Stockholm School of Economics
Department of Economics
Master's Thesis

THE HEALTH RETURNS TO EDUCATION

A STUDY OF SWEDISH TWINS

Abstract

Prior research has uncovered a large and positive association between education and health, but the literature suffers from difficulties to correctly control for unobserved factors correlated with both education and health, such as genetic traits and family background. This shortcoming may cause an ability bias that leads to an overestimation of the effect of education on health. Our thesis uses new data on Swedish monozygotic twins and a twin-differencing strategy to examine whether there is a direct effect of education on health. With twin-differencing we significantly reduce the bias from unobserved factors. In addition, we use data on IQ and birthweight to allow for abilities to differ between twins. Our results suggest that the effect of education on health is overestimated, and possibly entirely due to ability bias.

Key words: *health production, education, schooling, twins, returns to education, ability bias*

Authors: Ellen Bernhardtson♠ & Linnéa Graaf♣
Tutor: Magnus Johannesson
Examiner: Niklas Zethraeus
Discussant: Erik Dahlberg

Presentation: June 5, 2009, 10.15-12.00 in room 730

Acknowledgment: We would like to thank our tutor Magnus Johannesson for all his invaluable advice and support throughout the thesis work.

♠ 20191@student.hhs.se ♣ 20060@studenthhs.se

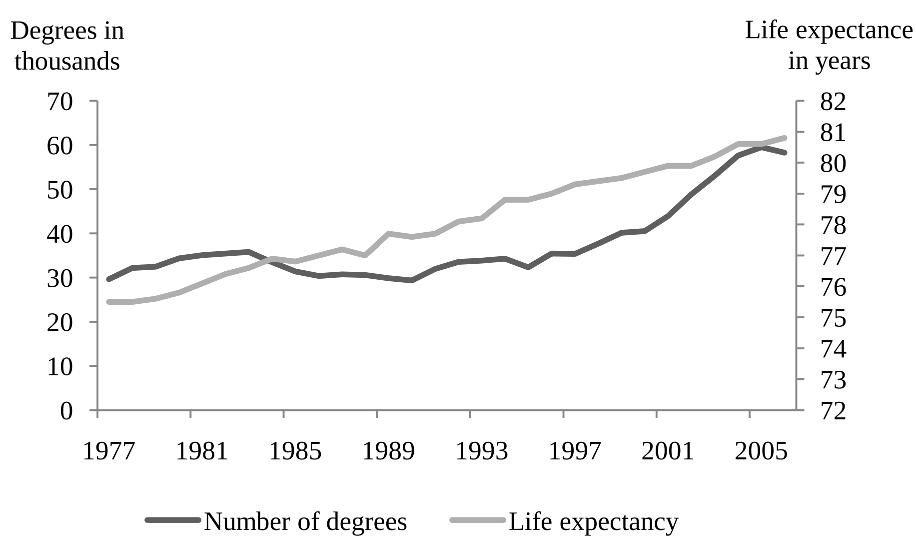
Table of contents

1. Introduction

The association between education and health is widely recognized and has been observed in many countries, time periods and for several measures of health. However, even though the magnitude and causality of this relationship have been much studied in the literature, results remain inconclusive (Cutler and Lleras-Muney 2008).

A frequent explanation of the link between education and health is related to the household production function and suggests that more educated people are more efficient producers of health, which implies a positive and causal impact of education on health. Another strand of literature argues that causality runs the other way, as students in better health profit more from education. Other studies raise doubts whether a causal relationship exists at all, or if it arises from omitted factors that are correlated with both education and health, such as genetic traits and family background (Cutler and Lleras-Muney 2008). These omitted factors are often referred to as abilities and, if not controlled for, their presence causes an overestimation of the effect of education on health, called ability bias. In this view, it cannot be ruled out that the entire effect of education on health is a result of ability bias.

Figure 1.1 Number of academic degrees and life expectancy in Sweden, 1977-2007.



Source: OECD, *Country statistical profiles* (various years) and Statistics Sweden, *Statistikdatabasen*.

Despite the so far inconclusive results, several countries use investments in education as a mean to reduce health inequalities in the population.[1] From a policy perspective it is hence crucial to determine whether there is a causal relationship between education and health, or if it is merely a consequence of overestimation due to ability bias.

Up to now, few studies have been able to correctly control for abilities, often because of difficulties observing and measuring them (Cutler and Lleras-Muney 2008). In other areas of research, a popular way of controlling for abilities without observing or measuring them is by using data on twins and employing a within-twin-pair differencing method (henceforth called twin-differencing).[2] To our knowledge, there is only one previous study using twin-differencing to estimate the effect of education on health. Surprisingly, and contrary to theory, this study finds no evidence of ability bias in previous estimates, but instead a stronger relationship between education and health when controlling for underlying abilities (Lundborg 2008). However, Lundborg (2008) makes the assumption of all abilities being equal within twin pairs while there is evidence that twins differ in certain aspects of ability, for instance IQ (Sandewall 2009). If abilities differ, twin-differencing also leads to overestimation of the effect of education on health.

With new data on Swedish monozygotic (MZ) twins based on a survey in 2005 and by adopting a twin-differencing method to control for abilities, we aim to reexamine whether there exists a direct relationship between education and health. In addition, we allow for abilities to differ between twins by using data on IQ and birthweight. To estimate the magnitude of the ability bias, we also examine the effect of education on health for cross-sectional data. As far as we know, no previous study uses a twin-differencing method to examine the relationship between education and health and also allows for ability differences within twin pairs.

We consider only the direct effects of education on health and not the indirect effects working through income and occupation. Policy implications, although interesting and important, will only be discussed briefly in the end of the thesis.

---

[1] See for instance the report "Tackling Health Inequalities: 10 Years on" from the UK Department of Health.

[2] Behrman and Taubman (1976), Taubman (1976), Ashenfelter and Krueger (1994) and Bonjour *et al.* (2003) are examples of studies that use twin-differencing.

This thesis is structured as follows: section two provides an overview of the theoretical background and the main findings of previous research. Section three describes the twin-differencing methodology and section four describes our MZ twin dataset. In section five our results are presented together with robustness checks. Section six includes a discussion on the results and in section seven we present our conclusions.

2. Theoretical background and previous research

This section provides a brief background to the different explanations of the observed relationship between education and health and some of the research on the subject. Since there is a large literature available, we highlight only the most influential work and the research most closely related to our study.

2.1 Three different explanations

There are basically three hypotheses explaining the link between education and health. The following section is based on Grossman and Kaestner (1997) where not indicated otherwise.

The first explanation suggests a causal relationship that runs from education to health. This explanation is closely linked to the household production function model and its defenders argue that education makes people more efficient producers of health. The effect can take two forms: productive efficiency, where more educated people obtain more health output from a given amount of inputs, and allocative efficiency, where more educated people are able to choose a better mix of health inputs than their less educated peers. A further explanation with the same direction of causality suggests that education changes preferences in a way that favors health relative to other commodities. However, this explanation cannot be completely distinguished from allocative efficiency.

The second explanation is referred to as the “third variable” explanation and suggests that health and education are related through unobservables and omitted variables, such as family background, genetic traits or personal characteristics. This explanation suggests that there is no causal relationship between education and health, but that the positive correlation results from omitted variables that affect education and health in the same way. As explained by Folland *et al.* (2007), people who choose a higher level of education may have unobserved characteristics which also make them more likely to be healthy. This explanation is what we aim to further examine in this thesis.

The third explanation suggests that healthier students more efficiently add to their stock of knowledge. This means that the positive correlation between education and health results from reverse causality; it runs from health to education.

2.2 Previous research

According to an overview of the empirical research on the relationship between education and health by Grossman (2006, p. 600), an influential researcher in the field and a proponent of the first explanation, "years of formal schooling completed is the most important correlate of good health". This effect is stable for different measures of health: self-reported health, mortality, disability, and work-loss days. Furthermore, education seems to be a more important correlate of health than both occupation and income.

There are a large number of studies related to the first explanation. One of the more influential is Wagstaff (1986). He uses data from the Danish Welfare Survey which includes nineteen indicators of health and control variables in the form of family size, sex, marital status and degree of urbanization. Wagstaff (1986) aggregates the nineteen indicators to one measure of the stock of health and reports a positive and significant effect of education on health. Gilleskie and Harrison (1998) more directly test the productive efficiency hypothesis by estimating a health production function with inputs such as regular exercise and doctor visits. In addition they control for past health through the number of chronic conditions and body mass index (BMI), which is a measure of obesity. Gilleskie and Harrison (1998) also report a significant and positive effect of schooling on health, except that for males an additional year of schooling slightly reduces the probability of being in excellent health.

Several studies deal with allocative efficiency. One of the earliest was Leigh (1983) who shows that most of the effect of education on health can be explained by decisions on smoking, exercise and occupation. This result is in accordance with allocative efficiency, but it also provides support for the theory that education influences preferences. More recent research uses the introduction of new information or technology to test for allocative efficiency. One example is de Walque (2004) who showed that cigarette smoking fell more rapidly when the education levels increased in the 1960s and 1970s. This suggests that those who are more educated make better use of the new information about the harmful effects of smoking when controlling for age, race, sex and family income.

In the case of Sweden, Bolin *et al.* (2002) use data from The Swedish Survey of Living Conditions and report that schooling raises the probability of being in the highest health category and reduces the probability of being in the lowest or intermediate categories.

A few studies challenge the abovementioned findings, such as Behrman *et al.* (1991) who find that income and marital status but not education are significant predictors of the conditional probability of death at a certain age.[3] Behrman et al. (1991, p.187) raise concerns about "unobserved heterogeneities" influencing their estimates but do not control for them.

As mentioned in the previous section, the second explanation suggests that education and health are related through omitted variables or unobservables. A major proponent of this hypothesis is Fuchs (1982). He refers to the relationship between health behavior and health and argues that, from an economic point of view, this can be described as a trade-off between current costs and future benefits. If individuals have different abilities to undertake such investments they can be said to have different time preferences. Differences in time preferences also apply to the choice of educational level. According to Fuchs (1982) people that are more future-oriented chose more schooling and make larger investments in their health. The results from Fuchs (1982) study, in which he tries to measure the time preference of individuals, give some, but rather weak support of a relationship between time preference and education. For health status, the effect of time preference is significant only for males and not for all measures of health.

