ISSN 1503-299X

WORKING PAPER SERIES

No. 9/2009

HEALTH AND ANTHROPOMETRIC FEATURES AS DETERMINANTS OF ANNUAL INCOME IN NORWAY

Ivar Pettersen

Department of Economics

Norwegian University of Science and Technology
N-7491 Trondheim, Norway
www.svt.ntnu.no/iso/wp/wp.htm

HEALTH AND ANTHROPOMETRIC FEATURES AS DETERMINANTS OF ANNUAL INCOME IN NORWAY

Ivar Pettersen

Dept. of economics, Norwegian University of Science and Technology

Abstract

Health is linked to income in various ways. In this study we try to quantify the effects of differences in health and appearances on annual income. Starting with a classical Mincer-equation for income we include health and anthropometric characteristics in order to assess the hypothesis. We also decompose the income-differentials using Oaxaca-Blinder-decomposition. Using data from the North-Trøndelag health survey we have a wide range of self-reported health-indicators as well as objective measures of anthropometric features. Different health-proxies, both somatic and mental, obesity and height are all significant factors for income using a sample of full-time employed individuals, but the effects are driven mainly by selection into employment. Taking both selection bias and potential endogeneity into account the effects of health on income are weak at best. Altogether the results do not indicate that variations in health are important to observed income-differences in Norway.

1. Introduction

In this analysis I estimate the effects of different health-statures under different assumptions about the relationship between health and income. We will use data on individuals to estimate income-premiums depending on health and anthropometric characteristics. The data we use are from the North-Trøndelag Health Survey (HUNT) and contain rich information on health and anthropometric measures. Some of these are self-reported while others are obtained from medical examinations. Health-proxies cover subjective somatic and mental indicators as well as objective measures of blood pressure and anthropometrics. Health is linked to income in various ways. Both theoretical and empirical studies have established this relationship with different assumptions on both causality and mechanisms behind. According to Grossman (1972) health may be viewed as a capital stock which can be invested in. An individual invests in health to increase consumption through work-effort. This identifies income as a determinant of health, which can increase the stock of health through different channels. This highlight the potential endogeneity-problem related to the studies between health and income. In the empirical analysis I will study employed individuals only. The rationale behind this is that we do not want to capture health-effects that work mainly through the ability to work at all. The fact that we do not have access to the wage-rate but rather the annual income forces through this compromise. Still, we want to project the effects of our findings on a wider group of individuals so we need to deal with the sample selection bias this creates. We also draw from Case and Paxson (2008) and rely on anthropometric features as proxies of cognitive ability. This analysis is a contribution into the literature on social inequalities in health. The effect of income on health has been studied for decades, but intuition and causality of this relationship is still an enigma (Deaton and Paxson, 1998). If we can estimate the effects of health on income, this results is useful in terms of interpreting the reverse relationship.

Equal pay for equal work is an expressed policy, but a lot of evidence does not support this objective. For any given job done, there seems to be discrepancies in pay depending on gender, race, health, looks and other attributes (see Currie and Madrian (1999) for a review). Some of these differences may be warranted in situations where attributes directly affect the productivity of the employee. Which attributes lessen productivity would depend on the work tasks at hand. For example miners would capitalize on physical strength while office-clerks would not suffer from the lack of it etc. These relationships taken into account, some of the observed discrepancies in wages and income may be interpreted as discrimination. In practise we have to realize that there are important unobservable factors which make it difficult to separate between discrimination and differences in productivity. The separation between the two sources of income differentials are also clouded due to selection into occupations based on individual characteristics.

In previous studies health is found to be an important determinant both in relation to labour market participation, see Stern (1996), and in turn earnings (Chowdhury and Nickell, 1985; Contoyannis and Rice, 2001). There is an existing literature of income-differences based on health, anthropometric features and other characteristics which represent physical stature. See Currie and Madrian (1999) for a review of literature linking health, income and health insurance. Some earlier studies take the effects of these indicators at face value while others focus on the fact that they really proxy some unobserved quality or trait. A good example of the latter is the study by Case and Paxson (2008) which focuses on height as a proxy for cognitive ability. They effectively show that height is important to income, but the effect of height is reduced as other indicators of cognitive ability are controlled for. Another work which has received a lot of attention is the paper by Hamermesh and Biddle (1994) which focus on the effect of beauty in the labour market. They do establish a relationship even when they control for work-categories in which one would expect beauty to be an important asset. These particular topics are not at the core of what we do, but their results and approaches carry into our empirical work and interpretations. Closer to our approach is Bartel and Taubman (1979). They used a set of objective health-indicators and estimated their importance on wages. They did find a number of effects, some which manifested into 30 % reductions in earnings. In contrast Jäckle (2007) estimates that a 10 percent increase in health satisfaction increases wages modestly by 0.09 to 0.88 % for men while the evidence for women are even weaker. This study is based on panel-data where a range of empirical problems related to endogeneity and selection are addressed. Contoyannis and Rice (2001) use the British Household Income Survey to study the link from health to wages. They find that reduced psychological health reduces wages for males, while wages for women are increasing in their assessment of health.

