The Ability of Being Healthy

An empirical analysis of cognitive ability and the effect on health

Abstract

In this paper an effort has been made to identify the contribution of cognitive ability on health and how cognitive ability influences the effect of education on health. This paper is an addition to the recent paper that tried to disentangle this education and ability effect on mortality (Bijwaard, Van Kippersluis, & Veenman, 2013). A Dutch cohort study has been used with data of almost 3000 recipients all born around 1940. With help of multiple regression analysis, a comparison with presence and absence of two different measurements for intelligence has been done for various models. This research found a positive and significant effect of education on self-assessed health reports

Keywords: Education, Health, IQ, Selection effect

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1. Introduction

"The life expectancy of high educated people is 6 to 7 years higher than that of the low educated people. Also high educated people live much longer in good health than low educated people" (CBS, 2012). A positive relation between education and health is one of the most established facts in academic research (Mazumder, 2012).

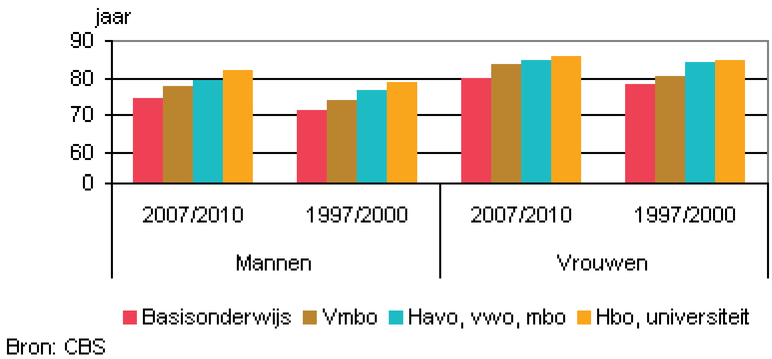

Figure 1: Life expectancy by birth to educational level for the Netherlands

It is assumed that a significant part of this difference comes from the causal effect of education on health. This causal effect comes most likely from difference in behavior between educational groups, such as smoking, drinking, diet, exercise, use of drugs, household safety and use of preventive medical care (Cutler, 2006). However, the effect could also be in the opposite direction: suffering from bad health as a child may prevent an individual from attaining school (Behrman, 2004) (Case, 2005). It also could be that exogenous factors both have an effect on education and health (Auld, 2005). These exogenous factors could lead to false interpretation of the effect of education and health, when not controlled for in a model. In order to separate the direct effect from third-factor effects numerous studies have been conducted with natural experiments in education. These studies used changes in policy and laws on compulsory schooling. These studies identify a small positive effect of education on health and mortality outcomes (Lleras-Muney, 2005); (Oreopoulos, 2006); (Van Kippersluis, O'Donnel, & Doorslaer, 2011), and sometimes even an insignificant effect (Albouy & Lequien, 2008); (Braakman, 2011); (Mazumder B. , 2008).

Some studies state that there might be a relation between childhood cognitive abilities and health outcomes in mid-life (Conti & Heckman, 2010) (Conti, Heckman, & Urzua, 2010) (Murasko, 2007). But it is assumed that real decline of health, partially due to behavior and factors in early life, is not really revealing its effect until an individual reaches the age of fifty (CBS, 2012). Until recently little research has been done concerning all the different socioeconomic factors of family background, childhood and later life performance (Bijwaard, Van Kippersluis, & Veenman, 2013). Controlling for a large set of different social variables like a background family's social class and IQ, they identify a treatment effect of education on health and a selection effect. This selection effect is the effect in extend to which a person "selects" him/herself in education levels. This selection procedure consists of various factors, such as intelligence, social background, educational facilities in the region and economic status of the parents. The treatment effect is the causal effect on health that can be assigned to educational achievements. They found that differences in mortality for lower ages are mainly due to the selection effect and for older ages the treatment effect grows in influence, the overall selection effect is on average 50%. The aim of this paper is to identify part of this selection effect, which probably over-estimates the treatment effect of education on health. Identifying this effect could have all kinds of policy implications, because maybe when looking at the gross effect of education on health without considering IQ too much effort and costs will be spend on leveling educational differences between groups. The questions this paper aims to answer are: In extend to which the effect of education on health can be explained by IQ and how does IQ affect health directly when controlling for education. The dataset used in this research will be the "Brabandtse Zesdeklassers", a cohort study of individuals born around 1940. With a regression analysis coefficients will be estimated for the main variables of interest, IQ and educational achievement, and for a number of control variables.

There are 2 main contributions of this research to this academic area of research. First, this research tries to identify the selection effect of cognitive ability into education, which will create a more untreated effect of education on health outcomes. Second, this research uses a more relevant sample of individuals than previous studies, namely aged around 55, and has a more relevant outcome variable than mortality for that age category, namely self-assessed health. It is probable that self-assessed health is a stronger variable to project health disparities between persons instead of mortality, because in their sixties not many people died yet. It is expected education will have a positive effect on self-assessed health in this study, consistent with the existing literature. Also it is expected the effect of education on health will decrease when controlling for IQ or other measurements of cognitive ability. This is because the effect of education on health will be partially enlarged by the selection effect on education when omitting cognitive ability from the model.

This study finds a significant effect of education on self-assessed health, which decreases when controlling for cognitive ability. This means intelligence plays a role in the selection effect of education. Only a minor direct effect of intelligence on health, i.e. not through education, is found. Two alternative measures for cognitive ability are used as substitutes, IQ and abstract thinking. It appears that the ability of analytical thinking and problem solving plays an important part in this process of explaining the effect of education and health. People who are more capable of thinking in an analytical and creative way experience better health.

This paper is structured as follows. Section 2 gives some background information and motivation on the data used, section 3 presents the method that is used to analyze the data. Section 4 contains the results and reviews them. Section 5 discusses the conducted research and an overall conclusion will be provided.

2. Data and descriptive statistics

The data used is from a Dutch cohort survey, “Brabandtse Zesdeklassers”. The dataset contains very detailed information about a person’s socioeconomic background, intelligence, education, career and a lot of variables on social en economic performance. The first interview was conducted in the spring and summer of 1952 and 5771 individuals were interviewed who were all approximately 12 years old. The initial random sample consisted of schoolchildren in the sixth grade of the primary schools of North Brabant, which is nowadays called “groep acht”. The questionnaire in 1952 contained 59 variables on family background and intelligence. In 1983 the data were rediscovered by Professor Joop Hartog and he organized a follow-up in order to collect further information on 143 variables, mainly aimed at educational achievements and labor market position. The present address of about 80% of the 1952 respondents could be traced in the Dutch civil administration, and a questionnaire was mailed to these in May 1983. This has been repeated in 1993 with an additional 214 variables. In 2009 the dataset has been updated with information on mortality. The overall response rate of both surveys was around 45%. Combining information from these three surveys and removing a number of defective or inconsistent records a database was constructed with records of 2998 individuals. These have all participated in the 1952 survey and in at least one of the two later surveys. Thus there are 2998 respondents from 1952, 2528 from 1983, 1956 from 1993, and 1486 from both 1983 and 1993. Also the number of variables was reduced from 416 to 70 to make the dataset easier to work with and to overcome some problem with multi-defined variables. For this research this dataset is used. The dataset is retrieved from the DANS[1]..

2.1 Dependent Variable

Self-assessed health from the study of 1993 is used as an outcome variable in order to measure health. Self-assessed health is believed to be a good predictor of actual health (Idler, 1997). Respondents were between 50 and 55 years old when reporting their health. At this age health disparities are likely to occur and behavior and factors in previous life start having its effect on health (CBS, 2012). The dataset contains information on health about 1923 individuals. In the 1993 survey people were asked to rate their health at a five point scale with 1 referring to excellent health, and 5 to very poor health. For the regression analysis the variable has been converted to a dummy variable with value 1, corresponding to good health (categories 1 and 2), and value 0 corresponding to poor health (categories 3, 4 and 5).