Other dimensions of ability are also investigated as potentially omitted variables. Hartog and Oosterbeek (1998) estimate the effect of education on health controlling for IQ and family background through parents' education and occupation as well as family social status as indicated by schoolteachers in sixth grade. They find a substantial effect of education on health, but the magnitude varies with level of education. While schooling at lower levels also improves health, the largest effect results from secondary level education. They also report that IQ has a

[3] See also Duleep (1986) and Menchik (1993) for similar results.

significant and independent effect on health even when schooling is controlled for, whereas family background has no impact on health.

Case *et al.* (2005) examines the third explanation and the possibility of reverse causality. They find that poor childhood health leads to lower educational attainment and poorer health as an adult. The results remain robust when controlling for family background in the form of social class, family income and parental health and education.

In his study of school children and eradication campaigns for hookworm in the early 1900s American South, Bleakley (2007) also investigate the reverse causality hypothesis. He finds that areas with high hookworm infection rates prior to the campaign experienced increases in school enrollment, attendance and literacy after treatment in comparison with less infected areas. However, there are indications that a substantial gain in income coincided with the campaigns.

Another strand of literature uses educational reforms as natural experiments to investigate the causality. The use of educational reforms as instruments for education is advantageous as the reforms most likely are uncorrelated with unobserved determinants of health. Lleras-Muney (2005, p. 189), criticizes earlier studies for not having "ascertained whether the relationship between education and health is causal" and use reforms of compulsory schooling laws in the U.S. to determine the direction of causality. Lleras-Muney (2005) finds a large and causal impact of education on mortality. The use of educational reforms as natural experiments have been criticized for only affecting those at the lower end of the education distribution, while having little or no effect on students planning to continue to further studies anyway.

To summarize, much of the previous research suggests a significant, positive and causal relationship running from education to health, but there are also indications that omitted variables influence the relationship or that it is due to reverse causality. Furthermore, there are underlying difficulties in the methods used in many of the previous studies that may lead to overstatement of the effect of education on health. These difficulties are related to omitted variables and are discussed in the following section.

2.3 Ability bias

According to Griliches (1979), a problem with controlling for variables influencing both education and health is that they often are unobservable or difficult to measure. Behrman and

Rosenzweig (1998) use the term ability as a label for all unmeasured endowments, including genetic traits, family background and personal characteristics.[4] We henceforth use their definition and refer to all omitted variables as abilities.[5] To not control for abilities, as mentioned earlier, may cause an overestimation of the health returns to education, a so called ability bias. Hill *et al.* (2008) describe ability bias (omitted variable bias in their nomenclature) as being caused by unobserved heterogeneity among individuals. That is, the correlation might be partially spurious and in fact reliant on ability factors that both affects health and is correlated with education.

More formally, consider an individual i, whose health is determined by the model:

$$H_i = \alpha_i + \beta E_i + \gamma A_i + u_i \qquad (1)$$

where E_i denotes education, A_i denotes ability and u_i is an unobserved random component. Let education be determined by the model:

$$E_i = \varphi A_i + v_i \qquad (2)$$

where A_i is the same ability as defined above and v_i is a random term specific to education. Using the ordinary least squares (OLS) method to estimate β results in a bias such that:

$$E(\beta_{OLS}) = \beta + \gamma \frac{\sigma_{AE}}{\sigma_E^2} \neq \beta \qquad (3)$$

As ability is thought to be positively correlated with both education and health, the estimate of β_{OLS} is assumed to be upward biased. Hence, there is a risk that estimations of the education effect on health in previous literature are upward biased, or even that the entire effect of education on health is due to ability bias.

Sibling methods are one approach to deal with unobserved abilities since socioeconomic background, genetic traits and, to some extent, personal characteristics are more likely to be similar between siblings than between randomly selected individuals (Griliches 1979). MZ twins

[4] Behrman and Rosenzweig (1998) discuss wage returns to education, but the same reasoning applies to health returns to education.

[5] We are aware that abilities in general are assumed to be cognitive abilities, and that the possibly omitted factors in this case cannot be considered pure 'abilities'. However, in line with previous research on the subject and as defined by Behrman and Rosenzweig (1998) we will label all such omitted factors ‘abilities’.

are of special interest since they, in addition to typically being raised under the same conditions, are genetically identical.[6] According to Behrman and Rosenzweig (1998) the magnitude of the ability bias can be estimated by comparing the effect of education on health from a sample of randomly selected individuals with a sample of MZ twins.

In the wage returns to education literature, a number of studies use twin methods to be able to control for and estimate a potential ability bias.[7] As these studies are closely related to our choice of subject, we find twin methods to be useful also to examine the health returns to education.

2.4 Health returns to education and twins

To our knowledge, there is only one previous study using twin-differencing to investigate the relationship between education and health.[8] In his paper, Lundborg (2008) uses a sample of 694 MZ twins from the U.S. to estimate the health returns to education, both in the form of self-assessed health and as the number of chronic conditions. Lundborg (2008, p. 12) finds "a strong and positive association between education and health" for both measures of health, with a more than one unit increase in the self-assessed health (0-10) when having at least a college degree, compared to no or some high school education. However, estimates based on the number of years of schooling show no significant association with health. Lundborg (2008) controls for twin-specific factors using a fixed effects (FE) model.

Interestingly, when comparing the FE estimates with the estimates from a population sample and when pooling the twin sample, the estimated effect of education on health actually increases for all educational levels, contrary to what is theoretically predicted as the FE estimates control for genetic traits and family background.

Lundborg's (2008) estimates rely on the assumption that abilities do not differ between twins. He discusses potential sources of ability differences such as parental treatment, birthweight, physical

[6] For a thorough discussion on MZ twins and family background, see among others Bonjour *et al*. (2003).
[7] See for instance Behrman and Taubman (1976), Taubman (1976), Ashenfelter and Krueger (1994) and Bonjour *et al.* (2003).
[8] Behrman *et al.* (1994) examine the effects of abilities (endowments in their nomenclature) in the household and marriage market using a twin-differencing method. Even though their purpose is not to examine health, BMI is included as a health indicator in some of the regressions. BMI is not a very comprehensive health indicator, but a high BMI is a sign of risk in health status. Though results are not precise, they indicate that schooling may be negatively related to BMI.

and mental health at the age of 16, but finds no evidence of these factors affecting differences in education between twins. However, other studies indicate that there are ability differences between twins correlated with both education and health that will bias the estimates if they are not controlled for (Sandewall 2009).

Another source of concern with Lundborg's (2008) study is that he, as mentioned earlier, finds no significant relationship between education and health when using numbers of years of schooling instead of educational levels. We find it reasonable to believe that these two measures of education are closely related and the fact that they lead to fundamentally different results is a reason for concern. Furthermore, Lundborg's (2008) sample of twins are significantly younger, more likely to be white, married or cohabiting, have higher income, better health and are more physically active than the population sample.

In summary, Lundborg's (2008) paper has the appealing feature of using a twin-differencing method to control for abilities that may influence the relationship between education and health. However, the fact that the effect of education on health is larger in the FE estimates, that the results differ considerably depending on the measure of education and that Lundborg (2008) does not allow for any differences in abilities between twins, suggest that there is reason to further examine the health returns to education using twin-differencing.

3. Empirical methodology

As outlined above, we believe that the most adequate method for the purpose of our study is a twin-differencing strategy using MZ twins to control for underlying abilities. The basis of our method follows Lundborg (2008).[9] However, we add to it some of the insights from Sandewall (2009) and previous research on ability differences between twins.

The aim of our study, to examine whether there exists a direct relationship between education and health when controlling for abilities, is a test of causality, but not a test of the direction of causality. In case we find no direct link between education and health, a causal relationship can be rejected. However, if our results indicate a direct relationship between education and health when controlling for abilities, causality can run either way. In accordance with much of the

[9] Lundborg (2008) uses an FE method and not twin-differencing but the two methods will result in equivalent estimates.

previous research, we model the relationship with causality running from education to health, but as pointed out, the opposite can also be true. We further assume the relationship between education and health to be linear, even though other functional forms are possible.[10]

First, consider an individual i of twin pair j, whose health, H_{ij}, is determined by the model:

$$H_{ij} = \alpha + \boldsymbol{\alpha}_m \boldsymbol{X}_j + \boldsymbol{\alpha}_n \boldsymbol{Y}_{ij} + \beta E_{ij} + \gamma A_{ij} + u_{ij} \tag{4}$$

where E_{ij} denotes education, A_{ij} denotes ability, X_j is a vector of observables, such as age and sex, that vary between, but not within, twin pairs and Y_{ij} is a vector of observables that vary between as well as within twin pairs, such as income and civil status. Let A_{ij} be defined broadly enough to allow E_{ij} and u_{ij} to be independent. Returns to education, β, and returns to ability, γ, are assumed to be equal across individuals. Education is assumed to be related to ability as defined by equation (2).

Under the standard twin assumption, abilities are assumed to be equal within a twin pair. A twin-differencing model for the relationship between education and health is then expressed as:

$$\Delta H_j = \boldsymbol{\alpha}_{nWP} \Delta \boldsymbol{Y}_j + \beta_{WP} \Delta E_j + \Delta u_j \tag{5}$$

where WP denotes within-twin pair.

The standard twin assumption is investigated by Sandewall (2009, p. 43) who finds that “inclusion of IQ in the wage equation causes within-pair point estimates for the returns to schooling to decline considerably”. Drawing on the similarities between wage and health returns to education and the study by Hartog and Oosterbeek (1998), we include IQ as a proxy for ability.

Assume that the relationship between IQ and ability can be specified as:

$$T_{ij} = \pi A_{ij} + \tau_{ij} \tag{6}$$

where T_{ij} is a measure of IQ and τ_{ij} is independent of A_{ij}.

[10] See for instance Cutler and Lleras-Muney (2008) for a note on functional forms for the relationship between education and health.