The rest of this paper is organized traditionally. First, we present an introduction with some basic motivation and minor theoretical arguments. Second, we provide some information on data and descriptive statistics. The results section follows some notes on empirical specification and the paper ends with a discussion of the results.

2. Model and Data

Mincer (1974) provided the theoretical foundation for the analysis of earnings. The primary object of the model was to formalize the relationship between education and earnings. The first model paved the way for estimating a relationship solely between earning and years of education. Further specifications added the effect of experience into the model. Human capital is formed as an interaction between education (s) and experience (exp) and is traditionally expressed as

$$(1.1)\ \ln y = \beta_0 + \beta_1 s + \beta_2 \exp + \beta_3 \exp^2 + u$$

In this paper, Mincers model of wages depending on human capital is extended with health as a stock of capital in itself and anthropometric features. The anthropometric features represent either additional proxies of ability (Case and Paxson, 2008) and/or sources of prejudice and (perhaps) real productivity determinants.

Self-selection into different types of employment on the basis of health will potentially reveal spurious relationships between health and income. In other words, the return of health capital may differ among work-categories. If choice of work depends partly of physical and mental stature and there are systematic differences in income-level between work categories, a relationship will be revealed on this basis alone. On example of such a mechanism is the existence of compensating wage differentials. The theory of compensating wage-differentials[1] explains differences in wages as a function of work-environment. Choosing to work under less attractive work-environments is probably dependent on an individual's health, and in turn this may create wage-differentials. Compensating wages may reward employees who take part in hazardous work tasks or work in

[1] Smith (1904): "the agreeableness or disagreeableness of the employment themselves... make up for a small pecuniary gain in some employments"

hazardous environments (French and Dunlap, 1998 and Ose, 2005). This calls for a model specification where work-characteristics play an important role in removing obvious spurious relationships between income and health. In equation (1.2) we have formalized that with a vector of health-proxies (*H*) and vector of work-characteristics (*W*). Also note that experience has been replaced by age in the equation. The reason for that is that information on experience is lacking from the data. A more thorough discussion of the consequences of this is included below.

$$(1.2)\ \ln y = \beta_0 + \beta_1 s + \beta_2 age + \beta_3 age^2 + H'\gamma + W'\delta + u$$

The contribution from Grossman (1972), which is derived from the human capital-tradition initiated by Becker (1964) and Ben-Porath (1967), is that health is potentially endogenous to income. One of the major implications of the Grossman-model is that the stock of health must be considered an individual choice. Investments in health depend on income, so under Grossman's framework income is a determinant of the individuals' stock of health. It is reason to believe that income is less important to health in Norway compared to other nation, partly because individual health insurances are not important in Norway. All individuals are covered by the national public health care system, which means that they have access to universal and free health-care services. Still, utilization of health services and investments in health are subject to personal preferences and in part opportunity. Larger companies employ company doctors which perform regular checkups of their employees, while employees within smaller enterprises may have to initiate such checkups on their own behalf. Access to training-facilities will also depend on local supply of such, and in some instances companies provide such facilities (gyms, training within work hours etc) exclusively for their employees. Either way, we do open for a reciprocal relationship between health and income in the empirical analysis.

The data available to study income-differences is from the North-Trøndelag Health Survey[2]. This survey was conducted in 1995 in a Norwegian county, with ca 65 000 respondents, representing 70 % of the adult population 19+. The survey consisted of a questionnaire, complemented with a medical examination. The medical examination collected data on height, weight, hip- , waist-circumference and blood pressure (and biological data, which are not relevant to this study). Annual income-data has been merged from official wage registers from Statistics Norway. The income is "income which qualifies for pension", meaning that capital income is not included.

[2] Nord-Trøndelag Health Study (The HUNT Study) is a collaboration between HUNT Research Centre (Faculty of Medicine, Norwegian University of Science and Technology NTNU), Nord-Trøndelag County Council and The Norwegian Institute of Public Health.