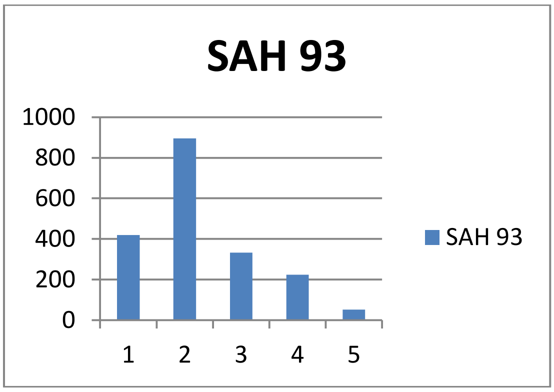

Figure 2: Self assessed health in original data

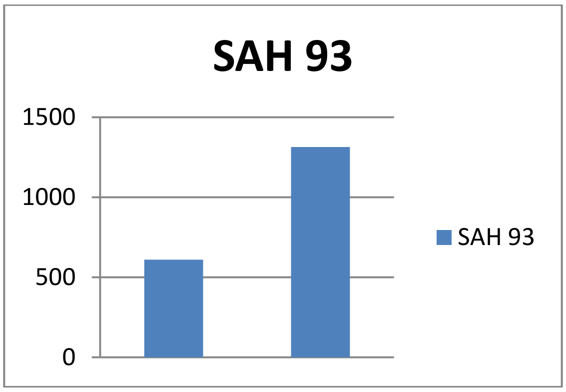

Figure 3: Self assessed health after aggregated variable (0,1)

Results of this transformation can be seen in the figures above. 1314 recipients (68%) are now labeled as being in good health. 609 recipients (32%) in the sample are labeled as being in poor health. By converting the five categories into two, a more distinct and unique sample

[1] (Data Archiving and Networked Services) www.dans.knaw.nl

is created when compared to a gradient scale which will be more suitable for a lineair regression and to identify the effect of the different variables.

2.2 Independent variables of interest

The most important independent variables for this research are IQ and education. All individuals were tested on their cognitive ability around age 12, in the original survey of 1952. IQ Is measured in 2 different ways in the Brabant study. First of all there is a modified LO-IV test. This LO-IV test was an existing intelligence test which was already calibrated for pupils of primary schools in Noord-Brabant, the study population. The test consisted of 6 smaller tests: patterns in number sequences, analogy laws in figures, analogy laws in words and similarities in concepts (similar, opposites and causal relations). The other method of measuring cognitive ability was a combination of two different tests. The first one was a test for measuring abstract thinking and problem solving, also known as the Raven Progressive Matrices test. This test is a replication of the British Progressive Matrices test, designed by Raven (1958). The Raven test is a test which measures problem solving abilities and does not require any general or vocabulary knowledge. Hence this test is considered to be a valid test for cognitive ability and analytical capabilities (Carpenter, 1990). The second one was a measurement for a pupil's vocabulary. It consisted of a list of words and pupils had to pick the right synonym for that word out of six options. The main role of the combination of the Progressive Matrices test and the vocabulary test was to control for the LO-IV test, because the LO-IV test decreased in credibility when it was modified into the six subtests.

Education is obtained from either the 1983 study or the 1993 study, divided into 6 different categories which are labeled 1 to 6 in the aggregated dataset from 2010. The corresponding educational degrees with the values can be seen below:

1	Kindergarten	4	Higher secondary school (HAVO, HBS, VWO)
2	Primary school	5	College (HBO)
3	Lower secondary school (LAVO, VGLO, MAVO)	6	University (WO)

In the population nobody has responded a value below 3. This makes sense as in The Netherlands primary school is compulsory since 1903. Most individuals didn't receive a higher educational degree than lower secondary school (67%). 13% obtained a higher secondary school degree, 16% a college degree and 4% completed university[2]. Interesting is the increase from categories 4 to 5. This can be explained by to the opportunity one has to obtain a higher degree (college or University) because future benefits are much larger than incurred extra costs.

2.3 Control variables

The standard control variables used in regular regression analysis of this type are gender and age. Gender is measured as a dummy variable for being female and Age is measured in years in 1993 and both are available for the complete sample. 40% of the sample population is female, which means they are underrepresented[3]. This is due to the follow-ups in 1983 and 1993 when special effort was paid to contacting male individuals, because researchers were interested in labor market position and the majority of women did not work in that time. Labour participation rate of women was less than 35%, on the contrary this was around 90% for men. Age is assumed to only show a minor effect on the outcome variable health since all individuals were around age 12 when interviewed and is therefore not included in the regression model. Another interesting variable in the dataset is the family's social class. This variable is based on the father's occupation, which is an accurate measurement for 1952 standards because in that time most of the time the father generated income to support the family. It is believed that social background of the family influences health outcomes positively (Verhaege, Pattyn, Bracke, Verhaege, & Van de Putte, 2012). The variable is divided into 3 categories, with 1 referring to a low social family class, 2 to an average social class and 3 to a high social family class. A common variable in these kinds of studies is a measurement of income. The dataset contains many variables about income in 1983 and 1993, but a lot of values are missing and variables are measuring for a part the same income. Only a little over 35% of the recipients filled in their annual income in 1993 and other measurements of income even have lower response. For this reason income is not taken into account in the analysis because it largely decreases the number of observations in the sample and including it in the analysis may lead to false conclusions on the effect of income on self-assessed health. This is because the missing variables decrease the significance of the model. Table 1 shows the descriptive statistics of all the variables used in the different models.

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[2] See Appendix 7.2

[3] See Appendix 7.2

Also 2 variables about job characteristics are included in the analysis. One is a variable that indicates if people are still working in 1993 or not. The main reason is that recent study shows that retire earlier in life affects reported health negatively because of the new environment and amount of stress that goes along with retirement. New research indicates that being retired decreases physical, mental and self-assessed health. The following results were obtained: Retirement decreases the likelihood of being in 'very good' or 'excellent' self-assessed health by about 40%. Retirement increases the probability of suffering from clinical depression by about 40% (Sahlgren, 2013). So it is assumed that still being active in a job positively affects self-assessed health. On the other hand being in bad health may prevent people from having a job or being able to work, which would mean there is reverse causality. In the sample there is data on 1944 individuals of whom 67 percent was still working in 1993. The last control variable included in the model is the steadiness of an individual's job. This is measured by being employed for at least 20 years until 1993. Being employed for 20 years indicates that a person has not been unemployed, and therefore can be used as a variable measuring partially unemployment of the sample of respondents. There are data on 1944 individuals, 39 percent was employed for less than 20 years and 61 percent was employed for more than 20 years[4].

2.4 Alternative Dependent Variable

As mentioned, self-assessed health appears to be a strong indicator for actual health and mortality (Idler, 1997) but may suffer from its subjectivity, as reporting differences in health may be partially influenced by factors like education (Bago d'Uva, Van Doorslaer, Lindeboom, & O'Donnell, 2008). In order to account for the possible subjectivity and bias that comes with reporting self-assessed health, there will also be an identical model with mortality as a dependent variable to control for the model with self-assessed health. Mortality is recorded for almost the complete sample of the 2998 individuals included in the 2010 database. The variable is identified from the mortality register in the period 1995-2009. The variable is a dummy where value 1 refers to an individual as being deceased and value 0 as being still alive. Since pupils were all born around 1940, mortality rates are reported from individuals aged 55 to 70. From the total sample of 2998 individuals 348 died in the period 1995-2009.

