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Efficiency of Health Investment: Education or Intelligence?*

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Abstract

In this paper we hypothesize that education is associated with a higher efficiency of health investment, yet that this efficiency advantage is solely driven by intelligence. We operationalize efficiency of health investment as the probability of dying conditional on a certain hospital diagnosis, and estimate a multistate structural equation model with three states: (i) healthy, (ii) hospitalized, and (iii) death. We use data from a Dutch cohort born around 1940 that links intelligence tests at age 12 to later-life hospitalization and mortality records. The results suggest that higher intelligence induces the higher educated to be more efficient users of health investment – intelligent individuals have a clear survival advantage for most hospital diagnoses – yet for unanticipated health shocks and diseases that require complex treatments such as COPD, education still plays a role.

Keywords: Education, Intelligence, Health, Multistate duration model

JEL Codes : C41, I14, I24

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1 Introduction

Health disparities across educational groups are widespread, and – strikingly – growing over time (Meara et al. 2008). While there has been considerable progress in recent years in unraveling the direction of causality, much less attention has been devoted to understanding the mechanisms through which the higher educated achieve their health advantage. In fact, very little is known about why the higher educated are healthier than their less-educated peers (Cutler and Lleras-Muney, 2008; Mazumder, 2012).

One often-cited hypothesis is that the higher educated are more efficient producers of health investment. This could be due to (i) "productive efficiency" or (ii) "allocative efficiency". The former hypothesis posits that higher education leads to a higher marginal product of a given set of health inputs. In simple terms, the higher educated understand the doctor better and use existing medical care more efficiently. The allocative efficiency hypothesis on the other hand argues that higher educated individuals choose different, more efficient inputs into health investment, typically thought to be caused by better health knowledge and a more receptive attitude towards new information.

While there is empirical evidence that higher educated individuals are more efficient users of health investment in terms of both productive and allocative efficiency (see Grossman, 2006 for an excellent review), it is not established whether this is actually the result of education per se. This is surprising for two reasons. First, much of the reasoning why higher educated individuals would be more efficient users of health investment equally holds for intelligence. For example, understanding the doctor better and adhering to complex treatments may be driven by intelligence rather than education.

Second, our reading of the literature on education and health outcomes is that at least half of the health disparities across educational groups is due to the selection of healthier, more able individuals into higher education (Conti and Heckman, 2010; Conti et al. 2010; 2011; Heckman et al. 2014; Bijwaard et al. 2015).[1] Hence, in recent years evidence is growing that the presumed health returns to education may be smaller than previously thought, which also raises the question to what extent it

[1] The reasoning is also corroborated by studies exploiting compulsory schooling reforms to establish the causal effect of education on health outcomes, which unanimously show that the causal effect of education on health outcomes is either much smaller than the correlation suggests (Lleras-Muney, 2005; Van Kippersluis et al. 2011; Meghir et al. 2013), or even entirely absent (Albouy and Lequien, 2009; Clark and Royer, 2014).

is the actual attainment of education that improves health investment efficiency.

In this paper we aim to answer two questions. First: Is education associated with a higher efficiency of health investment? We investigate the efficiency of health investment by studying survival probabilities conditional on a certain hospital diagnosis. While the data do not permit disentangling productive from allocative efficiency, the data do provide a unique opportunity to answer a second question: To what extent is intelligence driving the potential efficiency gains associated with education?

To the best of our knowledge, we are the first to test the hypothesis that higher intelligence gives the higher educated their efficiency advantage in terms of health investment. Rejecting or non-rejecting this hypothesis has important policy implications. If educational attainment increases the efficiency of health investment then learning itself and the associated improved knowledge have non-monetary returns in terms of health and survival gains. If instead most of the efficiency gains derive from intelligence, this suggests that supply-side interventions (e.g. longer consultation time, more explicit prescriptions for lower IQ individuals, or nudging) are more appropriate to reduce population disparities in health and survival.

The data used are from a Dutch cohort study of individuals born around 1940 that links intelligence tests at age 12 to follow-up surveys including education and self-reported health in 1993. A unique feature is that we have additionally linked the data to administrative records regarding hospitalizations between 1995 and 2005 and mortality between 1995 and 2011. We use a theoretical model with a health-state dependent utility function and stochastic mortality risk to formulate hypotheses. Testing the theoretical hypotheses requires estimating a multistate structural equation model with three states: (i) healthy, (ii) hospitalized, and (iii) death. The empirical model allows testing our hypotheses by decomposing the relative contributions of education and intelligence on the transitions between the three states.

The results suggest that the higher educated are more efficient users of health investment: they have a smaller probability to die within one year after hospital admittance even conditional on self-reported health and previous diagnoses. However, when accounting for selection into education based on intelligence, most of the efficiency gain is removed, in particular for males. It is mostly intelligent people who have a survival advantage for a given hospital diagnosis. Only for people with respiratory diseases, like COPD and pneumonia, we found large differences in survival by education even conditional on intelligence. In sum, the survival advantage among higher educated individuals seems to derive largely from intrinsic abilities like intelligence, yet education does have efficiency gains over and above intelligence for diseases that require complex adherence regimens such as COPD.

This paper is structured as follows. The theoretical framework to structure thoughts on the efficiency of health investment and the hypotheses are introduced in Section 2. Section 3 presents the multistate structural equation model to test the theoretical hypotheses. In Section 4 the Brabant data and the linked register data on hospitalization and mortality from Statistics Netherlands is discussed. Section 5 presents the empirical results. Section 6 concludes and provides a discussion of the results.

2 Theoretical background

Efficiency of health investment In the seminal health capital model, Grossman (1972) assumes that the health investment process is influenced by education E.[2] Higher educated individuals have a higher marginal product of the inputs into health investment, and hence education alters the effective quantity of these inputs. This argument is referred to as "productive efficiency" (Grossman, 1972; Michael and Becker, 1973). The alternative reason why education could appear in the health investment process is that it could alter the choice of inputs altogether, typically thought to be caused by acquisition of health knowledge. This hypothesis has become known as "allocative efficiency" (Rosenzweig and Schultz, 1981; Muurinen, 1982).

Empirically distinguishing between the two alternative hypotheses is an extremely challenging task.[3] One of the few studies that has made a brave attempt is Gilleskie and Harrison (1998), who estimated a structural production model for self-reported health, and provide tentative evidence that suggests both productive and allocative efficiency are at work. Kenkel (1991; 1995) provides evidence in favor of productive efficiency.[4]

[2]The dynamic equation for the health stock is given by $H_{t+1} - H_t = I_t[E] - d_t H_t$, where H is the health stock, I is health investment, d is the depreciation rate, and E is education.

[3]Grossman (2006) suggests estimating a structural model with health as dependent variable and all inputs into health production plus education as independent variables. In case the coefficient of education is non-zero, this proves "productive efficiency" since even with the universe of health production inputs, higher educated individuals still reach a higher level of health. In case the coefficient is zero, this proves the "allocative efficiency" hypothesis, since there will be no additional gain from education if all health production inputs are controlled for.

[4]Indirect evidence for allocative efficiency is given by Goldman and Smith (2002), Goldman and

Since it is very difficult, if not impossible, to observe all inputs into health production, measure health comprehensively, and account for the simultaneous endogeneity of both health care use and education with respect to health, we will not attempt to separate the two. Rather we investigate whether education is associated with any (productive or allocative) efficiency of health investment, and to what extent this potential efficiency gain is driven by intelligence.

We operationalize efficiency of health investment as *a lower probability of dying, and a higher probability of recovery, conditional on being admitted to the hospital for a given diagnosis.*

Theoretical framework To structure thoughts and generate predictions, we propose a stylized model somewhat similar to Murphy and Topel (2006), in which individuals maximize a utility function of the form:

$$\int_{t=0}^{\infty} U\Big\{U_H\big[C(t), L(t)\big], U_I\big[C(t), L(t)\big]\Big\}P^{(k)}(0,t)e^{-\rho t}dt \quad k=0,1 \tag{1}$$

where $U[\cdot]$ is the utility function with inputs from consumption $C(t)$ and leisure $L(t)$, and $P^{(k)}(0,t)$ is the transition probability for educational level k from age 0 to t. We envision a model in which utility per period derived from consumption and leisure is health dependent: $U_H[\cdot]$ is the utility when in good health, while $U_I[\cdot]$ is the utility when hospitalized.[5]

We assume that in adulthood there are three different states: (1) being healthy (H), (2) being hospitalized (I), and (3) death (D), where utility in death is normalized to zero. Hence, the matrix of transition probabilities P is a 3 by 3 matrix where the first row contains the transition probabilities from healthy to healthy, hospitalized, and death $\{P_{HH}, P_{HI}, P_{HD}\}$; the second row contains the transition probabilities from hospitalized to healthy, hospitalized, and death $\{P_{IH}, P_{II}, P_{ID}\}$; and no transitions are possible after death.

We assume that the transition process between the states is a Markov process and that the transition intensities $\lambda(\cdot)$ are constant over an age interval of one year, but depend on education. The transition rates from healthy to hospitalized (λ_{HI}),

Lakdawalla (2005), Lleras-Muney and Lichtenberg (2005), and Glied and Lleras-Muney (2008) who show that higher educated individuals adhere better to, and benefit more from, complex treatments for HIV and diabetes, and sooner adapt to evolving medical technologies; and Lange (2011) who shows that higher educated individuals process objective risk factors for cancer into their subjective probabilities.

[5] Obviously, the individual will also face a budget and time constraint, but analyzing a fully-fledged life cycle model is beyond the scope of this paper.

hospitalized to health (λ_{IH}), healthy to death (λ_{HD}) and hospitalized to death (λ_{ID}) jointly comprise a matrix of transition intensities

$$M(t) = \begin{pmatrix} -\big(\lambda_{HI}(t) + \lambda_{HD}(t)\big) & \lambda_{HI}(t) & \lambda_{HD}(t) \\ \lambda_{IH}(t) & -\big(\lambda_{IH}(t) + \lambda_{ID}(t)\big) & \lambda_{ID}(t) \\ 0 & 0 & 0 \end{pmatrix} \tag{2}$$

In turn, the transition probability matrix from age s to age t is given by

$$P(s,t) = \exp\big(M(s)\big) = V\Lambda(t-s)V^{-1} \tag{3}$$

where V is the matrix of eigenvectors of $M(t)$ and Λ is the exponentiated matrix of eigenvalues (see Appendix A for more details).

Hypotheses Following Grossman (1972) and subsequent literature, our first hypothesis is

Hypothesis 1: Education is associated with a higher efficiency of health investment.

The empirical test for hypothesis 1 requires comparing the transitions from the state hospitalized across educational groups

$$\begin{aligned} \mathrm{E}\Big[P^{(1)}_{ID}(t) - P^{(0)}_{ID}(t)\Big|X\Big] &< 0 \\ \mathrm{E}\Big[P^{(1)}_{IH}(t) - P^{(0)}_{IH}(t)\Big|X\Big] &> 0 \end{aligned} \tag{4}$$

where $P^{(1)}_{ID}(t)$ is the transition probability from hospitalized to death for the higher educated within a year for an individual aged t, and $P^{(0)}_{ID}(t)$ is the same transition probability for the lower educated. Likewise, $P^{(k)}_{IH}(t)$ refers to the transition probability from hospitalized to healthy for the higher ($k = 1$) and lower educated ($k = 0$).[6] The matrix X includes extensive controls for pre-existing health conditions, demographic characteristics, and hospital diagnoses.