Health variables

The main hypothesis is that when controlling for Mincer's standard set of regressors, an amount of the unexplained variance in income is due to differences in health or anthropometric features. The data available contains a lot of information on health, ranging from the standard self-assessed measures to self-reported indications on more specific health problems. We will utilize 5 different health-proxies, ranging from the purely subjective to objective measures of blood-pressure. On one end we use self-assessed health, which by a number of studies have been established as an important predictor of mortality (Schou, et al. 2006). Health is originally measured along a 4 category ordinal scale ranging from poor to very good. We use a dichotomous measure where good health is defined as reports of either good or very good health. Based on self-reported information on chronic and muscular / skeletal problems we have constructed two measures which both indicate the absence of such health-problems. A binary measure of mental health has been constructed based on the hospital-anxiety and depression scale (HAD)[3] (see Bjelland, et al. (2002) for a review). We also use a self-reported binary indicator of no current or previous heart-conditions. Another variable included in the analysis is a binary indicator of sickness absence. It controls for the self-reported occurrence of doctor-certified sickness absence during the last 12 months. This is not necessarily a health-proxy, but will control for any penalties related to absence, if indeed this variable serves as a proxy for prevalence of sickness absence.

In Table 1 we have reported the tetrachoric[4] correlations between the health-proxies we use. We observe that self-assessed health (SAH) is strongly correlated with the other proxies. That is, the absence of health problems related to chronic, muscular, mental and heart issues reflect strongly upon SAH. The other correlations are modest in comparison, but we observe that all correlations are positive and that muscular problems to some extent go together with mental health and chronic conditions.

Table 1 Tetrachoric correlations between health-proxies. Fully employed respondents only (N=25 112)

	Good health (SAH)	Good health (chronic)	Good health (mental)	Good health (muscle)	No heart disease
Good health (SAH)	1				
Good health (chronic)	0.4172	1			
Good health (mental)	0.4503	0.1484	1		
Good health (muscle)	0.5432	0.3703	0.2488	1	
No heart disease	0.3499	0.1012	0.1190	0.0957	1

[3] This score is calculated based on a number of responses in the questionnaire. The threshold value used to define individuals with mental health problems is 15. For more details see the above reference.

[4] These correlations take into account the binary nature of the health-proxies, see Edwards and Edwards (1984).

Anthropometric variables

We include four anthropometric measures which are all based on objective measurements during a medical examination. Height is measured in natural logs, and is thought to both represents some discrimination due to employer preferences and / or a proxy for ability. Obese and thin are calculated on the basis of body mass index (BMI). The quality of BMI as a health proxy and appearance-indicator depends on its ability to capture fatness or not. There is some agreement in the medical literature that BMIs are seriously flawed because they do not distinguish between fat from fat-free mass such as muscle and bone (Cawley and Burkhauser (2006)). We do not use BMI as a continuous indicator but base the definitions of obese and thin on these. The threshold values used for the two indicators are BMI >30 and BMI<18.5 respectively.

Table 2 Correlations between anthropometric variables. Fully employed respondents only (N=25 112)

	Height (ln)	Obese	Thin	Waist-hip ratio
Height (ln)	1			
Obese	-0.0989	1		
Thin	-0.0252	-0.0396	1	
Waist-hip ratio	0.3855	0.2511	-0.0901	1

The final anthropometric variable is the ratio between waist- and hip-circumference. This measure is probably superior to BMI in capturing the existence of unhealthy levels of body-fat, especially fat around the stomach. To a certain extent this could also represent some beauty-measure marginally affecting employers with certain preferences.

Other controls

Other controls are gender, age, age squared, years of education, marital status, work-hours per week, work-category, work posture and an indicator for shift-work. Descriptive statistics for all regressors are reported in Table 3. We do not have information on real work-experience and tenure so age and age squared is used as a proxy for experience. Mincer's approach to this was to calculate an experience proxy based on information on age and schooling. We have chosen not to do this, both based on specification tests which indicate that either specification goes, and that we have ordinal data on education. It is worth noting the work of Rosenzweig and Morgan (1976) work which illustrates that this specification will probably underestimate the returns from experience. Data on education is self-reported, coded along a 5-point ordinal scale ranging from primary-school only to university-education lasting more than four years. These categories are used to calculate a semi-continuous measure of education. The calculation of education takes into account changes in the length of compulsory primary schooling. Marital status is controlled for by indicator variables with unmarried as the reference category. This provides relative estimates for married, widow(er), divorced and separated respondents. Table 3 contains information on the self-reported stratifications of occupational categories as well as reports on most common work posture. Finally we include a measure of shift-work.