[4] See Appendix 7.2

Variable	Obs	Mean	Std. Dev.	Min	Max
SAH93	1923	.6833073	.4653074	0	1
Dead	2998	.1160774	.3203711	0	1
Female	2998	.4029353	.4905698	0	1
Educationmax	2645	3.577316	.9024758	3	6
Familyclass	2693	1.528407	.5489003	1	3
Steadyjob93	1944	.6059671	.4887677	0	1
Active93	1944	.6723251	.4694864	0	1
IQ	2732	101.597	14.24087	72	190
RavenTest	2588	102.1851	14.34632	74	147

Table 1: Descriptive statistics of the used variables

3. Methodology

The method used for analyzing the data is an ordinary least squares multiple regression model. Multiple regression is a linear transformation of the X variables such that the sum of squared deviations between observed and predicted Y is minimized. Y is accomplished by the following equation:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i,$$

The "β" values are called regression weights and are estimated in a way that minimizes the sum of squared deviations.

$$\sum_{i=1}^{N} (Y_i - Y'_i)^2$$

Dummy variables are self-assessed health as the dependent variable with good health valued as 1, and having a steady job, being active in 1993, mortality with being dead valued as 1 and gender with being female valued as 1 as independent variables. Valuing good health as 1 means that the coefficients of the independent variables will represent the effect of the probability of having good health. The dummy variables entered as predictor variables are coded 1 and 0, thus the regression weight is added or subtracted to the predicted value of Y depending upon whether it is positive or negative. The categorical variables are education in four categories and family social class in three categories. These variables will be used as factor variables in the regression analysis. This means that the coefficients of the categories are relative to the scores of the first category. So the coefficients of category 4, 5 and 6 from the education variable will be compared to category 3. Coefficients of category 2 and 3 from the social class variable will be compared to category 1 of that variable.

As mentioned before self-assessed health is used as dependent variable and the main variables of interest are IQ and highest degree of education obtained. When considering the effect of education on health there is probably a treatment effect and a selection effect (Bijwaard, Van Kippersluis, & Veenman, 2013). This treatment effect is the effect in extend to which educational choices influence health outcomes. The selection effect consists of various unobserved factors that determine educational choices and that influence health. Important factors in this selection effect are cognitive ability, social background, and economic status of parents. These factors will affect health through education, but also may have a direct effect on health. When focusing on cognitive ability the direct effects on health can be that more intelligent individuals can interpret health complaints better and can gather and process medical information better. The graph below shows a visualization of the selection effect into education. This model gives an impression when no control variables that contribute to the selection effect are taken into account.

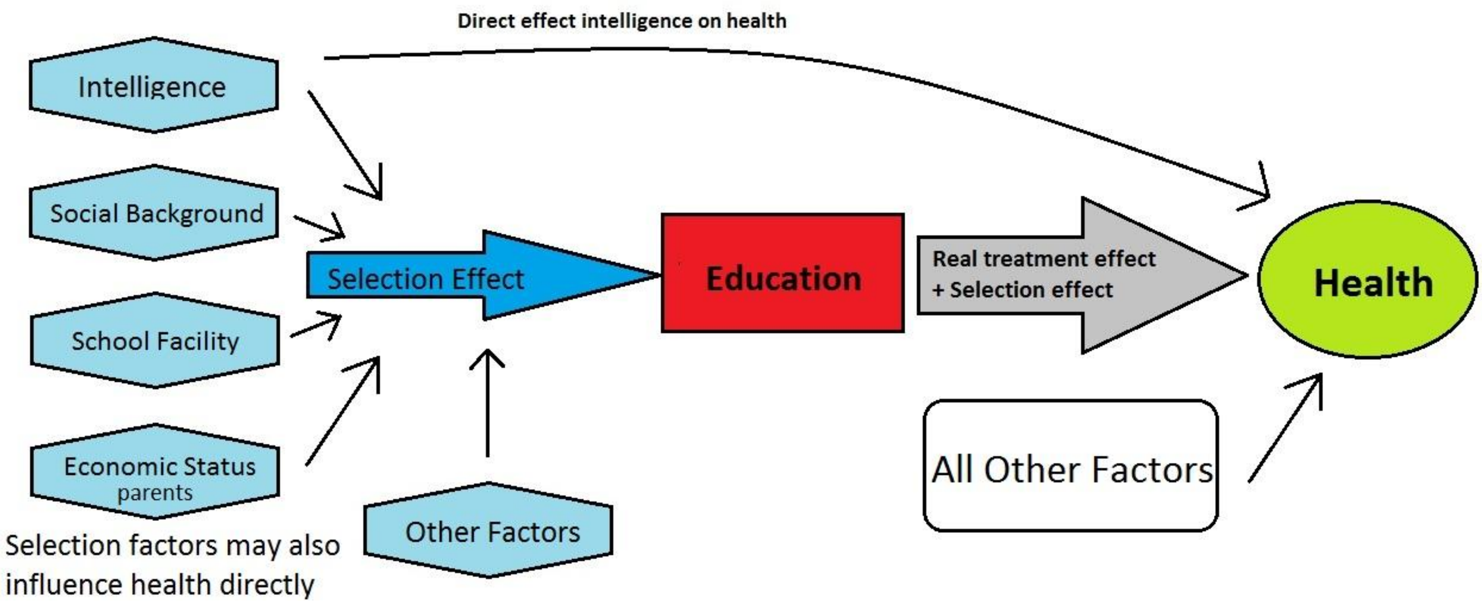


Figure 4: Effect of IQ on health

In order to identify this selection effect of intelligence on health the OLS regression is used with control variables to overcome selection bias. This is necessary because the recipients divided in the 2 categories of health outcomes will probably differ in many more factors than only intelligence and education. There is need to control for these differences as otherwise the probabilities in the model will be estimated wrong. When not controlled for these differences the effect of education might be over-estimated. This is because variables may contribute to the selection effect of education but when not included in the model the effect of these variables is completely attributed to education.

4. Results

In this section the main findings of the analysis will be discussed when measuring the effect of cognitive ability and education on health. First, the simple with and without comparisons will be presented with both health and mortality as dependent variables. Secondly, the same models will be presented only with more control variables included.

4.1 Simple model with and without intelligence on SAH

Table 1: Simple model with independent variable IQ and Raven Test, outcome SAH

Dependent	SAH93	SAH93	SAH93	SAH93
Female	0,0146	0,0129	0,017	0,0124
Educationmax 4	0,0749	0,0675	0,0914	0,0747
Educationmax 5	0,117	0,103	0,118	0,0897
Educationmax 6	0,232	0,211	0,21	0,168
IQ	.	0,00111	.	.
Raven Test	.	.	.	0,00307
Constant	0,644	0,533	0,642	0,355
N	1667	1667	1540	1540
α = 0,1				
α = 0,05				
α = 0,01				

Table 1 shows the results of a simple with and without comparison with self-assessed health in 1993 as the dependent variable, education, IQ, Raven Test and the dummy gender as independent variables. Column 2 shows the regression coefficients of the variables without controlling for IQ and there are all significant on the 0,05 percent or 0,01 per cent level, except from gender. The coefficients of education categories are positive and increasing with the degree of education. This is consistent with the existing literature that education has a positive effect on self-assessed health outcomes and therefore on actual health outcomes (Idler, 1997). The sign of the coefficient of gender is inconsistent with the existing literature, because in general female subjects report lower values of self-assessed health (Deeg & Kriegsman, 2003).

This is obviously a very simplified model and therefore not very accurate. The explanatory power is only around 1,6%, but it gives a nice implication of the effect of education on reported health without concerning other factors. In column 3 exactly the same model has been estimated, but then with IQ as third explaining variable. When comparing the coefficients of education in both models a clear drop in the effect can be observed when adding IQ to the model. Coefficients drop in order of category with respectively 0.0074, 0.014 and 0.021. So the higher the level of education obtained, the more IQ explains a part of the education effect on health. One may conclude from these outcomes that IQ plays an explanatory role when measuring the effect of education on health, without taking other factors into account. This supports the findings of (Bijwaard, Van Kippersluis, & Veenman, 2013) that the education effect can be split in a real treatment effect and a selection effect of IQ. According to this simple comparison the direct effect of IQ on health is only small (.00111) and insignificant. This could indicate that IQ mainly affects health through education than being an explanatory variable on its own. But from this model it cannot be identified for what part IQ influences the selection effect, as other factors also contribute to this selection effect.