Inserting equation (6) in equation (5), the twin-differencing model is expressed as:

$$\Delta H_j = \boldsymbol{\alpha}_{nWP}\Delta \boldsymbol{Y}_j + \beta_{WP}\Delta E_j + \lambda_{WP}\Delta T_j + \Delta u_j \qquad (7)$$

Cutler and Lleras-Muney (2008) present several studies finding that children with low birthweight obtain less education than children with higher birthweight, even among twins. Furthermore, a number of studies show that low birthweight is predictive of poor health as an adult. As birthweight influences both education and health, and may differ between twins, we include it as a proxy for ability. We assume birthweight to be related to ability in the same way as IQ, as stated by equation (7). The estimated twin-differencing model is:

$$\Delta H_j = \boldsymbol{\alpha}_{nWP}\Delta \boldsymbol{Y}_j + \beta_{WP}\Delta E_j + \psi_{WP}\Delta BW_j + \Delta u_j \qquad (8)$$

where BW denotes birthweight.

We estimate the coefficients of the twin-differencing equations (5), (7) and (8) using OLS regressions. The reason for estimating three separate equations instead of including IQ and birthweight in the same regression, which would be preferable, is due to data limitations. While IQ is likely to be a better measure of ability, data on birthweight is available for a lager sample.

We also estimate equation (4) on cross-sectional data using OLS regressions. Equation (4) is estimated both without any proxy for ability and with the inclusion of IQ and birthweight respectively. The cross-sectional sample is created by randomly selecting one twin in each twin pair. Including both twins in a pair would cause correlation between the observations in the sample. By randomly selecting one twin in each twin pair, correlation between observations is reduced, but causes variance to increase and significance levels to decrease slightly.[11]

The difference between cross-sectional estimates and twin-differencing estimates is used as a measure of ability bias in the education coefficient. In case the estimates do not differ there is no indication of ability bias, but if the twin-differencing coefficient is smaller there is evidence of ability bias in the cross-sectional estimates. If the twin-differencing estimate of the education coefficient is zero and/or insignificant this provides support that the entire effect of education on health is due to ability bias. More specifically, estimates of equation (4) without any proxy for

[11] Note that this procedure results in the same number of observations for the cross-sectional sample and the twin differences.

ability is compared to estimates of equation (5) and referred to as the standard regressions. Estimates of equation (4) including IQ or birthweight are compared to estimates of equation (7) and (8) respectively and referred to as the IQ and birthweight regressions.

Only equation (4), and its equivalents including IQ and birthweight, includes an intercept. However, contrary to what is stated in the model, we do not drop the intercept when estimating equation (5), (7) and (8), but rather include it as a test of twin pair similarities.

3.1 Health measures

We use two alternative methods, both widely recognized, to measure health: Rating Scale (RS) and EuroQol. Both measures are self-reported and generic in the sense that they do not depend on specified diseases. According to Lundborg (2008, p. 9) "self-reported health has been found to be a strong predictor of subsequent mortality".

In the RS method, the respondents assess his/her current health status on a "thermometer" scale with best imaginable health (100) and worst imaginable health status (0) as end points. Responses are then converted to a scale between one and zero. The RS method is easy to use and can be straightforwardly interpreted by respondents and it is therefore often used as a psychometric method.

EuroQol (also known as EQ-5D) is a health quality index which is widely used and increasingly accepted in economic evaluations (Brooks, 1996). As pointed out by Rabin and De Charro (2001), the EuroQol measure is also becoming popular in clinical trials.

In the EuroQol index, the respondents assess his/her health state in five different dimensions: mobility, self-care, usual activities, pain/discomfort and anxiety/depression. Each dimension has three levels of severity where one corresponds to no problems, two to moderate problems and three to extreme problems, resulting in $3^5 = 243$ possible health states. Using a time trade-off (TTO) survey, Dolan (1997) gives each of the possible health states a numeric value in the form of quality adjusted life years.[12] These values are then used to create a formula, presented in detail in the appendix, which is used to give all combinations of the five dimensions of health a value between -0.594 and 1. We use this formula to calculate EuroQol index values for our

[12] By valuing how many years (x) in perfect health that would be equivalent to ten years in a certain health state, a quality adjusted life year value of that state is given by x/10.

observations based on their responses to the five dimensions of health. A negative number means that an individual assesses his/her current health status as worse than being dead.

The TTO method, used in the EuroQol index, is based on a choice which involves a trade-off. The trade-offs can be theoretically interpreted by cardinal utility theory and used to create a cardinal index (Johannesson 1996). This means that a shift of a certain magnitude has the same effect irrespective of where on the scale it takes place. In other words, a shift from 0.2 to 0.4 is valued as much as a shift from 0.6 to 0.8.

3.2 Education measure

In accordance with a number of other studies, but contrary to Lundborg (2008), we use the number of years of education as our measure of schooling based on educational levels reported by Statistics Sweden.[13] We assume a linear relationship between educational levels and years of education completed. The construction of the education measure is further presented in the appendix.

3.3 Other explanatory variables

As discussed earlier, we include IQ and birthweight as regressors to control for ability differences within twin pairs.

Our IQ measure is based on enlistment records. Most Swedish men undergo testing for compulsory military service including an intelligence test designed to measure spatial intelligence, verbal ability, logical reasoning and technical comprehension. The test scores are then normalized by year and the sum across test scores are used as a raw IQ measure (Sandewall 2009). Birthweight is self-reported and measured in grams.

In addition to the aforementioned variables, we also include a number of control variables. Obviously, variables that cannot vary within a MZ twin pair, such as sex and age, are cancelled out when employing twin-differencing but are included in the cross-sectional regressions.

Naturally, age has an impact on health and is hence included to control for age and cohort-specific effects. There are also well-documented differences in health between men and women

[13] Ashenfelter and Krueger (1994), Behrman and Rosenzweig (1998) and Bonjour *et al*. (2003) are examples of studies using years of schooling instead of educational levels.

and therefore a dummy variable for sex is included in our regressions, where women are assigned a value of one.[14]

Civil status is included as a control variable as, according to Fuchs (2004), married men and women are generally healthier than their unmarried peers. Civil status is also correlated with education and income. There are two possible explanations of the relationship between civil status and health: 1) having a spouse will have a positive impact on the household production function or increase the demand for health, or 2) healthier men and women do better in the marriage market. Without making any assumptions about the underlying mechanism, we include a dummy for self-reported civil status, where zero corresponds to married and one to unmarried.

A vast literature has shown a significant effect of income on health (Cutler *et al.* 2006). In our model, income is measured as the average income from employment (sv. förvärvsinkomst) as reported by Statistics Sweden during the five years preceding the survey used (2001-05).

3.4 Multicollinearity

The explanatory variables included in our models naturally raise concerns about multicollinearity, as several of them can be expected to be linearly related to each other. The presence of multicollinearity makes it more difficult to estimate the regression coefficients. We are most concerned about potential collinearity between years of education completed, income and IQ.

The following section is based on Gujarati (2003). To test for multicollinearity, we compute collinearity statistics for our regressions: a variance-inflating factor (VIF), a tolerance value and a condition index (CI). The VIF shows how the variance of an estimator is inflated by the presence of multicollinearity. The tolerance value measures how much of the variance of each explanatory variable that is unique to that variable (the tolerance value is the inverse of the VIF). The CI is derived from eigenvalues, in which a standardized matrix of the explanatory variables is used to compute which explanatory variables contain the same information. A few rules of thumb can be used for the collinearity statistics: a VIF exceeding 10, a tolerance value less than 0.1 or a CI above 30 are indications of strong multicollinearity. A CI between 10 and 30 means

[14] For a discussion on differences in health between men and women see for instance Matthews *et al.* (1999).

moderate multicollinearity. We also compute the correlation between the explanatory variables, where correlations above 0.5 are signs of multicollinearity.

4. Data

Our dataset links the 2005 *Swedish Twin Studies of Adults: Genes and Environment* (STAGE) survey from the Swedish Twin Registry, which covers all Swedish twins born between 1959 and 1985, with data from Statistics Sweden and Swedish enlistment records. 25378 individuals participated in the STAGE survey which corresponds to a response rate of about 60 percent.

Of the 25378 individual twins, 7118 are MZ. Some of these MZ twins do not have their co-twin in the sample and are therefore excluded. This means that 7090 individual MZ twins, or 3545 MZ twin pairs, are included in our sample. Zygosity was determined by the Swedish Twin Registry using a battery of questions on physical similarity. The validity of this method is about 95 percent (Sandewall 2009).

Of the 3545 twin pairs, EuroQol and education data are available for 2174 twin pairs. This sample will henceforth be referred to as the EuroQol standard sample. The large decline in observations is mainly due to missing EuroQol data and only in very few cases because of missing education data. Also, if one twin is missing data, the co-twin has to be excluded. IQ data exists for 380 of the twin pairs, all of them males.[15] EuroQol, education and birthweight data are available for 1428 twin pairs. These two samples are referred to as the EuroQol IQ and EuroQol birthweight (BW) samples.

RS and education data exist for 2092 of the 3545 MZ twin pairs. This sample will henceforth be referred to as the RS standard sample. Also with this measure, the decline is mainly due to limited data on health and, again, the number of observations further decline by the exclusion of co-twins. IQ data is available for 372 of the twin pairs, all male, and birthweight data exists for 1373 pairs. These two samples are referred to as the RS IQ and RS birthweight samples. Note that these samples differ slightly from the EuroQol samples.

[15] Three pairs of female twins were excluded from the EuroQol and RS samples even though IQ data exists for them.

4.1 Descriptives and representativeness of sample

Presented below are descriptive statistics for our six different samples and for a Swedish reference population.

