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The Relation between the Quality of Life in Early Childhood and Later Life Health and Employment Status in the Netherlands

An Analysis Using Probit and Ordered Probit Models

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1 Introduction

In recent times of economic recession, governments have had to cut heavily on their spending. This has resulted in intense political debates over the decision in which areas to cut. Particularly the costs of a welfare state have been scrutinized upon, as many argue that some people benefit from it unfairly. In addition, it is seen as demotivating for the unemployed to start looking for jobs, as they can easily live of their state subsidies. Besides unemployment benefits, many other social securities have also been subject to debate. For example, in the Netherlands there have been parties pleading for reductions in child benefits (Halkes 2011). Other parties argued old age pensions should be reduced (Nu.nl 2012). So how can the government determine where to cut on expenditures, while affecting the well being of society as little as possible?

Of course this is a very hard, if not impossible, question to give one correct answer to. However, some interesting findings in the literature might help us on the way. Several recent studies have highlighted the importance of life circumstances in early childhood. For example, Case et al. (2005) find a very strong link between childhood health and economic situation and variables such as adult health, employment status and socio-economic status later in life, for data in the UK. Similar results have also been found in the United States (Case and Paxson 2008). These results suggest that children in good health will grow up to become more healthy adults, causing long-term benefits not only for these individuals, but also for society as a whole. More healthy adults will reach higher socio-economic status, hence generating more income, but also will have smaller chances of becoming an economic burden for the state due to unemployment. So it is very clear how such research can have important policy implications, especially in light of the political debates described above. Therefore, the suggested links between early childhood life circumstances and later life outcomes, such as health and employment status shall now be elaborated upon in more detail.

As suggested by Flores and Kalwij (2011), three theories that offer explanations for the above-described links can be distinguished. First, Barker (1995) proposes the fetal origins hypothesis, which argues that there is a direct link between fetal under nutrition and coronary heart disease (CHD). More specifically, he argues that under nutrition leads to disproportionate infant growth eventually resulting in raised blood pressure, in turn leading to CHD. In addition, Barker (1995) examined the influence of social classes, but found no evidence for any importance of this variable, suggesting the direct link between childhood health and adult health.

Second, a relatively strong body of literature uses life course models to explain the relation between illnesses and deprivation during childhood and the its long-term consequences. Pollit et al. (2005) explain that a variety of life course models have been proposed, which all attribute the risks of cardiovascular diseases (CVD) to life course socio-economic status (SES). Some models go as far as stating that early experiences directly affect the risk of CVDs, independent of SES throughout life and lifestyle in general (Kuh and Ben-Shlomo 2004; Power and Hertzman 1997). Kuh and Wadsworth (1993) conducted a study in Britain, which provided similar results. Even when controlling for a variety of factors, such as educational attainment and socioeconomic factors in adult life, a lower childhood SES and a serious illness between the age 5 and 15 significantly affected adult health at the age of 36 (Kuh and Wadsworth 1993).

Third, pathway models tend to obtain results different from the first two theories. This last group of models tends to focus on early life experiences that place individuals onto a certain life trajectory, which eventually impacts their adult health (Pollit et al. 2005). For example, Kuh et al.(2004) use the concept of chains of risk, where early life events influence later life experiences and decisions, hence affecting adult disease risk. On the other hand, Flores and Kalwij (2011) argue that when controlling for risk factors, the links between early life and later life health become significantly weaker in these so-called pathway models. An example is the Whitehall II study in Britain, conducted by Marmot et al. (2001), which shows that current SES is actually one of the most important predictors of CHD and other chronic diseases in adulthood, in contrast to the fathers social class for example.

All in all, the literature does not provide us with a single truth to the possible links between early life circumstances and adult life factors such as health and SES. Nevertheless, clear connections between the two phases of life have definitely been demonstrated. In addition to literature presented on the United Kingdom and United States, this study will present empirical evidence for the Netherlands. The connection between early life circumstances and adult health and employment status will be investigated. One of the aims of the research is to provide additional material that can be used for policy implications in light of recent political debate on cuts in government spending. More specifically; if strong links between early life and adult health and employment status are found, the research can be used to support those in favor of children benefits.

The structure of the paper is as follows. Section 2 will elaborate on the empirical framework of the research. Section 3 presents the results, while section 4 will summarize the findings and elaborate on the main conclusions. Section 5 discusses some of the limitations of this research and provides suggestions for further research.

2 Empirical Framework

2.1 Data

The data used to conduct the analysis comes from the Survey of Health, Ageing and Retirement in Europe (SHARE), which is a multidisciplinary and representative cross-national panel of the European population aged 50 and over. SHARE collects data on demographics, socioeconomic status, and detailed health status information. The survey has been conducted in three waves: the first in 2004, the second in 2007 and the third in 2011. This analysis is based on all Dutch respondents of the survey, with age 50-64, from all three waves. The final sample consists of 1604 respondents, of which 729 are female and 875 are male.

2.2 Model

As explained, the aim of this research is to see whether a link can be found between the quality of life in one's early childhood and later life health and employment status. To do so, the analysis has to be split up into two parts. First, an early life index (ELI) will be constructed, which will encompass a variety of different variables to represent the quality of life in early childhood. Second, this index will then be used in estimation to look at the effect it has on both later life health, as well as employment status.

The next subsection of this paper will elaborate in detail on the reasons behind constructing such an ELI, as well as the methods used to do so. For now, we will first explain the model that will be used in both parts of the analysis.

For both parts of the analysis, the dependent variable is not a regular continuous variable, but rather a discrete choice variable. The simplest example of such a variable is one with binary options *yes* or *no*. When dependent variables are categorical, ordinary OLS cannot be employed for estimation, because the predicted values may fall outside the 0-1 range. Rather, maximum likelihood estimation must be used with logit or probit models. Logit models assume a logistic distribution of the error term, while probit models assume a normal distribution, but results with either of the models are hardly different. For this research, the ordered probit model has been used and will now be elaborated upon.