When looking at column 4 and 5 the same comparison is presented, but this time with another measurement for IQ, the earlier mentioned “Raven Test”. The sample of this population is 127 observations smaller because not all recipients have data on the Raven Test. However, the model without the Raven Test remains pretty much the same compared to the model without IQ in the previous analysis. Interestingly enough the “Raven Test, the measurement of problem solving and abstract thinking, has an much larger effect on health than the general IQ test. The results of education are significant for all three levels of education. The coefficients of education decreased respectively 0.0167, 0.0283 and 0.042. This is on average more than two times as much as the previous model discussed. Also the direct effect of abstract thinking on reported health is almost 3 times higher than the effect of the general IQ test. The correlations coefficient of IQ and abstract thinking is almost 0.56. This implies the IQ test and the Raven test measure partially the same thing, which makes sense since a general IQ test consists of one part problem solving and one part vocabulary testing. The unique part of the Raven Test which is not also measured in the IQ test seems to be of importance because it reduces the effect of education on health more than IQ does and also the direct effect is bigger. The effect of the Raven test is significant on the 0.01 per cent level. Based on these outcomes one could say that the Raven Test shows greater influences than IQ, which would may indicate that the Raven Test plays a larger role in the selection effect of education and direct effect of intelligence on health. Since the Raven Test focuses on analytical abilities, an individual analytical abilities and abstract thinking seem to play a larger part than general IQ in influencing health outcomes, without controlling for other, obviously contributing, factors. Still this effect is minimal when compared to previous findings (Gottfredson, 2004) (Bijwaard, Van Kippersluis, & Veenman, 2013). They find that the possible selection effect of education is around fifty per cent of the total effect of education and that, along with other factors, cognitive ability plays a major role in explaining this selection effect. It has to be said they used a much more elaborate model compared to this research and the used mortality rates as outcome variable, but still results in this study are not even close to their findings. One explanation could be the difference in outcome variable, because although self-assessed health is a determent of mortality; it is still subjected to an amount of subjectivity from the respondent. Also many other factors should be taken into account when analyzing the effect of IQ and education; this will be conducted and analyzed further.

Nevertheless these results are consistent with new research in neuroscience. Researchers found a significant effect of the production of the monoamine dopamine in the brain and its effect on aging. Dopamine is produced in our brain and has many functions, including effects in behavior and cognition, movement, attention, motivation and reward, mood, sleep, and learning (Missale, Nash, Robinson, Jaber, & Caron, 1998). It is believed dopaminergic neuron firing increases when a reward is expected and depressed when the reward is not forthcoming. This makes it highly significant in learning and behaving. People with a high amount of dopamine receptors, and therefore the ability of processing a lot of dopamine, are believed to be better in problem solving, which is linked to analytical capabilities and creative and abstract thinking. Recent studies have implied that dopamine plays a significant and preventing role in age-related illnesses such as Parkinson's disease (Düzel, Bunzeck, Guitart-

Masip, & Düzel, 2010). This could explain the larger and more significant effect of abstract thinking on health partially and it is an interesting side path of this research and worth investigating, as there are possibilities to increase a person's dopamine levels and therefore potentially influencing health outcomes.

To monitor this model and its implications, this same model has been estimated with mortality as outcome variable. All variables contribute to the chance of "being not dead", as deceased in period 1995-2009 is referred to as value 1 in the dummy variable. The results of the regression can be seen below.

4.2 Simple model with and without intelligence on mortality

Table 2: Simple model with independent variable IQ and Raven Test, outcome mortality

Dependent	Mortality	Mortality	Mortality	Mortality
Female	-0,0503	-0,0489	-0,052	-0,0507
Educationmax 4	-0,0379	-0,0308	-0,0427	-0,0372
Educationmax 5	-0,0266	-0,0129	-0,0284	-0,0176
Educationmax 6	-0,0325	-0,0117	-0,0591	-0,0441
IQ	.	-0,00106	.	.
Raven Test	.	.	.	-0,00113
Constant	0,143	0,248	0,144	0,258
N	2403	2403	2216	2216
α = 0,1				
α = 0,05				
α = 0,01				

Table 2 shows the results of the regression similar to ones in table 1, but now with mortality as the dependent variable. The results are contradicting with the previous ones. There is not an education gradient, as we saw earlier, and also the results of education are not significant for any of the categories in both models, except for the fourth category in the model without a control for intelligence and the model with the Raven Test variable. When looking at the explanatory power of the model it is extremely low with less than one per cent. The only convincing evidence of the effect of cognitive ability on mortality is the intelligence variable. Both the IQ and the Raven test variable are significant in both models and contribute negatively to the probability of dying. It can be stated that the direct effect of cognitive ability on health is slightly positive with some confidence. However, the model is not very realistic because of the large selection bias that is probably present, due to exogenous variables that should be integrated into the model. All variables that influence the educational and/or self-assessed health variable are relevant for the model and in absence of these variables probabilities regarding health outcomes are over estimated. When looking at the descriptive statistics the contradicting outcomes of the model with mortality are probably due to the small number of deceased people in each category of education.

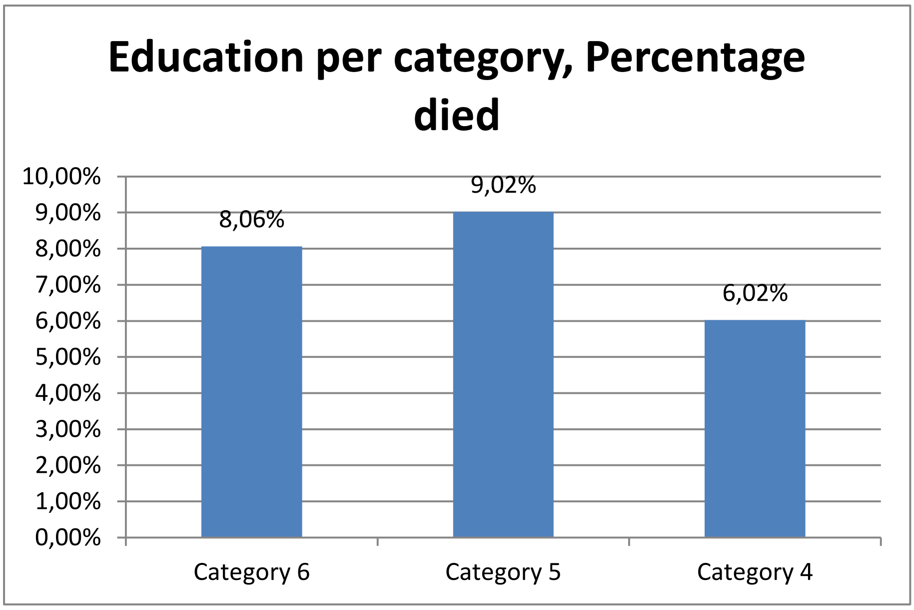


Figure 5: Percentage died per education category

Figure 5 shows the results of the percentage of people died within each category of education. It is likely that our sample in 1993 is too young (around 60 years old) to show a contributing effect in mortality. These findings are contradicting with earlier findings on American datasets (Lleras-Muney, 2005) (Deaton, 2001). One explanation could be they used much more control variables and a more elaborate model, which enabled them to extrapolate the results to predict health outcomes of the recipients at higher age. Also they rearranged the education variable into own categories with different thresholds then the six category's used here. The model with mortality as an outcome variable will also be used in the extended model which contains more control variables to see whether the contradicting results remain.

4.3 Extended model with and without intelligence on SAH

Table 3: Extended model with independent variable IQ and Raven Test, outcome SAH

Dependent	SAH93	SAH93	SAH93
Female	0,156	0,153	0,151
Educationmax 4	0,0581	0,0514	0,0425
Educationmax 5	0,0734	0,0617	0,0465
Educationmax 6	0,127	0,108	0,0863
Familyclass 2	0,0624	0,0634	0,0643
Familyclass 3	0,155	0,152	0,14
Steadyjob93	0,0744	0,0738	0,0746
Active93	0,24	0,24	0,241
IQ	.	0,000923	.
Raven Test	.	.	0,003
Constant	0,356	0,265	0,0547
N	1411	1411	1411
α = 0,1			
α = 0,05			
α = 0,01			

Table 3 shows an extended regression analysis with 3 new variables included compared to the simplistic model in table 1 and 2. These are a variable for the class of the background family measured by the job of the father, whether the recipient was employed for more than 20 years in a row and whether the recipient was still active during the data collection of 1993. When controlling for these variables education drops its effect. This is also what you would expect because it is very likely education is only one of many factors that would explain health. All coefficients show a positive relation to health. The sample is smaller than in the simple model due to missing values in the dataset. The variables are less significant compared to the simple model but the model itself is still significant, probably because still a large sample is included in the model. The model still has a small explanatory power, just fewer than 10 per cent, but it is a large increase compared to the simple with and without comparison which indicates these factors definitely play a role in the establishment of experienced health.