Table 4.1 Sample descriptives

	Means (std. err.)			
Variables	**Population**	**EuroQol standard**	**EuroQol IQ**	**EuroQol BW**
		n=4348	n=760	n=2856
Female	49.06%	63.90%	0.00%	73.30%
Age	33.96	32.77 (7.40)	37.58 (5.02)	33.01 (7.34)
Married	33.06%	29.20%	42.80%	31.20%
Years of education	12.56	13.35 (2.17)	13.20 (2.35)	13.40 (2.11)
Average 5 year income (SEK)	205550	191966 (134154)	313218 (161213)	189724 (127556)
EuroQol	-	0.8956 (0.1554)	0.9153 (0.1272)	0.8916 (0.1592)
	Population	**RS standard**	**RS IQ**	**RS BW**
		n=4184	n=744	n=2746
Female	49.06%	63.60%	0.00%	72.90%
Age	33.96	32.80 (7.41)	37.66 (5.05)	33.08 (7.33)
Married	33.06%	29.40%	43.40%	31.30%
Years of education	12.56	13.33 (2.15)	13.18 (2.38)	13.38 (2.09)
Average 5 year income (SEK)	205550	193136 (134760)	313917 (161798)	191242 (127962)
RS	-	0.8310 (0.1434)	0.8320 (0.1308)	0.8350 (0.1436)

* *Source:* Statistics Sweden, *Statistikdatabasen* (manual searches for individuals born 1959-85 in the subsections *Befolkning* and *Utbildning*).
All figures from 2005 to be comparable with our samples.
Data on standard deviation is not available from Statistics Sweden.

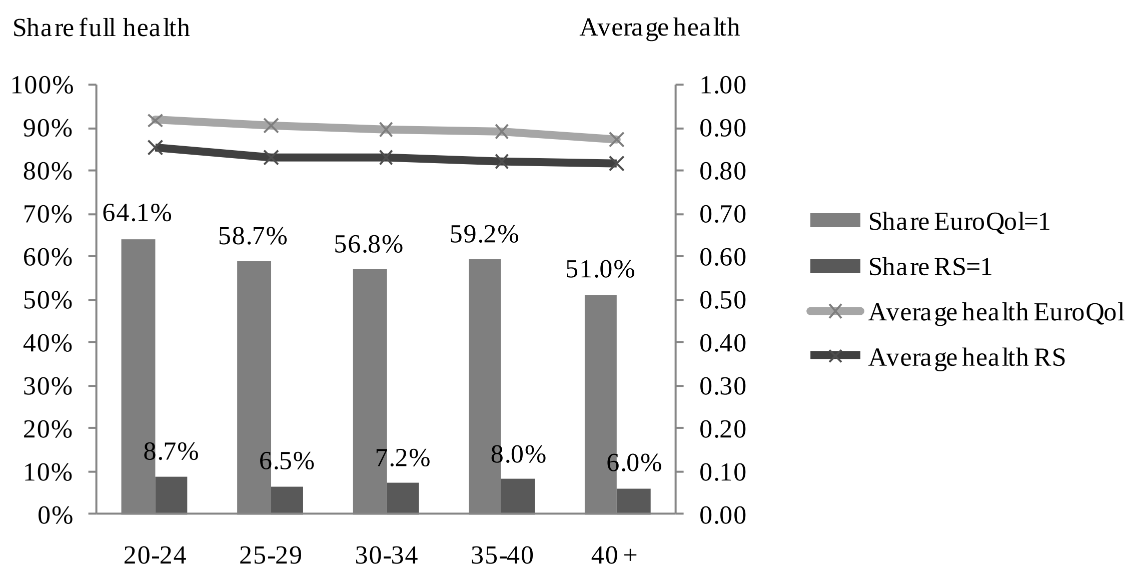
For both measures of health, the standard and birthweight samples are slightly younger, more likely to be female, less likely to be married, have completed more years of education and have lower average income than the reference population. The IQ samples are older, more likely to be married, have higher average income and have completed more years of education than the reference population. The fact that the IQ samples differ from the other samples is natural as IQ data only is available for men born between 1959 and 1976. This means that the IQ samples have a higher average age than the other samples, have worked for more years but not yet retired, and as a consequence have higher income than the other samples but also than the reference population. The fact that the IQ samples are much more likely to be married is not really intuitive, but the rate is probably in line with statistics for their age group.

4.2 Data concerns

The fact that 20 percent of our respondents were between 20 and 25 years old when the survey was conducted means that many of them have several years of education left to complete. Other studies, like Lundborg (2008) and Cutler and Lleras-Muney (2008), only include respondents over 25 years of age to avoid this problem. However, we include this group in our standard regressions to not lose too many observations and hence statistical power, but we also run control regressions excluding all individuals under 25 years of age.

Furthermore, the data does not distinguish between being unmarried and cohabiting from being single. Therefore, unmarried are coded into the same group as divorced and widows/widowers. Considering the low average age of our sample, and the fact that many young people live together for a long time without being married, this is a weakness with our measure of civil status. The low average age in our sample also causes our income variable to be a far from perfect measure of lifetime income.

Figure 4.2 Health measure characteristics per age group.



As shown in *Figure 4.2*, a large fraction of respondents has a EuroQol index value equal to one which means full health. This is a source of concern, especially for the younger age groups as these groups also have small variation in the EuroQol measure. On the other hand, the within-twin-pair correlation for the EuroQol index is 0.33, which indicates that there is sufficient variation within pairs. The RS measure has a much smaller fraction with full health and only moderate clustering around the values 0.80, 0.85 and 0.90. The within pair correlation is 0.32 for RS while the correlation between the EuroQol and RS measures is 0.54.

The within-twin-pair correlation for IQ is 0.83. For education the corresponding figure is 0.69 and for birthweight it is 0.70. The correlation between years of education and IQ is 0.52 for the cross-sectional IQ sample and 0.20 for twin differences. All figures are in line with what Sandewall (2009) reports from other studies.

5. Results

Presented in this section are the results from our OLS estimates of the twin-differencing equations (5), (7) and (8) as well as estimates of equation (4) for cross-sectional data, without any proxy for ability and with the inclusion of IQ or birthweight as proxies. As mentioned earlier, the cross-sectional data consists of a random sample of one twin in each twin pair. Estimates of equation (4) including both twins in each twin pair and other additional regressions referred to are available in the appendix. To facilitate the discussion on the results, we set the significance level to five percent. The standard regressions assuming equal abilities between twins are presented first.

5.1 Standard regressions

Table 5.1 Cross-sectional OLS estimates of equation (4) on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.877	0.032	27.631	0.000
Age	-0.003	0.001	-5.194	0.000
Sex	-0.041	0.007	-5.613	0.000
Civil status	0.006	0.008	0.761	0.447
Income 5y avr	1.37E-07	0.000	4.067	0.000
Education years	0.009	0.002	5.467	0.000
n	R^2	Adj. R^2	F	Sig.
2174	0.055	0.053	25.342	0.000

Table 5.2 Twin-differencing OLS estimates of equation (5) on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.001	0.004	0.193	0.847
Civil status	0.008	0.008	0.984	0.325
Income 5y avr	3.39E-08	0.000	0.852	0.395
Education years	0.005	0.002	2.122	0.034
n	R^2	Adj. R^2	F	Sig.
2174	0.003	0.001	2.031	0.107

Table 5.3 Cross-sectional OLS estimates of equation (4) on RS.

	B	Std. Error	t	Sig.
Constant	0.869	0.029	29.986	0.000
Age	-0.003	0.001	-5.309	0.000
Sex	-0.010	0.007	-1.529	0.127
Civil status	-0.018	0.007	-2.371	0.018
Income 5y avr	8.93 E-08	0.000	3.029	0.002
Education years	0.004	0.001	3.027	0.002
n	R^2	Adj R^2	F	Sig:
2092	0.025	0.022	10.588	0.000

Table 5.4 Twin-differencing OLS estimates of equation (5) on RS.

	B	Std. Error	t	Sig.
Constant	-0.002	0.004	-0.419	0.675
Civil status	0.004	0.009	0.445	0.656
Income 5y avr	1.06 E-07	0.000	2.117	0.034
Education years	0.000	0.003	0.148	0.882
n	R^2	Adj. R^2	F	Sig.
2092	0.003	0.001	1.592	0.189

For both EuroQol and RS, the above results support the existence of an ability bias as the education coefficient is smaller in the twin-differencing regressions. Our results are thus contrary to Lundborg (2008) who finds no evidence of ability bias. However, our results differ somewhat between the health measures, both in the magnitude of coefficients and in significance levels. For RS, the education coefficient declines to zero and turns insignificant in the twin-differencing regression, which means that a twin with one more year of education than his/her co-twin does not, on average, have better health. For the EuroQol measure, the education coefficient decreases by almost 50 percent in the twin-differencing regression, but remains positive and significant. This means that a twin with one more year of schooling compared to his/her co-twin has, on average, a EuroQol index that is 0.005 units higher. Note that the F-value is insignificant in both twin-differencing regressions, which indicates that none of the regressors have a significant impact on health.

The income coefficient is positive both in the cross-sectional and twin-differencing regressions on RS, but for the EuroQol index the income effect becomes insignificant for twin differences.

In accordance with expectations, ageing reduces health by 0.003 for every additional life year in both health measures. Being female has a negative effect on health, but the coefficient is only significant for the EuroQol measure. As mentioned before, both these variables are cancelled out in the twin-differencing regressions.

In the cross-sectional regression on RS, civil status is significant and has the predicted negative sign, which means that unmarried individuals have worse health than their married peers. For the EuroQol index, on the other hand, civil status has a positive sign but is insignificant. In the twin-differencing regressions the effect of civil status is not significant for either health measure. The ambiguous results are probably a consequence of the shortcomings in the civil status measure discussed in the data section.

For both measures of health, the intercept becomes insignificant and very small in the twin-differencing regressions as predicted in the models. Adjusted R^2 levels are low for both measures of health, less than six percent for the cross-sectional regressions and 0.1 percent for twin differences.

5.2 Regressions with IQ

Presented below are the regression results for equation (4) and (7), where the assumption of equal abilities between twin pairs is relaxed and IQ is included as a proxy for ability.

Table 5.5 Cross-sectional OLS estimates of equation (4), with IQ on EuroQol.