The simplest version of a (regular) probit model is the binomial probit model, where the dependent variable has options 1 and 0. Hence, the predicted value of the dependent variable refers to the probability op the occurrence of option 1. The corresponding regression equation is

$$y^* = \beta \boldsymbol{x} + \epsilon \tag{1}$$

where $\mathbf{x}$ is a set of independent variables. We assume $\epsilon \sim N(0, 1)$. The corresponding probability for such a model is

$$Prob(Y = 1) = \Phi(\beta' \boldsymbol{x}) \tag{2}$$

with Φ being the standard normal probability function.[1]

However, if we now extend this model to include dependent variables that have more than two options, things get slightly more complicated. Rather than obtaining a single probability from estimation, we now get a set of probabilities; one for every category of the dependent variable. Although the categories of the dependent variable can also represent a set of unordered options, we will now elaborate on a model were the outcome categories are of an ordered nature. The range of outcomes are then coded with integers, which represent a ranking. The idea is that the difference between category 1 and 2 is not necessarily the same as between category 3 and 4, but the ranking is. Take for example, an opinion rating with options 1) excellent, 2) very good, 3) good and 4) poor. The interpretation of the differences between these categories will vary highly between respondents, but the ranking of 1 being the best and 4 the worst is the same for everyone.

For an ordered probit model we start with the same regression equation 1 as for the binomial probit. However, the interpretation of the probabilities differs substantially. If we have four categories we get

[1] $\Phi(y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{y} e^{\frac{-x^2}{2}} \mathrm{d}x$

$$
\begin{aligned}
y = 1 &\quad if \quad y^* \leq \mu_0 \\
y = 2 &\quad if \quad \mu_0 \leq y^* \leq \mu_1 \\
y = 3 &\quad if \quad \mu_1 \leq y^* \leq \mu_2 \\
y = 4 &\quad if \quad \mu_2 \leq y^*
\end{aligned} \tag{3}
$$

where the μ's are unknown parameters to be estimated. So for the example of an opinion survey, respondents will choose the category that lies closest to their personal answer. As with a binomial probit, we assume the error term to be normally distributed across observations and normalize its mean to 0 and variance to 1. We then obtain the following probabilities

$$
\begin{aligned}
Prob(y = 1) &= \Phi(\mu_0 - \beta'\boldsymbol{x}) \\
Prob(y = 2) &= \Phi(\mu_1 - \beta'\boldsymbol{x}) - \Phi(\mu_0 - \beta'\boldsymbol{x}) \\
Prob(y = 3) &= \Phi(\mu_2 - \beta'\boldsymbol{x}) - \Phi(\mu_1 - \beta'\boldsymbol{x}) \\
Prob(y = 4) &= 1 - \Phi(\mu_2 - \beta'\boldsymbol{x})
\end{aligned} \tag{4}
$$

Figure 1 below provides a graphical representation of these probabilities. The sum of all four probabilities will add up to 1, which is the surface under the normal distribution curve.

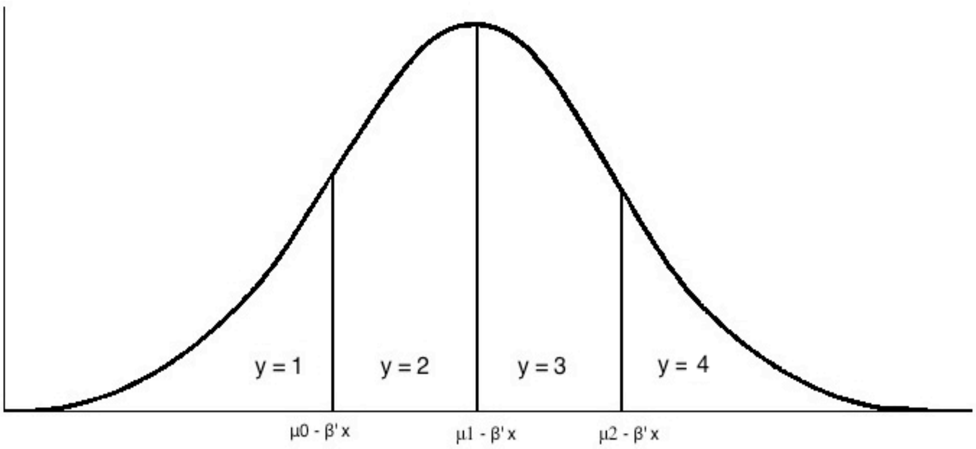

Figure 1: Probabilities in the Ordered Probit Model

So we now understand how to obtain the probabilities for each category from the set of independent variables included in the regression equation. Next, we will have a look at the marginal effects of these variables and how to interpret such effects.

In ordinary OLS, marginal effects are often the same as the regression coefficients obtained from estimation. In probit models, however, this is not the case. When taking the derivatives of the equations in (4), we obtain the following marginal effects for the ordered probit model:

$$\begin{aligned}
\frac{\delta Prob(y=1)}{\delta \boldsymbol{x}} &= \phi(\mu_0 - \beta'\boldsymbol{x})\beta \\
\frac{\delta Prob(y=2)}{\delta \boldsymbol{x}} &= [\phi(\mu_0 - \beta'\boldsymbol{x}) - \phi(\mu_1 - \beta'\boldsymbol{x})]\beta \\
\frac{\delta Prob(y=3)}{\delta \boldsymbol{x}} &= [\phi(\mu_1 - \beta'\boldsymbol{x}) - \phi(\mu_2 - \beta'\boldsymbol{x})]\beta \\
\frac{\delta Prob(y=4)}{\delta \boldsymbol{x}} &= \phi(\mu_2 - \beta'\boldsymbol{x})\beta \qquad (5)
\end{aligned}$$

with ϕ being the normal density function.[2]

The question that remains is of course, how to interpret such marginal effects? If we look back at figure 1, Greene (2000) provides a hands-on interpretation: increasing one of the x's, while holding β and μ constant is equivalent to shifting the whole distribution slightly to the right. It is easy to understand that, assuming β is positive, $Prob(y = 1)$ will decrease, while $Prob(y = 4)$ will increase. What happens to both $Prob(y = 2)$ and $Prob(y = 3)$ remains ambiguous and is generally very hard to tell.