The results are intuitively right. Being raised in a better social class contributes positively to health. This is associated with things like having a better awareness of healthy behavior, like eating habits, exercise, smoking and drinking (Cutler, 2006). The variable Familyclass also takes away a large part of the effect of education in all categories, as can be seen when comparing the extended with the simple model. Also the correlation effect between the two variables is substantial (0.26). It seems right to conclude that individuals raised in better social classes are also stimulated more to achieve high educational degrees. Educated parents may convince their children about the importance of a good education, and also it is likely that there is more understanding and familiarity from the family and the individual with attaining school and college.

The positive effect of having a steady job can be explained in a few ways. Having a steady job probably means having a better income to support yourself than an unemployed person. Also it probably means someone with a steady job has a more stable personal life. Nevertheless this factor is can also be subjected to reverse causality. A healthier person is more likely to work because he might be more able to work than a person who suffers from a serious disease. This problem is also the case of the "active93" variable, which refers to the fact a person is still working in 1993. According to this analysis a person who is still working has a great and highly significant chance to experience a good health. However, there are also a lot of explanations that would support this finding. Earlier mentioned research indicates that being retired decreases physical, mental and self-assessed health (Sahlgren, 2013). As with the steadyjob93 variable, a working individual probably has a higher income then unemployed or retired individuals, which gives you the financial power to maintain a healthier lifestyle.

When looking at column 3 with IQ added as independent variable the same effect occur as in the simple model. However reducing significance, IQ decreases the effect of education on health, another token of prove that there is a selection effect. In absolute figures adding the extra variables reduces the effect of adding IQ on education only small, because the coefficients drop respectively 0.0067, 0.0117 and 0.019. However, the relative effect of IQ increases, since education decreases around 40% for categories 4 and 5 and almost 50% for category 6 by adding the extra variables and did almost nothing for the effect of IQ. Especially the high educated is reduced a lot which makes the differences between education categories smaller, supposing that the effect of having good educational achievements is most likely to be overestimated without controlling for other variables.

In column 4 the observation in the first model that abstract thinking has a greater and more convincing effect than general IQ remains supported. While the Raven Test variable lowers the estimates of the education categories more than IQ, the estimates of education also become less significant than the model with IQ. Education coefficients in the model with the

Raven Test drop 0.0156, 0.0269 and 0.0407. This is more than in the model with IQ and therefore it may be that cognitive ability plays a larger role in the selection effect of education. Estimates for all 3 education categories become insignificant compared to the model without an intelligence variable, which means the Raven Test variable explains probably a large part of the effect of education on health. The cognitive ability measurement is highly significant. Since effects of adding the Raven Test variable hold and the relative power of the Raven Test increased drastically, it is convincing to say that analytical capabilities are the main factor in cognitive ability explaining the role of cognitive ability in the selection effect described.

4.4 Extended model with and without intelligence on mortality

Table 4: Extended model with independent variable IQ and Raven Test, outcome mortality

Dependent	Mortality	Mortality	Mortality
Female	-0,0592	-0,0578	-0,0573
Educationmax 4	-0,0653	-0,061	-0,0587
Educationmax 5	-0,0454	-0,0379	-0,0338
Educationmax 6	-0,0708	-0,0585	-0,0529
Familyclass 2	0,00905	0,00842	0,00818
Familyclass 3	0,136	0,138	0,142
Steadyjob93	0,0186	0,0191	0,0186
Active93	-0,0391	-0,0389	-0,039
IQ	.	-0,000596	.
Raven Test	.	.	-0,00129
Constant	0,16	0,218	0,289
N	1422	1422	1422
α = 0,1			
α = 0,05			
α = 0,01			

As seen in table 4 the contradicting results regarding mortality do not disappear. Estimates become more significant, but still there is no education gradient. The only interesting and significant outcome is the Raven test variable. This outcome is significant and also reduces the effect of education more than the general IQ variable. The problem described earlier with the simple models probably still applies to the outcomes found in the extended model. In order to make convincing statements about mortality and the effect of education and cognitive ability, our sample probably has to be older to truly estimate more significant and therefore reliable effects.

5 Discussion and Conclusion

In this paper an effort has been made to identify the contribution of cognitive ability to health and how cognitive ability influences the effect of education on health. This paper is an addition to the recent paper that tried to disentangle this education and ability effect on mortality (Bijwaard, Van Kippersluis, & Veenman, 2013). A Dutch cohort study has been used with data of almost 3000 recipients all born around 1940. With help of multiple regression analysis, a comparison with presence and absence of two different measurements for intelligence has been done for various models. This research found a positive and significant effect of education on self-assessed health reports.

The treatment effect of education can be divided into a real treatment effect and a selection effect. When controlling for cognitive ability the effect of all educational classes decreases. The research has found that analytical capabilities seem to play a substantial role in this selection effect and in the direct effect of intelligence on health. Effects of analytical capabilities are around twice as large as the effect of IQ in both the selection and the direct effect and are also more significant. The effect of IQ and analytical capabilities found are not very large, and tend to affect health mostly through education. The direct effect of IQ controlling for education was very small and for IQ also not significant. The decrease in the effect of education, when controlling for cognitive ability, was especially high for the higher educated individuals. Effects of education were for almost 25% explained through the Raven Test, the earlier discussed analytical and problem solving test.

When considering mortality as an outcome no significant effect of intelligence can be found and the results of education on mortality are non-gradient and contradicting. This is probably due to a limitation of the dataset used, since all recipients were followed between age 50 and 70 to get mortality data. Therefore too few people actually died to identify a relation and it made effects insignificant.

Still having a job seems to have great impact on reported health, but this effect may also be driven by reverse causality, as being healthy also implies being able to work. Also an important positive factor is the background social class of an individual. Individuals raised in high social classes seem to be healthier and therefore this variable may also account for a part of the selection effect of education on health. These persons may be more stimulated to achieve a higher educational degree because they also have educated parents. It could also be these persons are more aware of healthy living habits like eating and drinking.

A caveat of the research conducted is the amount of control variables included in the analysis. Of the extended model the explanatory power was very low, just under 10%. Obviously there are numerous factors and choices a person makes in his life which affect a person's health. Variables like personal income and partner income, marital status, number of children, job characteristics, eating habits, exercise and maybe even genetically factors are all candidates to include in research of this type. Also these variables can be linked to education. For example income and job characteristics are obviously partially determined by education, so the effect of education in this presented model can still be biased. Unfortunately not all variables were clear or present in the dataset. Really thorough research would off course ask for a dataset with many variables, were collection varies from childhood to old age. This would come with gigantic effort and would take a very long time. There are not many datasets that contain these factors, but the Brabant study is a dataset with extensive list of variables which makes it possible to identify some important factors and directions when considering health and mortality outcomes.

This study shows the importance of accounting for cognitive ability when measuring health outcomes, especially when related to education. Not much research has been conducted on this topic and further research is necessary to identify the effect of intelligence on heath, and to specify for what amount intelligence plays a role in the selection effect of education. An interesting new field of research is finding out why abstract thinking seems to play such a bigger role in this process than IQ. This is can be an opening for a more neurologic approach of health outcomes, as parts of the brain are responsible for abstract thinking and could induce important policy applications.

6. Literature

Albouy, V., & Lequien, L. (2008). Does compulsory education lower mortality? *Journal of Health Economics 28(1)*, 155-168.

Auld, M. C. (2005). Schooling cognitive ability and health. *Health Economics*, 1019-1034.

Bago d'Uva, T., Van Doorslaer, E., Lindeboom, M., & O'Donnell, O. (2008). Does reporting heterogeneity bias the measurement of health disparities. *Journal of Health Economics 17*, 351-375.

