Inequality in health versus inequality in lifestyles

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Abstract: Repeated Norwegian cross-sectional data for the period 2005 to 2011 are used to compare sources of inequality in health, as represented by self-assessed health and obesity, with sources of inequality in lifestyles that are central to the production of health, as represented by physical activity, cigarette smoking and dietary behavior. Sources of overall inequality and socioeconomic inequality in these lifestyle and health indicators are compared by estimating probit models, and by decomposing the explained part of the associated Gini and concentration indices with respect to education and income. As potential sources of inequality, we consider education, income, occupation, age, gender, marital status, psychological traits and childhood circumstances. Our results suggest that sources of inequality in health are not necessarily representative of sources of inequality in underlying lifestyles. While education is generally an important source of overall inequality in both lifestyles and health, income is unimportant in all lifestyle indicators except physical activity. In several cases, education and income are clearly outranked by other factors in terms of explaining overall inequality, such as gender in eating fruits and vegetables and age in fish consumption. These results suggest that it is important to decompose both overall inequality and socioeconomic inequality in different lifestyle and health indicators. In indicators where other factors than education and income are clearly most important, policy makers should consider to target these factors to efficiently improve overall population health.

JEL classification: D39, I12, I14

Key words: concentration index, Gini index, health inequality, inequality in lifestyle indicators, socioeconomic status, Norway

1 Introduction

In Norway as in many other countries, reducing health inequalities represent a key goal for health policy (Commission on Social Determinants of Health, 2008; Norwegian Ministry of Health and Care Services, 2006). Considerable efforts have been made to improve our understanding of health inequalities, including attempts at identifying their sources. In particular, decomposition techniques for the Gini index and the concentration index have made it possible to quantify the contribution of single observable factors to overall health inequalities and socioeconomic inequalities in health (e.g., Wagstaff *et al.*, 1991; van Doorslaer *et al.*, 2004; Wagstaff and van Doorslaer, 2004).

Important determinants of health include many of our daily lifestyles. It is well documented that smoking, nutritional intake, alcohol consumption, physical activity as well

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as other lifestyles have major health effects that also are considered to be public health issues (Norwegian Ministry of Health and Care Services, 2012). Lifestyle indicators are sometimes included in studies that employ the above decomposition of inequality techniques. There are two main groups of such studies. First, several empirical studies have employed decomposition techniques to consider to what extent lifestyle indicators contribute to overall health inequalities and socioeconomic inequalities in health (Balia and Jones, 2008; Rosa Dias, 2009; Vallejo-Torres and Morris, 2010; Tubeuf *et al.,* 2012). For example, using British longitudinal data, Balia and Jones (2008) found that six observable lifestyle indicators in 1984/85 accounted for approximately 25% of the explained part of the Gini index for predicted mortality in 2003. Second, recognizing their importance to health, some studies have employed decomposition of inequality techniques directly on lifestyle indicators themselves, rather than health outcomes. Examples of such studies are Costa-Font and Gil (2008) and Ljungvall and Gerdtham (2010), who both found significant income-related inequalities in obesity[1] and Combes *et al.* (2011), who found that alcohol consumption in Sweden is pro-rich.

While both the above groups of studies provide important insights, we are not aware of any studies that have used decomposition techniques to compare sources of inequality across important lifestyle and health indicators using the same sample of individuals and a common set of explanatory factors. Our objective is to empirically investigate and compare sources of inequality in important health and lifestyle indicators by using one sample and a common set of explanatory variables. The use of one sample removes sample specific variation as a potential source of variation across the various lifestyle and health indicators. Furthermore, a common set of explanatory variables increases the comparability across the different indicators. Repeated cross-sectional data from the Norwegian Monitor Survey for the period 2005 to 2011 are used in our analyses. We take a broad approach by assessing both overall inequality and different versions of socioeconomic inequality in lifestyles and health. Thus, we estimate and decompose Gini indices of overall inequality and concentration indices with respect to education and income. This analysis can provide useful policy insights. For example, income may represent a leading source of overall inequality in self-assessed health (SAH), but explain very little of the variation in consumption of fruits and vegetables. If the leading source of inequality in consumption of fruits and vegetables is gender, a public policy that aims at reducing income inequalities in SAH by reducing the value added tax on fruits and vegetables is unlikely to be successful in reducing the inequality in consumption. An information campaign specifically targeted at convincing men to eat more fruits and vegetables is likely to be more successful.

Our health indicators are SAH and obesity, and our lifestyle indicators are the frequency of physical activity, smoking, consumption of fish and consumption of fruit, berries and vegetables. These four lifestyle indicators are closely associated with the risk of adverse health outcomes, including type II diabetes, cardiovascular disease and certain types of cancer (World Health Organization, 2003).

As potential sources of inequality, we consider education, income, occupation, age, gender, marital status, psychological traits and childhood circumstances. Numerous studies have agreed on the importance of current socioeconomic status as measured by income, education or occupation in explaining health inequalities (e.g., Wagstaff *et al.*, 1991; van Doorslaer and Jones, 2003; Wagstaff and van Doorslaer, 2004). Evidence on the importance of psychological traits such as the rate of time preference, risk aversion and self-control in

[1] Sometimes obesity is viewed as a lifestyle (e.g., Balia and Jones, 2008; Tubeuf *et al*., 2012), however, obesity is also a health indicator by itself (e.g., Goodman *et al*., 2003). In this study, obesity is viewed as a health indicator.

affecting health is also accumulating (van der Pol, 2011; O'Donoghue and Rabin, 2006). Furthermore, a number of studies have shown that differences in childhood circumstances such as fetal nutrition, social support and parental socioeconomic status contribute to inequalities in adult lifestyles and health (Case *et al.*, 2005; Rosa Dias, 2009; Rosa Dias, 2010; Trannoy *et al.*, 2010; Tubeuf *et al.*, 2012). Differences in childhood circumstances represent opportunities that are beyond personal responsibility and, therefore, they represent sources of inequality that many consider to be socially unacceptable.