In words, hypothesis (4) entails that for a given hospital diagnosis, a given state of self-reported health, and conditional on demographics and social background, the higher educated are more efficient users of health investment (i.e. have a lower

[6]The probability to remain in hospital, P_{II}, is the complement of the two probabilities in (4), and is extremely low since the probability to be in hospital again after exactly one year is very low.

probability of dying conditional on being admitted to the hospital).[7]

Hypothesis 2: Conditioning on intelligence, education does not improve the efficiency of health investment

Individuals choose their educational attainment E in adolescence on the basis of their intelligence θ and other characteristics X_E:

$$E = E\big[\theta, X_E\big], \tag{5}$$

Since both θ and X_E may additionally influence the transition probabilities, education is endogenous with respect to health investment. The central thesis of this paper is that the reason why higher educated individuals understand the doctor better and understand the dangers of smoking, plausibly derives at least partly from their better cognitive skills. Therefore we account for intelligence θ in the transition probabilities, and the empirical tests of Hypothesis 2 can be formulated as

$$\begin{aligned} \mathrm{E}\Big[P^{(1)}_{ID}(t) - P^{(0)}_{ID}(t)\Big|X,\theta\Big] &= 0 \\ \mathrm{E}\Big[P^{(1)}_{IH}(t) - P^{(0)}_{IH}(t)\Big|X,\theta\Big] &= 0 \end{aligned} \tag{6}$$

3 Methodology

Our empirical approach is an extension of the structural equation framework developed by Conti et al. (2010) and Bijwaard et al. (2015). The model consists of three parts: (i) a binary educational choice depending on latent abilities and other covariates, (ii) potential outcomes depending on the choice of education, latent abilities, and other covariates, and (iii) a measurement system for the latent abilities.

[7] Since only a fraction of individuals die in the hospital, it is also informative to study transitions from the healthy state to future hospitalizations and mortality, after conditioning on previous hospital diagnoses.

$$\begin{aligned} \mathrm{E}\Big[P^{(1)}_{HD}(t) - P^{(0)}_{HD}(t)\Big|X\Big] &< 0 \\ \mathrm{E}\Big[P^{(1)}_{HH}(t) - P^{(0)}_{HH}(t)\Big|X\Big] &> 0 \end{aligned}$$

Educational choice The binary indicator for education E_i is defined as 1 if individual i took any education beyond primary school, and 0 if not:

$$E_i = \begin{cases} 1 & \text{if } E_i^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where we assume E_i^* is an underlying latent utility which is continuous and linear, and depends on latent intelligence θ, and observed characteristics X^E:

$$E_i^* = \gamma X_i^E + \alpha_E \theta_i + \upsilon_{iE} \tag{8}$$

with υ_E being an error term independent of X^E and θ. We assume that υ_E is normally distributed, which implies that we have a probit model for the educational choice. We fix the variance at 1 since the variance is not identified in a probit model.

Multistate potential hazard outcomes The second part is the potential outcomes part, in which there are two potential outcomes depending on whether the individual chose to pursue education beyond primary school or not. Bijwaard et al. (2015) defined the potential outcomes in terms of the mortality hazard. Here we extend the model to a multistate model, with three states: (i) healthy, (ii) hospitalized; and (iii) death.

For each of the four transition rates (from healthy to hospitalized and vice versa, and from healthy and hospitalized to death) we have two potential transition rates. We define $\lambda_{HD}^{(1)}(t)$ as the mortality rate from the healthy state for an individual with education level beyond primary school ($E_i = 1$), and $\lambda_{HD}^{(0)}(t)$ as the mortality rate from the healthy state for an individual with an education level equal to primary school ($E_i = 0$). Similar definitions are used for the other transition rates.

We assume a Gompertz proportional hazard model in age for the two potential mortality rates from healthy, which has been shown to be an accurate representation of mortality between the ages of 30 and 80 (e.g. Gavrilov and Gavrilova, 1991; Cramer, 2012). Both potential hazards depend on the latent ability θ, and observed characteristics while healthy X^H:

$$\begin{aligned} \lambda_{HD}^{(0)}(t|X^H, \theta) &= \exp\bigl(a_{HD0} t + \beta_{HD0} X_i^H + \alpha_{HD0} \theta_i\bigr) \\ \lambda_{HD}^{(1)}(t|X^H, \theta) &= \exp\bigl(a_{HD1} t + \beta_{HD1} X_i^H + \alpha_{HD1} \theta_i\bigr) \end{aligned} \tag{9}$$

with t age in years. The hazard of becoming hospitalized is assumed constant conditional on the individuals socio-demographics, health and previous health investments captured in X^H

$$\begin{aligned}
\lambda_{HI}^{(0)}(t|X^H,\theta) &= \exp\big(\beta_{HI00} + \beta_{HI0}X_i^H + \alpha_{HI0}\theta_i\big) \\
\lambda_{HI}^{(1)}(t|X^H,\theta) &= \exp\big(\beta_{HD10} + \beta_{HI1}X_i^H + \alpha_{HI1}\theta_i\big)
\end{aligned} \tag{10}$$

Since the duration of stay in hospital is never longer than a few months, we define the transition rates from hospitalized in terms of days in hospital (τ). Both the mortality rate as well as the recovery rates from the hospitalized-state are assumed to be exponential. Thus, for $k = \{H, D\}$ we have the transition rates

$$\begin{aligned}
\lambda_{Ik}^{(0)}(\tau|X^I,\theta) &= \exp\big(\beta_{Ik00} + \beta_{HI0}X_i^I + \alpha_{Ik0}\theta_i\big) \\
\lambda_{Ik}^{(1)}(\tau|X^I,\theta) &= \exp\big(\beta_{Ik10} + \beta_{HI1}X_i^I + \alpha_{Ik1}\theta_i\big)
\end{aligned} \tag{11}$$

In all the transition rates the effect of latent intelligence on the hazard is captured by α. We assume a discrete distribution with three points of support for latent intelligence $\theta_l, l = 1, 2, 3$. This is similar to including unobserved heterogeneity in the transition rates that is correlated over the different rates, and for identification the unobserved heterogeneity needs to have a finite mean. We restrict θ to have zero mean, i.e. $\sum p_l\theta_l = 0$, where p_l is the probability that $\theta = \theta_l$. This restricts one of the three support-points θ_3 and from the restriction that the probabilities p_l sum up to one, the probability p_3.

Measurement system for intelligence The final part of the model is the measurement equation, linking one or two intelligence scores M_{ik} ($k = 1, 2$) linearly with the discrete points of support of latent intelligence θ:

$$M_{ik} = \delta_k X_i^M + \alpha_{M_k}\theta_i + \upsilon_{iM_k} \tag{12}$$

with υ_{M_k} independent of X^M and θ. We assume that υ_{M_k} is normally distributed with variance $\sigma^2_{M_k}$. The full likelihood function is given in Appendix B.

After estimating the transition rates in (9), (10), and (11), which depend on observed and unobserved factors, we calculate the one-year transition probabilities using the one-to-one translation given by equations (2) and (3). Using the delta-method and the derivative of the transition matrix we can derive the variance-covariance of the components of the transition matrix. This allows testing the theoretical hypotheses 1 (equation 4) and 2 (equation 6).

4 Data and descriptive statistics

The data are from a Dutch cohort born between 1937 and 1941. The survey was held in 1952 among 5,823 pupils of the sixth (last) grade of primary schools in the Dutch province of Noord-Brabant, and hence is referred to as the "Brabant data". In 1983 and 1993 attempts to trace all initial respondents of the Brabant-cohort were made, with overall response rates of around 45 percent (2,998 individuals). Hartog (1989) investigated the non-response for the 1983 survey and found no attrition bias in a wage analysis. The Brabant data are subsequently linked to hospitalization records for the years 1995-2005 inclusive, and the mortality register and municipality register for the years 1995-2011 inclusive. Given that the individuals in our sample are born between 1937 and 1941, this implies that we follow hospitalizations between ages 55 and 68, and mortality from age 55 until 75.[8] The hospital discharge register contains data on both inpatient and day care patients of all general and academic hospitals in the Netherlands. Since the administrative registers are available since 1995, only 86 percent of the 2,998 individuals could be traced in the municipality register in 1995, leaving us with a working sample of 2,579 individuals.

Endogenous variables: In the analysis we distinguish between three states. Individuals are "healthy" if they are alive and non-hospitalized, "hospitalized" if they are alive but hospitalized for at least one day, and "death" if they are not alive. In our sample, 409 individuals, or 16 percent, died during the period 1995-2011 (of which 14 percent died in hospital). Average number of hospital stays (with overnight stay) over the period 1995-2005 is 1, with more than 25 percent of the hospital admissions due to circulatory problems, 15 percent due to neoplasms, 11 percent due to digestive problems, and 5 percent due to respiratory problems.

Our main variable of interest is *Education*, defined as the highest level of education attended, in two categories: (1) *Primary Education*, including those who attended at most (extended)[9] primary school and (2) *Above Primary Education*, including those who attended lower vocational education such as the lower agricultural school or lower polytechnic schools, lower general secondary school, higher

[8] Of the Dutch population 1940 cohort, only 6.8 percent died between the ages of 12 and 55 – Human Mortality Database, University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany). Available at www.mortality.org or www.humanmortality.de (data downloaded on July 30, 2012).

[9] At the time, pupils had to stay in school for at least 8 years, or until they reached the age of 14. Since regular primary school only consisted of 6 grades, some schools offered an additional 2-year extended primary school ("vglo").

general secondary school, and higher vocational education or university.

Table 1 presents descriptive statistics and shows that 14 percent did not continue school after primary school forming the *Primary Education* category, leaving 86 percent forming the *Higher Education* category (34 percent attended *Lower Vocational Education*, 34 percent have *General Secondary Education* and the other 18 percent attended *Higher Vocational or University Education*). The lower educated have a higher mortality before the end of the observation window and they enter hospital more often. They also remain in hospital for a longer period. The lower educated are more often admitted for circulatory and respiratory diagnoses, while the higher educated more often for neoplasms.

Intelligence is modelled as a latent variable. In the Brabant data there are two separate measurements for intelligence, both measured in the final grade of primary school: (i) the IQ progressive matrices test, which focuses on mathematical ability and is a replication of the British test designed by Raven (1958), and (ii) a Vocabulary test (picking synonyms). The timing of the intelligence test at age 12 avoids possible reverse causality from education to intelligence (Deary and Johnson, 2010). The Raven test is considered to be a 'pure' measurement of problem solving abilities, as it does not require any linguistic or general knowledge (Dronkers, 2002). Table 1 shows that the intelligence test designed by Raven has an average of 102 (96 among the lower educated and 103 among the higher educated).

Control variables: A fairly standard set of socio-demographic control variables such *Age*, sex (*Male*), *Birth Rank*, and *Family Social Class* is included in all models. Family social class is measured in three categories from lowest to highest depending on father's occupation (see Bijwaard et al. 2015 for details). We additionally know whether the child had to work in the parent's farm or company, defining the binary indicator *Child Works*.

Factors additionally influencing the measurements of intelligence, X^M include *School Type* and the *Number of Teachers*. Additional factors influencing the educational choice, X^E, include *Repeat*, which defines the number of classes that children had to repeat, *Teacher's Advice* regarding further education of the child, and the *Preference of the Parents* concerning the education of the pupil.

Finally, to test whether higher educated individuals are more efficient users of health investment, we intend to keep health status and the type of (previous) health investments constant. Therefore, from the state healthy, the set of control variables X^H includes *Self-reported health* in three categories (measured in 1993), whether

Hospitalized before during the observation period, and the *Last diagnosis* in case of a hospitalization (neoplasm, circulatory, respiratory, or digestive system). From the state hospitalized, the set of control variables X^I includes self-reported health, whether it was a *Repeated admittance*, whether it was an *Acute* admission, and the main diagnosis of the admission (neoplasm, circulatory, respiratory, or digestive system).[10] The categories of all control variables are defined in Table 1, which also includes descriptive statistics.

5 Results

5.1 Basic model without control variables

To get a first impression of the impact of education on the efficiency of health investment we start with estimating a basic model by education level without any control variables. The estimated parameters are reported in Table 2. Next, we calculate the implied transition intensities, and using (3) we calculate the transition probabilities for a one year interval. In Figure 1 the four relevant transition probabilities are depicted. It is immediately clear that individuals who continued beyond primary education have a higher (lower) probability to recover (die) within one year of hospital admittance. From the healthy state, the probability to die within one year is lower and the probability to remain healthy is higher for higher educated individuals. All these differences are statistically significant.[11] This is an indication that our first hypothesis, education improves the efficiency of health investment, holds. In the remainder we will only focus on the transition probability from hospital to death within one year, because the other transitions probabilities give very similar insights.