It is worth noting that ethnicity and race really are considered unimportant in this study. Immigrants from outside the western world consisted in 1995 of 1 percent of the population in the county of North-Trøndelag[5]. The questionnaire was available in Norwegian only, so the probability of capturing features of the immigrant population is miniscule at best.

[5] In 2008 this has increased to 2.7 percent.

Table 3 Descriptive statistics on regressors, separated by gender and samples

Sample	Fully employed respondents				Employed			
Gender	Men		Women		Men		Women	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Yrs of education	12	3	13	3	12	3	12	3
Age	43	11	42	10	43	11	42	11
Age^2	1944	936	1884	866	20	10	19	9
Work hours per week	39	3	37	4	38	10	30	11
Unskilled	0.14	0.35	0.14	0.35	0.13	0.34	0.18	0.38
Skilled	0.26	0.44	0.05	0.22	0.24	0.43	0.05	0.21
Low white collar	0.08	0.27	0.35	0.48	0.08	0.27	0.35	0.48
White collar	0.14	0.35	0.30	0.46	0.13	0.34	0.27	0.44
Executive	0.16	0.36	0.08	0.27	0.15	0.36	0.05	0.22
Chauffeur	0.05	0.23	0.00	0.06	0.05	0.22	0.00	0.06
Farmer	0.10	0.30	0.04	0.19	0.13	0.34	0.05	0.23
Fisher	0.01	0.07	0.00	0.02	0.01	0.08	0.00	0.03
Selfemp academic	0.01	0.09	0.00	0.07	0.01	0.10	0.00	0.07
Self-employed	0.05	0.22	0.04	0.18	0.06	0.24	0.04	0.18
Good health (SAH)	0.87	0.34	0.85	0.36	0.85	0.35	0.83	0.37
Good health (chronic)	0.82	0.38	0.80	0.40	0.81	0.39	0.78	0.42
Good health (mental)	0.92	0.28	0.90	0.29	0.91	0.28	0.90	0.30
Good health (muscle)	0.63	0.48	0.57	0.49	0.62	0.49	0.56	0.50
No heart disease	0.98	0.15	0.99	0.07	0.97	0.16	0.99	0.08
Blood pressure(ln)	4.91	0.11	4.83	0.13	4.91	0.11	4.84	0.13
Height (ln)	5.19	0.04	5.11	0.03	5.18	0.04	5.11	0.03
Obese	0.12	0.33	0.12	0.33	0.13	0.33	0.13	0.34
Thin	0.00	0.04	0.01	0.08	0.00	0.04	0.01	0.09
Waist-hip ratio	0.89	0.05	0.78	0.06	0.89	0.05	0.78	0.06
Shift worker	0.20	0.40	0.24	0.43	0.21	0.41	0.26	0.44
Mostly sitting	0.35	0.48	0.35	0.48	0.34	0.47	0.29	0.45
Frequent walking	0.27	0.44	0.35	0.48	0.26	0.44	0.37	0.48
Walking and lifting	0.23	0.42	0.29	0.45	0.23	0.42	0.32	0.47
Heavy lifting	0.15	0.36	0.02	0.13	0.18	0.38	0.02	0.14
Unmarried	0.30	0.46	0.24	0.43	0.29	0.46	0.22	0.41
Married	0.62	0.48	0.64	0.48	0.63	0.48	0.67	0.47
Widow(er)	0.01	0.08	0.02	0.14	0.01	0.08	0.02	0.16
Divorced	0.06	0.23	0.09	0.29	0.06	0.23	0.07	0.26
Separated	0.01	0.12	0.02	0.14	0.01	0.12	0.01	0.12
Certified absence	0.27	0.44	0.34	0.47	0.27	0.44	0.34	0.47
N	11925		7791		13546		13230	

Samples

There are a number of associations an individual can have in relation to the labour-market, ranging from mere eligibility to being fully employed. Eligibility in the sense that the respondents are old enough, not too old and not kept out for other reasons (in jail etc). Health obviously plays a role for the probability of being within the labour-force. Severe health-problems may lead to early retirement (in form of disability-pensions) that keep individuals out of the labour-force long term, or even throughout their entire adult lives. Next, as a member of the labour-force, employment will depend on a number of both individual and regional characteristics. Among the individual characteristics it is natural to consider health as a partial determinant of employment. Finally, choosing or being able to work full time is most probably a function of health.