2 Data

The Norwegian Monitor Survey is a nationally representative and repeated cross-sectional survey of adults aged 15–95 years. The survey has been conducted every second year since 1985 and is one of Norway's most comprehensive consumer and opinion surveys. The institution behind the survey (Ipsos Norway) recruits respondents through a short telephone interview, and those who accept to participate receive a paper-based questionnaire by mail. The questions about body height and weight and parental education were not included in the survey before 2005, and therefore data from 2005 to 2011 are used. Our sample is further restricted to include only respondents between the ages of 25 and 74 years because we want to study individuals who have completed most of their education and started earning their own income, and because the data includes relatively few respondents between the ages of 75 and 95 years. After deleting observations with missing information for any relevant variables (2,622 observations), we obtain a final sample of 10,591 observations.

The questions related to our six lifestyle and health indicators are based on various types of categorical scales. For example, the respondents are asked to indicate their frequency of eating (i) fruits and berries (denoted fruits) and (ii) vegetables on a 10-point scale ranging from "never/less than once per month" to "four times per day". Similarly, physical activity has an eight-point frequency scale ranging from "never" to "once or more per day". A third frequency scale is used for fish consumption, while our data on cigarette smoking allows for distinguishing between daily smokers and non-smokers. SAH is based on the typical 5-point scale ranging from "very bad" to "very good" health, while body mass index and corresponding obesity status is based on self-reported height and weight.

To keep the analysis simple, we have chosen to dichotomize each lifestyle and health indicator. However, to check the robustness of our results, we have also reiterated our analysis using mainly ordinal lifestyle and health indicators. The results and conclusions in our study are generally not sensitive to choice of variable definitions – see section 4.3 for details.

Variable descriptions and means are shown in Table 1. In order to present results consistently, we have "reversed" our two unhealthy lifestyle and health indicators by defining them as non-smoking and non-obesity. Approximately 60% of the respondents exercise at least twice per week, 41% eat fruits or vegetables at least twice per day, 78% eat fish for dinner at least once per week, and 79% are not daily smokers. Approximately 87% of the respondents report that they are not obese and 73% report their health status as either "good" or "very good".

Education is categorized into four groups, ranging from having completed only lower secondary education or less to having obtained a university or college degree. We create one dummy variable for each of the educational groups. The original survey question pertaining to household income included nine response alternatives, each representing a specific income interval. Based on this question, we have constructed a semi-continuous income measure by (i) setting household income to the mid-point value of each income interval, (ii) adjusting for inflation over the 2005–2011 survey period and (iii) adjusting for

household size by dividing the resulting income measure by the square root of household size (Organisation for Economic Co-operation and Development, 2008).

Table 1: Variable descriptions and means

Variable	Description	Mean
Lifestyles		
Physical activity	Do physical activity at least twice per week: 1	0.599
Fruit and vegetables	Eat fruit, berries or vegetables at least twice per day: 1	0.407
Fish	Eat fish for dinner at least once per week: 1	0.779
Non-smoking	Not smoking cigarettes daily: 1	0.793
Health		
Non-obesity	Body mass index (BMI) (weight in kg/height in meter^2) < 30: 1	0.873
Self-assessed health (SAH)	Self-assessed health is "good" or "very good": 1	0.726
Demographics	(Ref. categories are: "Age 25–34" and "Married/Cohabitant")	
Age 35–44	Age 35–44: 1	0.256
Age 45–54	Age 45–54: 1	0.216
Age 55–64	Age 55–64: 1	0.198
Age 65–74	Age 65–74: 1	0.134
Female	Female: 1	0.480
Household has children	If any children is living in household: 1	0.487
Widow	If widowed: 1	0.035
Divorced	If divorced: 1	0.081
Single	If single: 1	0.115
Socioeconomic status	(Ref. category is "Lower secondary education"	
Upper secondary education	If highest education is upper secondary education or less: 1	0.321
Some college/university	If highest education is some college/university: 1	0.241
College/university degree	If highest education is college/university with degree: 1	0.340
Household income	Household income / Square root of household size [a)]	4.191
Occupation	(Ref. category is: "Non-manual worker")	
Skilled manual	If skilled manual worker: 1	0.197
Unskilled manual	If unskilled manual worker: 1	0.065
On social security/benefit	If on social security or disability benefit: 1	0.080
Other occupation	If unemployed, student, homemaker, retired or other: 1	0.263
Psychological traits		
Pay in installments	Like to pay in installments: 1 [b)]	0.146
Life insurance	Household has purchased life insurance: 1	0.484
Self-control	Feel self-control over life outcomes: 1 [c)]	0.851
Childhood circumstances	(Ref. cats. are: "Poor childhood" and "Lower parental education")	
Childhood econ. average	If family's economic situation normal when 10–15 years old: 1	0.657
Childhood econ. rich	If family well-endowed when 10–15 years old: 1	0.137
Parental upper secondary	Parent(s) highest education upper secondary school: 1	0.232
Parental college/university	Parent(s) highest education college/university: 1	0.279

Notes: Variable descriptions and sample means using survey weights. Data pooled from survey years 2005, 2007, 2009 and 2011, in total 10,591 individual observations. [a)] Household income in Norwegian kroner (NOK)/ 100,000, with sample minimum 0.275, maximum 12.462 and standard deviation 1.668. [b)] Respondent "partly agrees" or "totally agrees" in that he/she likes to purchase in installments. [c)] Respondent "partly disagrees" or "totally disagrees" to the statement: "It is of little use to plan for the future, since what happens in life is mostly a matter of being lucky or unlucky anyway".