[10]Unfortunately, the sample size does not permit controlling for even finer levels of diagnoses. Nonetheless, with these very small numbers we did check the exact International Classification of Diseases (ICD) 9 codes within the larger diagnose groups. It follows that for circulatory and digestive diseases, the sub diagnoses are very similar across educational groups (e.g. coronary atherosclerosis or angina pectoris in the case of circulatory diseases, and inguinal hernia and gallbladder in case of digestive diseases). However, for neoplasms and respiratory diseases this is not the case. In particular, for respiratory diseases among the lower educated it is mainly COPD, while higher educated seem to suffer more often more pneumonia and milder lung diseases.

[11]The formal tests of the significance of the difference in this basic model, the stratified model, and the structural model are reported in Table 6 to 10 in appendix C.

5.2 Stratified model including control variables

The previous analysis ignores that higher educated individuals differ in characteristics from lower educated individuals, and that the diagnosis at hospital admission is different across educational groups. In this subsection we include the control variables discussed in section 4, but continue to assume that the education choice is exogenous (stratified models by education level). The results correspond to equations (4) in the theoretical framework. Table 3 reports all the coefficients, first the transition rates from healthy and second the transition rates from hospitalized.

Based on these estimates we calculate the transition probabilities for a one year period, for each education level separately, and depict the transition probability from hospital to death in the left panel of Figure 2. The transition probability from hospital to death by education becomes less distinct and insignificant for young (below 70) people. Still, individuals with only primary education have a higher probability to die within a year of hospital admittance when they are older than 70. These individuals also have a higher probability to die within a year when healthy (not shown). These results indicate that education improves the efficiency of health investment, at least when over 70. Hence, we cannot reject hypothesis 1 and confirm earlier findings that education is associated with improved efficiency of health investment.

With respect to the control variables, the results in Table 3 also indicate that the transition rate from healthy to hospitalized (2$^{\text{nd}}$ and 4$^{\text{th}}$ column) and death (3$^{\text{rd}}$ and 5$^{\text{th}}$ column) are heavily influenced by earlier hospitalizations, and gender.[12] The higher educated are more prone to return to hospital with neoplasms, and less prone to return for respiratory diseases. Higher educated males are more likely to (re-)enter hospital compared to high educated females. When individuals had cancer at their previous hospitalization their mortality is five times as high. For the lower educated, respiratory diagnoses also increase the mortality by a factor five. The second part of Table 3 reports the parameters of the transition rates out of hospital, to either healthy or death. Individuals admitted with neoplasms are more likely to die (especially higher educated) and less likely to recover. Respiratory diseases also lead to less recovery and higher mortality. An emergency-admittance to the hospital increases the mortality and decreases the recovery.

[12] All, except the transition from hospital to death, parameters differ significantly between the two education levels. Note that the transition probability, as opposed to the hazard, from hospitalized to death can still differ significantly across educational groups since this probability also depends on the other hazards (see Appendix A).

5.3 Structural model including intelligence

Next we estimate the full structural model in which both the education choice and the transition rates depend on latent intelligence, corresponding to equation (6) in the theoretical framework. Table 4 reports the parameter estimates of the structural model. Again, all parameters of the transition hazards, except for the hazard from hospital to death, differ significantly by education. Intelligence plays a major role in explaining the transition rates from healthy (first row of Table 4). A higher intelligence leads to a lower admittance rate for both education groups and a lower death rate for the higher educated. Another difference with the results from the stratified transition rates in Table 3 is that the impact of the previous hospital admittance is reduced. The coefficients of the transition hazards from hospitalized are shown in the second part of Table 4. Intelligence significantly affects the recovery rate. The other coefficients are very similar to the estimated coefficients for the transition rates in the stratified model in Table 3.

Based on the estimated coefficients of the structural model we calculate the transition probabilities for a one year period. The implied difference in transition probability from hospital to death (and the 95% confidence intervals) is depicted in the right panel of Figure 2. We see that the difference between the two education groups has dropped after accounting for the effect of intelligence on educational choice and the transitions between states. The difference between the education levels is now for the whole age range insignificant. Thus, the evidence shows that accounting for intelligence removes most of the difference in the efficiency of health investment between higher and lower educated individuals.

5.4 Heterogeneity

Next we look at a few specific groups and how education affects their efficiency of health investment. In calculating the transition probabilities we use the estimated coefficients for some specific groups of both the stratified models and the structural model. In Figure 3 we depict the transition probability from hospital to death for females. The educational gains for females are higher than for men. Still, after accounting for intelligence these gains are insignificant.

We included four different diagnoses at hospital admission in our model. Figure 4 shows the transition probability to die within one year after admission for these four different diagnoses Neoplasms and respiratory diseases (COPD, pneumonia) are both major causes of death. However, the impact of education on mortality of these diagnoses is very different. When people enter hospital and are diagnosed with cancer, survival is the same for higher and lower educated. The small efficiency gain of the higher educated at higher ages is removed after controlling for intelligence. On the contrary, for respiratory diseases we find a large educational gain of survival after hospitalization, especially at later ages, which is only marginally reduced after controlling for intelligence. A 75 year old individual with only primary education admitted to hospital with a respiratory diseases has a 13% chance to die within a year, while a higher educated individual aged 75 years with a respiratory disease has only 3% chance to die. Digestive and circulatory diseases have much lower mortality and show only a marginal gain in health efficiency by education.

Finally, we look at the probability to die within a year for individuals admitted to hospital with acute problems (i.e. entered through the ER). Acute hospitalizations are unanticipated and have been used before as health shocks (Garcia-Gomez et al. 2013). In Figure 5 we depict the impact of acute admission to hospital for the stratified (left) and the structural model (right). For unanticipated health shocks, the higher educated have a strong survival advantage. At age 75, the one-year probability to die after an unanticipated health shock is 3 times higher among the lower educated compared to the higher educated (6% vs. 2%). This difference does not diminish, and if anything becomes even larger, after accounting for intelligence. This suggests that when confronted with an unanticipated health shock, the higher educated are more efficient users of health investment, and we reject hypothesis 2 for this type of hospital admissions.

5.5 Robustness checks

In this section we present a couple of robustness checks, results of which are all available upon request. First, one may be worried that the variables included in X^H and X^I such as self-reported health and (previous) hospital admissions are endogenous with respect to education. While the inclusion of these variables allows investigating efficiency gains for a given health status and hospital diagnosis, one may be worried that the endogeneity of these variables leads to a bias in the comparison of transition probabilities across educational groups, due to the "bad control" problem. Therefore, we re-estimated all models excluding these potentially endogenous variables, and results are very similar.

Second, we tested robustness to the definition of the educational choice. While it is convenient to define a binary indicator of education, we may lose some important variation across educational levels within the higher educated group. To test this, we re-define education as comprising four levels, where we split the higher educated further into lower vocational education, general secondary education, and higher vocational/university. Figure 6 shows the basic educational disparities in survival and hospitalizations across four levels of educational attainment, and shows that the largest disparity is between those attending only primary education and the rest, while the differences across the other three groups is minimal. This gives comfort that our binary representation of education is justified.

Third, we have estimated models with more flexible duration dependence in the transitions between healthy and hospitalized. In the base Gompertz model we assume that the transitions are constant with respect to age, conditional on the health status and previous diagnoses of the individual. When estimating piecewise constant models without the previous diagnoses, the age dependence is positive and statistically significant. When adding the previous diagnoses, the age dependence of the transitions hazards is very limited, and in some cases even negative. This suggests that previous diagnoses account for the age-dependence in the transitions, and constant durations are a reasonable assumption. Importantly, in- or excluding the duration dependence does not change any of our conclusions.

Finally, apart from the Raven test we have estimated models in which we added an additional measurement for intelligence, namely the Vocabulary test. Since efficiency of health investment may in part derive from verbal and communication skills, it is worth extending the definition of intelligence to include this component too. The results prove robust to adding the vocabulary test.

6 Discussion

Higher educated individuals are healthier and live longer than their lower educated peers. In this paper we formulate two testable hypotheses regarding the sources of these disparities on basis of a theoretical framework that allows for transitions between the states healthy, hospitalized, and death: (i) education is associated with a higher efficiency of health investment, and (ii) conditional on intelligence, education does not improve the efficiency of health investment. We exploit a cohort study among 2,579 individuals with intelligence measures around age 12 linked to survey information regarding educational attainment, and administrative records regarding hospitalizations and mortality. The resulting dataset provides a rare opportunity to test these two theoretical hypotheses.

In line with previous research we find evidence for an association between education and the efficiency of health investment: higher educated individuals are less likely to die during middle-age after a hospitalization. These results hold even for a given health status and given a certain diagnosis. Hence, we cannot reject our first hypothesis. When accounting for the role of intelligence using a structural equation model, the association between education and the efficiency of health investment disappears. This suggests that intelligence accounts for a substantial proportion of the survival advantage of higher educated individuals.

Analyses investigating heterogeneity in the effects further suggest that the relative impact of education compared to intelligence is stronger for females, for unanticipated health shocks, and for respiratory diseases that require complex treatment such as COPD. Hence, while on average intelligence seems to drive most of the educational disparities in survival gains, for unanticipated health events and for diseases that require difficult adherence regimens, education does improve the efficiency of health investment over and above intelligence.

In terms of policy implications, since intelligence is more important than education for the efficiency of health investment, nudging policies that alters people's behavior without forcing them (see Thaler and Sunstein, 2008) may provide health improvements for all education and intelligence levels. Most people value their health but persist in behaving in ways that undermine it. For highly intelligent people it is easier to reflect on their health behavior and adjust it when necessary. Since nudging can change behavior non-deliberately, thus without using the cognitive system, it could offer new possibilities for encouraging efficient use of health investment to improve survival chances among the least cognitively able. For example, one could change the default option for breathing exercise for COPD patients from one year to half a year, and exclude it from the deductible.

The results further suggest that for diseases that require complex adherence regimens and for unanticipated health shocks, education does seem to provide survival benefits. While we cannot rule out that some non-cognitive abilities such as perseverance and self-control contribute to this educational gain in survival, the results are suggestive that superior (health) knowledge and other skills taught at school imply a non-monetary return: enhanced survival probabilities for certain diseases.

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Tables

Table 1: Descriptive statistics by education level

	Primary	Above primary	All
	14%	86%	
Mortality			
Died	23%	15%	16%
% of which died in hospital	16%	12%	14%
Hospitalization			
# Hospital stays	1.1	0.9	0.9
Emergency entry	49%	43%	44%
Length of stay (days)	10.2	9.3	9.7
Intelligence			
Raven p.m. test	96.29	103.05	102.04
Vocabulary test	94.16	102.73	101.42
Diagnosis at admission			
Neoplasm	11%	16%	15%
Circulatory	30%	25%	26%
Respiratory	11%	4%	5%
Digestive	12%	11%	11%
Control variables			
Male	61%	58%	58%
Birth Rank	2.82	2.44	2.50
Family Socioeconomic Status[1]			
Lowest	66%	47%	49%
Middle	23%	45%	41%
Highest	0%	3%	3%
Child Works	37%	22%	24%
School Religion[1]			
Roman-Catholic	82%	74%	74%
Protestant	14%	19%	19%
Public	4%	7%	7%
Number of Teachers	6.68	6.95	6.92
Repeat[1]			
No Repetition of Grade	33%	66%	61%
Repeated Once	37%	24%	26%
Repeated Twice or More	24%	6%	8%
Teacher's Advice[1]			
Continue Primary School	49%	18%	23%
Lower Vocational Education	37%	35%	36%
Lower Secondary Education	3%	27%	23%
Higher Secondary Education	1%	15%	13%
Preference of the Parents[1]			
Work in Family Company	16%	10%	11%
Paid Work without Vocational Education	33%	7%	10%
Paid Work with Vocational Education	11%	6%	7%
General Secondary Education	19%	65%	58%

[1] Due to missings, percentages do not add up to 100% within Family social class, school religion, repeat, teacher's advice and preference of the parents

Table 2: Parameter estimates simple (no covariates included) stratified model by education level

	Primary education		Above primary	
from healthy[a]	to hospitalized	to death	to hospitalized	to death
(log) constant	−2.209	−12.609	−2.496	−12.122
	(0.050)	(1.794)	(0.023)	(0.846)
age	−	0.126	−	0.112
		(0.027)		(0.013)
from hospitalized[b]	to healthy	to death	to healthy	to death
(log) constant	−2.357	−5.748	−2.255	−6.032
	(0.051)	(0.277)	(0.023)	(0.152)

[a] Duration time from healthy is years since birth.