Behrman, J. R. (2004). Returns to birthweight. *The Review of Economics and Statistics*, 586-601.

Bijwaard, G., Van Kippersluis, H., & Veenman, J. (2013). De invloed van opleiding en intelligentie op gezondheid. *Economisch Statistische Berichten*, 280-283.

Bijwaard, G., Van Kippersluis, H., & Veenman, J. (2013). Education and health: the role of cognitive ability. *Tinbergen institute discussion paper*, 1-40.

Braakman, N. (2011). The causal relation between education, health and health related behaviuour: Evidence from a natural expiriment in England. *Journal of Health Economics*, 753-763.

Carpenter, P. (1990). What one intelligence test measures: a theoretical account of processing in the Raven Progressive Matrices Test. *Psychological Review 97(3)*, 404-431.

Case, F. P. (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics*, 365-389.

CBS. (2012, 6 27). Opgehaald van http://statline.cbs.nl/StatWeb/publication/?VW=T&DM=SLNL&PA=81173NED&D1=0-1&D2=a&D3=0&D4=l&HD=110829-0959&HDR=G3,G2,T&STB=G1

CBS. (2012, February 7). *Kloof in levensverwachting tussen hoog- en laagopgeleiden blijft even groot*. Opgehaald van Centraal Bureau voor de Statistiek: http://www.cbs.nl/nl-NL/menu/themas/gezondheid-welzijn/publicaties/artikelen/archief/2012/2012-feb07-glv-opleiding-art.htm

Conti, G., & Heckman, J. (2010). Understanding the early origins of the education-health gradient: A framework that can also be applied to analyze gene-environment interactions. *Perspectives on Psychological Sience 5(5)*, 585-605.

Conti, G., Heckman, J., & Urzua, S. (2010). The education-health gradient. *American Economic Review Papers and Proceedings*, 100: 234-238.

Cutler, L.-M. (2006). *Education and Health: Evaluating Theories and Evidence.* National Bureau of Economic Research.

Deaton, P. (2001). Mortality, Education, Income and Inequality in American Cohorts. *National Bureau of economic Research*, 129-170.

Deeg, J., & Kriegsman, D. (2003). Concepts of Self-Rated Health: Specifying the Gender Difference in Mortality Risk. *The Gerontologist*, 376-386.

Düzel, E., Bunzeck, N., Guitart-Masip, M., & Düzel, S. (2010). NOvelty-related motivation of anticipation and exploration by dopamine (NOMAD): implication of healthe aging. *Neuroscience & Behavioural Reviews*, 660-669.

Gottfredson. (2004). Intelligence Predicts Health and Longevity, but Why? *Current Directions in Psychological Science*, 1-4.

Idler, B. (1997). *Journal of Health and Social Behaviour 38*, 21-37.

Idler, B. (1997). Self-rated health and mortality: a review of twenty-seven community studies. *Journal of Health and Social Behaviour*.

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the United States. *Review of Economic Studies*, 189-221.

Mazumder. (2012). The effects of health and education on mortality. *Nordic Economic Policy Review*, 261-301.

Mazumder, B. (2008). Does education improve health: A reexamination of the evicende from compulsory schooling laws. *Economic Perspectives 33(2)*.

Missale, C., Nash, S., Robinson, S., Jaber, M., & Caron, M. (1998). Dopamine Receptors: From Structure to Function. *Physiological Reviews*, 189-225.

Murasko, J. (2007). lifecourse study on education and health: The relationship between childhood psychosocial resources and outcomes in adolescence and young adulthood. *Social Schience Research*, 1348-1370.

Oreopoulos, P. (2006). Estimating average and local average treatment effect of education when compulsory school laws really matter. *American economic Review 96(1)*, 152-175.

Sahlgren, G. (2013). Work longer, live healthier: the relationship between economic activity, health and government policy. *Institute of Economics Affairs*.

Van Kippersluis, H., O'Donnel, O., & Doorslaer, E. v. (2011). Long run returns to education: does schooling lead to an extended old age? *Journal of Human Resources 46(4)*, 695-721.

Verhaege, P., Pattyn, E., Bracke, P., Verhaege, M., & Van de Putte, B. (2012). The association betwee nnetwor ksocia lcapita land self-rated health: Pouring old wine in new bottles. *Health and Place 18*, 358-365.

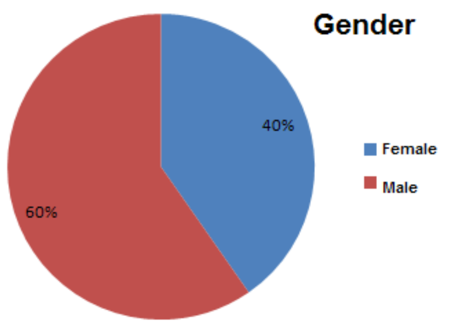
7. Appendix

7.1 Descriptive statistics variables

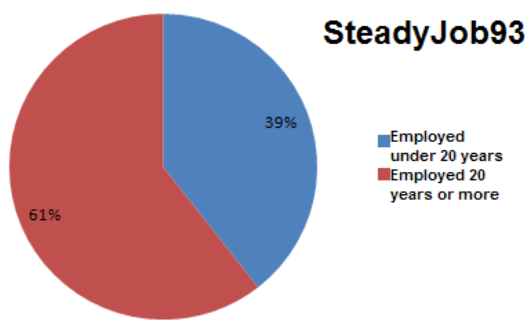
Variable	Obs	Mean	Std. Dev.	Min	Max
SAH93	1923	.6833073	.4653074	0	1
Dead	2998	.1160774	.3203711	0	1
Female	2998	.4029353	.4905698	0	1
Educationmax	2645	3.577316	.9024758	3	6
Familyclass	2693	1.528407	.5489003	1	3
Steadyjob93	1944	.6059671	.4887677	0	1
Active93	1944	.6723251	.4694864	0	1
IQ	2732	101.597	14.24087	72	190
RavenTest	2588	102.1851	14.34632	74	147

7.2 Independent Variable graphs

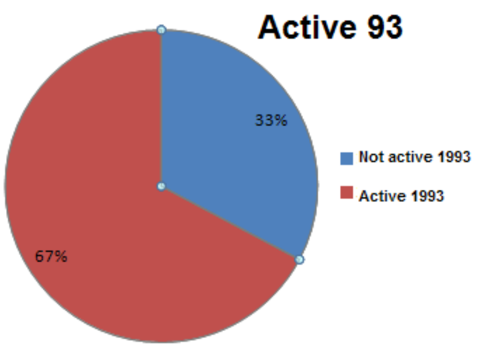
Graph 1



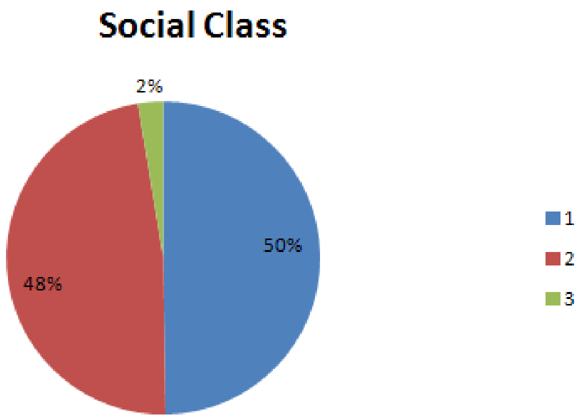
Graph 2



Graph 3



Graph 4



Graph 5

7.3 Simple with and without regression IQ on SAH93

Source	SS	df	MS
Model	6.44489787	4	1.61122447
Residual	349.833446	1662	.210489438
Total	356.278344	1666	.213852548

Number of obs =	1667
F(4, 1662) =	7.65
Prob > F =	0.0000
R-squared =	0.0181
Adj R-squared =	0.0157
Root MSE =	.45879