Three variables are included as measures of psychological traits. These measures may be somewhat crude, but the use of preferences for paying in installments and the procurement of life insurance to proxy the rate of time preference and the risk averseness, respectively, is not uncommon (Cutler *et al.*, 2011; Loewenstein and Prelec, 1992). Approximately 15% of the respondents in the sample indicate a high rate of time preference by liking to pay in installments, 48% indicate to be risk averse by purchasing life insurance, and 15% indicate a lack of self-control by believing that future outcomes primarily depend on being lucky or unlucky.

Childhood circumstances are measured by the educational level of the parent with the highest level of education and the economic conditions during childhood. Approximately two-thirds of the respondents describe the economic situation of their family as normal when being 10–15 years old, and approximately 14% considered their family to be well-off at that time. One or both the parents of approximately 28% of the respondents had attended either a college or university.

3 Empirical methods

Our procedure for decomposing overall inequality and socioeconomic inequality in lifestyles and health consists of four steps. In the first step, we estimate probit models for our six dichotomous lifestyle and health indicators y. Each probit model controls for the variables x in Table 1 listed under the headings demographics, socioeconomic status, occupation, psychological traits and childhood circumstances, as well as survey year dummies.

In the second step, we calculate linear predictions, $\hat{y}_{im}$, for each lifestyle and health indicator (m = physical activity,..., SAH) and for each individual (i = 1,..., N) in the sample. We follow Balia and Jones (2008) and use the predicted linear index functions from the probit models in the first step, rather than the observed outcomes, to calculate and decompose the Gini and concentration indices in the subsequent steps. The use of linear predictions ensures sufficient variation in the outcome variables for which to calculate the Gini indices. For purposes of the later inequality indices, we want these predicted variables to take only nonnegative values (Erreygers and Van Ourti, 2011). Therefore, in each calculation we subtract the minimum predicted value in the sample (Balia and Jones, 2008), as shown in Equation (1):

$$\hat{y}_{im} = \hat{\beta}' \mathrm{X_i} - \hat{\beta}' \mathrm{X_j} \text{ where } \hat{\beta}' \mathrm{X_j} = \min(\hat{\beta}' \mathrm{X_i}). \quad (1)$$

In the third step, we calculate Gini indices and education- and income-related concentration indices based on the predictions from the second step. The Gini index measures to what extent a variable y (e.g., physical activity) is equally distributed within a population. This index has a range of [0, 1], where 0 and 1 indicate minimum and maximum levels of overall inequality in y. The closely related concentration index measures the relationship between y and the distribution of a socioeconomic status indicator (e.g., education). The concentration index has a range of [-1, 1], where 1 (-1) indicates extreme cases in which all "good health" is found among those in the absolute highest (lowest) socioeconomic status group (Wagstaff *et al.*, 1991). Suppressing subscript m and i, the concentration index C for $\hat{y}$ is given by:

$$C_{\hat{y}} = (2/\mu_{\hat{y}})\mathrm{cov}(\hat{y}, r), \quad (2)$$

where r is the fractional rank of the chosen socioeconomic indicator, with $r_i = i/N$, with i = 1 and $i = N$ for the individuals with the lowest and highest values of socioeconomic status,

respectively, and $\mu_{\hat{y}}$ is the mean value of $\hat{y}$ (O'Donnell *et al*., 2008).[2] The Gini index is obtained by replacing r of the socioeconomic status indicator in Equation (2) with the fractional rank of $\hat{y}$ (Wagstaff and van Doorslaer, 2004).

In the fourth step, the Gini and concentration indices from the third step are decomposed into their contributing factors. Thus, we estimate the contribution of each explanatory variable to the explained part of the Gini index and the education- and income-related concentration index in each of the six predicted lifestyle and health variables (the $\hat{y}$'s). The decomposition formula for the concentration index is given by:

$$C_{\hat{y}} = \sum_k (\hat{\beta}_k \bar{x}_k / \mu_{\hat{y}}) C_k, \tag{3}$$

where $\hat{\beta}_k$ is the estimated coefficient for variable k from the probit models in first step, $\bar{x}_k$ is the mean value of variable k and C_k is the concentration index for variable k with respect to the chosen socioeconomic status indicator (O'Donnell *et al*., 2008). Thus, for example, two conditions must be fulfilled for gender to make an important contribution to the education-related concentration index in SAH. First, the marginal effect of gender on SAH, after controlling for the other regressors and being scaled by the mean value of gender, must be strong. Second, gender and education must be strongly correlated, i.e., the concentration index of gender with respect to education must be large. The Gini index is also decomposed using Equation (3), but now with C_k representing the concentration index of variable k with respect to the predicted lifestyle or health variable $\hat{y}$ (Balia and Jones, 2008).

Note that because we calculate and decompose Gini and concentration indices using the linear predictions from the probit models, which are additive in the regressors, there are no residual terms in Equation (3). Thus, we decompose only the deterministic or explained part of overall inequality and socioeconomic inequality in lifestyles and health (Balia and Jones, 2008; van Doorslaer and Jones, 2003).

We also note that there is an ongoing debate on how to measure inequality. We employ the standard version of the concentration index as proposed by Wagstaff *et al.* (1991). Other versions include the 'normalized' concentration index for binary variables as proposed by Wagstaff (2005), and the 'corrected' concentration index as proposed by Erreygers (2009). These and yet other inequality measures have different properties. Choice of inequality measure should be made based on the focus and nature of the data in a study. This choice is particularly important in studies that focus on assessing the degree or level of inequality in health indicators, which may be sensitive to choice of inequality measure. Our study focuses mainly on decomposing inequality into its contributing sources, which is less sensitive to choice of inequality measure (O'Donnell *et al.*, 2012). For thorough discussions on properties and choice of inequality measures, see Erreygers and Van Ourti (2011), Kjellsson and Gerdtham (2013), Allanson and Petrie (2014), and Kjellsson *et al.* (2015).