[b] Duration time from hospitalized is days since hospital admission.

Table 3: Parameter estimates stratified model by education level

	Primary education		Above primary	
from healthy[a]	to hospitalized	to death	to hospitalized	to death
Male	−0.212	0.727**	0.179**	0.717**
	(0.109)	(0.289)	(0.049)	(0.137)
Child is working - base is "No"				
Yes	0.071	0.124	0.136+	0.240
	(0.114)	(0.272)	(0.055)	(0.147)
Missing	−0.352	−1.124	−0.114	0.181
	(0.213)	(0.617)	(0.083)	(0.200)
Family Socioeconomic Status - base is "Low"				
Middle	−0.084	−0.097	−0.040	0.135
	(0.133)	(0.328)	(0.049)	(0.128)
High	−0.084	−0.097	0.217	0.540
	(0.133)	(0.328)	(0.131)	(0.318)
Missing	−0.492+	−0.787	0.013	0.377
	(0.244)	(0.674)	(0.123)	(0.318)
Birthrank - base is "First"				
Second	0.175	−0.589	0.016	−0.130
	(0.185)	(0.409)	(0.071)	(0.176)
Third or Fourth	0.453**	−0.328	0.026	−0.195
	(0.165)	(0.375)	(0.066)	(0.167)
Fifth or higher	0.385+	−0.074	0.073	−0.312
	(0.170)	(0.357)	(0.065)	(0.171)
Missing	0.768**	0.848	0.027	−0.681
	(0.292)	(0.655)	(0.131)	(0.374)
Health status in 1993 - base is "good"				
Poor health	0.419**	−0.604	0.445**	0.317
	(0.149)	(0.519)	(0.066)	(0.189)
Missing	−0.121	0.420	0.042	0.186
	(0.123)	(0.294)	(0.053)	(0.137)
Hospitalization and last diagnosis				
Has been in hospital	1.194**	0.663+	1.351**	0.988**
	(0.135)	(0.299)	(0.056)	(0.142)
Neoplasm	0.789**	1.576**	1.109**	1.659**
	(0.218)	(0.537)	(0.082)	(0.176)
Circulatory	0.404**	0.114	0.444**	0.302
	(0.161)	(0.428)	(0.071)	(0.187)
Respiratory	1.047**	1.696**	0.475**	0.143
	(0.208)	(0.491)	(0.141)	(0.421)
Digestive	0.148	−0.060	−0.155	−0.186
	(0.207)	(0.557)	(0.110)	(0.278)
(log) constant	−2.992	−13.325	−3.318	−11.584
	(0.189)	(1.933)	(0.069)	(0.902)
Age	–	0.125	–	0.087
		(0.028)		(0.014)

[a] Duration time from healthy is years since birth.
$^{+}p < 0.05$ and $^{**}p < 0.01$

Table 3: Parameter estimates stratified model by education level (continued)

	Primary education		Above primary	
from hospitalized[b]	to healthy	to death	to healthy	to death
Male	−0.100	−0.124	0.092	0.128
	(0.114)	(0.589)	(0.050)	(0.335)
Child is working - base is "No"				
Yes	-0.428^{**}	0.299	0.077	−0.736
	(0.117)	(0.650)	(0.056)	(0.453)
Missing	0.072	−0.017	−0.069	−1.081
	(0.220)	(1.162)	(0.085)	(0.667)
Birthrank - base is "First"				
Second	0.059	–	−0.071	-0.918^{+}
	(0.194)		(0.072)	(0.451)
Third or Fourth	0.004	–	-0.169^{**}	−0.009
	(0.177)		(0.067)	(0.491)
Fifth or higher	0.007	–	-0.201^{**}	0.261
	(0.183)		(0.065)	(0.461)
Missing	−0.190	–	-0.380^{**}	0.664
	(0.273)		(0.122)	(0.844)
Health status in 1993 - base is "good"				
Poor health	0.077	0.274	-0.172^{**}	−0.204
	(0.129)	(0.630)	(0.064)	(0.435)
Previous hospitalization and last diagnosis				
Repeated admittance	−0.036	1.127	-0.110^{+}	0.556
	(0.107)	(0.783)	(0.047)	(0.338)
Neoplasm	−0.331	1.419^{+}	-0.313^{**}	2.695^{**}
	(0.187)	(0.657)	(0.069)	(0.502)
Circulatory	0.044	0.645	−0.033	0.692
	(0.139)	(0.796)	(0.061)	(0.580)
Respiratory	-0.413^{+}	–	0.145	1.545^{**}
	(0.200)		(0.118)	(0.739)
Digestive	0.069	–	0.263^{**}	−1.317
	(0.168)		(0.079)	(0.675)
Acute	-0.428^{**}	1.270	-0.365^{**}	1.410^{**}
	(0.106)	(0.778)	(0.049)	(0.361)
(log) constant	−1.772	−8.183	−1.912	−8.736
	(0.211)	(1.158)	(0.072)	(0.709)

[a] Duration time from hospitalized is days since hospital admission.
$^{+}p < 0.05$ and $^{**}p < 0.01$

Table 4: Parameter estimates structural model by education level

	Primary education		Above primary	
from healthy[a]	to hospitalized	to death	to hospitalized	to death
Intelligence	-0.537^{**}	-0.142	-0.561^{**}	-0.649^{**}
	(0.159)	(0.137)	(0.161)	(0.196)
Male	-0.256	0.750^{**}	0.238^{**}	0.717^{**}
	(0.147)	(0.301)	(0.067)	(0.137)
Child is working - base is "No"				
Yes	0.315	0.160	0.076	0.756^{**}
	(0.164)	(0.282)	(0.073)	(0.151)
Missing	0.072	-2.005^{+}	0.003	0.261
	(0.319)	(0.789)	(0.114)	(0.160)
Family Socioeconomic Status - base is "Low"				
Middle	-0.029	-0.035	-0.224^{**}	-0.012
	(0.184)	(0.339)	(0.065)	(0.142)
High	-0.029	-0.035	0.198	0.487
	(0.184)	(0.339)	(0.195)	(0.371)
Missing	-0.698^{+}	-0.462	0.010	0.535
	(0.328)	(0.661)	(0.153)	(0.334)
Birthrank - base is "First"				
Second	0.758^{+}	-0.355	0.107	-0.011
	(0.302)	(0.440)	(0.096)	(0.192)
Third or Fourth	1.034^{**}	-0.117	0.105	-0.157
	(0.286)	(0.413)	(0.085)	(0.183)
Fifth or higher	0.659^{+}	0.073	0.113	-0.343
	(0.265)	(0.383)	(0.086)	(0.189)
Missing	1.368^{**}	1.375^{+}	-0.103	-0.835^{+}
	(0.437)	(0.651)	(0.166)	(0.396)
Health status in 1993 - base is "good"				
Poor health	0.739^{**}	-0.352	0.463^{**}	0.350
	(0.221)	(0.535)	(0.089)	(0.204)
Missing	-0.158	0.590	0.077	0.160
	(0.174)	(0.318)	(0.069)	(0.150)
Hospitalization and last diagnosis				
Has been in hospital	0.397^{+}	0.364	0.849^{**}	0.278
	(0.203)	(0.369)	(0.071)	(0.171)
Neoplasm	1.151^{**}	1.871^{**}	1.184^{**}	2.073^{**}
	(0.254)	(0.553)	(0.100)	(0.188)
Circulatory	0.555^{**}	0.104	0.636^{**}	0.732^{**}
	(0.185)	(0.438)	(0.083)	(0.198)
Respiratory	0.248	1.663^{**}	0.254	0.204
	(0.272)	(0.545)	(0.181)	(0.449)
Digestive	0.394	0.168	-0.053	-0.102
	(0.245)	(0.560)	(0.124)	(0.288)
(log) constant	-3.779	-15.990	-3.396	-14.901
	(0.366)	(2.164)	(0.088)	(1.069)
Age	–	0.159	–	0.137
		(0.031)		(0.016)

[a] Duration time from healthy is years since birth.
$^{+}p < 0.05$ and $^{**}p < 0.01$

Table 4: Parameter estimates structural model by education level (continued)

	Primary education		Above primary	
from hospitalized[b]	to healthy	to death	to healthy	to death
Intelligence	0.092^{+}	0.238	0.116**	0.129
	(0.044)	(0.183)	(0.038)	(0.138)
Male	−0.062	0.062	0.056	0.095
	(0.116)	(0.594)	(0.051)	(0.336)
Child is working - base is "No"				
Yes	−0.494**	0.246	0.084	−0.669
	(0.121)	(0.657)	(0.057)	(0.459)
Missing	−0.068	−0.320	0.045	−0.999
	(0.229)	(1.179)	(0.087)	(0.669)
Birthrank - base is "First"				
Second	−0.066	–	−0.100	0.829
	(0.205)		(0.074)	(0.458)
Third or Fourth	−0.096	–	−0.176**	−0.030
	(0.185)		(0.069)	(0.493)
Fifth or higher	−0.045	–	−0.187**	0.214
	(0.187)		(0.067)	(0.462)
Missing	−0.288	–	−0.330**	0.593
	(0.279)		(0.123)	(0.847)
Health status in 1993 - base is "good"				
Poor health	−0.153	0.079	−0.196**	−0.270
	(0.135)	(0.669)	(0.066)	(0.440)
Previous hospitalization and last diagnosis				
Repeated admittance	0.127	1.562	0.073	0.736
	(0.124)	(0.845)	(0.055)	(0.389)
Neoplasm	−0.297	1.534^{+}	−0.263**	2.740**
	(0.188)	(0.670)	(0.071)	(0.504)
Circulatory	0.047	0.436	−0.074	0.648
	(0.139)	(0.793)	(0.061)	(0.581)
Respiratory	−0.309	–	0.178	1.572^{+}
	(0.203)		(0.120)	(0.738)
Digestive	0.030	–	0.247**	1.288
	(0.171)		(0.080)	(0.676)
Acute	−0.406**	1.352	−0.340**	1.458**
	(0.107)	(0.779)	(0.049)	(0.368)
(log) constant	−1.576	−7.983	−1.837	−8.626
	(0.228)	(1.157)	(0.074)	(0.715)

[b] Duration time from hospitalized is days since hospital admission.
$^{+}p < 0.05$ and $^{**}p < 0.01$