For the i-th observation the log-likelihood function for the example ordered probit model, used throughout this section, is given by

$$\begin{aligned}
ln\ L_i(\mu,\beta) = [y_i = 1]ln[\Phi(\mu_0 - \beta'\boldsymbol{x}_i)] + [y_i = 2]ln[\Phi(\mu_1 - \beta'\boldsymbol{x}_i) - \Phi(\mu_0 - \beta'\boldsymbol{x}_i)] \\
+ [y_i = 3]ln[\Phi(\mu_2 - \beta'\boldsymbol{x}_i) - \Phi(\mu_1 - \beta'\boldsymbol{x}_i)] + [y_i = 4]ln[1 - \Phi(\mu_2 - \beta'\boldsymbol{x}_i]
\end{aligned} \qquad (6)$$

For the estimated β coefficients, presented in section 3 later in this paper, the log-likelihood equation is maximized. This is expressed by the following equation:

$$\widehat{\beta} = argmax(\beta) \sum_{i=1}^{n} ln\ L_i(\mu,\beta) \qquad (7)$$

2.3 Variables

2.3.1 The Quality of Life in Early Childhood

Health is a complicated variable to measure properly. Self-reported health indexes are often very unreliable, for a variety of reasons. First, when a research is aimed at looking for links between someones health and employment status, people tend to give biased answers. Dwyer and Mitchell (1999) explain that "people who enjoy their work will downplay their health problems and work longer, while those who dislike their work may exaggerate health problems and retire sooner". In addition, early retirement benefits are only given out to those deemed incapable to work, which creates an extra financial incentive to identify yourself as incapable. This is referred to as the justification hypothesis, which gains strong support in the literature (Bound 1989; Chirikos and Nestel 1984). So it is especially the impact of health on the ability to work that is often exaggerated by respondents. Second, as Bound (1989) rightly points out, people are asked for subjective judgments, hence these judgments cannot be expected to be fully comparable across

[2] $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$

respondents. This will create measurement error in the self-reported health variable. Lastly, an additional problem arises due to the fact that we are looking at the health in someones childhood. This will have been 50 or more years ago for the respondents by the time they are asked to give a rating to their childhood health status. It is very likely that most will not be able to remember something so long ago very accurately. This lack of remembering will create under-reporting of health problems, as Blackwell et al. (2001) remark, which will cause the childhood health status to be overestimated. To avoid all these problems there are alternative, more reliable, options to measure childhood health. One of them, first proposed in Bound et al. (1998), is to create a health index.

In this paper, we will create an index similar to such a health index. Instead of only objective health-related variables, however, we will predict self-reported childhood health (SRCH) using a whole range of objective measures of childhood health, socio-economic status (SES) and other forms of well-being. This predicted index, referred to as Early-Life Index (ELI) from now on, will be an overall measure of the quality of life during a person's childhood. Creating such an index, allows us to aggregate a variety of measures of the quality of life into one, while ameliorating the biases of self-reported variables. In particular, this ELI shall be estimated through the following:

$$SRCH = \gamma \mathbf{x} + v \tag{8}$$

where $\mathbf{x}$ is the set of objective measures of health, SES and other forms of well-being. We assume $v \sim N(0, 1)$.

SRCH is originally measured on a 5-point scale, with an additional category if *health varied a great deal*. However, as table 1 shows, the categories *health varied a great deal*, *poor* and *fair* are all relatively small. Therefore, we merged these three categories to create a 4-point scale, running from 1) excellent to 4) fair/poor. If someones health varied a great deal during childhood, we see this as a sign of rather bad health, which justifies adding this category with the lowest categories of the scale.

	Number of Observations	**Percentage**
Excellent	455	28.38
Very Good	380	23.69
Good	575	35.85
Fair	149	9.29
Poor	35	2.18
Health Varied a Great Deal	10	.62

Table 1: Initial Measurement Categories of Self-Reported Child Health

The incorporated objective measures of health, SES and well-being will now be elaborated upon. Most of these objective variables have been picked in accordance with Flores and Kalwij (2011).

A number of studies used adult height as a proxy for childhood health status (Floud et al. 1990; Fogel 1993). The idea behind this is that the overall well-being and health in the early stages of a child's life have a great influence on the extend to which the child will grow. Of course there are much more general height differences, between regions in the world for example, but since our research is only looking at the Netherlands this should create no problems. In addition, three other variables used to proxy childhood health are included. The first is a dummy variable for whether the respondent ever suffered from a period of hunger during childhood (ages 0-15). Second, a dummy variable is included to indicate whether the respondent suffered from chronic conditions during childhood. Chronic childhood conditions are defined as having long-lasting effects on health (also see Case (2005)). Third, a dummy variable was included to indicate whether a respondent ever spent more than a month in bed because of illness during childhood.

In addition to objective measures for health, several variables to indicate SES during childhood were also included. All four variables report the respondent's circumstances at age 10. The first is the number of rooms per person in the household, which is a proxy variable for the parents' financial status. Another proxy for financial status that is included is whether the child's parents were home-owners when the child was born. The third variable, used to proxy for the level of education of the parents, is a dummy for whether there were more than enough books to fill one bookcase (25) in the parental house at the time. Results for OECD data obtained by Cavapozzi et al. (2011) provide strong support for the use of these proxies, as correlation between the rooms variable and average income of households and between the books variable and average years of education were found to be very high. Fourth, a dummy variable that indicates whether the primary breadwinner worked as a farmer or in an elementary occupation is included to capture household work status of the family at the time.

Finally, some other variables are included that do not specifically belong to SES or health, but do provide additional interesting information. These include: a dummy for whether the child is born in an urban area and a dummy for the child's relative position in school in both mathematics and language, where 1 is better than average. See table 2 for the descriptive statistics of all relevant variables used for the ELI.

	Mean	**Standard Error**
SRCH	2.32	1.01
length	172.755	9.01
hunger	.01	.102
chronic conditions	.14	.35
bed	.17	.37
rooms	.83	.35
home-owners	.28	.45
books	.55	.50
farmer	.23	.42
urban	.56	.50
math	.89	.30
language	.87	.34

Table 2: Descriptive Statistics of Early Life Variables

2.3.2 Later Life Health, Employment Status and Control Variables

Once the ELI has been constructed, we want to look at the effect it has on both later life health and employment status. In order to measure later life health we use a self-reported health variable, which initially was classified into five categories. Because the last two categories, poor and fair, only had very few observations, these were pooled together into fair/poor. So the modified scale for Self-Reported Later life Health (SRLH) runs from 1) excellent to 4) fair/poor. One might wonder why we would use such a self-reported health variable for later life health, while first arguing that such self-reported variables are not very trustworthy. However, there a few reasons why we will do so nonetheless. First, there is a slight difference between having a self-reported as a predictor than as an outcome variable. When a right-side variable is not correctly specified this causes much bigger problems, as the error term and independent variables will become correlated for example. When it concerns a left-side variable on the other hand, most of the problems will disappear into the error term. This is of course also not optimal, but at least the entire regression does not become inconsistent. So to check for robustness of our results, we will also run the regression with BMI as a proxy for health. We acknowledge that BMI does not capture all aspects of someones health, but we believe that by running both regressions separately, general conclusions can still be drawn from the results.