In Table 4 we have focused on individual characteristics such as income, work hours and health-proxies. For five different samples we have provided descriptive statistics which provide some indications that health makes a difference. We are not challenging any conventional wisdom when we identify health as a factor filtering out respondents left-to right along the samples defined in the table. We are also not in the process of making any normative judgments on the pattern between health and association to different degrees of employment, but rather aim at exposing health as a determinant in a context where is has no place. As a consequence the samples we use in the empirical analysis refer to the two rightmost columns in Table 4. We realize that health is relevant for entering these samples, but choose the samples based on both practicalities and more sound arguments. One important practical reason is the fact that a lot of information on work-characteristics is available only for the sample which respondents in some way are employed. We expect sorting of individuals into different professional categories, and to take such into account we need to identify these categories. If there is sorting into professional categories based on health, and if there are traces of compensating wage-differentials based on physical strain, a lack of control for the former will manifest itself into a relationship between health and income. In a way we trade this problem for another, namely the potential selection bias. Further, we do not want to pick up effects related to health-related exits from employment, represented by pairs of observations characterized by low income and poor health. Selecting samples based on criteria correlated with health, introduce biases which limit the general interpretations of our results, but we do address such issues empirically.

What we observe in Table 4 is that there is a gradient in labour-market participation by health. This is most pronounced for self-assessed health where we observe an 8 percentage-points difference in the share of respondent reporting good health between the working-age sample and the fully employed. The second largest health-gradient with respect to job-attachment is for the respondent with chronic health-problems. The three other health-proxies show flatter “gradients”, with heart-diseases as the least important.

Table 4 An overview over the share of healthy stratified by labor-force attachment.

	Samples				
	All (19 yrs+)	Working age	In labour force[6]	Employed	Fully employed
Means frequencies of:					
income95	1159	1443	1620	1758	2026
Work hours per week	27	30	32	34	38
Age	50	44	43	43	42
Good health (SAH)	73 %	78 %	82 %	83 %	86 %
Good health (chronic)	71 %	75 %	78 %	79 %	81 %
Good health (mental)	83 %	87 %	88 %	89 %	91 %
Good health (muscle/skeletal)	56 %	57 %	58 %	59 %	61 %
No heart disease	93 %	97 %	98 %	98 %	99 %
N min	43703	39845	36928	34694	25042
N max	65600	52291	45022	39956	25158

Turning to the data on income, what indications are there that income is systematically lower for poor-health individuals? Table 5 contains information on the average “good-health premium”. Grouped vertically into 8 different age-groups the numbers in the cells represent the income-premium for the healthy compared to the unhealthy, for five different health proxies. The age-groups are defined to ensure an equal number of respondents in each age-group. The income-numbers are controlled for differences in gender, education, work-category and work hours[7]. For all, but four cells, the premium is positive. The premiums vary from -3% to 7%, the negative premium is related to obesity, while the largest are for the youngest group of respondents with indications of mental problems. The way obese is defined means that the obese earn systematically less that the reference group. In general it is worth noting that there is no systematic increase in premiums with age, so if we pretend that this illustrates a development over time, these premiums have not increased nor decreased over time. Still, the fact that we observe such an amount of positive premiums given a rich set of controls warrants a deeper dive into the nature of the relationship

[6] Defined as individuals being either employed, self-employed, unemployed or house workers (housewives mostly)

[7] Annual income was regressed on a set of indicator variables. The sum of the constant and the residuals from these regressions formed the basis for the relative differences reported.

Table 5 Estimated health-premiums. Controlled for differences in gender, education, work-category and work hours. Sample: fully employed respondents.

Health proxy / age group	19-27	28-33	34-38	39-43	44-48	49-53	54-60	61-67
Good health (SAH)	0 %	3 %	2 %	5 %	2 %	3 %	2 %	1 %
Good health (chronic)	5 %	3 %	5 %	3 %	2 %	1 %	3 %	5 %
Good health (mental)	7 %	2 %	1 %	4 %	0 %	2 %	3 %	4 %
Good health (muscle/skeletal)	-2 %	0 %	3 %	3 %	1 %	2 %	2 %	5 %
Obese	0 %	0 %	1 %	-2 %	-1 %	-2 %	0 %	3 %

3. Empirical Approach and Results

We start by estimating a model based on a classical Mincer-equation, sequentially including additional controls for family and job-characteristics. Finally we include sets of both health-indicators and anthropometric variables, which represent the main focus of this study. These specifications represent a baseline specification and provide a reference point to the other specifications. Extensions to these models focus on addressing selection bias and the potential endogeneity of the health-measures used. First and foremost the fact that we use a restricted sample of respondents does not mean that problems regarding selection into employment are to be disregarded. We treat this as an omitted variable bias (Heckman, 1979). A control for this is implemented including the inverse mills ratio as a control in all model-specifications which are extensions to the reference models.[8] Finally we will explore income-differences using the Blinder-Oaxaca-decomposition. These have traditionally been used to address the issue and provide alternative information on the causes of observed differences in income.