Figures

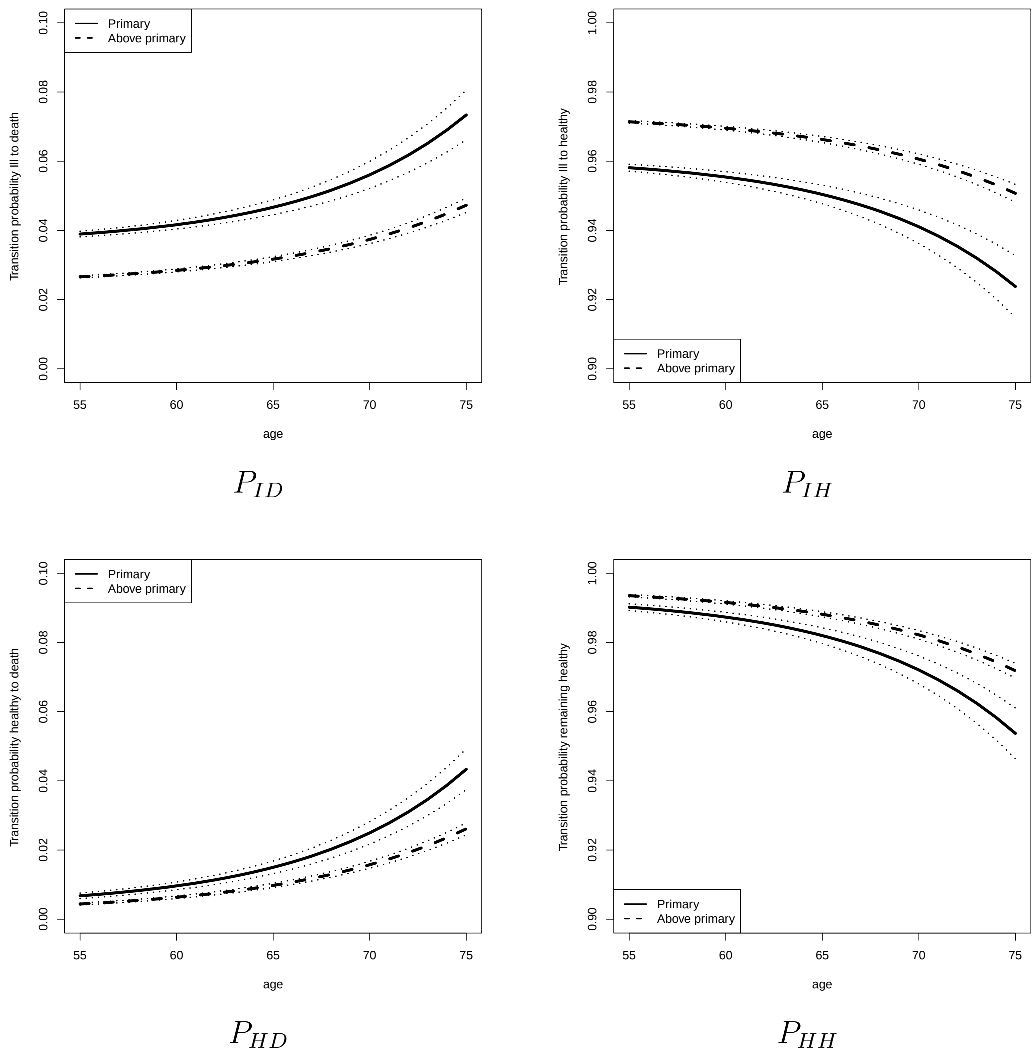
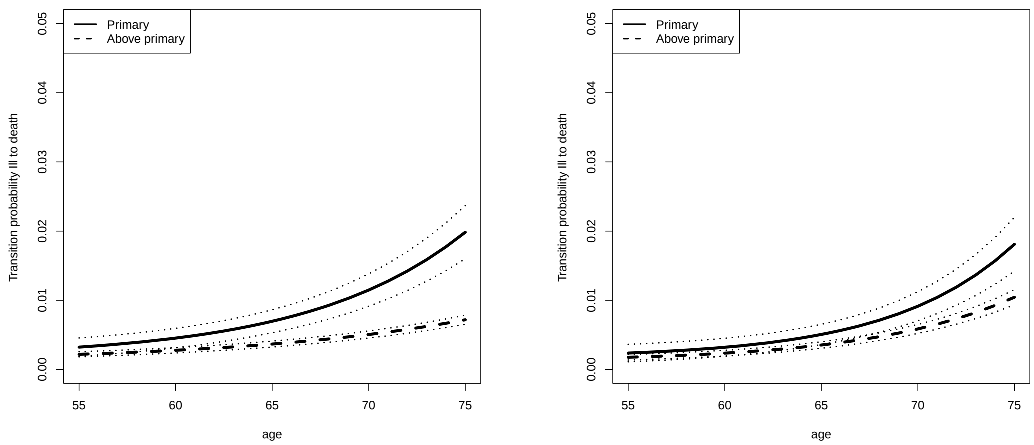
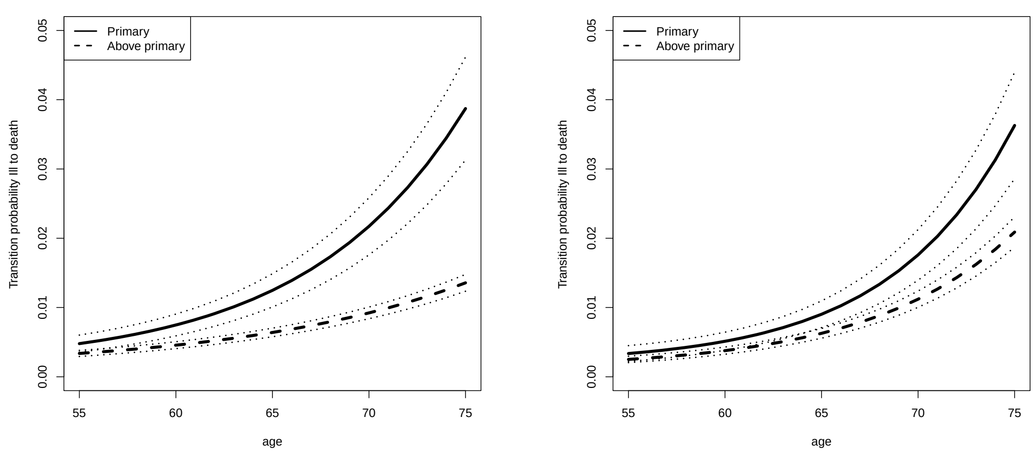


Figure 1: Transition probability over a one year period (and the 95% confidence intervals) by age and education level (model without covariates)



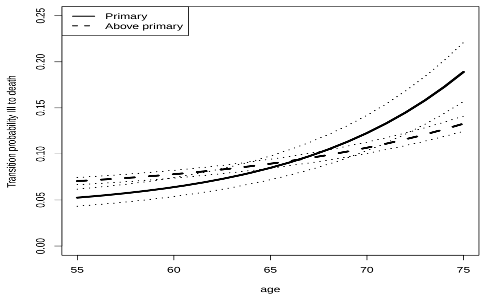
P_{ID}, **stratified** P_{ID}, **structural**

Figure 2: Transition probability over a one year period (and the 95% confidence intervals) from hospitalized to death by education level (stratified and structural model)

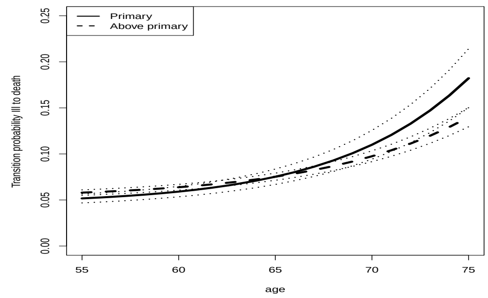


P_{ID}, **stratified** P_{ID}, **structural**

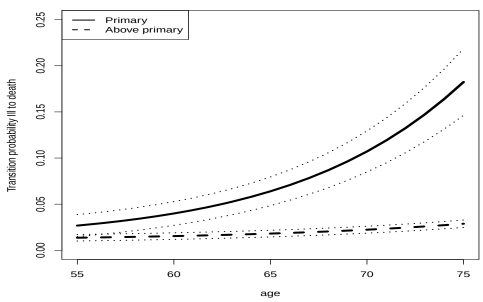
Figure 3: Transition probability over a one year period (and the 95% confidence intervals) from hospitalized to death by education level (stratified and structural model): FEMALES



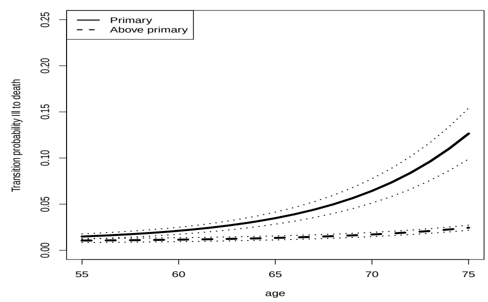
neoplasm, stratified



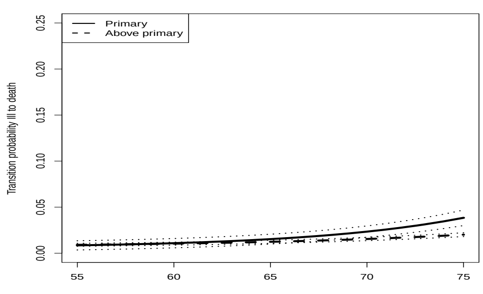
neoplasm, structural



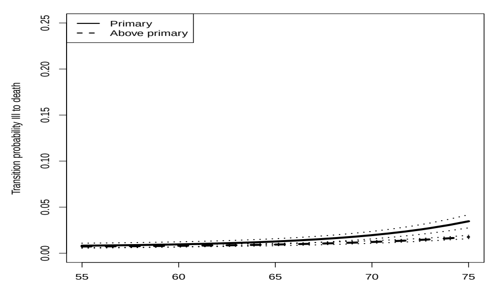
respiratory, stratified



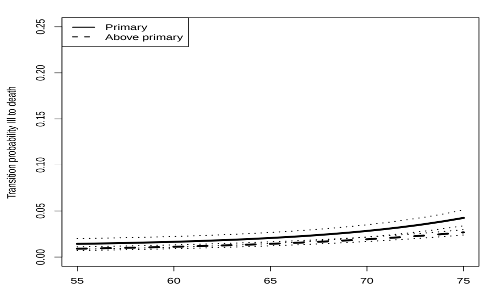
respiratory, structural



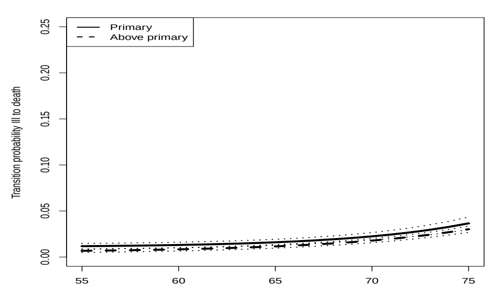
digestive, stratified



digestive, structural

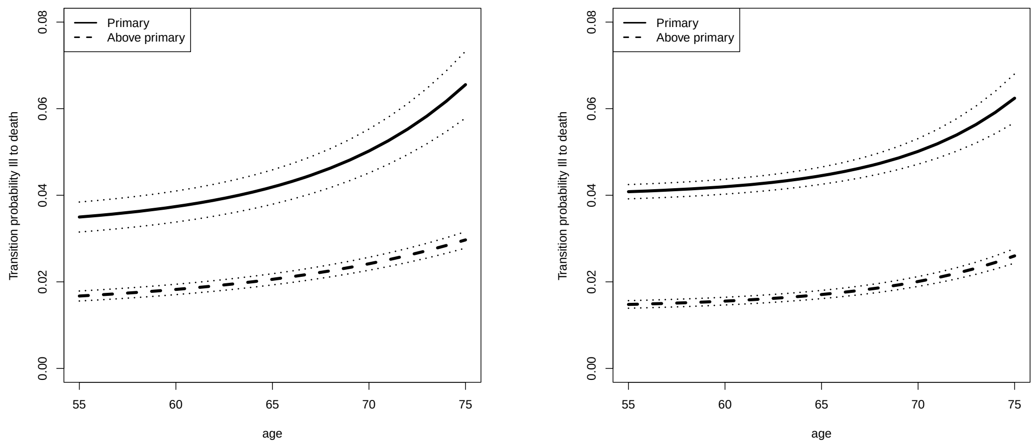


circulatory, stratified



circulatory, structural

Figure 4: Transition probability from hospitalized to death over a one year period by age and education level (stratified and structural model): DIAGNOSES



acute, stratified **acute, structural**

Figure 5: Transition probability from hospitalized to death over a one year period by age and education level (stratified/structural model): ACUTE