4 Results

4.1 The probit models

Table 2 reports the results of the probit models for lifestyles and health. Even though our main focus is on the subsequent decomposition of inequality analyses, we briefly note the following main results from the probit models in Table 2.

[2] Because our education indicator is categorical and our income indicator is semi-continuous, we follow Chen and Roy (2009) and give equal fractional rank, r, to ties (their average fractional rank), rather than sorting people with equal income or education randomly or by variables other than income or education.

Table 2: Probit models for lifestyles and health

	Physical activity	Fruit and vegetables	Fish	Non-smoking	Non-obesity	Self-assessed health
Education						
Upper secondary education	0.078	0.063	0.043	0.026	-0.081	-0.016
Some college/university	**0.216**	**0.212**	**0.268**	**0.288**	-0.068	*0.100*
College/university degree	**0.291**	**0.304**	**0.337**	**0.491**	0.076	**0.159**
Income						
Household income	**0.059**	**0.030**	0.015	***0.022***	**0.042**	**0.095**
Age						
Age 35–44	-0.015	*0.098*	**0.217**	**-0.209**	***-0.158***	**-0.266**
Age 45–54	**0.158**	**0.175**	**0.447**	**-0.299**	-0.069	**-0.248**
Age 55–64	*0.094*	**0.272**	**0.746**	**-0.187**	-0.046	**-0.438**
Age 65–74	***0.140***	**0.357**	**0.965**	0.035	0.036	**-0.360**
Gender						
Female	**0.186**	**0.508**	**0.144**	**-0.104**	***0.090***	0.039
Occupation						
Skilled manual	*0.074*	-0.065	-0.018	-0.067	0.061	0.022
Unskilled manual	-0.007	***-0.166***	***-0.145***	**-0.334**	-0.060	**-0.209**
On social security/benefit	0.012	***-0.116***	-0.057	**-0.279**	**-0.217**	**-1.195**
Other occupation	**0.160**	-0.030	0.006	0.018	0.023	**-0.142**
Psychological traits						
Pay in installments	***-0.078***	**-0.103**	**-0.128**	**-0.118**	**-0.329**	-0.039
Life insurance	0.037	-0.002	0.035	*0.056*	-0.023	**0.080**
Self-control	**0.135**	0.063	0.045	**0.233**	0.010	**0.208**
Childhood circumstances						
Childhood econ. average	-0.004	**0.035**	**0.040**	***0.039***	***0.040***	**0.036**
Childhood econ. rich	-0.001	0.019	0.067	0.026	**0.215**	**0.153**
Parental upper secondary	0.017	0.051	-0.013	***-0.099***	*0.081*	0.031
Parental college/university	0.052	**0.187**	0.041	*0.073*	**0.219**	***0.092***
Other variables						
Household has children	*-0.072*	-0.021	**0.125**	0.049	0.026	**0.114**
Widow	0.087	*-0.123*	**-0.236**	-0.038	0.081	*0.139*
Divorced	**0.146**	*-0.084*	**-0.289**	**-0.341**	0.095	0.026
Single	***0.124***	***-0.111***	**-0.261**	**-0.167**	***-0.144***	-0.046
2007	-0.002	***0.087***	**0.175**	0.062	**-0.158**	-0.031
2009	0.035	**0.250**	0.066	**0.123**	**-0.175**	-0.039
2011	**0.152**	**0.258**	**0.180**	**0.278**	**-0.210**	*-0.071*
Constant	**-0.558**	**-1.196**	-0.112	**0.421**	**1.059**	***0.228***
McKelvey & Zavoina R^2	0.061	0.114	0.117	0.141	0.065	0.221

Notes: The probit models were estimated using sample weights and robust standard errors. Probit parameters in **bold**, ***bold italics*** and *italics* are statistically significant at the 1%, 5% and 10% levels, respectively. See Table 1 for the definition of variables and relevant reference categories. All results are based on 10,591 observations.

First, there are clear education gradients in the four lifestyle indicators. Second, higher income is also significantly associated with healthier lifestyles, except in the case of eating fish for dinner. Third, the two health indicators, non-obesity and SAH, are significantly associated with income, but less clearly associated with education; only the association between having a university or college degree and SAH is statistically

significant at the 5% level. Fourth, in some lifestyle and health indicators, one single explanatory factor stands out as particularly important. Marginal effects from the probit models in Table 2 suggest that, on average, women are about 19 percentage points more likely than men to eat fruit and vegetables at least twice per day; older people are much more likely than younger people to eat fish for dinner at least once per week; and people who receive social security or disability benefits are 42.5 percentage points less likely than others to report being in good or very good health. Finally, our indicators of psychological traits and childhood circumstances are significantly associated with several lifestyle and health indicators. A high rate of time preference is negatively associated with consumption of fruits and vegetables and fish, and positively associated with smoking and obesity; self-control is positively associated with physical activity, non-smoking and SAH; and good childhood circumstances are significantly associated mainly with our two health indicators, non-obesity and SAH.