The specifications which treat the health-proxies as endogenous regressors need to address both the endogeneity and sample selection bias. Leaning on Wooldridge (2002) a potential strategy is to include the inverse Mills' ratio as an ordinary regressor and do necessary adjustments to the selection equation. These adjustments include dropping endogenous regressors from the selection-equation and replacing them with the instrumental variables. A model with endogeneity- and sample selection problems can then be estimated using 2-stage least squares. The fact that the endogeneous regressors are binary in nature has no bearing on the estimation, as a linear prediction in the first step is acknowledged in the literature (Wooldridge, 2002). An alternative is to use predicted linear probabilities from a first step probit-analysis as instruments for the binary endogenous regressor. This has been tried but did very little to change the estimates so the original approach was kept.

[8] Based on a probit-model with a set of identifying variables we calculate the inverse mills ratio.

It is a reasonable to assume that health-problems are more important in certain job-categories. This would provide fewer penalties to productivity in the presence of health-problems in some sectors than in others. It is also likely that employees seek a career based on some physical characteristics, including health. A poor health endowment will to some extent pave the way for more investments in human capital in order to make a living in an industry not sensible to such personal traits. Individuals will sort themselves into occupations where the penalty of poor health is small or non-existent. Still, there are reasons to believe that individuals of all statues of health are present in all job-categories, so this self-selection is incomplete. To test such hypotheses we construct models where health is allowed to interact with occupational categories.

In Table 6 the results from the estimated Mincer-equations are reported. The specifications range from the classic naïve specification to a fully specified equation where health-proxies, anthropometric feature and other controls are included[9]. Health-proxies and anthropometric features are added sequentially to illustrate the impact these have on the classic measures of human-capital. Results from one sample only are reported. Results based on the other sample are reported in Appendix table 3.

Columns (a) and (b) in Table 6 show that in the most naïve Mincer-specification, the returns from education are similar for men and woman. Controlling for other work-characteristics, the returns from education are reduced, the point-estimates are about 50 percent if their original sizes. So, comparing individuals in the same occupational category, with the same common work posture and shift-arrangements reveal a return from an additional year of education of 1.4 and 2.3 percent for men and woman respectively. These estimates are low compared to previous studies on Norwegian data. Raaum (1999) reviewed current work on returns to education in Norway. The elasticities found in previous studies[10] range from 0.04 to 0.06, compared to 0.02 to 0.04 in this study (not controlling for health). The semi-continuous measure of years of education in this study may partly cause these discrepancies, together with the fact that some of the other studies have pooled both genders.

Adding health and anthropometric features does nothing to change the returns from education, even though most of the health proxies are significantly different from zero. Individuals assessing their health as good, with no chronic diseases or mental problems have, on average, significantly higher annual income than respondents with poorer health. The income-premiums range from 2 to 5 percent, the highest recorded for women. The gender-difference in point estimates is hardly significant given that the confidence intervals overlap. There are gender-differences related to the

---

[9] All health-proxies are estimated conditional on all other health-proxies. See Table 9 for estimates of the gross effects of proxies individually.

[10] Based on work using annual income as outcome.

effects of muscular problems. Women gain from the absence of these problems while these conditions have no bearing on the income of men.