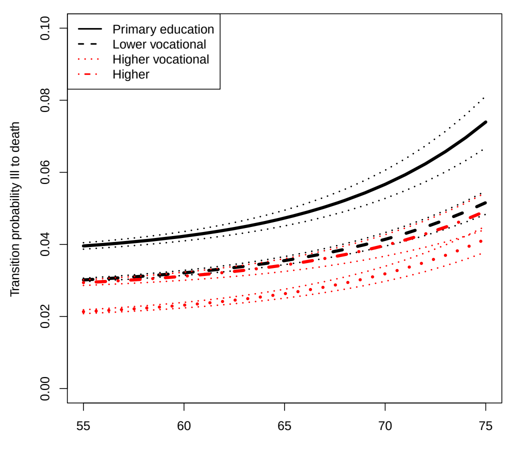


Figure 6: Transition probability from hospitalized to death over a one year period (and the 95% confidence intervals) by age and FOUR education levels (model without covariates)

A Transition probabilities

From (2) and (3) we can derive the analytical solution of the transition probabilities:

$$\begin{aligned}
P_{HH}(s,t) &= \frac{1}{\theta_1-\theta_2}\Big[(\lambda_{HI}+\lambda_{HD}+\theta_1)e^{\theta_2(t-s)} - (\lambda_{HI}+\lambda_{HD}+\theta_2)e^{\theta_1(t-s)}\Big]\\
P_{II}(s,t) &= \frac{1}{\theta_1-\theta_2}\Big[(\lambda_{HI}+\lambda_{HD}+\theta_1)e^{\theta_1(t-s)} - (\lambda_{HI}+\lambda_{HD}+\theta_2)e^{\theta_2(t-s)}\Big]\\
P_{HI}(s,t) &= \frac{\lambda_{HI}}{\theta_1-\theta_2}\Big[e^{\theta_1(t-s)} - e^{\theta_2(t-s)}\Big]\\
P_{IH}(s,t) &= \frac{\lambda_{IH}}{\theta_1-\theta_2}\Big[e^{\theta_1(t-s)} - e^{\theta_2(t-s)}\Big]
\end{aligned}$$

with two non-zero eigenvalues

$$\begin{aligned}
\theta_1 &= -\frac{1}{2}(\lambda_{HI}+\lambda_{IH}+\lambda_{HD}+\lambda_{ID}) + \frac{1}{2}\sqrt{(\lambda_{HI}+\lambda_{HD}-\lambda_{IH}-\lambda_{ID})^2+4\lambda_{HI}\lambda_{IH}}\\
\theta_2 &= -\frac{1}{2}(\lambda_{HI}+\lambda_{IH}+\lambda_{HD}+\lambda_{ID}) - \frac{1}{2}\sqrt{(\lambda_{HI}+\lambda_{HD}-\lambda_{IH}-\lambda_{ID})^2+4\lambda_{HI}\lambda_{IH}}
\end{aligned}$$

and

$$\theta_1-\theta_2 = \sqrt{(\lambda_{HI}+\lambda_{HD}-\lambda_{IH}-\lambda_{ID})^2+4\lambda_{HI}\lambda_{IH}}$$

The probability to die at age t, the transition to death, is $1-P_{HH}(s,t)-P_{HI}(s,t)$ for an individual who is healthy at s and $1-P_{IH}(s,t)-P_{II}(s,t)$ for an individual ill at s.

Kalbfleisch et al. (1983) derive the derivatives of $P(t)$ (provided that $\theta_1 \neq \theta_2 \neq 0$). For $k \in \{HI, HD, IH, ID\}$ we have

$$\frac{\partial P(s,t)}{\partial \lambda_k} = VG_kV^{-1} \tag{A.1}$$

where $G_k(t)$ is and 3 x 3 matrix with (i,j)th element is $M_{ij}^{(k)}$ times $A_{ij}(s,t)$ with

$$A(s,t) = \begin{pmatrix} (t-s)e^{\theta_1(t-s)} & \frac{e^{\theta_1(t-s)}-e^{\theta_2(t-s)}}{\theta_1-\theta_2} & 0\\ \frac{e^{\theta_1(t-s)}-e^{\theta_2(t-s)}}{\theta_1-\theta_2} & (t-s)e^{\theta_2(t-s)} & 0\\ 0 & 0 & 0 \end{pmatrix}$$

and $M_{ij}^{(k)}$ is the (i,j)th element of $V^{-1}(\partial M/\partial\lambda_k)V$. The $\partial M/\partial\lambda_k$ matrices are very simple. e.g.

$$\frac{\partial M}{\partial \lambda_{ID}} = \begin{pmatrix} 0 & 0 & 0\\ 0 & -1 & 1\\ 0 & 0 & 0 \end{pmatrix}$$

B Likelihood

The likelihood contribution of the first spell (either healthy to hospitalized or healthy to death) for individual i, who is only observed (left-truncated) after t_{i0}, is given by

$$\begin{aligned} L_{i1} = & \int \Big[\Phi\big(\gamma X_i^E + \alpha_E \theta\big) \cdot \lambda_{HI}^{(1)}(t_i|X^H,\theta)^{\Delta_{HIi}} \lambda_{HD}^{(1)}(t_i|X^H,\theta)^{\Delta_{HDi}} \cdot \\ & \qquad S_H^{(1)}(t_i|X,\theta)/S_H^{(1)}(t_{i0}|X,\theta)\Big]^{E_i} \\ & \times \Big[\Phi\Big(-\gamma X_i^E - \alpha_E\theta\Big) \cdot \lambda_{HI}^{(0)}(t_i|X^H,\theta)^{\Delta_{HIi}} \lambda_{HD}^{(0)}(t_i|X^H,\theta)^{\Delta_{HDi}} \cdot \\ & \qquad S_H^{(0)}(t_i|X,\theta)/S_H^{(0)}(t_{i0}|X,\theta)\Big]^{1-E_i} \frac{1}{\sigma_M}\phi\Big(\frac{M_i - \delta_1 X_i^M - \alpha_M\theta}{\sigma_M}\Big)\, dH(\theta|T > t_{i0}) \end{aligned}$$

with $\Delta_{HIi} = 1$ if individual i enters hospital before dying and $\Delta_{HDi} = 1$ if individual i dies before entering hospital. The 'total' survival of individual i, the probability that he survives and stays out of hospital up till age t_i is

$$S_H^{(k)}(t|X,\theta) = \exp\Big(-\int_0^t \lambda_{HI}^{(k)}(s|X^H,\theta) + \lambda_{HD}^{(k)}(s|X^H,\theta)\, ds\Big) \quad k = 0,1$$

The distribution of the latent skills conditional on survival up to t_{i0} is

$$dH(\theta|T > t_{i0}) = \frac{\Phi\big(\gamma X_i^E + \alpha_E\theta\big) S_H^{(1)}(t_{i0}|X,\theta) + \Phi\big(-\gamma X_i^E - \alpha_E\theta\big) S_H^{(0)}(t_{i0}|X,\theta) h(\theta)}{\int \Phi\big(\gamma X_i^E + \alpha_E\theta\big) S_H^{(1)}(t_{i0}|X,\theta) + \Phi\big(-\gamma X_i^E - \alpha_E\theta\big) S_H^{(0)}(t_{i0}|X,\theta) h(\theta)\, d\theta}$$

The second spell in the multistate model (only for those who have not died) is either from hospitalized back to healthy or from hospitalized to death. Let $\tau_{i1} = t_{2i} - t_{1i}$, the time since entry to the hospital. Then, the likelihood contribution of the second spell is

$$L_{i2} = \frac{\int f_2(\tau_{i1}|t_{i1},X,\theta)\Big[\Phi\big(\gamma X_i^E + \alpha_E\theta\big) S_H^{(1)}(t_{i1}|X,\theta) + \Phi\big(-\gamma X_i^E - \alpha_E\theta\big) S_H^{(0)}(t_{i1}|X,\theta)\Big] h(\theta)\, d\theta}{\int \Big[\Phi\big(\gamma X_i^E + \alpha_E\theta\big) S_H^{(1)}(t_{i1}|X,\theta) + \Phi\big(-\gamma X_i^E - \alpha_E\theta\big) S_H^{(0)}(t_{i1}|X,\theta)\Big] h(\theta)\, d\theta}$$

with

$$f_{i2}(\tau_{i1}|t_{i1}, X, \theta) =$$
$$\Big[\lambda^{(1)}_{IH}(\tau_{i1}|X^I, t_{i1}, \theta)^{\Delta_{IHi}} \lambda^{(1)}_{ID}(\tau_{i1}|X^I, t_{i1}, \theta)^{\Delta_{IDi}} S^{(1)}_I(t_{i2}|X, \theta)/S^{(1)}_I(t_{i1}|X, \theta)\Big]^{E_i}$$
$$\times \Big[\lambda^{(0)}_{IH}(\tau_{i1}|X^I, t_{i1}, \theta)^{\Delta_{IHi}} \lambda^{(0)}_{ID}(\tau_{i1}|X^I, t_{i1}, \theta)^{\Delta_{IDi}} S^{(0)}_I(t_{i2}|X, \theta)/S^{(0)}_I(t_{i1}|X, \theta)\Big]^{1-E_i}$$

with $\Delta_{IHi} = 1$ if individual i leaves hospital before dying and $\Delta_{IDi} = 1$ if individual i dies in hospital and for $k = 0, 1$

$$S^{(k)}_I(t_{i2}|X, \theta) = S^{(k)}_H(t_{i1}|X, \theta) \exp\Big(-\int_{t_{i1}}^{t_{i1}} \lambda^{(k)}_{IH}(s|X^I, \theta) + \lambda^{(k)}_{ID}(s|X^I, \theta)\, ds\Big)$$

The (possible) third spell in the multistate model is either from healthy back to hospitalized or from healthy to death. Then, the likelihood contribution of the third spell is

$$L_{i3} = \frac{\int f_3(t_{i3}|\theta)\Big[\Phi\big(\gamma X^E_i + \alpha_E\theta\big)S^{(1)}(t_{i2}|X, \theta) + \Phi\big(-\gamma X^E_i - \alpha_E\theta\big)S^{(0)}(t_{i2}|X, \theta)\Big]h(\theta)\, d\theta}{\int \Big[\Phi\big(\gamma X^E_i + \alpha_E\theta\big)S^{(1)}(t_{i2}|X, \theta) + \Phi\big(-\gamma X^E_i - \alpha_E\theta\big)S^{(0)}(t_{i2}|X, \theta)\Big]h(\theta)\, d\theta}$$

with

$$f_3(t_{i3}|t_{i2}, X, \theta) =$$
$$\Big[\lambda^{(1)}_{HI}(t_{i3}|X, \theta)^{\Delta_{HIi}} \lambda^{(1)}_{HD}(t_{i3}|X, \theta)^{\Delta_{HDi}} S^{(1)}(t_{i3}|X, \theta)/S^{(1)}(t_{i2}|X, \theta)\Big]^{E_i}$$
$$\times \Big[\lambda^{(0)}_{HI}(t_{i3}|X, \theta)^{\Delta_{HIi}} \lambda^{(0)}_{HD}(t_{i3}|X, \theta)^{\Delta_{HDi}} S^{(0)}(t_{i3}|X, \theta)/S^{(0)}(t_{i2}|X, \theta)\Big]^{1-E_i}$$

$\Delta_{HIi} = 1$ if individual i enters (for the second time) hospital before dying and $\Delta_{HDi} = 1$ if individual i dies before entering hospital (for the second time) and for $k = 0, 1$

$$S^{(k)}(t_{i3}|X, \theta) = S^{(k)}_I(t_{i2}|X, \theta) \frac{S^{(k)}_{HI}(t_{i3}|X, \theta)}{S^{(k)}_{HI}(t_{i2}|X, \theta)} \frac{S^{(k)}_{HD}(t_{i3}|X, \theta)}{S^{(k)}_{HD}(t_{i2}|X, \theta)}$$

The likelihood contributions for fourth and later spells are similar. The full likelihood (of individual i) is the product of all these terms, L_{i1}, L_{i2}, L_{i3}, etc.