4.2 Decomposing inequality

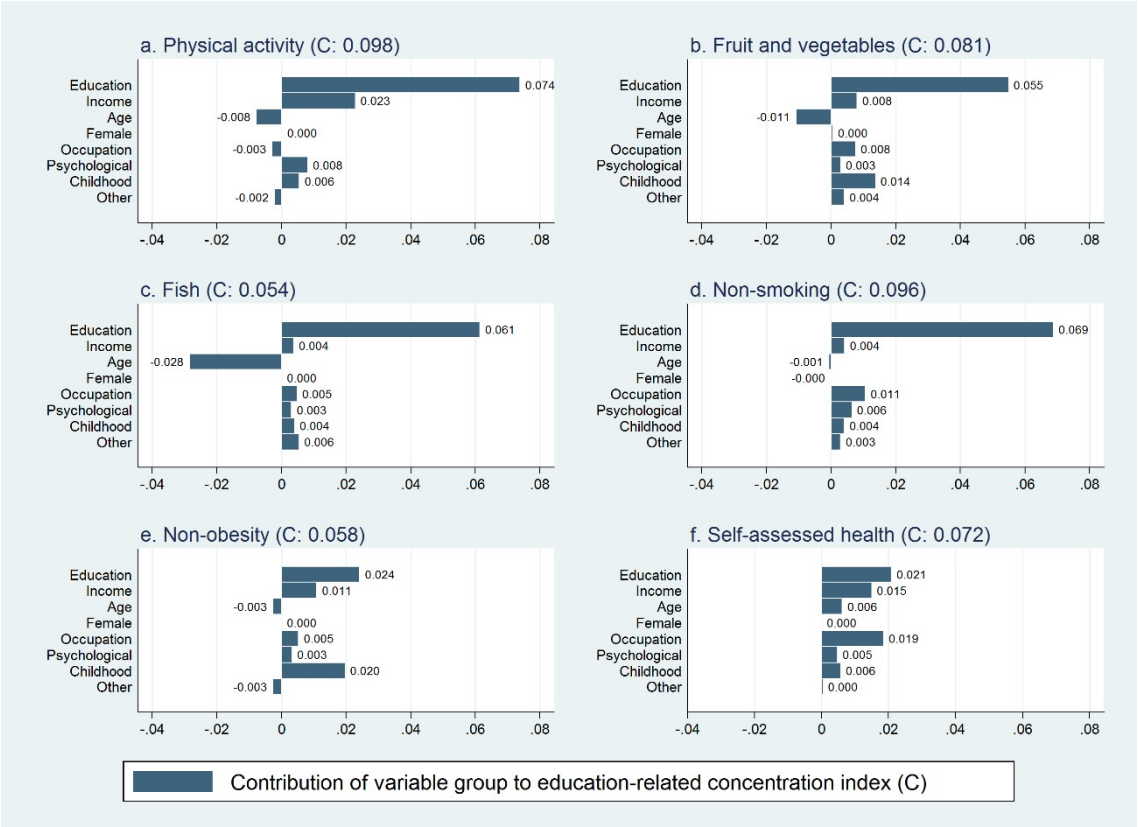
The overall inequalities in lifestyles and health as measured by the Gini index, and socioeconomic inequalities in lifestyles and health as measured by the education- and income-related concentration indices are investigated in this section. The indices have been calculated and decomposed according to Equations (2) and (3), and the results are shown in Figures 1–3.

Figure 1 shows the estimated concentration index with respect to education in each predicted lifestyle and health indicator, and the absolute contribution of each group of explanatory variables to this index. Figure 2 shows the corresponding results for the concentration index with respect to income. Figure 3 shows the estimated Gini indices and the percentage contribution of each group of explanatory variables to these indices. To better visualize the results of the decomposition analysis, we summarize and collect the 27 explanatory variables in each probit model in Table 2 to form the eight larger variable groups that are used in Figures 1–3. The eight groups are labeled as education, income, age, female, occupation, psychological, childhood and other. The full results of the decomposition analyses in Figures 1–3 are available in Table S1-S6 in the supplementary material to this paper.

The concentration index with respect to education (Figure 1) varies between 0.054 and 0.098. Education-related inequalities are strongest in physical activity and non-smoking, and smallest in fish consumption and non-obesity. Not surprisingly, education itself is the leading contributor to the education-related concentration index in all lifestyles and health indicators, explaining on average 56.9% of the index.[3] While education is the clearly dominating contributor to the education-related concentration index in the four lifestyle indicators, this is not the case in the two health indicators. In non-obesity, childhood circumstances (0.020) contributes almost equally much as education itself (0.024). In SAH, both income (0.015) and occupation (0.019) make important contributions in addition to education itself (0.021).

[3] Note that these mean percentage contributions have been calculated directly as the ratios of the contribution of education and income to the calculated concentration index in each lifestyle and health indicator. Unlike in the case of the Gini index, variable groups can make both positive and negative contributions to the concentration index, as illustrated in Figures 1 and 2. Therefore, it is less straightforward to work with relative or percentage contributions in the case of the concentration index than in the case of the Gini index.