However, there is one complication with the variable BMI that must be solved before we can proceed to the analyses. The effect of BMI on another variable or another variable on BMI is hard to interpret, because there is a preferred range for BMI, rather than just higher or lower is better. The World Health Organization reports that a BMI between 18.5 and 25 lies in a healthy range (WHO 2004). Therefore, we have created a dummy variable which equals 1 when a person has a BMI in this range and 0 when he/she does not. So throughout the paper, whenever there is referred to the variable BMI, this is a dummy that indicates whether someones has a healthy BMI or not.

Initially, the employment status variable in the SHARE data set consisted of four categories: *employed*, *retired*, *unemployed* and *sick/disabled*. However, for the purpose of this research a dummy variable was created, where one equals employed and zero is assigned for all other categories. This, because a particular order between these four categories is hard to establish. It is clear that employed will be the most preferred, hence will get the highest rank. However, it becomes ambiguous what the ranking will be between the remaining three categories. Another option could have been to use a multinomial probit model for this regression, but we find only 186 observations for *sick/disabled* and only 43 for *unemployed*. This would create problems with a multinomial probit, as the other two categories are much larger. Therefore, we will use a regular probit model to perform the analysis, with a dummy for employed.

In the regressions for both later life health and employment status, there is a set of variables for which should be controlled, such as: age, BMI, marital status, educational attainment and gender. It must be noted that marital status is a dummy where 1 means married and gender is a dummy where 1 means male. Furthermore, the value for educational attainment is a score from the International Standard Classification of Education (ISCED), prominently used in the literature. The scale runs from 1 to 5. Table 3 provides the descriptive statistics for all later life variables.

2.4 Assumptions

Important to note is that the data from the SHARE dataset was gathered in three waves, hence some respondents may have participated in the survey twice or even all three times. To make sure these respondents are not seen as separate observations, the variable *wave* has been included as a control variable. In addition, when running the analyses 782 clusters were found and subsequently

	Mean	Standard Error
SRLH	2.76	.97
employed	.52	.50
age	57.38	4.09
BMI	.42	.49
marital status	.82	.39
educational attainment	2.74	1.69
gender	.55	.50

Table 3: Descriptive Statistics of Later Life Variables

adjusted for in the standard errors. Clustered standard errors are also automatically robust, meaning possible heteroskedasticity has been controlled for in the standard errors as well.

3 Results

This section has been split up into two parts. First, the estimation of the Early Life Index will be presented. Second, this ELI is used to examine the links between the quality of life in early childhood, and later life health and employment status. The word "link" is deliberately used in this context, as identifying true causal relationships between concepts so far apart like childhood circumstances and later life health or employment status is highly problematic. All analyses have been run with the software package STATA 12, using the commands *oprobit* and *probit*.

3.1 The Early Life Index

Estimating equation 8 yields the following coefficients, shown in table 4. As can be seen, only four of the independent variables turn out to be significant predictors for SRCH, at the 5% level: length, chronic conditions, bed and language. The log-likelihood value for this regression is -2023.6288 and McFadden's pseudo-R^2 = .05.

	Coefficient	Std. Err.	z-score
length*	-.011	.004	-2.26
hunger	.653	.525	1.24
chronic conditions*	.342	.142	2.40
bed*	.815	.130	6.25
rooms	.012	.110	.11
home-owners	.032	.097	.33
books	-.051	.083	-.61
farmer	.047	.102	.46
urban	.084	.089	.94
math	.023	.146	.16
language*	-.281	.117	-2.41

Note: * significant at 5% level

Table 4: Regression Coefficients for Objective Measures

As explained before; the marginal effects of independent variables on the outcome probabilities are not equal to the coefficients in (ordered) probit models. Each independent variable yields a separate marginal effect for every category of the outcome variable. Table 5 shows these effects for all four categories of SRCH. It must be noted that for dummy variables, marginal effects are calculated differently than for continuous variables. For dummies, the marginal effect is equal to the change in probability when switching the dummy from 0 to 1. If we look at the marginal effects in more detail, we see that the sign of the effect is always the same for the first categories and then switches to the opposite for the third and fourth category. To understand why this is, we must think back to how to interpret these marginal effects: they represent the shift of the normal curve (see figure 1), holding β and μ constant. If we take the coefficient for the variable *bed*, which is positive, we automatically get a negative marginal effect for the first category. This, because shifting the curve means the probability for the first category becomes smaller. Because we have four categories in total the same will happen to the second category and so there is also a positive marginal effect here. In the same fashion we find a negative marginal effect of *bed* for the third and fourth category, because a shift of the curve will decrease the probability for these categories. So from this example we can see why it makes sense that all signs are the same for first two categories and then switch for the last two.

	Excellent	***Very Good***	***Good***	***Fair/Poor***
length	.004(.002)	.001(.000)	-.002(.001)	-.002.001)
hunger	-.168(.095)	-.079(.080)	.080(.011)	.167(.172)
chronic conditions	-.103(.039)	-.032(.017)	.064(.021)	.071(.035)
bed	-.217(.026)	-.091(.021)	.108(.014)	.120(.040)
rooms	-.004(.036)	-.001(.008)	.003(.024)	.002(.020)
home-owners	-.010(.032)	-.002(.007)	.007(.021)	.006(.018)
books	.017(.027)	.004(.006)	-.011(.018)	-.009(.015)
farmer	-.016(.033)	-.003(.008)	.010(.022)	.009(.019)
urban	-.028(.030)	-.006(.006)	.018(.020)	.015(.016)
math	-.008(.049)	-.002(.010)	.005(.033)	.004(.026)
language	.086(.005)	.025(.013)	-.054(.020)	-.058(.027)

Note: Std. Errors are in parentheses.

Table 5: Marginal Effects on Outcome Probabilities of SRCH

Let us have a look at the cutoff points that lie between the different categories. Since the SRCH variable has four outcome categories, we naturally find three cutoff values: $\mu_0 = -2.53$, $\mu_1 = -1.88$ and $\mu_2 = -.65$

Interesting to see is what the predicted probabilities for SRCH are, using the mean values for all independent variables. We then find: $Prob(SRCH = 1 \mid \boldsymbol{x}) = .268$, $Prob(SRCH = 2 \mid \boldsymbol{x}) = .246$, $Prob(SRCH = 3 \mid \boldsymbol{x}) = .383$ and $Prob(SRCH = 4 \mid \boldsymbol{x}) = .104$. So we see that, given our objective measures of health, SES and other forms of well-being, the probability that someone reports itself in the category *good* is highest, followed by *excellent*, then *very good* and last *fair/poor*.