C Additional Tables

Table 5: Parameter estimates structural model by education level (continued)

	Education[c]	Raven test[d]
Intelligence	0.137^{+}	1
	(0.063)	
Male	-0.252^{**}	-0.887
	(0.083)	(0.528)
Child is working - base is "No"		
Yes	-0.207^{+}	-3.767^{**}
	(0.091)	(0.627)
Missing	-0.281^{+}	-1.103
	(0.137)	(0.899)
Family Socioeconomic Status - base is "Low"		
Middle	0.361^{**}	2.570^{**}
	(0.094)	(0.543)
High	0.396	4.242^{**}
	(0.453)	(1.636)
Missing	-0.511^{**}	-4.342^{**}
	(0.175)	(1.294)
Birthrank - base is "First"		
Second	-0.137	0.468
	(0.122)	(0.785)
Third or Fourth	-0.074	-0.263
	(0.113)	(0.733)
Fifth or higher	-0.057	-3.053^{**}
	(0.111)	(0.729)
Missing	0.104	-0.654
	(0.304)	(1.469)
School religion - base is "Catholic"		
Protestant	0.311^{**}	0.626
	(0.106)	(0.682)
Other	0.388^{+}	5.051^{**}
	(0.195)	(1.124)
Number of teachers - base is "5-8 teachers"		
≤ 4	-0.147	-3.837^{**}
	(0.100)	(0.725)
9-12	0.058	0.410
	(0.096)	(0.631)
Missing	0.314	0.843
	(0.215)	(1.298)
Constant	2.109	3.621
	(0.206)	(0.741)

[c] Education choice probit model.

[d] IQ-measurement linear model, centered around IQ = 100.

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

Table 5: Parameter estimates structural model by education level (continued)

	Education[c]	Raven test[d]	θ
Teacher's advice - base is "Lower vocational school"			
Continued primary school	-0.264^{**}		
	(0.090)		
Lower general secondary school	0.459^{**}		
	(0.165)		
Higher general secondary school	0.538^{+}		
	(0.255)		
Missing	-0.543^{+}		
	(0.250)		
Repeat grade - base is "None"			
Once	-0.295^{**}		
	(0.087)		
Twice	-0.709^{**}		
	(0.118)		
Missing	0.751		
	(0.411)		
Preference of the parents - base is "Only vocational education"			
Work in own company	-0.885^{**}		
	(0.190)		
Work without education	-1.357^{**}		
	(0.185)		
Work with education	-0.921^{**}		
	(0.198)		
General secondary school	-0.345		
	(0.179)		
Missing	-0.923^{**}		
	(0.184)		
Distribution of θ			
θ_1			-5.310
			(1.525)
θ_2			0.426
			(0.129)
θ_3			-2.628
			(0.758)
p_1			0.012
			(0.003)
p_2			0.871
			(0.002)
p_3			0.118
			(0.015)

[c] Education choice probit model.
[d] IQ-measurement linear model.
$^{+}p < 0.05$ and $^{**}p < 0.01$

Table 6: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education (model without covariates)

	primary	above primary	diff.	std diff.
age				
55	3.9%	2.7%	$-1.24\%^*$	(0.10%)
56	3.9%	2.7%	$-1.25\%^*$	(0.11%)
57	4.0%	2.7%	$-1.26\%^*$	(0.12%)
58	4.0%	2.8%	$-1.28\%^*$	(0.13%)
59	4.1%	2.8%	$-1.30\%^*$	(0.14%)
60	4.2%	2.8%	$-1.32\%^*$	(0.15%)
61	4.2%	2.9%	$-1.35\%^*$	(0.17%)
62	4.3%	3.0%	$-1.38\%^*$	(0.19%)
63	4.4%	3.0%	$-1.41\%^*$	(0.21%)
64	4.5%	3.1%	$-1.45\%^*$	(0.23%)
65	4.7%	3.2%	$-1.50\%^*$	(0.26%)
66	4.8%	3.3%	$-1.55\%^*$	(0.29%)
67	5.0%	3.4%	$-1.62\%^*$	(0.33%)
68	5.2%	3.5%	$-1.69\%^*$	(0.37%)
69	5.4%	3.6%	$-1.77\%^*$	(0.42%)
70	5.6%	3.7%	$-1.87\%^*$	(0.47%)
71	5.9%	3.9%	$-1.98\%^*$	(0.53%)
72	6.2%	4.1%	$-2.10\%^*$	(0.60%)
73	6.5%	4.3%	$-2.25\%^*$	(0.68%)
74	6.9%	4.5%	$-2.42\%^*$	(0.77%)
75	7.3%	4.7%	$-2.61\%^*$	(0.87%)

$^*p < 0.05$.

Table 7: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education (models with covariates, reference individual)

	Stratified				Structural			
	(0)[a]	(1)[b]	diff.	std diff.	(0)[a]	(1)[b]	diff.	std diff.
age								
55	0.3%	0.2%	−0.10%	(0.16%)	0.2%	0.2%	−0.06%	(0.21%)
56	0.3%	0.2%	−0.11%	(0.16%)	0.2%	0.2%	−0.06%	(0.21%)
57	0.4%	0.2%	−0.13%	(0.16%)	0.3%	0.2%	−0.07%	(0.21%)
58	0.4%	0.3%	−0.14%	(0.16%)	0.3%	0.2%	−0.07%	(0.21%)
59	0.4%	0.3%	−0.16%	(0.17%)	0.3%	0.2%	−0.08%	(0.22%)
60	0.5%	0.3%	−0.18%	(0.17%)	0.3%	0.2%	−0.09%	(0.22%)
61	0.5%	0.3%	−0.20%	(0.17%)	0.3%	0.3%	−0.09%	(0.22%)
62	0.5%	0.3%	−0.22%	(0.18%)	0.4%	0.3%	−0.10%	(0.22%)
63	0.6%	0.3%	−0.25%	(0.18%)	0.4%	0.3%	−0.12%	(0.23%)
64	0.6%	0.3%	−0.29%	(0.19%)	0.5%	0.3%	−0.13%	(0.23%)
65	0.7%	0.4%	−0.33%	(0.20%)	0.5%	0.4%	−0.15%	(0.24%)
66	0.8%	0.4%	−0.38%	(0.21%)	0.6%	0.4%	−0.18%	(0.24%)
67	0.8%	0.4%	−0.43%	(0.22%)	0.6%	0.4%	−0.20%	(0.25%)
68	0.9%	0.4%	−0.49%*	(0.24%)	0.7%	0.5%	−0.24%	(0.26%)
69	1.0%	0.5%	−0.56%*	(0.26%)	0.8%	0.5%	−0.28%	(0.28%)
70	1.1%	0.5%	−0.64%*	(0.28%)	0.9%	0.6%	−0.33%	(0.30%)
71	1.3%	0.5%	−0.74%*	(0.30%)	1.0%	0.7%	−0.39%	(0.33%)
72	1.4%	0.6%	−0.84%*	(0.33%)	1.2%	0.7%	−0.46%	(0.36%)
73	1.6%	0.6%	−0.97%*	(0.37%)	1.4%	0.8%	−0.54%	(0.40%)
74	1.8%	0.7%	−1.11%*	(0.41%)	1.6%	0.9%	−0.64%	(0.45%)
75	2.0%	0.7%	−1.27%*	(0.45%)	1.8%	1.0%	−0.77%	(0.50%)

[a] Transition probability for $E = 0$, primary education.
[b] Transition probability for $E = 1$, above primary education.
$^{*}p < 0.05$.

Table 8: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education: FEMALES

	Stratified				Structural			
	(0)[a]	(1)[b]	diff.	std diff.	(0)[a]	(1)[b]	diff.	std diff.
age								
55	0.5%	0.3%	−0.14%	(0.15%)	0.3%	0.3%	−0.08%	(0.21%)
56	0.5%	0.4%	−0.16%	(0.16%)	0.4%	0.3%	−0.09%	(0.22%)
57	0.6%	0.4%	−0.19%	(0.16%)	0.4%	0.3%	−0.10%	(0.22%)
58	0.6%	0.4%	−0.22%	(0.17%)	0.4%	0.3%	−0.11%	(0.22%)
59	0.7%	0.4%	−0.25%	(0.18%)	0.5%	0.3%	−0.12%	(0.23%)
60	0.7%	0.5%	−0.29%	(0.19%)	0.5%	0.4%	−0.14%	(0.23%)
61	0.8%	0.5%	−0.34%	(0.20%)	0.6%	0.4%	−0.15%	(0.24%)
62	0.9%	0.5%	−0.39%	(0.22%)	0.6%	0.5%	−0.18%	(0.25%)
63	1.0%	0.6%	−0.45%	(0.24%)	0.7%	0.5%	−0.20%	(0.26%)
64	1.1%	0.6%	−0.53%*	(0.26%)	0.8%	0.6%	−0.24%	(0.27%)
65	1.2%	0.6%	−0.61%*	(0.29%)	0.9%	0.6%	−0.28%	(0.29%)
66	1.4%	0.7%	−0.70%*	(0.32%)	1.0%	0.7%	−0.32%	(0.31%)
67	1.6%	0.7%	−0.81%*	(0.35%)	1.2%	0.8%	−0.38%	(0.34%)
68	1.7%	0.8%	−0.94%*	(0.39%)	1.3%	0.9%	−0.45%	(0.38%)
69	1.9%	0.9%	−1.08%*	(0.44%)	1.5%	1.0%	−0.54%	(0.43%)
70	2.2%	0.9%	−1.25%*	(0.49%)	1.8%	1.1%	−0.64%	(0.48%)
71	2.4%	1.0%	−1.44%*	(0.55%)	2.0%	1.3%	−0.76%	(0.54%)
72	2.7%	1.1%	−1.66%*	(0.61%)	2.3%	1.4%	−0.91%	(0.62%)
73	3.1%	1.2%	−1.91%*	(0.69%)	2.7%	1.6%	−1.08%	(0.71%)
74	3.4%	1.3%	−2.19%*	(0.78%)	3.1%	1.8%	−1.29%	(0.82%)
75	3.9%	1.4%	−2.52%*	(0.87%)	3.6%	2.1%	−1.54%	(0.94%)

[a] Transition probability for $E = 0$, primary education.
[b] Transition probability for $E = 1$, above primary education.
$^{*}p < 0.05$.

Table 9: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education: diagnosis