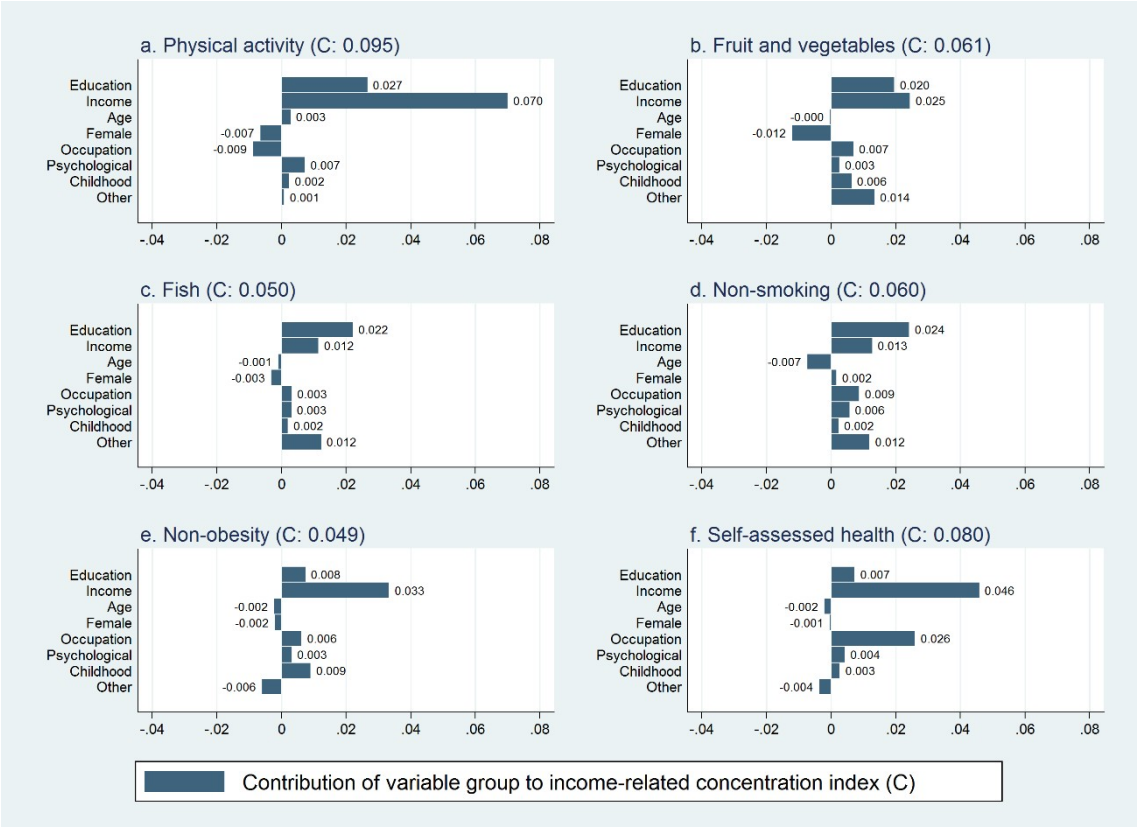
Figure 1: Decomposition of the explained part of the education-related concentration indices in lifestyles and health



Notes: Calculations based on results of the probit models as reported in Table 2 and associated predicted linear index functions for lifestyles and health. The estimated index and the absolute contribution of each group of explanatory variables are shown. The variable group "Other" includes having children in the household, marital status and survey years. Full results of the decomposition analysis in this figure are provided in Table S1-S6 in the online supplementary material to this paper.

The concentration index with respect to income (Figure 2) varies between 0.049 (non-obesity) and 0.095 (physical activity). Income itself makes an important contribution to the income-related concentration index in all lifestyles and health indicators, explaining on average 41.6% of the index. Note, however, that while education was the clearly dominating contributor to the education-related concentration index in the four lifestyle indicators and less dominating in the two health indicators (Figure 1), the reverse pattern is found for the income-related concentration index (Figure 2). While income is the clearly dominating contributor to the income-related concentration index in the two health indicators, non-obesity and SAH, education is actually the most important contributor to the income-related concentration index in both fish consumption and non-smoking. In consumption of fruits and vegetables, education (0.020) contributes almost equally much as income itself (0.025). Education makes an important contribution also in physical activity (0.027), but here income itself is clearly the most important factor (0.070).

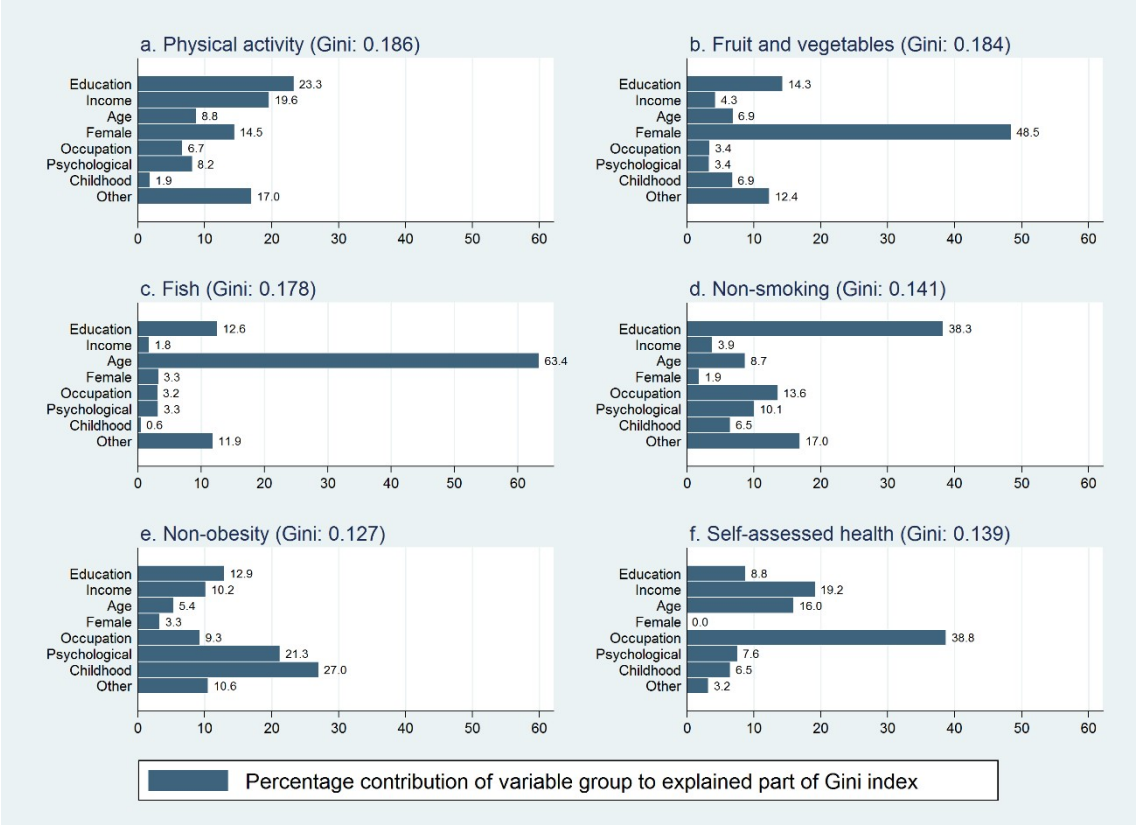
Figure 2: Decomposition of the explained part of the income-related concentration indices in lifestyles and health