Now that we have estimated Self-Reported Childhood Health using objective measures of health, SES and other forms of well-being, we have enough information to construct an objective Early Life Index. To do so, we will use the predicted probability for a respondent to fall in category 1 or 2, *excellent* and *very good*, which we will call ELI from here on. We combine the probabilities for the two categories to get a more spread-out range of observations. It is arbitrary whether we use categories 1 and 2 combined, or 3 and 4 combined as the probability for the latter will just be 1 minus the probability for the former. Figure 2 shows a histogram of the index.

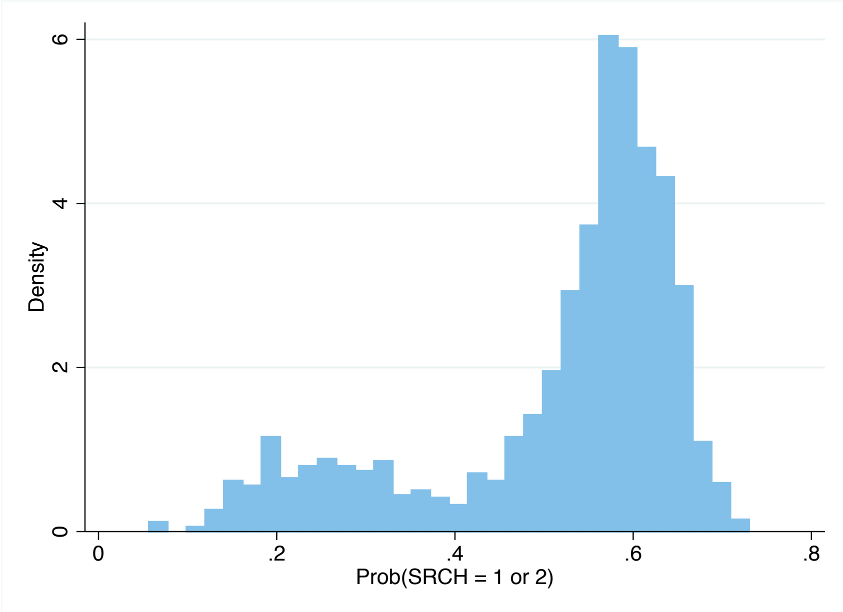

Figure 2: Histogram of Early Life Index

3.2 ELI and Later Life Health

The next step in the analysis is to use the the constructed ELI and look at the effects it has on later life health. As explained in section2.3.2 regressions will be run with both BMI and a self-reported variable as a proxy for later life health. Table 6 shows the ordered probit results for the effect of the ELI on Self-Reported Later life Health (SRLH). The log-likelihood value for the regression is -1978.2589 and McFadden's pseudo-R^2 = .04. The cutoff-values between the four categories are as follows: $\mu_0 = -3.75$, $\mu_1 = -3.11$ and $\mu_2 = -1.84$.

	Coefficient	**Std. Err.**	***z*-score**
ELI*	-.914	.243	-3.76
employed*	-.443	.072	-6.16
age*	-.026	.009	-2.91
BMI*	-.341	.065	-5.22
marital status*	-.275	.091	-3.01
educational attainment*	-.071	.020	-3.54
gender	-.04	.070	-.062

Note: * significant at 5% level

Table 6: Regression Coefficients for SRLH

We find that all variables except for gender are significant at the 5% level. Particularly interesting to see is that indeed the ELI has a significant effect on SRLH. Let us now turn to the marginal effects, shown in table 7, to be able to interpret what the effects of the independent variable on SRLH really are.

From table 7 we can see that all marginal effects are positive for the first two categories, which is generally as expected. A higher ELI; being employed; having a healthy BMI; being married and a higher education all lead to a higher probability of falling into category 1 or 2, which basically

	Excellent	*Very Good*	*Good*	*Fair/Poor*
ELI	.195(.053)	.129(.035)	-.058(.020)	-.266(.071)
employed	.094(.015)	.062(.011)	-.026(.007)	-.129(.021)
age	.006(.002)	.004(.001)	-.002(.001)	-.008(.003)
BMI	.075(.015)	.047(.009)	-.025(.007)	-.097(.018)
marital status	.053(.016)	.040(.014)	-.007(.004)	-.086(.030)
educational attainment	.015(.004)	.010(.003)	-.004(.002)	-.021(.006)
gender	.009(.015)	.006(.010)	-.003(.002)	-.013(.021)

Note: Std. Errors are in parentheses.

Table 7: Marginal Effects on Outcome Probabilities of SRLH

means a higher probability of having better self-reported health. Yet, the positive effect for age is in opposite direction, as one would expect a higher age to be associated with lesser health. Especially the marginal effect of the ELI is relatively large, lending support for the hypothesis that there is indeed a link between this ELI and later life health.

Just as we did for SRCH, we can estimate the probabilities for a respondent to fall into either of the outcome categories of SRLH. We find: $Prob(SRLH = 1 \mid \boldsymbol{x}) = .132$, $Prob(SRLH = 2 \mid \boldsymbol{x}) = .182$, $Prob(SRLH = 3 \mid \boldsymbol{x}) = .472$ and $Prob(SRLH = 4 \mid \boldsymbol{x}) = .214$. So for self-reported health later in life - which comes down to current self-reported health - the predicted probability is actually highest for the category *good*. This is in line with the actual observations, where *good* had the most observations, followed by *fair/poor*, *very good* and *excellent*. So while the predicted probability to fall into a certain category differs from the actual percentage of observations that falls into that category, the ranking of categories is the same.
All in all, the results so far seem to support the hypothesized links between early childhood quality of life and later life health. Let us now use BMI as a proxy for health and compare the results. A regular probit will be used for estimation, as BMI is just a dummy variable.

When running the regression, we find a log-likelihood value of -1072.0569 and McFadden's pseudo-R^2= .02. Table 8 shows the results.

	Coefficient	**Std. Err.**	***z*-score**
ELI	-.019	.312	-.06
employed	-.017	.089	-.19
age	-.002	.011	-.18
marital status	-.128	.111	-1.15
educational attainment*	.089	.026	3.39
gender*	.234	.090	2.60

Note: * significant at 5% level

Table 8: Results for BMI

Interestingly, the regression with BMI as a proxy for health leaves us with quite different results than before. Most of the variables that used to be significant predictors are now insignificant, including ELI. Only educational attainment and gender are significant, while the latter was insignificant before. Both have positive regression coefficients, indicating that higher education as well as being male has a positive effect on the probability of having a healthy BMI.

