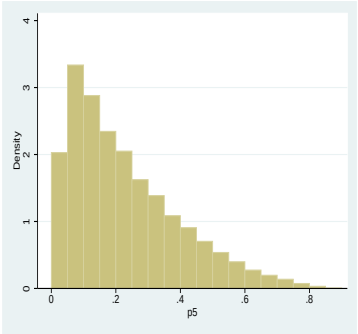


Full secondary



Post secondary



Higher

Figure D.6: Cumulative incidence curves by cause of death (CVD), hospitalization and education level

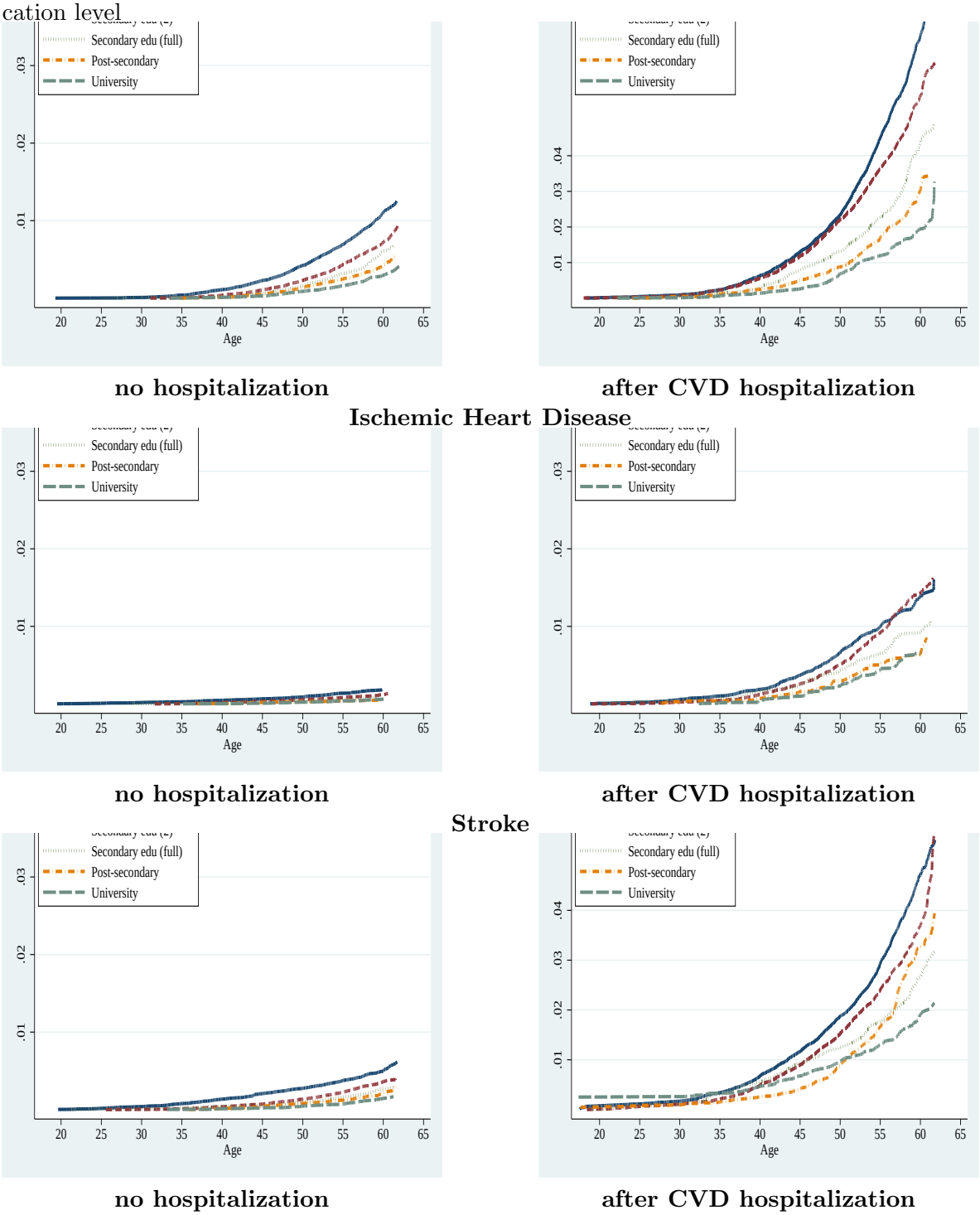
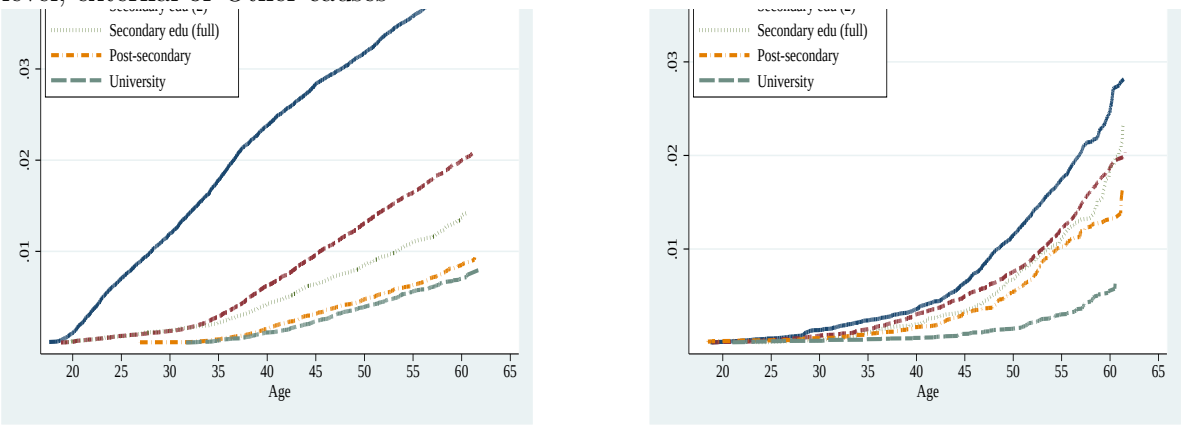