Notes: Calculations based on results of the probit models as reported in Table 2 and associated predicted linear index functions for lifestyles and health. The estimated index and the absolute contribution of each group of explanatory variables are shown. The variable group "Other" includes having children in the household, marital status and survey years. Full results of the decomposition analysis in this figure are provided in Table S1-S6 in the online supplementary material to this paper.

The percentage contribution of different groups of explanatory factors to the Gini index of overall inequality in lifestyles and health is shown in Figure 3. Not surprisingly, education and income are less important in explaining overall inequality (Figure 3) than education-related (Figure 1) and income-related (Figure 2) inequality in lifestyles and health. However, education is the clearly dominating contributor to the Gini index in non-smoking (38.3%) and is also the most important contributor in physical activity (23.3%). Education makes relatively important contributions to the Gini index also in the four remaining lifestyle and health indicators, ranging from 8.8% in SAH, to 14.3% in consumption of fruits and vegetables. Income is not the leading contributor of overall inequality in any of the six lifestyle and health indicators, but makes important contributions in SAH (19.2%), non-obesity (10.2%) and physical activity (19.6%). However, income is unimportant in explaining overall inequality in the remaining three lifestyles indicators, with Gini contributions of 4.3% in the consumption of fruit and vegetables, 1.8% in the consumption of fish and 3.9% in non-smoking.

Figure 3: Decomposition of the explained part of the Gini indices in lifestyles and health



Notes: Calculations based on results of the probit models as reported in Table 2 and associated predicted linear index functions for lifestyles and health. The estimated index and the percentage contribution of each group of explanatory variables are shown. The variable group "Other" includes having children in the household, marital status and survey years. Full results of the decomposition analysis in this figure are provided in Table S1-S6 in the online supplementary material to this paper.

In four out of six lifestyle and health indicators, one factor stands out as the clearly most important contributor to the Gini index of overall inequality. First, gender explains as much as 48.5% of the Gini index in consumption of fruit and vegetables. Note that gender explains only 0.6% of the corresponding concentration index with respect to education (Figure 1). This result can be explained by a concentration index for gender with respect to education that is close to zero. Second, in fish consumption, age is the clearly most important factor, explaining 64.8% of the Gini index. Third, education is the key contributor to overall inequality in non-smoking (38.3%). Finally, the most important contributor to overall inequality in SAH is occupational status (38.8%). Occupational status consists of five different categories (Table 1). The category "On social security/benefit" alone accounts for 33.0% of the Gini index in SAH.

In the two remaining indicators, physical activity and non-obesity, there is no single factor that stands out as being clearly most important. In physical activity, education is the most important factor (22.3%), followed by income (19.6%) and gender (14.5%). The most important factor in non-obesity is childhood circumstances (27.0%), followed by psychological traits (21.3%) and education (12.9%). Childhood circumstances make relatively important contributions also in consumption of fruits and vegetables (6.9%), non-smoking (6.5%) and SAH (6.5%), while psychological traits make relatively important contributions also in non-smoking (10.1%), physical activity (8.2%) and SAH (7.6%).

4.3 Robustness

To check the robustness of the results, we have reiterated our analysis using alternative definitions for all outcome variables except non-smoking (for which there is no more information to utilize). More specifically, we have estimated ordered probit and interval regression models, obtained the resulting linear predictions and decomposed the associated Gini and concentration indices. In these models, physical activity, consumption of fruit and vegetables and consumption of fish are defined in terms of 8–10 monotonically increasing frequency categories. Body mass index (BMI) was divided into four groups: (i) BMI < 25.0 (47.8% of the sample); (ii) 25.0 ≤ BMI < 30 (39.5%); (iii) 30 ≤ BMI < 35 (9.8%); and (iv) BMI ≥ 35.0 (2.9%). SAH is defined using the usual 5-point ordinal scale ranging from "very bad" to "very good" and is estimated using both ordered probit and interval regression. The interval regression uses the McMaster Health Utility Index Mark III (HUI) to rescale the ordinal responses to the SAH question as proposed by van Doorslaer and Jones (2003).

The Gini decompositions from these alternative variable definitions are in most cases very similar to the Gini decompositions in our main specifications (Figure 3). Although there is some variation in the percentage contribution of different groups of explanatory variables to the Gini index, the order of importance of different groups of explanatory variables remains the same across different definitions of the dependent variables. There is, however, one exception to this pattern. The contribution of gender to the Gini index is much higher in the four-category BMI variable (35.4%) than in non-obesity (3.3%). This increased contribution is offset by smaller contributions of other factors to the Gini index in the four-category BMI variable than in non-obesity; these reduced contributions are particularly noticeable for income (nine percentage points reduction), paying in installments (eight percentage points reduction) and childhood circumstances (nine percentage points reduction). The sensitivity of the BMI variable seems to be largely driven by the fact that while males and females are relatively equally distributed in terms of obesity status (BMI ≥ 30), being overweight (25.0 ≤ BMI < 30) is much more common among males (47.6%) than females (30.7%).