So when we use BMI as a proxy for health the results do not back up the evidence found earlier when using the self-reported health varialble. Rather, we obtain the opposite result that ELI is not linked to BMI. However, there might be a relatively simple explanation for this. BMI as an indicator for health solemnly looks at health in the sense of being fit or in shape, by comparing your weight to your height. But most of the literature discussing the relationship between quality of life in early childhood and later life health argued that the link runs through chronic diseases, such as CVDs for example. If this would be true, it is actually very likely that you will not find evidence of this link when using BMI, because it can be perfectly possible that respondents are within the healthy BMI range but still have all kinds of other medical problems. Therefore, this contradictory result should not be attributed with too much weight.

3.2.1 Gender Differences in Later Life Health

Throughout this paper we have so far never considered men and women to be any different. However, there might be reason to believe that this in fact is the case. When we think about health it is not hard to imagine that there might be differences in health and how men and women perceive health. Especially for the self-reported health variable, it could have big consequences if men and women judge good and bad health differently, which in turn would affect the estimated relationship between the ELI and later life health. But also for BMI, it could very well be that there are differences between men and women. Therefore, we must check whether it would in fact be better to estimate the regression separately for men and women. To do so, we will perform a likelihood-ratio test (LR test). [3]

The LR test compares the model where the regression is estimated separately for men and women with the original regression. To be able to perform such a test, models must be nested, which is the case for us. For the model where SRLH is our proxy for later life health, we find LR-$\chi^2(9) = 9.37$ with $p = .40$. This means that the unconstrained model - where men and women are estimated separately - is not significantly better than the constrained model, so we can conclude that we do not have to estimate them separately for SRLH. For the model where BMI is our proxy for later life health we get LR-$\chi^2(6) = 19.12$ with $p < .01$. So in fact we find that for this model, it would be better to estimate separately for men and women. Table 9 and 10 show these separate results for men and women.

For men, the log-likelihood value is -591.51768 with McFadden's pseudo-$R^2 = .02$, while for women log-likelihood = -470.97949 with McFadden's pseudo-$R^2 = .02$. Several interesting observations arise from the tables above.

Firstly, educational attainment is still found to be significant for men and women separately just as it had been significant before. Second, however, the Early Life Index has become significant now that we estimate it separately for both groups. Moreover, we see that for men ELI has a positive effect on BMI, while for women the effect is in fact negative. This also explains why, when the groups were combined, no significant effect was found because both effects canceled each other out. The negative effect for women, however, is rather strange as it suggests a higher ELI would result in a lower probability of having a healthy BMI. Employed, age and marital status are still insignificant for both men and women when estimated separately.

[3] It must be noted that to be able to perform the LR-test in STATA, analyses had to be run without clustered standard errors, while for all other analyses clustered standard errors are used. Although there is a slight difference between the two, we do not expect results to be affected much. The same goes for LR-tests used later in this paper.

	Coefficient	**Std. Err.**	***z*-score**
ELI*	.774	.440	1.76
employed	.061	.122	.49
age	-.008	.015	-.50
marital status	-.040	.145	-.28
educational attainment*	.085	.035	2.43

Note: * significant at 5% level

Table 9: Separate Results for BMI (Men)

	Coefficient	**Std. Err.**	***z*-score**
ELI*	-.947	.440	-2.15
employed	-.083	.131	-.64
age	.003	.017	.17
marital status	-.253	.173	-1.46
educational attainment*	.100	.040	2.48

Note: * significant at 5% level

Table 10: Separate Results for BMI (Women)

3.3 ELI and Employment Status

From the relationship between early childhood health and later life health it is not hard to move towards employment status. Later life health obviously has quite a direct effect on employment status, but a more indirect effect might also be possible. When the literature discusses the possible relationship between the quality of early life and later life variables it mostly runs through long-term diseases with a chronic nature. Especially such problems can also be imagined to have quite a strong impact on employment status in later life. Therefore, we have analyzed the link between the ELI and employment status, using a probit model. This because employment status is a dummy variable with 1 being employed, as explained before. Table 11 present the results. Log-likelihood = -858.81222 and McFadden's pseudo-R^2 = .23

	Coefficient	**Std. Err.**	***z*-score**
ELI*	.605	.311	1.95
SRLH*	-.249	.043	-5.79
BMI	-.067	.087	-.78
age*	-.166	.012	-13.95
marital status	-.011	.119	.09
educational attainment*	.134	.026	5.08
gender*	-.564	.090	-6.24

Note: * significant at 5% level

Table 11: Results for Employment Status

Not surprisingly we find that SRLH has a significant negative effect on employment status. Remember that this is the direction that was expected, because the higher the value for SRLH the worse you report your health to be, so the lower SRLH the higher the probability of being employed. Our other proxy for health - BMI - is not significant, which can again be attributed to the fact that is does not capture those parts of health that we hypothesize to have the most effect on employment: long-term and chronic problems, rather than over- or underweight. If we turn to the

ELI, we see that it has significant positive effect, even when controlling for later life health. This is an interesting result, as it shows us that the effect does not only run trough later life health, but also has some sort of direct effect on employment status. The positive effect means the higher the probability of falling into the best two categories of quality of early life, the higher the probability of being employed when over 50.

For our remaining variables, we find that age is also significant and negative, which makes sense: when someone gets older, the chances of being employed decrease. Education is also significant and in the expected positive direction. Marital status is not significant, while gender is significant, but negative. This last result is interesting as it suggest that the higher probability of being a man results in a lower probability of being employed. Since gender has a significant effect, let us perform a likelihood-ratio test to see whether we should perform this regression separately for men and women.

3.3.1 Gender Differences in Employment Status

When we perform the LR-test we find a LR-$\chi^2(7) = 25.80$ with $p < .01$. This result is in line with the significant gender variable and indeed we should run the model separately for men and women. Table 12 and 13 present these separate results.