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.014642	.0230431	0.64	0.525	-.0305547	.0598386
Educationmax						
4	.0749171	.0358355	2.09	0.037	.0046297	.1452045
5	.1166862	.0295983	3.94	0.000	.0586324	.1747401
6	.2323604	.0554957	4.19	0.000	.1235115	.3412092
_cons	.6436436	.0172552	37.30	0.000	.6097995	.6774878

Source	SS	df	MS
Model	6.77664584	5	1.35532917
Residual	349.501698	1661	.210416435
Total	356.278344	1666	.213852548

Number of obs =	1667
F(5, 1661) =	6.44
Prob > F =	0.0000
R-squared =	0.0190
Adj R-squared =	0.0161
Root MSE =	.45871

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.0129068	.0230806	0.56	0.576	-.0323633	.0581768
Educationmax						
4	.0674675	.0363172	1.86	0.063	-.0037647	.1386997
5	.1029873	.0315401	3.27	0.001	.0411247	.1648499
6	.2112961	.0579667	3.65	0.000	.0976006	.3249915
IQ	.0011132	.0008866	1.26	0.209	-.0006257	.0028521
_cons	.5333617	.0895078	5.96	0.000	.3578018	.7089217

7.4 Simple with and without regression Raven test on SAH93

Source	SS	df	MS
Model	5.47124218	4	1.36781054
Residual	324.541095	1535	.211427424
Total	330.012338	1539	.214432968

Number of obs	= 1540
F(4, 1535)	= 6.47
Prob > F	= 0.0000
R-squared	= 0.0166
Adj R-squared	= 0.0140
Root MSE	= .45981

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.017021	.0238546	0.71	0.476	-.02977	.0638121
Educationmax						
4	.0913698	.0373243	2.45	0.014	.0181578	.1645818
5	.1177452	.0315818	3.73	0.000	.0557971	.1796934
6	.2098392	.0605102	3.47	0.001	.0911478	.3285307
_cons	.6419796	.0180797	35.51	0.000	.6065161	.6774431

Source	SS	df	MS
Model	8.22375684	5	1.64475137
Residual	321.788581	1534	.209770913
Total	330.012338	1539	.214432968

Number of obs	= 1540
F(5, 1534)	= 7.84
Prob > F	= 0.0000
R-squared	= 0.0249
Adj R-squared	= 0.0217
Root MSE	= .45801

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.0123967	.0237952	0.52	0.602	-.0342779	.0590714
Educationmax						
4	.0747488	.0374599	2.00	0.046	.0012708	.1482268
5	.0897035	.0323964	2.77	0.006	.0261576	.1532494
6	.1683405	.0613518	2.74	0.006	.0479982	.2886828
efiqa	.0030695	.0008474	3.62	0.000	.0014074	.0047316
_cons	.3350207	.0866324	3.87	0.000	.1650903	.5049511

7.5 Simple with and without regression IQ on Dead

Source	SS	df	MS
Model	1.87840494	4	.469601235
Residual	237.784516	2398	.099159515
Total	239.662921	2402	.099776404

Number of obs	= 2403
F(4, 2398)	= 4.74
Prob > F	= 0.0008
R-squared	= 0.0078
Adj R-squared	= 0.0062
Root MSE	= .3149

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0503271	.0131752	-3.82	0.000	-.0761629	-.0244912
Educationmax						
4	-.0378828	.0195787	-1.93	0.053	-.0762756	.0005101
5	-.0265571	.0180068	-1.47	0.140	-.0618676	.0087534
6	-.0325016	.0331342	-0.98	0.327	-.0974762	.032473
_cons	.1433769	.0097562	14.70	0.000	.1242455	.1625083

Source	SS	df	MS
Model	2.32486747	5	.464973493
Residual	237.338054	2397	.099014624
Total	239.662921	2402	.099776404

Number of obs	= 2403
F(5, 2397)	= 4.70
Prob > F	= 0.0003
R-squared	= 0.0097
Adj R-squared	= 0.0076
Root MSE	= .31467

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0488704	.0131834	-3.71	0.000	-.0747224	-.0230183
Educationmax						
4	-.0307995	.0198467	-1.55	0.121	-.0697179	.008119
5	-.0129352	.0191029	-0.68	0.498	-.0503952	.0245248
6	-.0117318	.0345245	-0.34	0.734	-.0794327	.055969
IQ	-.0010646	.0005013	-2.12	0.034	-.0020477	-.0000815
_cons	.248399	.0504098	4.93	0.000	.1495476	.3472503

7.6 Simple with and without regression Raven test on Dead

Source	SS	df	MS
Model	2.03004918	4	.507512295
Residual	215.103525	2211	.09728789
Total	217.133574	2215	.098028702

Number of obs	=	2216
F(4, 2211)	=	5.22
Prob > F	=	0.0004
R-squared	=	0.0093
Adj R-squared	=	0.0076
Root MSE	=	.31191

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0520435	.0134762	-3.86	0.000	-.0784708	-.0256163
Educationmax						
4	-.0426921	.0203083	-2.10	0.036	-.0825175	-.0028668
5	-.0283721	.0190057	-1.49	0.136	-.065643	.0088988
6	-.0591303	.0361896	-1.63	0.102	-.1300995	.0118389
_cons	.1443026	.0101059	14.28	0.000	.1244846	.1641206

Source	SS	df	MS
Model	2.55691046	5	.511382093
Residual	214.576664	2210	.097093513
Total	217.133574	2215	.098028702

Number of obs	=	2216
F(5, 2210)	=	5.27
Prob > F	=	0.0001
R-squared	=	0.0118
Adj R-squared	=	0.0095
Root MSE	=	.3116

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.050708	.0134749	-3.76	0.000	-.0771328	-.0242832
Educationmax						
4	-.0371627	.0204264	-1.82	0.069	-.0772197	.0028942
5	-.0175516	.0195467	-0.90	0.369	-.0558833	.0207802
6	-.0441403	.0367217	-1.20	0.229	-.1161529	.0278723
efiqa	-.0011349	.0004872	-2.33	0.020	-.0020903	-.0001795
_cons	.2577087	.0497195	5.18	0.000	.1602069	.3552105

7.7 Extended with and without regression IQ on SAH93

Source	SS	df	MS
Model	28.7471491	8	3.59339364
Residual	274.045197	1402	.19546733
Total	302.792346	1410	.214746345

Number of obs	= 1411
F(8, 1402)	= 18.38
Prob > F	= 0.0000
R-squared	= 0.0949
Adj R-squared	= 0.0898
Root MSE	= .44212

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.1555275	.0294011	5.29	0.000	.0978525	.2132024
Educationmax						
4	.0581116	.0380325	1.53	0.127	-.0164951	.1327182
5	.0734175	.032281	2.27	0.023	.0100932	.1367418
6	.1269419	.0602854	2.11	0.035	.0086825	.2452012
Familyclass						
2	.0623956	.0245168	2.55	0.011	.0143021	.1104892
3	.1550631	.0797247	1.94	0.052	-.0013295	.3114558
Steadyjob93	.0744386	.0511653	1.45	0.146	-.0259302	.1748074
Active93	.2402316	.0499277	4.81	0.000	.1422906	.3381726
_cons	.3558325	.0329043	10.81	0.000	.2912856	.4203794

Source	SS	df	MS
Model	28.9340671	9	3.21489634
Residual	273.858279	1401	.195473432
Total	302.792346	1410	.214746345

Number of obs	= 1411
F(9, 1401)	= 16.45
Prob > F	= 0.0000
R-squared	= 0.0956
Adj R-squared	= 0.0897
Root MSE	= .44212

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.1532798	.0294913	5.20	0.000	.0954279	.2111316
Educationmax						
4	.0514385	.0386404	1.33	0.183	-.0243608	.1272378
5	.0617492	.0344162	1.79	0.073	-.0057637	.1292622
6	.1080825	.0632961	1.71	0.088	-.0160829	.2322479
Familyclass						
2	.0633974	.0245386	2.58	0.010	.015261	.1115337
3	.1520908	.0797839	1.91	0.057	-.004418	.3085996
Steadyjob93	.0737703	.0511707	1.44	0.150	-.0266091	.1741497
Active93	.2399793	.0499291	4.81	0.000	.1420354	.3379232
IQ	.0009229	.0009438	0.98	0.328	-.0009285	.0027744
_cons	.2649462	.0985959	2.69	0.007	.0715347	.4583576