	Including IQ				Control, without IQ			
	B	Std. Error	t	Sig.	B	Std. Error	t	Sig.
Constant	0.890	0.071	12.560	0.000	0.911	0.068	13.366	0.000
Age	-0.002	0.001	-1.843	0.066	-0.002	0.001	-1.864	0.063
Civil status	-0.031	0.013	-2.399	0.017	-0.030	0.013	-2.337	0.020
Income 5y avr	1.15E-07	0.000	2.802	0.005	1.11E-07	0.000	2.713	0.007
Education years	0.008	0.003	2.613	0.009	0.006	0.003	2.382	0.018
IQ	-0.009	0.008	-1.086	0.278				
n	R^2	Adj. R^2	F	Sig.	R^2	Adj. R^2	F	Sig
380	0.080	0.067	6.468	0.000	0.077	0.067	7.787	0.000

Table 5.6 Twin-differencing OLS estimates of equation (7) on EuroQol.

	Including IQ				Control, without IQ			
	B	Std. Error	t	Sig.	B	Std. Error	t	Sig.
Constant	-0.002	0.008	-0.246	0.806	-0.002	0.008	-0.252	0.802
Civil status	0.008	0.013	0.635	0.526	0.009	0.013	0.655	0.513
Income 5y avr	1.02E-07	0.000	1.873	0.062	1.02E-07	0.000	1.874	0.062
Education years	0.015	0.004	3.407	0.001	0.015	0.004	3.515	0.000
IQ	0.003	0.016	0.207	0.836				
n	R^2	Adj. R^2	F	Sig.	R^2	Adj. R^2	F	Sig.
380	0.044	0.034	4.296	0.002	0.044	0.036	5.729	0.001

As shown in *Table 5.5*, including IQ in the EuroQol equation (4) does not alter the basic results from the standard cross-sectional EuroQol regression. The IQ coefficient is not significant and the sign of the coefficient is negative, contrary to expectations. However, note that the results in *Table 5.5* cannot be directly compared with those in *Table 5.1* as the IQ sample differs from the standard sample. A control regression on the cross-sectional IQ sample without including IQ is presented in *Table 5.5*. The intercept, education, income and civil status coefficients have the expected signs and are significant. A slight increase in significance and size can be noted for the education coefficient when including IQ.

The civil status coefficient becomes negative and significant in the cross-sectional IQ regression, which most likely is a consequence of sample characteristics. As mentioned earlier, the IQ sample has a higher average age than the other samples and the shortcomings of the civil status measure is likely to decrease with age as, intuitively, more couples get married instead of only cohabiting.

Adding twin differences in IQ to the standard twin model does not affect the education coefficient, which is still positive and significant, as shown in *Table 5.6*. Again, this result cannot directly be compared to *Table 5.2* due to sample differences. A control regression on twin differences, without including differences in IQ, is also presented in *Table 5.6*. The results show a similar size and significance of the education coefficient as when including IQ.

Table 5.5 and *Table 5.6* show an increase in the size of the education coefficient when regressing twin differences in comparison to the cross-sectional sample. Even though IQ cannot be assumed to be a perfect measure of ability, it would be reasonable to assume that it would capture some of the ability effect in the cross-sectional regression and some of the ability differences between twins. Hence, the education coefficient in the twin-differencing regressions is expected to decrease in comparison with the control regressions. But in this case, the education coefficient is larger in the twin-differencing regression which implies that the unobserved abilities are better controlled for in the cross-sectional sample. However, as the IQ sample is relatively small causing a loss of statistical power, we are reluctant to draw any conclusions based on the above results.

Table 5.7 Cross-sectional OLS estimates of equation (4), with IQ on RS.

	Including IQ				Control, without IQ			
	B	Std. Error	t	Sig.	B	Std. Error	t	Sig.
Constant	0.915	0.077	11.901	0.000	0.939	0.075	12.558	0.000
Age	-0.003	0.001	-1.915	0.056	-0.003	0.001	-1.885	0.060
Civil status	-0.019	0.014	-1.342	0.180	-0.017	0.014	-1.214	0.225
Income 5y avr	1.49E-07	0.000	3.407	0.001	1.41E-07	0.000	3.252	0.001
Education years	-0.001	0.003	-0.243	0.808	-0.003	0.003	-0.913	0.362
IQ	-0.011	0.009	-1.290	0.198				
n	R^2	Adj. R^2	F	Sig.	R^2	Adj. R^2	F	Sig.
372	0.041	0.028	3.137	0.009	0.037	0.037	3.499	0.008

Table 5.8 Twin-differencing OLS estimates of equation (7) on RS.

	Including IQ				Control, without IQ			
	B	Std. Error	t	Sig.	B	Std. Error	t	Sig.
Constant	0.011	0.008	1.269	0.205	0.011	0.008	1.280	0.202
Civil status	-0.003	0.014	-0.229	0.819	-0.004	0.014	-0.270	0.788
Income 5y avr	3.56E-08	0.000	0.623	0.534	3.56E-08	0.000	0.622	0.534
Education years	0.002	0.005	0.448	0.655	0.002	0.005	0.343	0.732
IQ	-0.009	0.017	-0.556	0.579				
n	R^2	Adj. R^2	F	Sig.	R^2	Adj. R^2	F	Sig.
372	0.002	-0.009	0.211	0.932	0.001	-0.007	0.179	0.910

For the RS measure, education has no effect on health neither in the cross-sectional regression, nor when regressing twin differences. The first result is surprising and contrary to the results presented in *Table 5.3*. Also in the control regression, included in *Table 5.7*, the education coefficient is insignificant and even negative. In both the above tables, IQ is insignificant with a negative coefficient, contrary to our expectations. For the twin-differencing regression, presented in *Table 5.8*, the income effect becomes zero and insignificant when adding IQ. The coefficients in control regression, also included in *Table 5.8*, are of about the same size and significance as when including IQ. Again, we believe that the inconclusive results are due to the small sample size and we are not willing to draw any conclusions based on these results.

5.3 Regressions with birthweight

Birthweight as a proxy for ability is positive but insignificant in all four regressions. The other variables are only marginally affected by the inclusion of birthweight as the size and significance of coefficients are almost the same as in the standard regressions. The results are presented in the appendix. As the birthweight samples are much similar to the standard samples we see no reason to include control regressions as in the case with IQ.

5.4 Multicollinearity

In none of the regressions do the collinearity statistics exceed the rules of thumb for severe multicollinearity as defined by Gujarati (2003), except for the variables age and years of education completed. In several cases, however, there are indications of moderate multicollinearity involving age, education and IQ. Due to limitations of scope, we chose to not include the collinearity statistics in the appendix. There is high correlation, above 0.5, between the income and age variables and the education and IQ variables. This is another sign of possible multicollinearity in our regressions, which may help explaining the inconclusive results when including IQ. For twin differences, correlations are low and multicollinearity is thus not an issue in these regressions. Correlation tables are included in the appendix.

5.5 Robustness checks

Presented below are a number of robustness checks performed in order to test the sensitivity of our results to negative health indices, the presence of young individuals and measure of education.

For some of the observations, the calculated EuroQol index values are negative. The presence of negative EuroQol index values is somewhat problematic as there is no clear theoretical interpretation of the health status "worse than dead" (Burström *et al.* 2001). Even though our data only include four negative values we run the standard regressions setting these negative EuroQol indices to zero.

Table 5.9 Cross-sectional OLS estimates of equation (4) with no EuroQol index<0.

	B	Std. Error	t	Sig.
Constant	0.877	0.032	27.695	0.000
Age	-0.003	0.001	-5.188	0.000
Sex	-0.041	0.007	-5.615	0.000
Civil status	0.006	0.008	0.781	0.435
Income 5y avr	1.37E-07	0.000	4.070	0.000
Education years	0.009	0.002	5.472	0.000
n	R^2	Adj. R^2	F	Sig.
2174	0.055	0.053	25.367	0.000

Table 5.10 Twin-differencing OLS estimates of equation (5) with no EuroQol index<0.

	B	Std. Error	t	Sig.
Constant	0.001	0.004	0.164	0.869
Civil status	0.008	0.008	0.987	0.324
Income 5y avr	3.33E-08	0.000	0.838	0.402
Education years	0.005	0.002	2.134	0.033
n	R^2	Adj. R^2	F	Sig.
2174	0.003	0.001	2.044	0.106

The results are only marginally different from those of the standard regressions and hence negative EuroQol indices have no practical implications for the reliability of our estimates.

As discussed earlier, most studies on health returns only include individuals from 25 years of age, as younger individuals may not have completed their education. To check the robustness of the EuroQol and RS standard regressions, we estimate the cross-sectional and twin-differencing regressions excluding all individuals under the age of 25.

Table 5.11 Cross-sectional OLS estimates of equation (4), from 25 years of age, on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.851	0.038	22.470	0.000
Age	-0.003	0.001	-3.627	0.000
Sex	-0.046	0.008	-5.550	0.000
Civil status	0.007	0.008	0.814	0.416
Income 5y avr	1.38E-07	0.000	3.894	0.000
Education years	0.009	0.002	5.291	0.000
n	R^2	Adj. R^2	F	Sig.
1860	0.059	0.056	23.108	0.000

Table 5.12 Twin-differencing OLS estimates of equation (5), from 25 years of age, on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.001	0.004	0.155	0.877
Civil status	0.005	0.008	0.640	0.522
Income 5y avr	3.45E-08	0.000	0.833	0.405
Education years	0.004	0.002	1.632	0.103
n	R^2	Adj. R^2	F	Sig.
1860	0.002	0.000	1.231	0.297

Table 5.13 Cross-sectional OLS estimates of equation (4), from 25 years of age, on RS.

	B	Std. Error	t	Sig.
Constant	0.819	0.035	23.699	0.000
Age	-0.002	0.001	-3.175	0.002
Sex	-0.006	0.008	-0.793	0.428
Civil status	-0.017	0.008	-2.234	0.026
Income 5y avr	1.08E-07	0.000	3.476	0.001
Education years	0.005	0.002	3.201	0.001
n	R^2	Adj. R^2	F	Sig.
1792	0.024	0.021	8.630	0.000

Table 5.14 Twin-differencing OLS estimates of equation (5), from 25 years of age, on RS.