	Coefficient	**Std. Err.**	***z*-score**
ELI	.315	.438	.72
SRLH*	-.215	.058	-3.71
BMI	-.004	.117	-.04
age*	-.151	.016	-9.55
marital status	-.216	.143	-1.51
educational attainment*	.151	.034	4.38

Note: * significant at 5% level

Table 12: Separate Results for Employment (Men)

	Coefficient	**Std. Err.**	***z*-score**
ELI*	1.03	.461	2.25
SRLH*	-.302	.066	-4.61
BMI	-.095	.127	-.74
age*	-.194	.018	-10.56
marital status*	.394	.2-4	1.93
educational attainment*	.092	.042	2.23

Note: * significant at 5% level

Table 13: Separate Results for Employment (Women)

For men, the log-likelihood value is -485.69787 with McFadden's pseudo-$R^2 = .19$ and for women, the log-likelihood value is -360.21326 with McFadden's pseudo-$R^2 = .25$. As far as health is concerned, the results do not change as SRLH is still significant for both men and women separately and BMI is not for either. However, when we compare the effects for ELI we find an interesting result. ELI appears only to have a significant (positive) effect on employment for women, but not for men. This suggests that the significant effect obtained earlier for all respondents is mainly driven by the significant effect it has for women. Also interesting is that marital status, which did not give a significant result before, is significant for women, when estimated separately. The positive effect indicates that a higher probability of being married results in a higher probability of being employed for women. Lastly, the results that age and education had significant effects do not change when estimated separately for men and women (nor do the directions of the effects).

4 Conclusion

Now that all of the results have been presented, it is time to elaborate on the most interesting findings. Then, lastly, we will turn back to the political debate with which we started this paper and discuss some of the policy implications of these findings.

The first goal of this research was to construct an objective measure for the quality of life in one's early childhood, which we have called the Early Life Index (ELI). This because self-reported variables are found not to be very reliable, for a variety of reasons mentioned earlier. To construct the ELI, we let self-reported childhood health be predicted be a range of objective measures for socio-economic status, health and well-being. Significant effects are found for the variables length, chronic conditions, bed and language. More specifically, for length we find that a 10 centimeter increase in length results in a 4% increase in probability to fall into the best health category (*excellent*) and a 2% decrease in the probability to fall into the worst health category (*fair/poor*). People that are classified as having had chronic health problems in early childhood have a 10.3% lower chance to fall into the best health category and a 7.1% higher chance to fall into the worst health category. For people that have been in bed for more than a month because of illness the marginal effect is even stronger: a 21.7% lower chance of falling into the best health category and a 12% higher chance of falling into the worst health category. Lastly, there is a 8.6% higher chance of falling into the best health category for children that performed above average in language in early childhood, and a 5.8% lower chance to fall into the worst health category.

As expected, three out of four health related variables proved to be significant predictors for self-reported health; only the dummy variables for whether someone had ever experienced a period of serious hunger did not. This could be due to the fact that remembering such a period can be difficult and the distinction between little hunger and an actual period of hunger can vary highly between respondents. More surprisingly, none of the proxies for socio-economic status in early childhood showed a significant effect on self-reported childhood health. Finally, although we find that if a child is more than average in language correlates with its health status, its relative position in math does not.

The ELI constructed from this first part of the analysis is a predicted probability for a respondent to fall into one of the two best health categories, *excellent* and *very good*, using the objective measures of health, SES and well being. The mean value for this probability was found to be 51.4%. So just over half of the sample is predicted to have an excellent or very good early childhood health.

When we used the self-reported variable as a proxy for later life health we found that all variables, except gender, were significant. In particular, we found that an increase of 10% in the probability of falling into the best two health categories in early life results in a 2% increase in the probability of falling into the best health category in later life. Similarly, the same 10% increase leads to a 2.7% decrease to fall into the worst health category in later life. For people that are employed we find a 9.4% higher probability of falling in the best health category and a 12.9% lower probability of falling in the worst health category. For the age variable, results suggest that a 10-year increase age leads to a 6% increase to fall into the best health category and an 8% decrease to fall into worst health category. However, this relationship was expected to be the other way around as higher age is often related to worse health conditions. For people with a healthy BMI we find that they have a 7.5% higher chance of falling into the best self-reported health category and a 9.7% lower chance for the worst category. Married people have a 5.3% higher probability to fall in the best health category and an 8.6% lower probability to fall in the worst health category. Lastly, a 1-point increase on the ISCED scale for educational attainment leads to a 1.5% increase in the probability of falling in the best health category and 2.1% decrease of falling in the worst category.

Through a LR-test we checked whether the model would be better when testing for men and women separately. As the fact that gender was an insignificant predictor already suggested, this was found not to be the case and so we did not look at separate results with self-reported health as the proxy for later life health. Instead, we moved to look at the results with BMI as a proxy for health.

With BMI as the outcome variable we obtained very different results, as only education and gender showed to be significant predictors. For education we find a 1-point increase on the ISCED scale leads to an 8.9% increase in the probability of having a healthy BMI. Additionally, males seem to have a 23.4% higher probability of having a healthy BMI than females do, when controlling for all other variables. This is quite a rigorous result, which definitely suggested looking at results for men and women separately. The LR-test confirmed that this indeed proves to be a better model.

Interestingly, the effect of ELI on BMI becomes significant for both men and women when estimated separately. This because the signs are opposite: for men we find a 10% increase in the probability of having excellent or very good childhood health leads to a 7.7% increase in the probability of having a healthy BMI, while for women a 10% increase in this probability leads to a 9.5% decrease in probability of having a healthy BMI. The first result seems very logical, but the result for women is rather strange and hard to explain.

Next, we examined the effect of the Early Life Index on later life employment status, while controlling for a set of variables. We find that indeed ELI has a significant effect, as well as SRLH, age, education and gender. For ELI, an increase of 10% in the probability of having excellent or very good childhood health results in a 6.1% increase in the probability of being employed. For self-reported later life health we find an decrease in one health category (e.g. from excellent to very good) leads to a 25% decrease in the probability of being employed. A 1-year increase in age leads to a 16.6% decrease in the probability of being employed. This seems like a rather strong effect, but this is mainly because all respondents are aged 50 and over, hence are coming closer and closer to retirement. Concerning education, we find a 1-point increase on the ISCED scale leads to 13.4 increase in the probability of being employed. Last, for gender we find that males have a 56.4% lower probability of being employed than women do.

This last result again suggests large gender differences and when we perform a LR-test we indeed find that estimating the regressions separately for men and women yields a better model. For the self-reported later life health variable, a 1 health-category decrease leads to a 21.5% decrease in probability of being employed for men and a 30.2% decrease for women. For the Early

Life Index, however, we have found a more surprising result. When estimated separately, the effect of ELI on employment is only significant for women, where an 10% increase in the probability of having an excellent of very good childhood health leads to a 10.3% increase of being employed. Similarly, marital status also becomes only significant for women when estimated separately: a 1% increase of being married leads to a .39% increase in the probability of being employed. A 1-year increase in age leads to a 15.4% decrease in the probability of being employed for men, and a decrease of 19.4% for women. Lastly, a 1-point increase on the ISCED scale leads to a 15.1% increase of being employed for men, while only a 9.2% increase for women.