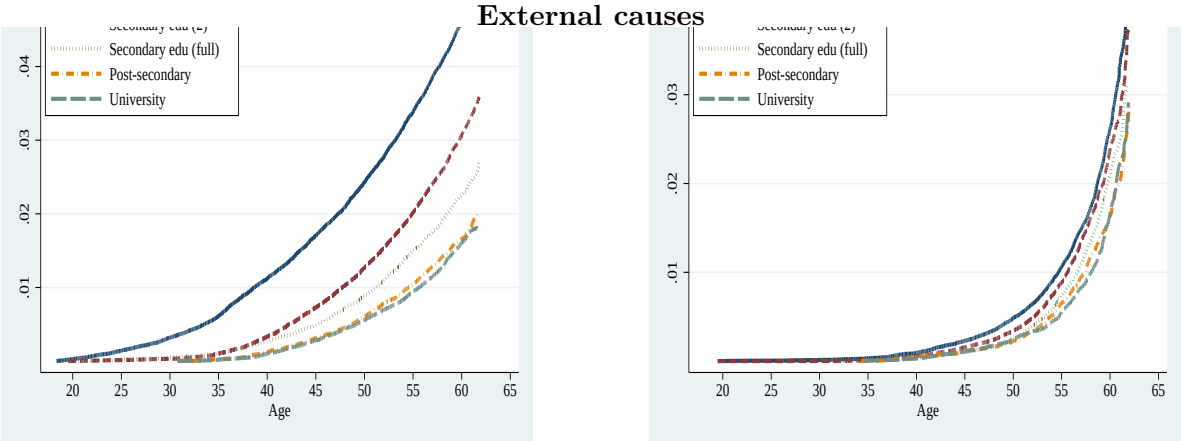


Figure D.7: Cumulative incidence curves by cause of death, hospitalization and education level, external or Other causes



no hospitalization **after CVD hospitalization**

External causes



no hospitalization **after CVD hospitalization**

Other causes