	B	Std. Error	t	Sig.
Constant	0.001	0.005	0.187	0.852
Civil status	0.004	0.009	0.456	0.649
Income 5y avr	1.08E-07	0.000	2.067	0.039
Education years	-0.001	0.003	-0.483	0.629
n	R^2	Adj. R^2	F	Sig.
1792	0.004	0.002	1.700	0.165

For the EuroQol measure, results are almost unchanged for the cross-sectional regression. For twin differences, on the other hand, the education coefficient is now smaller and not significant, which indicates that the entire effect of education on health may be due to ability bias. For the

RS measure, the results are almost unchanged in comparison with the standard regressions. These results provide evidence in favor of the second explanation, where omitted variables cause the observed correlation between education and health, and are also more useful for comparison with other studies.

To test if there is any sensitivity to the measure of education, as in Lundborg's (2008) study, a regression with educational levels instead of years is included in the appendix. Even though the number of years of education is also based on educational levels, reducing the levels to four degrees gives an indication on whether the results are sensitive to the measure of education.

By using dummies for educational degrees, we allow for the health function to be discrete instead of continuous. If, for instance, attending high school has a significant effect on health, but attending college or attaining a college degree gives no incremental increase in health status this is captured by the use of dummies. In the cross-sectional regressions the baseline is elementary school and the categories high school, some college studies and college degree are assigned dummies. For the twin-differencing regressions, the baseline is equal education for both twins in a twin pair. The same categories are used for twin differences as in the cross-sectional regressions, but to capture the difference between twins there is one dummy for each possible combination of education degrees which takes the value -1 or 1 depending on which twin has the highest education.

The test does not alter our previous findings, as all degree dummies are significant for both the cross-sectional regressions and only one of the dummies remain significant in the twin-differencing regression on RS, while all dummies are insignificant for EuroQol. Thus, our results remain contrary to Lundborg's (2008), also for educational levels.

6. Discussion

The previous section presents estimates of the effect of education on health when controlling for abilities by the use of twin differences, and also when allowing for abilities to differ between twins. For the standard regressions, both the EuroQol and the RS measures show the same tendency, that the size and significance of the education coefficient decrease in the twin-differencing regressions, which provides support for the existence of ability bias in the cross-sectional estimates.

However, the two measures of health yield somewhat different results. For the EuroQol measure, education has a direct effect on health also for twin differences, but it is overestimated in the cross-sectional regression due to ability bias. For the RS measure, controlling for ability removes the entire effect of education on health.

It is important to note that the two health measures are not strictly comparable. While a value of zero in the RS measure means “worst imaginable health state”, a value of zero on the EuroQol index corresponds to a health state equal to death (as there are imaginable health states in the EuroQol measure that are considered worse than being dead, the scales differ). Furthermore, economists often stress that the TTO method, on which the EuroQol measure is based, has a stronger theoretical foundation than the RS measure as it is based on choice, which can be linked to cardinal utility theory. For the RS measure, it is unclear to what extent the scale can be given a cardinal interpretation.[16]

On the other hand, the formula used to compute the EuroQol index numbers was calculated from British data and assigned to the individuals in our sample without them being faced with the trade-off themselves. Hence, our two health measures cannot be seen as a direct comparison between the RS and TTO methods. Furthermore, other studies, such as Badia *et al.* (1999), suggest that the RS could in fact be considered more feasible and, to some extent, even more reliable than the TTO method.

A further issue, particularly relevant in twin-differencing methods, discussed by Sandewall (2009), is the importance of variation in the education and health measures.[17] The RS measure provides more variation, which is also stable over age groups, than the EuroQol measure and has a much smaller fraction of respondents with “full health”. If there is a high degree of similarity in the ability, education and health measures, twin-differencing does not contribute as much in terms of removing the ability bias (Sandewall 2009). In the EuroQol standard sample, 692, or 32 percent of the twin pairs have the same EuroQol index number and years of education

[16] See Johannesson (1996) for a discussion on the RS and TTO methods.
[17] As Sandewall’s (2009) study is concerned with wage returns to education, he discusses the importance of variation in the education and income measures.

completed. For RS, 239 pairs, or eleven percent, have the same RS value and education.[18] Obviously, there is a much higher degree of similarity in the EuroQol than in the RS samples. Drawing on Sandewall (2009), in case the degree of similarity was smaller in the EuroQol samples, it is possible that the estimated ability bias would be larger. By excluding all individuals under 25 years of age, variation in the EuroQol measure increases and, consequently, the degree of similarity decreases. The education coefficient in the twin-differencing regression then becomes slightly smaller compared to the cross-sectional sample and turns insignificant. This result is in line with that of the RS standard regression, where the entire effect of education on health disappears for twin differences.

An often raised concern with the twin-differencing method is measurement error in the education variable. If education is misreported, the measurement error will be aggravated by differencing as "differencing reduces the amount of true variation without reducing the measurement error to the same extent" (Sandewall 2009, p. 20). As a consequence, the estimated effect of education on the dependent variable will be downward biased (Griliches 1979). Using independent measures of education as instruments is a popular solution to the measurement error problem. Although a valid concern, measurement error is mainly an issue in self-reported education data and not in register data, which our measure of education is based on. Further, the reliability of Swedish education register data has been tested and was found to be high (Isacsson 2004).

Allowing for ability differences by including IQ and birthweight in the regressions do not add to the understanding of the effect of education on health. But, as pointed out earlier, the IQ sample is small and limited to men in a short age span. Further, the IQ variable is highly correlated with other explanatory variables, which is a sign of multicollinearity in our regressions. The birthweight sample is larger, but data is self-reported, thus there is risk of measurement error in the variable which will be aggravated by twin-differencing, as discussed above. Our inconclusive results when including IQ and birthweight should not be seen as support for the standard twin assumption, but rather as reason for more research on ability differences between twins.

To summarize, our results show that the effect of education on health decreases when controlling for abilities. This is an indication that the health returns to education are overestimated in the

[18] Note that, by assumption, abilities do not differ within twin pairs.

literature, or even that the entire effect of education is due to ability bias. In line with the second explanation, our results question a causal link between education and health and are hence contrary to the findings in much of the previous literature. However, while the use of twin-differencing can control for many of the possibly omitted factors, referred to as abilities, we doubt that the ability bias can be fully controlled for without recognizing ability differences between twins. We believe that understanding the ability differences between twins has much to add to the research on health returns to education.

From a policy perspective, it is important to gain further knowledge about the relationship between education and health, as our results indicate that investments in education may have no direct effect on health. Of course there are other positive effects of investments in education, but it is of great interest to find out whether they can be considered part of a health policy. Further, in case education has no direct impact on health, it remains to settle which factors, common to a twin pair, that have a significant impact on health.

From an international perspective, our sample is at the higher end of the education distribution and it is possible that the relationship between education and health is different at other parts of the distribution. For instance, in developing countries where a majority of the population has no, or only a few, years of schooling, education may have a significant effect on health. In addition, differences in birthweight between twins, or other ability factors, may also have a larger impact on education and health in developing countries. Our findings are based on the assumption that the relationship between education and health is linear, but that does not have to be the case.

7. Conclusions

With new data on Swedish MZ twins and a twin-differencing method to control for abilities we examine the relationship between education and health. As the effect of education on health decreases or even disappears in the twin-differencing regressions, our results suggest that unobserved abilities bias the cross-sectional estimates of the effect of education on health. This provides evidence that the health returns to education are overestimated in the literature or, possibly, that the entire effect of education is due to ability bias. Contrary to many previous studies, we find reason to question whether education has a direct effect on health.

Since this is one of the first studies to extensively control for abilities, generally referred to as omitted variables, that influence the relationship between education and health and as our results question many of the previous findings, there is clearly a need for further research on the subject. From a policy perspective, it is important to settle whether education policies can be thought of as health policies. We believe that twin-differencing is a useful method for this purpose, but to further avoid bias in the estimates, ability differences between twins must be recognized.

8. References

Ashenfelter, O. and Krueger, A. (1994), "Estimates of the Economic Return to Schooling from a New Sample of Twins." *The American Economic Review*, Vol. 84, No. 5, 1157-1173.

Badia X., Monserrat S., Roset, M. and Herdman M. (1999), "Feasibility, Validity and Test-retest Reliability of Scaling Methods for Health States: The Visual Analogue Scale and the Time Trade-off." *Quality of Life Research*, Vol. 8, No. 4, 303-310.

Behrman, J. R. and Rosenzweig, M. R. (1998), "'Ability' Biases in Schooling Returns and Twins: A Test and New Estimates." Population Aging Research Center (PARC) Working Paper Series No. 97-12, University of Pennsylvania.

Behrman, J. R., Rosenzweig, M. R. and Taubman, P. (1994), "Endowments and the Allocation of Schooling in the Family and in the Marriage Market: The Twins Experiment." *The Journal of Political Economy*, Vol. 102, No. 6, 1131-1174.

Behrman, J. R., Sickles, R., Taubman, P. and Yazbeck, A. (1991), "Black-White Mortality Inequalities." *Journal of Econometrics*, Vol. 50, No. 1-2, 183-203.

Behrman, J. R. and Taubman, P. (1976), "Intergenerational Transmission of Income and Wealth." *American Economic Review*, Vol. 66. No. 3, 436-440.

Bleakley, H. (2007), "Disease and Development: Evidence from Hookworm Eradication in the American South." *The Quarterly Journal of Economics*, Vol. 122, No. 1, 73-117.

Bolin, K., Jacobson, L. and Lindgren, B. (2002), "The Demand for Health and Health Investments in Sweden." In Lindgren, B. (eds.), *Individual Decisions for Health*. London: Routledge.

Bonjour, D., Cherkas, L. F., Haskel, J. E., Hawkes, D. D. and Spector, T. D. (2003), "Returns to Education: Evidence from U.K. Twins." *The American Economic Review*, Vol. 93, No. 5, 1799-1812.

Brooks, R. (1996), "EuroQol: the Current State of Play." *Health Policy*, Vol. 37, No.1, 53-72.

Burström, K., Johannesson, M. and Diderichsen, F. (2001), "Swedish Population Health-Related Quality of Life Results Using the EQ-5D." *Quality of Life Research*, Vol. 10, No. 7, 621-635.