We have also reiterated our analysis using alternative inequality measures and decomposition procedures. First, we have decomposed the concentration indices with respect to education and income using the observed binary outcomes instead of predicted linear variables. Second, as an alternative to the Gini index of overall inequality, we have decomposed the explained variance from the predicted linear variables using simple regression techniques (Shorrocks, 1982; Fields, 2003; Fiorio and Jenkins, 2010; Tubeuf *et al*., 2012). The use of observed instead of predicted variables and the variance decomposition approach produced results that were very similar to the results in our main specification.

5 Discussion

A number of studies have employed decomposition of inequality techniques to consider the contribution of lifestyle indicators to inequality in health (e.g., Balia and Jones, 2008; Rosa Dias, 2009; Vallejo-Torres and Morris, 2010; Tubeuf *et al.*, 2012). Other studies have employed such decomposition techniques directly on lifestyle indicators themselves (Costa-Font and Gil, 2008; Ljungvall and Gerdtham, 2010; Combes *et al*., 2011). The objective of this study has been to directly compare sources of inequality across important lifestyle and health indicators using the same sample of individuals with a common set of explanatory factors. Sources of overall inequality and socioeconomic inequality in four lifestyle indicators and two health indicators are compared by estimating probit models, and by

decomposing the explained part of the associated Gini indices and concentration indices with respect to education and income.

Our results suggest that sources of inequality in health are not necessarily representative of sources of inequality in underlying lifestyles. While education is generally an important source of overall inequality (the Gini index) in both lifestyles and health, income is unimportant in all lifestyle indicators except physical activity. In several cases, education and income are clearly outranked by other factors in terms of explaining overall inequality, such as gender in eating fruits and vegetables and age in fish consumption.

Socioeconomic inequalities in health are consistent, often strong and by many considered unfair (Olsen, 2011). This issue has therefore received much attention in recent years, both among policy makers (Commission on Social Determinants of Health, 2008) and in the health inequality literature (Cutler *et al*., 2011; van Doorslaer and Van Ourti, 2011). Other sources of inequality in health and lifestyles, such as age and gender, are frequently referred to as being legitimate or unavoidable (Olsen, 2011). However, it is clearly possible to avoid, for example, gender differences in the consumption of fruit and vegetables, and achieving this is a workable policy goal through, for example, the use of nutrition information campaigns that specifically target men. To the extent that the main health policy goal is to efficiently improve overall population health and reduce overall health inequalities, one should search for key sources of population differences in single, important production factors of health, including important lifestyles, and in turn design tailored policies for each of these factors. Alternatively, if sources of inequality in health other than socioeconomic status are considered legitimate or unavoidable, one should be aware that the importance of education and income in explaining overall inequality may vary substantially across different lifestyle and health indicators, as suggested by the results of this study, and policies should be targeted accordingly.

That said, our results generally suggest that education contributes more to overall inequality in lifestyles than to overall inequality in health, and thus reducing educational inequalities in health through improved lifestyle habits among lower education groups may be efficient. On the other hand, the small contribution of income to overall inequality in most of our lifestyle indicators suggest that income differences in lifestyles may not be very important in explaining why we often observe large income inequalities in health. Instead, in line with several other studies (Case and Deaton, 2005; van Kippersluis *et al*., 2010), we find that occupational status – and in particular being on social security – is a very important contributor to both overall inequality and income inequality in SAH. While it is inherently complex to establish causal mechanisms, other studies have hypothesized that this result may reflect an effect that runs from poor health to premature exits from the labor force, which in turn affects income negatively because of the shift from earning wages to relying on social security payments (Case and Deaton, 2005; van Kippersluis *et al*., 2010).

Childhood circumstances make relatively important contributions to overall inequality in consumption of fruits and vegetables, non-smoking, SAH and especially obesity, where maternal education is the leading contributor to the Gini index. Several other studies have shown that differences in childhood circumstances such as fetal nutrition, social support and parental socioeconomic status contribute to inequalities in adult lifestyles and health (Case *et al.,* 2005; Rosa Dias, 2009, 2010; Trannoy *et al.,* 2010; Tubeuf *et al.,* 2012). Differences in childhood circumstances represent differences in opportunities that are beyond personal responsibility and are therefore socially unacceptable. A policy that could moderate the effects of childhood circumstances on dietary behavior and obesity is the introduction of a publicly funded school lunch program.

The above results suggest that it is useful to conduct analyses of both socioeconomic inequality and overall inequality in lifestyles and health. For example, if our study had

focused solely on educational inequalities in the consumption of fruit and vegetables, we would have labeled gender as an unimportant factor, but missed the fact that gender is in fact considerably more important than education in explaining consumption of fruit and vegetables. We do not propose to include analyses of both socioeconomic inequality and overall inequality in all studies. However, before focusing on sources of socioeconomic inequality in one or several health and lifestyle indicators, it is useful to decompose overall inequality (Gini index or similar measures) in these indicators to check whether education and income are important factors in the first place. For indicators where other factors than education and income are clearly most important, policy makers should consider to target these factors.

The results of this study must be considered in light of its limitations. In particular, our analysis employs repeated cross-sectional data, and thus we are not able to fully capture the dynamic nature of health production, nor are we able to capture possible feedbacks between socioeconomic status, lifestyles and health (Cutler *et al*., 2011). There are also complex interrelations between several of our groups of explanatory variables, including childhood circumstances, socioeconomic status, occupational status and psychological traits. Therefore, the results of this study are mainly of descriptive nature, as the data generally do not allow for causal inference. Some of our key variables may also include measurement error because of incompleteness and the reliance on self-reported data, although, for example, SAH has been shown to be highly correlated with several objective health measures (Idler and Benyamini, 1997). Finally, in this study we have only decomposed the explained part of overall inequality and socioeconomic inequality in lifestyles and health; it is inherently complex to model lifestyle and health indicators at the individual level, and as is common, a large share of the total variation in our outcome variables are therefore left unaccounted for.

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