	Stratified				Structural			
	(0)[a]	(1)[b]	diff.	std diff.	(0)[a]	(1)[b]	diff.	std diff.
age				diagnosis: *neoplasm*				
55	5.3%	7.1%	1.80%	(1.17%)	5.2%	5.8%	0.63%	(0.60%)
56	5.4%	7.2%	1.75%	(1.18%)	5.3%	5.9%	0.61%	(0.61%)
57	5.6%	7.3%	1.68%	(1.20%)	5.4%	6.0%	0.59%	(0.63%)
58	5.9%	7.5%	1.61%	(1.22%)	5.5%	6.1%	0.56%	(0.64%)
59	6.1%	7.6%	1.51%	(1.25%)	5.7%	6.2%	0.52%	(0.66%)
60	6.4%	7.8%	1.40%	(1.28%)	5.9%	6.4%	0.47%	(0.69%)
61	6.7%	8.0%	1.27%	(1.32%)	6.1%	6.6%	0.41%	(0.72%)
62	7.1%	8.2%	1.11%	(1.37%)	6.4%	6.8%	0.34%	(0.77%)
63	7.5%	8.4%	0.92%	(1.43%)	6.7%	7.0%	0.25%	(0.83%)
64	8.0%	8.7%	0.71%	(1.51%)	7.1%	7.2%	0.14%	(0.90%)
65	8.5%	8.9%	0.45%	(1.60%)	7.5%	7.5%	0.01%	(0.99%)
66	9.1%	9.2%	0.15%	(1.70%)	8.0%	7.9%	−0.17%	(1.10%)
67	9.8%	9.6%	−0.20%	(1.83%)	8.6%	8.2%	−0.37%	(1.24%)
68	10.5%	9.9%	−0.60%	(1.97%)	9.3%	8.7%	−0.61%	(1.40%)
69	11.3%	10.3%	−1.06%	(2.14%)	10.1%	9.2%	−0.90%	(1.59%)
70	12.3%	10.7%	−1.60%	(2.34%)	11.0%	9.8%	−1.25%	(1.83%)
71	13.3%	11.1%	−2.21%	(2.56%)	12.1%	10.4%	−1.67%	(2.10%)
72	14.5%	11.6%	−2.91%	(2.82%)	13.3%	11.1%	−2.16%	(2.41%)
73	15.8%	12.1%	−3.70%	(3.12%)	14.7%	12.0%	−2.74%	(2.79%)
74	17.3%	12.7%	−4.60%	(3.45%)	16.3%	12.9%	−3.43%	(3.22%)
75	18.9%	13.3%	−5.62%	(3.83%)	18.2%	14.0%	−4.23%	(3.72%)
age				diagnosis: *circulatory diseases*				
55	1.4%	0.9%	−0.52%	(0.71%)	1.2%	0.7%	−0.50%	(0.52%)
56	1.5%	0.9%	−0.52%	(0.71%)	1.2%	0.7%	−0.50%	(0.52%)
57	1.5%	1.0%	−0.52%	(0.71%)	1.2%	0.7%	−0.49%	(0.52%)
58	1.6%	1.0%	−0.53%	(0.71%)	1.3%	0.8%	−0.49%	(0.52%)
59	1.6%	1.1%	−0.53%	(0.71%)	1.3%	0.8%	−0.48%	(0.52%)
60	1.7%	1.1%	−0.54%	(0.71%)	1.3%	0.8%	−0.47%	(0.52%)
61	1.7%	1.2%	−0.55%	(0.72%)	1.4%	0.9%	−0.47%	(0.52%)
62	1.8%	1.2%	−0.56%	(0.72%)	1.4%	0.9%	−0.46%	(0.53%)
63	1.9%	1.3%	−0.58%	(0.73%)	1.5%	1.0%	−0.46%	(0.53%)
64	2.0%	1.4%	−0.60%	(0.73%)	1.5%	1.1%	−0.45%	(0.54%)
65	2.1%	1.4%	−0.63%	(0.74%)	1.6%	1.2%	−0.45%	(0.54%)
66	2.2%	1.5%	−0.67%	(0.75%)	1.7%	1.3%	−0.44%	(0.55%)
67	2.3%	1.6%	−0.71%	(0.76%)	1.8%	1.4%	−0.44%	(0.56%)
68	2.5%	1.7%	−0.76%	(0.78%)	1.9%	1.5%	−0.45%	(0.57%)
69	2.6%	1.8%	−0.83%	(0.80%)	2.1%	1.6%	−0.45%	(0.59%)
70	2.8%	1.9%	−0.91%	(0.82%)	2.3%	1.8%	−0.46%	(0.54%)
71	3.1%	2.1%	−1.00%	(0.85%)	2.5%	2.0%	−0.48%	(0.57%)
72	3.3%	2.2%	−1.11%	(0.89%)	2.7%	2.2%	−0.50%	(0.62%)
73	3.6%	2.3%	−1.24%	(0.93%)	3.0%	2.4%	−0.53%	(0.67%)
74	3.9%	2.5%	−1.39%	(0.98%)	3.3%	2.7%	−0.58%	(0.74%)
75	4.3%	2.7%	−1.57%	(1.05%)	3.7%	3.0%	−0.64%	(0.83%)

[a] Transition probability for $E = 0$, primary education.
[b] Transition probability for $E = 1$, above primary education.
$^{*}p < 0.05$.

Table 9: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education: diagnosis (continued)

	Stratified				Structural			
	(0)[a]	(1)[b]	diff.	std diff.	(0)[a]	(1)[b]	diff.	std diff.
age	diagnosis: *respiratory diseases*							
55	2.7%	1.4%	−01.32%	(1.44%)	1.5%	1.1%	−0.44%	(0.67%)
56	2.9%	1.4%	−01.49%	(1.45%)	1.6%	1.1%	−0.51%	(0.67%)
57	3.1%	1.4%	−01.69%	(1.47%)	1.7%	1.1%	−0.60%	(0.68%)
58	3.4%	1.5%	−01.91%	(1.49%)	1.8%	1.1%	−0.70%	(0.69%)
59	3.7%	1.5%	−02.16%	(1.51%)	2.0%	1.1%	−0.82%	(0.71%)
60	4.0%	1.5%	−02.45%	(1.54%)	2.1%	1.2%	−0.97%	(0.73%)
61	4.4%	1.6%	−02.78%	(1.58%)	2.3%	1.2%	−1.13%	(0.75%)
62	4.8%	1.6%	−03.15%	(1.63%)	2.5%	1.2%	−1.33%	(0.79%)
63	5.3%	1.7%	−03.57%*	(1.69%)	2.8%	1.3%	−1.56%	(0.83%)
64	5.8%	1.8%	−04.05%*	(1.76%)	3.1%	1.3%	−1.83%*	(0.88%)
65	6.4%	1.8%	−04.58%*	(1.85%)	3.5%	1.3%	−2.14%*	(0.95%)
66	7.1%	1.9%	−05.19%*	(1.96%)	3.9%	1.4%	−2.51%*	(1.04%)
67	7.8%	2.0%	−05.87%*	(2.08%)	4.4%	1.5%	−2.94%*	(1.15%)
68	8.7%	2.0%	−06.64%*	(2.23%)	5.0%	1.5%	−3.45%*	(1.28%)
69	9.6%	2.1%	−07.51%*	(2.41%)	5.7%	1.6%	−4.04%*	(1.44%)
70	10.7%	2.2%	−08.48%*	(2.61%)	6.4%	1.7%	−4.72%*	(1.64%)
71	11.9%	2.3%	−09.57%*	(2.85%)	7.4%	1.8%	−5.52%*	(1.86%)
72	13.3%	2.5%	−10.79%*	(3.13%)	8.4%	2.0%	−6.45%*	(2.14%)
73	14.7%	2.6%	−12.15%*	(3.44%)	9.6%	2.1%	−7.53%*	(2.45%)
74	16.4%	2.7%	−13.67%*	(3.80%)	11.0%	2.3%	−8.77%*	(2.83%)
75	18.2%	2.9%	−15.36%*	(4.21%)	12.7%	2.5%	−10.20%*	(3.26%)
age	diagnosis: *digestive diseases*							
55	0.9%	0.9%	0.06%	(0.61%)	0.8%	0.7%	−0.09%	(0.48%)
56	0.9%	0.9%	0.04%	(0.61%)	0.8%	0.7%	−0.10%	(0.48%)
57	0.9%	1.0%	0.02%	(0.61%)	0.9%	0.8%	−0.11%	(0.48%)
58	1.0%	1.0%	0.00%	(0.61%)	0.9%	0.8%	−0.12%	(0.49%)
59	1.0%	1.0%	−0.02%	(0.61%)	0.9%	0.8%	−0.14%	(0.49%)
60	1.1%	1.0%	−0.05%	(0.62%)	1.0%	0.8%	−0.16%	(0.49%)
61	1.2%	1.1%	−0.08%	(0.62%)	1.0%	0.8%	−0.18%	(0.49%)
62	1.2%	1.1%	−0.13%	(0.63%)	1.1%	0.8%	−0.21%	(0.49%)
63	1.3%	1.1%	−0.17%	(0.63%)	1.1%	0.9%	−0.24%	(0.50%)
64	1.4%	1.2%	−0.23%	(0.64%)	1.2%	0.9%	−0.28%	(0.50%)
65	1.5%	1.2%	−0.29%	(0.65%)	1.3%	0.9%	−0.33%	(0.51%)
66	1.7%	1.3%	−0.37%	(0.66%)	1.4%	1.0%	−0.39%	(0.52%)
67	1.8%	1.3%	−0.45%	(0.68%)	1.5%	1.0%	−0.46%	(0.54%)
68	2.0%	1.4%	−0.55%	(0.69%)	1.6%	1.1%	−0.54%	(0.55%)
69	2.1%	1.5%	−0.67%	(0.72%)	1.8%	1.1%	−0.63%	(0.58%)
70	2.3%	1.5%	−0.80%	(0.75%)	2.0%	1.2%	−0.74%	(0.61%)
71	2.6%	1.6%	−0.95%	(0.78%)	2.2%	1.3%	−0.88%	(0.64%)
72	2.8%	1.7%	−1.13%	(0.82%)	2.4%	1.4%	−1.04%	(0.69%)
73	3.1%	1.8%	−1.33%	(0.87%)	2.7%	1.5%	−1.22%	(0.75%)
74	3.5%	1.9%	−1.56%	(0.93%)	3.1%	1.6%	−1.44%	(0.83%)
75	3.8%	2.0%	−1.83%	(1.01%)	3.5%	1.8%	−1.71%	(0.92%)

[a] Transition probability for $E = 0$, primary education.
[b] Transition probability for $E = 1$, above primary education.
$^{*}p < 0.05$.

Table 10: Transition probability *from hospital to death*, $P_{ID}(t)$, within one year and difference by education: emergency admittance

	Stratified				Structural			
	(0)[a]	(1)[b]	diff.	std diff.	(0)[a]	(1)[b]	diff.	std diff.
age								
55	3.5%	1.7%	$-1.82\%^*$	(0.42%)	4.1%	1.5%	$-2.60\%^*$	(0.36%)
56	3.5%	1.7%	$-1.84\%^*$	(0.43%)	4.1%	1.5%	$-2.61\%^*$	(0.36%)
57	3.6%	1.7%	$-1.85\%^*$	(0.43%)	4.1%	1.5%	$-2.62\%^*$	(0.36%)
58	3.6%	1.8%	$-1.87\%^*$	(0.43%)	4.1%	1.5%	$-2.62\%^*$	(0.37%)
59	3.7%	1.8%	$-1.89\%^*$	(0.43%)	4.2%	1.5%	$-2.63\%^*$	(0.37%)
60	3.7%	1.8%	$-1.91\%^*$	(0.44%)	4.2%	1.6%	$-2.64\%^*$	(0.37%)
61	3.8%	1.9%	$-1.94\%^*$	(0.44%)	4.2%	1.6%	$-2.66\%^*$	(0.37%)
62	3.9%	1.9%	$-1.98\%^*$	(0.45%)	4.3%	1.6%	$-2.67\%^*$	(0.37%)
63	4.0%	2.0%	$-2.02\%^*$	(0.46%)	4.3%	1.6%	$-2.69\%^*$	(0.38%)
64	4.1%	2.0%	$-2.07\%^*$	(0.47%)	4.4%	1.7%	$-2.72\%^*$	(0.38%)
65	4.2%	2.1%	$-2.13\%^*$	(0.48%)	4.5%	1.7%	$-2.75\%^*$	(0.39%)
66	4.3%	2.1%	$-2.20\%^*$	(0.50%)	4.5%	1.8%	$-2.78\%^*$	(0.40%)
67	4.5%	2.2%	$-2.28\%^*$	(0.52%)	4.6%	1.8%	$-2.82\%^*$	(0.41%)
68	4.6%	2.3%	$-2.37\%^*$	(0.55%)	4.7%	1.9%	$-2.87\%^*$	(0.42%)
69	4.8%	2.3%	$-2.48\%^*$	(0.58%)	4.9%	1.9%	$-2.93\%^*$	(0.44%)
70	5.0%	2.4%	$-2.60\%^*$	(0.61%)	5.0%	2.0%	$-3.01\%^*$	(0.47%)
71	5.3%	2.5%	$-2.75\%^*$	(0.66%)	5.2%	2.1%	$-3.09\%^*$	(0.50%)
72	5.5%	2.6%	$-2.92\%^*$	(0.71%)	5.4%	2.2%	$-3.20\%^*$	(0.54%)
73	5.8%	2.7%	$-3.11\%^*$	(0.77%)	5.6%	2.3%	$-3.32\%^*$	(0.59%)
74	6.2%	2.8%	$-3.33\%^*$	(0.84%)	5.9%	2.5%	$-3.47\%^*$	(0.65%)
75	6.6%	3.0%	$-3.59\%^*$	(0.92%)	6.2%	2.6%	$-3.64\%^*$	(0.73%)

[a] Transition probability for $E = 0$, primary education.
[b] Transition probability for $E = 1$, above primary education.
$^*p < 0.05$.