Case, A., Fertig, A. and Paxson, C. (2005), "The Lasting Impact of Childhood Health and Circumstances." *Journal of Health Economics*, Vol. 24, No. 2, 365–389.

Cutler D., Deaton A. and Lleras-Muney A. (2006), "The Determinants of Mortality." *Journal of Economic Perspectives*, Vol. 20, No.3, 97-120.

Cutler, D. and Lleras-Muney, A. (2008), "Education and Health: Evaluating Theories and Evidence." In House, J. S., Kaplan, G. A., Pollack, H. and Schoeni, R. F. (eds.), *Making Americans Healthier: Social and Economic Policy as Health Policy*. New York: Russell Sage Foundation.

De Walque, D. (2004), “Education, Information, and Smoking Decisions: Evidence from Smoking Histories, 1940–2000.” Working Paper No. 3362. World Bank, Washington, DC.

Dolan, P. (1997) “Modeling Valuations for EuroQol Health States.” *Medical Care*, Vol. 35, No. 11, 1095-1108.

Duleep, H. O. (1986), “Measuring the Effect of Income on Adult Mortality Using Longitudinal Administrative Record Data.” *Journal of Human Resources*, Vol. 21, No. 2, 238-251.

Folland, S., Goodman, A. C. and Stano, M. (2007), *The Economics of Health and Health Care*. New Jersey: Pearson Prentice Hall.

Fuchs, V. R. (1982), “Time Preference and Health: an Exploratory Study.” In Fuchs, V. R. (eds.), *Economic Aspects of Health*. Chicago: University of Chicago Press.

Fuchs, V. R. (2004), “Reflections on the Socio-economic Correlates of Health.” *Journal of Health Economics*, Vol. 23, No. 4, 653–661

Gilleskie, D.B. and Harrison, A. L. (1998), “The Effect of Endogenous Health Inputs on the Relationship between Health and Education.” *Economics of Education Review*, Vol. 17, No. 3, 279–297.

Griliches, Z. (1979), “Sibling Models and Data in Economics: Beginnings of a Survey.” *The Journal of Political Economy*, Vol. 87, No. 5, 37-64.

Grossman, M. (2006), “Education and Nonmarket Outcomes.” In Hanushek, E. and Welch, F. (eds.), *Handbook of the Economics of Education Volume I*. Amsterdam: North-Holland.

Grossman, M. and Kaestner, R. (1997), “Effects of Education on Health.” In Behrman, J. R. and Stacey, N. (eds.), *The Social Benefits of Education*. Ann Arbor: The University of Michigan Press.

Gujarati, D. (2003), *Basic Econometrics*. Boston: McGraw-Hill.

Hartog, J. and Oosterbeek, H. (1998), “Health, Wealth and Happiness: Why Pursue a Higher Education?” *Economics of Education Review*, Vol. 17, No. 3, 245–256.

Hill, R. C., Griffiths, W. E. and Guay, C. L. (2008), *Principles of Econometrics*. New Jersey: Wiley.

Isacsson, G. (2004), “Estimating the Economic Return to Educational Levels Using Data on Twins.” *Journal of Applied Econometrics*, Vol.19, No. 1, 99-119.

Johannesson, M. (1996), *Theory and Methods of Economic Evaluation of Health Care*. Dordrecht: Kluwer Academic Publishers.

Leigh, J. P. (1983), “Direct and Indirect Effects of Education on Health.” *Social Science and Medicine*, Vol. 17, No. 4, 227–234.

Lleras-Muney, A. (2005), “The Relationship between Education and Adult Mortality in the United States.” *The Review of Economic Studies*, Vol. 72, No. 1, 189-221.

Lundborg, P. (2008), “The Health Returns to Education – What Can We Learn from Twins?” Discussion Paper No. 3399. The Institute for the Study of Labor (IZA), Bonn.

Matthews, S., Manorb, O. and Powera, C. (1999), “Social inequalities in health: are there gender differences?” *Social Science and Medicine,* Vol. 48, No. 1, 49-60.

Menchik, P. L. (1993), “Economic Status as a Determinant of Mortality among Black and White Older Men: Does Poverty Kill?” *Population Studies*, Vol. 47, No. 3, 427-436.

OECD, *Country statistical profiles*, various issues. Available [online]: http://stats.oecd.org/wbos/viewhtml.aspx?queryname=18170&querytype=view&lang=en [2009-05-17].

Rabin, R. and De Charro, F. (2001), “EQ-5D: a Measure of Health Status from the EuroQol Group.” *Annals of Medicine*, Vol. 33, No. 5, 337-343.

Sandewall, Ö. (2009), “The Co-twin Methodology and Returns to Schooling – an Empirical Critique.” Mimeo, London School of Economics.

Statistics Sweden, *Statistikdatabasen*. Available [online]: http://www.ssd.scb.se/databaser/makro/start.asp [2005-05-17].

Tackling Health Inequalities: 10 Years On (2009). Available [online]: http://www.dh.gov.uk/en/Publicationsandstatistics/Publications/PublicationsPolicyAndGuidance/DH_098936 [2009-05-17].

Taubman, P. (1976), “The Determinants of Earnings: Genetics, Family, and Other Environments; A Study of White Male Twins.” *American Economic Review*, Vol. 66, No. 5, 858-870.

Wagstaff, A. (1986), “The Demand for Health: Some New Empirical Evidence.” *Journal of Health Economics*, Vol. 5, No. 3, 195-233.

Appendix I - Methodology

EuroQol

The responses to the five dimensions of health in the EuroQol measure (mobility, self-care, usual activities, pain/discomfort and anxiety/depression), are referred to with five digit code numbers. For instance, 11223 means that the individual has no problems walking about or with self-care, has some problems with performing usual activities and some pain, and is extremely anxious or depressed.

From the answers to a TTO survey from the UK, Dolan (1997) fits an additive model using dummies corresponding to each severity level. That is, the health stock is initially set to one and the sum of all moderate or severe states is then subtracted together with so called structural shifts. One of these structural shifts is an intercept that represents a shift away from full health, which means that if a person has responded two or three in any of the health dimensions the intercept, α, is subtracted. If the person has responded three in any of the dimensions another constant, *N3*, is subtracted. The resulting model can be expressed as:

$$H = 1 - S$$

where

$$S = (\alpha + \beta_1 M_2 + \beta_2 S_2 + \beta_3 A_2 + \beta_4 P_2 + \beta_5 D_2 + \beta_6 M_3 + \beta_7 S_3 + \beta_8 A_3 + \beta_9 P_3 + \beta_{10} D_3 + N3)$$

The estimates from Dolan's (1997) model are presented in *Table A1.1*. The coefficients are used to calculate EuroQol index values for our observations based on their responses to the five dimensions of health. Naturally, different individuals value the same health status differently, but the EuroQol measure should be considered the mean value a population would give a certain health state.

Table A1.1 TTO coefficients for EuroQol

DIMENSION	COEFFICIENT
Constant (a)	0.081
Mobility	
level 2	0.069
level 3	0.314
Self-care	
level 2	0.104
level 3	0.214
Usual activity	
level 2	0.036
level 3	0.094
Pain/discomfort	
level 2	0.123
level 3	0.386
Anxiety/depression	
level 2	0.071
level 3	0.236
N3	0.269
adjusted r^2	0.46

Source: Dolan (1997), *Modeling Valuations for EuroQol Health States*.

For instance, the response 11223 would give a EuroQol index of:

$$1-(\alpha+\beta_3 A_2+\beta_4 P_2+\beta_{10} D_3+\beta_{11} N3)=1-(0.081+0.036+0.123+0.236+0.269)=0.255$$

Education measure

Table A1.2 Education levels with corresponding years and dummies.

Category*	Years	Educational level*	Dummy
1	8	Elementary school (sv. "förgymnasial utbildning"), less than 9 years	Baseline
2	9	Elementary school (sv. "förgymnasial utbildning"), 9/10 years	Baseline
3	11	High school, maximum 2 years	D High School
4	12	High school, more than 2 years but maximum 3 years	D High School
5	14	Higher education (sv. "eftergymnasial utbildning") less than 2 years or high school degree in technical subjects, 4 years	D Some College
6	16	Higher education (sv. "eftergymnasial utbildning"), 3 years or longer	D College Degree
7	20	Doctoral studies	D College Degree

*Source: Statistics Sweden

The educational levels and categories in our data are defined by Statistics Sweden in the Swedish Education Nomenclature. We convert the levels to number of years of education completed based on the information given on educational level, see *Table A1.2*. The first category, less than 9 years of elementary school, is difficult to define but as only a very small fraction of individuals (about 1/10,000) do not finish elementary school in Sweden, the category is not of great importance. The majority of individuals in our sample started school before elementary school was changed from nine to ten years, category 2 is therefore set to nine years. Category 3 is set to eleven years, even though it may correspond to less than two years of high school studies, as we believe that those who studied at high school level should be distinguished from those not studying at high school level at all. Category 4 is set to 12 years of education as standard high school education is three years. Higher studies, as defined by category 5, are set to 14 years of education with the same reasoning as for Category 3. Category 6 is set to 16 years as the standard university program is four years. Doctoral studies, category 7, are set to 20 years of education as a doctoral program often is about four years. Using educational levels to compute the corresponding years of education completed is not a perfect measure of years of education, but in the case of Sweden education is highly standardized and hence there should not be a large discrepancy between our measure of educational years and the actual number of years spent in school.

Appendix II - Results

Regressions for all observations

Presented below are the regression results for equation (4) when including all observations in the sample, i.e. both twins in each twin pair.

Table A2.1 Cross-sectional OLS estimates of equation (4) on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.889	0.021	41.743	0.000
Age	-0.003	0.000	-7.886	0.000
Sex	-0.034	0.005	-6.685	0.000
Civil status	-0.006	0.006	-1.040	0.298
Income 5y avr	1.28E-07	0.000	5.804	0.000
Education years	0.008	0.001	7.802	0.000
n	R^2	Adj. R^2	F	Sig.
4348	0.050	0.049	46.002	0.000

Table A2.2 Cross-sectional OLS estimates of equation (4) on RS.