Table 6 Naïve mincer-regressions. Sample: fully employed respondents

	Dependent variable: ln annual income									
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
Educ yrs	0.034***	0.039***	0.016***	0.024***	0.015***	0.024***	0.015***	0.024***	0.015***	0.024***
	(28.2)	(26.1)	(11.4)	(10.5)	(11.1)	(10.4)	(11.2)	(10.4)	(10.9)	(10.3)
Age	0.10***	0.10***	0.072***	0.093***	0.073***	0.091***	0.073***	0.092***	0.073***	0.093***
	(28.4)	(20.1)	(18.4)	(16.9)	(18.4)	(16.7)	(18.5)	(16.9)	(18.5)	(16.6)
Age_sq	-0.10***	-0.100***	-0.074***	-0.092***	-0.075***	-0.089***	-0.075***	-0.090***	-0.075***	-0.091***
	(-25.9)	(-17.7)	(-17.6)	(-15.2)	(-17.5)	(-14.7)	(-17.5)	(-14.9)	(-17.5)	(-14.7)
Work-hours	0.0048***	0.013***	0.0078***	0.016***	0.0077***	0.016***	0.0078***	0.016***	0.0077***	0.016***
	(3.15)	(7.31)	(4.86)	(8.40)	(4.78)	(8.55)	(4.85)	(8.46)	(4.83)	(8.38)
SAH					0.020*	0.032*	0.026**	0.049***	0.025**	0.042**
					(1.66)	(1.85)	(2.06)	(2.71)	(1.98)	(2.36)
CHRONIC					0.041***	0.039***	0.043***	0.045***	0.042***	0.041***
					(4.04)	(2.83)	(4.21)	(3.23)	(4.15)	(2.93)
MENTAL (HAD)					0.036**	0.036	0.037**	0.037*	0.036**	0.037*
					(2.37)	(1.64)	(2.43)	(1.72)	(2.34)	(1.69)
MUSCLE					0.0019	0.015	0.0039	0.023**	0.0041	0.020*
					(0.24)	(1.39)	(0.50)	(2.11)	(0.52)	(1.87)
HEART DIS					0.031	-0.047	0.036	-0.039	0.033	-0.049
					(1.10)	(-0.78)	(1.29)	(-0.66)	(1.17)	(-0.82)
Blood Pres(ln)					0.039	-0.059	0.041	-0.053	0.048	-0.017
					(1.11)	(-1.43)	(1.17)	(-1.29)	(1.35)	(-0.41)
Certified absence							0.026***	0.070***	0.026***	0.071***
							(3.08)	(6.45)	(3.10)	(6.46)
Height (ln)									0.39***	0.39**
									(3.50)	(2.52)
Obese									0.0017	-0.037*
									(0.14)	(-1.87)
Thin									-0.13	-0.17
									(-1.21)	(-1.59)
Waist-hip ratio									-0.092	-0.13
									(-1.09)	(-1.39)
Gender	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*
Other ctrls	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	15060	9907	11957	7959	11940	7951	11940	7951	11925	7791
adj R^2	0.207	0.186	0.278	0.225	0.280	0.226	0.281	0.230	0.281	0.232

*** p<0.01, ** p<0.05, * p<0.1. Robust t-statistics below estimates. Other controls are marital status, work-hours per week, work posture and an indicator for shift-workers.

Doctor-certified sick-leave has a positive conditional association with annual income, for both men and women. Replacing the variable with an indication for self-certified sick-leave reveal similar results, but if we proxy absence using an indicator of a long-term spell of sick-leave during the last 12 months we get negative significant estimates. One interpretation of the former results may be that employers do not define sick-leave as a normative bad, but favour employees which use short-term sick-leave to avoid longer spells.

Taller men and women earn on average more than their shorter peers. The estimated elasticity is about 0.4 for both men and women. Being obese has no effect on income for men but women receive a penalty of about 4 percent of annual pay for the condition.

Table 7 contains the information already reported in Table 6, but also reports estimates using another sample. We observe that for the employed sample, including part-time employees, the effects of good health are higher compared to the fully employed sample. This is an indication that we capture the effects of health as a determinant of part-time work.[11] The same three health-proxies matter for employed as for the fully employed, but using the sample for fully employed we also identify no incidence of heart problems as a determinant of income. Additionally there is some indication that respondents without muscular problems receive an income-premium. Another result to take away from the table is that the estimated effects are similar for men and woman. This also applies to the controls for height, while the effects of certified absence are stronger for women.

Controlling for non-random samples

In an attempt to generalize these results we need to address sample selection bias. The samples we use are selected on the basis of hours worked. This means that for the purpose of analysis of income determination, the sample is non-random. As mentioned above we do realize that that health matters in terms of the probability of being part of these samples, but that is perhaps not undesirable. If someone has poor health, part-time work would be preferred to leaving the labor-force altogether. We control for selection bias using the inverse Mills ratio (IMR). The selection equations for the two samples differ due to the fact that we cannot use work-characteristics to predict employment. Not being employed means no such information is available. Details on the selection-equations are reported in Appendix table 2[12].

[11] Even if we control for the number of work-hours per week. This information is self-reported and some degree of misreports of this variable is expected. Also, the fact that they work full weeks does not mean that they have worked *all* weeks during the year.

[12] The exclusion restrictions are two binary indicators increasing in family-size, number of kids living at home, non-working spouse and an indicator for whether or not the respondents are born in the current municipality. The idea behind the last variable is that individuals do not move into unemployment. In fact the effect is negative on employment, so this hypothesis is not supported. F-tests indicate the exclusion restrictions are relevant. F-statistics range from 44 to 71. The validity of these restrictions is not tested. The non-linear nature of the selection-equations clouds any inference on overidentifying restrictions.