Now that we have provided a summary of the findings of this research, let us turn back to the initial topic of the paper. First, an (objective) index for one's quality of life in early childhood was successfully constructed, although it was found that the health variables were most important for this index. Second, the expected relationship between this Early Life Index and later life health was found in the expected direction, when using a self-reported variable as a proxy. The results showed no differences between men and women. However, when using BMI as a proxy for health a significant relationship in the expected direction was found for men, but for women the relationship turned into the opposite direction. Although a strange result in itself, it should not be given to much attention as we believe BMI is not a very good proxy for later life health in the first place. This because it only captures unhealthiness in weight/length ratio while most of the hypothesized relationships between early and later life health come through chronic diseases that do not necessarily affect BMI. Last, a direct relationship between the Early Life Index and employment status was found, even while controlling for later life health variables. Although in the expected positive direction, results show that the significant relationship between the two was only driven by the effect for women, as for men it turned insignificant.

If we look back at the initial political debate with which we started this paper, some remarks can now be made. For the Netherlands, this research lends support to those in favor of child benefits. It has been demonstrated that the quality of life in early childhood has a positive effect on later life health and especially the health aspect of early childhood is important in this respect. In addition, a direct positive relation was found between the quality of early life and one's later life employment status, even when controlling for later life health. So when the government supports families with young children, these children will grow up to be more healthy adults, as well as have a higher chance of remaining employed in their later life (assuming the money is spent well, and mainly used for the health of the child). Both of these consequences in turn are good for the government economically, as they mean less expenditures on health and unemployment benefits in the future.

5 Discussion

Some limitations of this research must briefly be elaborated upon, to put the findings in perspective. In addition, suggestions for further research will be provided.

First, it must be acknowledged that using a self-reported variable is never optimal and so further research could repeat the analyses using a more objective proxy for later life health, or even a later life health index. In similar fashion, BMI is not a very good proxy for health either, especially in the context of this research. Second, though outside the scope of this research, further research could use a multinomial probit model to investigate the relation between early life and employment status, using the regular employment variable rather than a dummy. Third, if the entire relation between early life and later life variables is perceived to be different for men and women, then further research could construct an entirely separate Early Life Index and look at all results separately for men and women. Also, to check for robustness of the results different type of models could be used to estimate the same regressions as in this paper. Lastly, this paper has only looked at the Netherlands, but it would be very interesting to use similar data for other countries and see if the same results are obtained, although the literature has already done so for a few.

References

Barker, D.J.P. (1995) *Fetal Origins of Coronary Heart Disease.* British Medical Journal. Vol. 311, No. 6998, pp. 171-174

Blackwell, D.L., Hayward, M.D. and Crimmins, E.M. (2001) *Does Childhood Health Affect Chronic Morbidity in Later Life?* Social Science and Medicine. Vol. 52, No. 8, pp. 1269-1284

Bound, J. (1989) *Self-Reported vs. Objective Measures of Health in Retirement Models.* Working Paper Series, No. 2997. National Bureau of Economic Research

Bound, J., Schoenbaum, M., Stinebrickmner, T.R. and Waidmann, T. (1998) *The Dynamic Effects of Health on the Labor Force Transitions of Older Workers.* Working Paper Series, No. 6777. National Bureau of Economic Research

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

Case, A. and Paxson, C. *Height, Health, and Cognitive Function at Older Ages.* The American Economic Review. Vol. 98, No. 2, pp. 463-467

Cavapozzi, D., Christell, G. and Paccagnella, O. (2011) *Childhood, Schooling and Income Inequality.* The Indiviual and the Welfare State. Springer Berlin Heidelberg

Chirikos, T.N. and Nestel, G. (1984) *Economic Determinants and Consequences of Self-Reported Work Disability.* Journal of Health Economics. Vol. 3, No. 2, pp. 117-136

Dwyer, D.S. and Mitchell, O.S. (1999) *Health Problems as Determinants of Retirement: Are Self-Rated Measures Endogenous?* Journal of Health Economics. Vol. 18, No, 2, pp. 173-193

Flores, M. and Kalwij, A. (2011) *The Associations between Early Life Circumstances and Later Life Health and Employment in the Netherlands and Spain.* Working Paper. No. 4

Floud, R., Wachter, K.W. and Gregory, A. (1990) *Height, Health and History: Nutritional Status in the United Kingdom, 1750-1980.*Cambridge studies in population, economy, and society in past time. Cambridge University Press

Fogel, R.W. (1993) *New Sources and New Techniques for the Study of Secular Trends in Nutritional Status, Health Mortality, and the Process of Aging.* Historical Working Paper Series, No. 26. National Bureau of Economic Research.

Greene, W.H. (2000) *Econometric Analysis.* Prentice Hall.

Halkes, J. (2011) *PVDA pleit voor Afschaffen Kinderbijslag Grootverdieners.* Metronieuws

Kuh, D.J.L and Ben-Shlomo, Y. (2004) *A Life Course Approach to Chronic Disease Epidemiology.* Life Course Approach to Adult Health Series. Oxford University Press

Kuh, D.J.L., Power, C., Blane, D. and Bartley, M.J. (2004) *Social Pathways between Childhood and Adult Health.* A Life Course Approach to Chronic Disease Epidemiology. Oxford University Press.

Kuh, D.J.L. and Wadsworth, M.E.J. (1993) *Physical Health Status at 36 years in a British National Birth Cohort.* Social Science and Medicine. Vol. 37, No. 7, pp 905-916

Marmot, M., Shipley, M., Brunner, E. and Hemingway. (2001) *Relative Contribution of Early Life and Adult Socioeconomic Factors to Adult Morbidity in the Whitehall II Study.* Journal of Epidemiology and Community Health. Vol. 55, No. 5, pp. 301-307

Pollit, R., Rose, K. and Kaufman, J. (2005) *Evaluating the Evidence for Models of Life Course Socioeconomic Factors and Cardiovascular Outcomes a Systematic Review.* BMC Public Health. Vol. 5, No. 1

Power, C. and Hertzman, C. (1997) *Social and Biological Pathways Linking Early Life and Adult Disease.* British Medical Bulletin. Vol. 53, No. 1, pp. 210-221

Unknown Author. (2012) *Partijen Wilden Ruim 14 Miljard Euro Bezuinigen.* Nu.nl

WHO. (2004) *BMI Classification.*