7.8 Extended with and without regression Raven test on SAH93

Source	SS	df	MS
Model	28.7471491	8	3.59339364
Residual	274.045197	1402	.19546733
Total	302.792346	1410	.214746345

Number of obs	=	1411
F(8, 1402)	=	18.38
Prob > F	=	0.0000
R-squared	=	0.0949
Adj R-squared	=	0.0898
Root MSE	=	.44212

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.1555275	.0294011	5.29	0.000	.0978525	.2132024
Educationmax						
4	.0581116	.0380325	1.53	0.127	-.0164951	.1327182
5	.0734175	.032281	2.27	0.023	.0100932	.1367418
6	.1269419	.0602854	2.11	0.035	.0086825	.2452012
Familyclass						
2	.0623956	.0245168	2.55	0.011	.0143021	.1104892
3	.1550631	.0797247	1.94	0.052	-.0013295	.3114558
Steadyjob93	.0744386	.0511653	1.45	0.146	-.0259302	.1748074
Active93	.2402316	.0499277	4.81	0.000	.1422906	.3381726
_cons	.3558325	.0329043	10.81	0.000	.2912856	.4203794

Source	SS	df	MS
Model	31.0981383	9	3.45534871
Residual	271.694208	1401	.193928771
Total	302.792346	1410	.214746345

Number of obs	=	1411
F(9, 1401)	=	17.82
Prob > F	=	0.0000
R-squared	=	0.1027
Adj R-squared	=	0.0969
Root MSE	=	.44037

SAH93	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	.1510481	.0293134	5.15	0.000	.0935452	.208551
Educationmax						
4	.0424825	.0381475	1.11	0.266	-.0323499	.1173149
5	.0465333	.0330678	1.41	0.160	-.0183345	.1114011
6	.0863455	.0611692	1.41	0.158	-.0336476	.2063386
Familyclass						
2	.0643343	.0244265	2.63	0.009	.0164179	.1122507
3	.1404804	.0795207	1.77	0.078	-.0155122	.2964729
Steadyjob93	.0745723	.0509636	1.46	0.144	-.0254008	.1745454
Active93	.2406955	.049731	4.84	0.000	.1431402	.3382507
efiqa	.002996	.0008605	3.48	0.001	.0013081	.004684
_cons	.0546961	.0924903	0.59	0.554	-.1267382	.2361305

7.9 Extended With and without regression IQ on Dead

Source	SS	df	MS
Model	2.30419164	8	.288023955
Residual	135.01789	1413	.095554062
Total	137.322082	1421	.096637637

Number of obs	=	1422
F(8, 1413)	=	3.01
Prob > F	=	0.0023
R-squared	=	0.0168
Adj R-squared	=	0.0112
Root MSE	=	.30912

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0592219	.0205094	-2.89	0.004	-.099454	-.0189898
Educationmax						
4	-.0653399	.0263858	-2.48	0.013	-.1170994	-.0135804
5	-.0454086	.0225545	-2.01	0.044	-.0896526	-.0011646
6	-.0707721	.0418396	-1.69	0.091	-.1528466	.0113024
Familyclass						
2	.0090545	.0170813	0.53	0.596	-.0244529	.042562
3	.1357298	.0557278	2.44	0.015	.0264117	.2450479
Steadyjob93	.0186406	.035759	0.52	0.602	-.0515058	.088787
Active93	-.0390583	.0348632	-1.12	0.263	-.1074474	.0293309
_cons	.1596726	.0229188	6.97	0.000	.1147141	.2046311

Source	SS	df	MS
Model	2.38279174	9	.264754638
Residual	134.93929	1412	.095566069
Total	137.322082	1421	.096637637

Number of obs	=	1422
F(9, 1412)	=	2.77
Prob > F	=	0.0032
R-squared	=	0.0174
Adj R-squared	=	0.0111
Root MSE	=	.30914

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0577601	.0205739	-2.81	0.005	-.0981187	-.0174014
Educationmax						
4	-.0610477	.0268085	-2.28	0.023	-.1136365	-.0084589
5	-.0378645	.024041	-1.57	0.115	-.0850244	.0092955
6	-.0585076	.0439734	-1.33	0.184	-.1447679	.0277527
Familyclass						
2	.0084217	.0170966	0.49	0.622	-.0251158	.0419592
3	.1376466	.0557713	2.47	0.014	.028243	.2470502
Steadyjob93	.0190685	.0357643	0.53	0.594	-.0510885	.0892254
Active93	-.0388886	.0348659	-1.12	0.265	-.107283	.0295059
IQ	-.0005957	.0006569	-0.91	0.365	-.0018844	.0006929
_cons	.2183116	.0686009	3.18	0.001	.083741	.3528822

7.10 Extended with and without regression Raven Test on Dead

Source	SS	df	MS
Model	2.74310425	9	.304789362
Residual	134.578977	1412	.09531089
Total	137.322082	1421	.096637637

Number of obs =	1422
F(9, 1412) =	3.20
Prob > F =	0.0008
R-squared =	0.0200
Adj R-squared =	0.0137
Root MSE =	.30872

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0573231	.0205024	-2.80	0.005	-.0975415	-.0171048
Educationmax						
4	-.0586523	.0265358	-2.21	0.027	-.1107062	-.0065984
5	-.0337905	.0231673	-1.46	0.145	-.0792365	.0116555
6	-.0529352	.042605	-1.24	0.214	-.1365112	.0306408
Familyclass						
2	.0081814	.0170644	0.48	0.632	-.0252929	.0416557
3	.1419385	.055732	2.55	0.011	.0326121	.2512649
Steadyjob93	.0185856	.0357135	0.52	0.603	-.0514715	.0886428
Active93	-.0390236	.0348188	-1.12	0.263	-.1073257	.0292785
efiqa	-.0012883	.0006003	-2.15	0.032	-.0024659	-.0001106
_cons	.2889532	.0644461	4.48	0.000	.1625328	.4153737

Source	SS	df	MS
Model	2.30419164	8	.288023955
Residual	135.01789	1413	.095554062
Total	137.322082	1421	.096637637

Number of obs =	1422
F(8, 1413) =	3.01
Prob > F =	0.0023
R-squared =	0.0168
Adj R-squared =	0.0112
Root MSE =	.30912

Dead	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Female	-.0592219	.0205094	-2.89	0.004	-.099454	-.0189898
Educationmax						
4	-.0653399	.0263858	-2.48	0.013	-.1170994	-.0135804
5	-.0454086	.0225545	-2.01	0.044	-.0896526	-.0011646
6	-.0707721	.0418396	-1.69	0.091	-.1528466	.0113024
Familyclass						
2	.0090545	.0170813	0.53	0.596	-.0244529	.042562
3	.1357298	.0557278	2.44	0.015	.0264117	.2450479
Steadyjob93	.0186406	.035759	0.52	0.602	-.0515058	.088787
Active93	-.0390583	.0348632	-1.12	0.263	-.1074474	.0293309
_cons	.1596726	.0229188	6.97	0.000	.1147141	.2046311

7.11 Correlations

	SAH93	Dead	Female	Educat~x	Family~s	Active93	Stead~93	IQ	efiqa
SAH93	1.0000								
Dead	-0.0555	1.0000							
Female	-0.0094	-0.0723	1.0000						
Educationmax	0.1369	-0.0561	-0.1199	1.0000					
Familyclass	0.1116	0.0124	0.0215	0.2668	1.0000				
Active93	0.2460	-0.0007	-0.5002	0.1729	0.0349	1.0000			
Steadyjob93	0.2065	0.0193	-0.5839	0.1704	-0.0006	0.8647	1.0000		
IQ	0.0885	-0.0509	0.0145	0.4316	0.1024	0.0642	0.0586	1.0000	
efiqa	0.1242	-0.0746	0.0206	0.2921	0.0833	0.0199	0.0153	0.5588	1.0000