	B	Std. Error	t	Sig.
Constant	0.849	0.020	41.589	0.000
Age	-0.002	0.000	-6.327	0.000
Sex	-0.005	0.005	-1.119	0.263
Civil status	-0.007	0.005	-1.296	0.195
Income 5y avr	1.03E-07	0.000	4.877	0.000
Education years	0.004	0.001	3.610	0.000
n	R^2	Adj. R^2	F	Sig.
4184	0.018	0.016	14.980	0.000

Table A2.3 Cross-sectional OLS estimates of equation (4), with IQ on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.910	0.053	17.287	0.000
Age	-0.003	0.001	-2.883	0.004
Civil status	-0.028	0.009	-2.990	0.003
Income 5y avr	1.21E-07	0.000	3.852	0.000
Education years	0.007	0.002	2.988	0.003
IQ	-0.007	0.006	-1.223	0.222
n	R^2	Adj. R^2	F	Sig.
760	0.065	0.058	10.417	0.000

Table A2.4 Cross-sectional OLS estimates of equation (4), with IQ on RS.

	B	Std. Error	t	Sig.
Constant	0.850	0.056	15.310	0.000
Age	-0.001	0.001	-1.404	0.161
Civil status	-0.009	0.010	-0.921	0.357
Income 5y avr	1.17E-07	0.000	3.508	0.000
Education years	0.001	0.002	0.216	0.829
IQ	-0.013	0.007	-2.030	0.043
n	R^2	Adj. R^2	F	Sig.
744	0.022	0.015	3.298	0.006

Table A2.5 Cross-sectional OLS estimates of equation (4), with birthweight on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.862	0.031	28.140	0.000
Age	-0.003	0.001	-6.123	0.000
Sex	-0.034	0.007	-4.849	0.000
Civil status	0.002	0.007	0.305	0.760
Income 5y avr	1.27E-07	0.000	4.350	0.000
Education years	0.009	0.001	6.687	0.000
Birthweight	2.43E-06	0.000	0.475	0.635
n	R^2	Adj. R^2	F	Sig.
2856	0.050	0.048	25.095	0.000

Table A2.6 Cross-sectional OLS estimates of equation (4), with birthweight on RS.

	B	Std. Error	t	Sig.
Constant	0.807	0.029	28.298	0.000
Age	-0.002	0.000	-4.875	0.000
Sex	-0.008	0.006	-0.026	0.196
Civil status	0.002	0.006	0.383	0.701
Income 5y avr	9.15 E-8	0.000	3.394	0.001
Education years	0.005	0.001	4.140	0.000
Birthweight	7.06 E-6	0.000	1.481	0.139
n	R^2	Adj. R^2	F	Sig.
2746	0.023	0.021	10.900	0.000

Birthweight regressions

Included in this section are the regressions results for equation (4) and (8) where birthweight is included as a proxy for ability.

Table A2.7 Cross-sectional OLS estimates of equation (4), with birthweight on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.897	0.043	20.984	0.000
Age	-0.004	0.001	-4.953	0.000
Sex	-0.039	0.010	-4.085	0.000
Civil status	-0.012	0.010	-1.280	0.201
Income 5y avr	1.20E-07	0.000	2.951	0.003
Education years	0.010	0.002	4.783	0.000
Birthweight	5.29E-08	0.000	0.007	0.994
n	R^2	Adj. R^2	F	Sig.
1428	0.055	0.051	13.829	0.000

Table A2.8 Twin-differencing OLS estimates of equation (8) on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.001	0.005	0.138	0.890
Civil status	0.007	0.010	0.725	0.469
Income 5y avr	3.29E-08	0.000	0.620	0.535
Education years	0.006	0.003	2.108	0.035
Birthweight	-5.29E-06	0.000	-0.477	0.633
n	R^2	Adj. R^2	F	Sig.
2174	0.004	0.001	1.351	0.249

Table A2.9 Cross-sectional OLS estimates of equation (4), with birthweight on RS.

	B	Std. Error	t	Sig.
Constant	0.780	0.040	19.463	0.000
Age	-0.002	0.001	-3.401	0.001
Sex	-0.007	0.009	-0.751	0.453
Civil status	0.003	0.009	0.318	0.750
Income 5y avr	1.06E-07	0.000	2.564	0.010
Education years	0.007	0.002	3.994	0.000
Birthweight	5.43E-06	0.000	0.797	0.426
n	R^2	Adj. R^2	F	Sig.
1373	0.029	0.025	6.769	0.000

Table A2.10 Twin-differencing OLS estimates of equation (8) on RS.

	B	Std. Error	t	Sig.
Constant	-0.002	0.005	-0.412	0.680
Civil status	-0.010	0.009	-1.088	0.277
Income 5y avr	8.83E-08	0.000	1.829	0.068
Education years	0.003	0.003	1.323	0.186
Birthweight	4.31E-06	0.000	0.427	0.669
n	R^2	Adj. R^2	F	Sig.
1373	0.004	0.002	1.536	0.189

Pearson correlations

Presented below are correlation tables for the EuroQol samples. We do not include the corresponding tables for the RS samples as they are almost identical. “*” indicates that the correlation is significant at the 0.05 level (2-tailed) and “**” indicates that the correlation is significant at the 0.01 level (2-tailed).

Table A2.11 Correlations, cross-sectional standard sample.

Variable	Sex	Civil status	Education years	Income 5y avr	Age
Sex	1.00				
Civil status	-0.03	1.00			
Education years	.043*	-.050*	1.00		
Income 5y avr	-.255**	-.305**	.043*	1.00	
Age	0.00	-.424**	-.103**	.573**	1.00

Table A2.12 Correlations, twin-differencing standard sample.

Variable	Civil status	Education years	Income 5y avr
Civil status	1.00		
Education years	0.03	1.00	
Income 5y avr	0.01	-.078**	1.00

Table A2.13 Correlations, cross-sectional IQ sample.

Variable	Age	Civil status	Education years	Income 5y avr	IQ
Age	1.00				
Civil status	-.244**	1.00			
Education years	-.175**	-.120*	1.00		
Income 5y avr	.321**	-.256**	.250**	1.00	
IQ	-0.03	-.141**	.517**	.232**	1.00

Table A2.14 Correlations, twin-differencing IQ sample.

Variable	Civil status	Education years	Income 5y avr	*IQ*
Civil status	1.00			
Education years	0.09	1.00		
Income 5y avr	.104*	0.00	1.00	
IQ	0.10	.197**	0.00	1.00

Table A2.15 Correlations, cross-sectional birthweight sample.

Variable	Age	Sex	Civil status	Education years	Income 5y avr	Birthweight
Age	1.00					
Sex	-0.01	1.00				
Civil status	-.420**	-0.05	1.00			
Education years	-.104**	0.02	0.04	1.00		
Income 5y avr	.549**	-.240**	-.260**	.078**	1.00	
Birthweight	-.053*	-.078**	0.00	0.04	-0.01	1.00

Table A2.16 Correlations, twin-differencing birthweight sample.

Variable	Civil status	Education years	Income 5y avr	Birthweight
Civil status	1.00			
Education years	0.02	1.00		
Income 5y avr	0.00	-.067*	1.00	
Birthweight	0.01	0.04	0.03	1.00

Educational level regressions

Estimates of the standard regressions when measuring education in levels instead of years are presented below.

Table A2.17 Cross-sectional OLS estimates of equation (4), with educational levels on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.894	0.029	30.404	0.000
Age	-0.003	0.001	-5.185	0.000
Sex	-0.041	0.007	-5.622	0.000
Civil status	0.006	0.008	0.747	0.455
Income 5y avr	1.43E-07	0.000	4.241	0.000
High school	0.088	0.019	4.534	0.000
Some College	0.117	0.020	5.817	0.000
College	0.112	0.020	5.654	0.000
n	R^2	Adj. R^2	F	Sig.
2174	0.062	0.059	20.245	0.000

Table A2.18 Twin-differencing OLS estimates of equation (5), with educational levels on EuroQol.

	B	Std. Error	t	Sig.
Constant	0.001	0.004	0.300	0.764
Civil status	0.007	0.008	0.887	0.375
Income 5y avr	3.31E-08	0.000	0.818	0.413
Elementary & High School	-0.002	0.022	-0.073	0.942
Elementary & Some College	0.070	0.064	1.085	0.278
Elementary & College Degree	-0.074	0.081	-0.914	0.361
High School & Some College	-0.010	0.012	-0.850	0.395
High School & College Degree	-0.016	0.015	-1.071	0.284
Some College & College Degree	0.010	0.013	0.764	0.445
n	R^2	Adj. R^2	F	Sig.
2174	0.003	0.000	0.740	0.656

Table A2.19 Cross-sectional OLS estimates of equation (4), with educational levels on RS.

	B	Std. Error	t	Sig.
Constant	0.828	0.026	32.043	0.000
Age	-0.003	0.001	-5.146	0.000
Sex	-0.011	0.007	-1.564	0.118
Civil status	-0.016	0.007	-2.196	0.028
Income 5y avr	8.98E-08	0.000	3.065	0.002
High school	0.096	0.017	5.749	0.000
Some College	0.097	0.018	5.534	0.000
College	0.103	0.017	5.995	0.000
n	R^2	Adj. R^2	F	Sig.
2092	0.037	0.034	11.560	0.000

Table A2.20 Twin-differencing OLS estimates of equation (5), with educational levels on RS.

	B	Std. Error	t	Sig.
Constant	-0.002	0.004	-0.656	0.512
Civil status	-0.001	0.007	-0.178	0.858
Income 5y avr	9.82E-08	0.000	2.610	0.009
Elementary & High School	0.065	0.020	3.229	0.001
Elementary & Some College	0.025	0.059	0.422	0.673
Elementary & College Degree	0.030	0.075	0.395	0.693
High School & Some College	-0.002	0.011	-0.178	0.859
High School & College Degree	-0.013	0.014	-0.949	0.343
Some College & College Degree	-0.001	0.012	-0.127	0.899
n	R^2	Adj. R^2	F	Sig.
2092	0.009	0.005	2.314	0.180