Table 7 The effects of health-proxies and anthropometric features on ln annual income. Separated by gender. Two different samples.

	Dependent variable: ln annual income					
	(a)	(b)	(c)	(d)	(e)	(f)
SAH	0.045***	0.047***	0.052***	0.029***	0.025**	0.042**
	(4.47)	(3.36)	(3.59)	(2.77)	(1.98)	(2.36)
CHRONIC	0.053***	0.063***	0.043***	0.041***	0.042***	0.041***
	(6.44)	(5.54)	(3.58)	(4.87)	(4.15)	(2.93)
MENTAL (HAD)	0.045***	0.034**	0.051***	0.038***	0.036**	0.037*
	(3.64)	(2.08)	(2.84)	(3.00)	(2.34)	(1.69)
MUSCLE	0.0088	0.016*	0.0028	0.012*	0.0041	0.020*
	(1.31)	(1.78)	(0.29)	(1.84)	(0.52)	(1.87)
HEART DIS	0.060**	0.085**	-0.013	0.026	0.033	-0.049
	(2.12)	(2.49)	(-0.28)	(1.00)	(1.17)	(-0.82)
SYS BP(ln)	-0.014	0.046	-0.064*	0.026	0.048	-0.017
	(-0.52)	(1.19)	(-1.71)	(0.95)	(1.35)	(-0.41)
Certified absence	0.075***	0.045***	0.092***	0.047***	0.026***	0.071***
	(11.0)	(4.65)	(9.64)	(7.03)	(3.10)	(6.46)
Height (ln)	0.37***	0.30**	0.40***	0.40***	0.39***	0.39**
	(3.87)	(2.39)	(2.88)	(4.43)	(3.50)	(2.52)
Obese	-0.012	0.0066	-0.029*	-0.013	0.0017	-0.037*
	(-1.13)	(0.48)	(-1.84)	(-1.26)	(0.14)	(-1.87)
Thin	-0.11*	-0.29**	-0.048	-0.17*	-0.13	-0.17
	(-1.82)	(-1.99)	(-0.76)	(-1.93)	(-1.21)	(-1.59)
Waist-hip ratio	-0.17**	-0.20**	-0.069	-0.14**	-0.092	-0.13
	(-2.54)	(-2.02)	(-0.79)	(-2.19)	(-1.09)	(-1.39)
N	26776	13546	13230	19716	11925	7791
adj R^2	0.376	0.282	0.336	0.306	0.281	0.232
Gender	Both	Men	Women	Both	Men	Women
Sample		Employed			Fully employed	

*** p<0.01, ** p<0.05, * p<0.1. Robust t-statistics below estimates. Other controls are gender (columns (a) and (d), age, age squared, years of education, marital status, work-hours per week, work-category, work posture and an indicator for shift-workers.

In Table 8 we observe that the coefficients in front of the IMRs are negative and significantly different from zero. The significance level provides evidence that the observables in the models do not account for the selection process. Since the IMRs are derived from the first step probit equations, and the IMRs are inversely related to the probabilities of being fully employed/employed this is an indication that ”high” employment is associated with an above average income.

Table 8 The effects of health-proxies and anthropometric features on ln annual income. Separated by gender. Two different samples. Controlling for selection bias.

	Dependent variable: ln annual income			
	(a)	(b)	(e)	(f)
SAH	0.0069	-0.00072	0.011	0.037**
	(0.47)	(-0.030)	(0.65)	(2.00)
CHRONIC	0.034***	0.021	0.044***	0.035**
	(3.04)	(1.29)	(3.61)	(2.55)
MENTAL (HAD)	0.023	0.0018	0.015	0.042**
	(1.34)	(0.070)	(0.86)	(2.13)
MUSCLE	0.0054	0.024**	0.018**	0.0041
	(0.68)	(2.25)	(1.97)	(0.42)
HEART DIS	0.014	-0.10	0.054	-0.028
	(0.44)	(-1.58)	(1.59)	(-0.57)
SYS BP(ln)	0.035	-0.056	0.041	-0.067*
	(0.98)	(-1.35)	(1.06)	(-1.79)
Certified absence	0.026***	0.071***	0.044***	0.092***
	(3.09)	(6.46)	(4.56)	(9.61)
Height (ln)	0.37***	0.34**	0.25*	0.37***
	(3.37)	(2.14)	(1.94)	(2.64)
Obese	0.0036	-0.031	0.011	-0.027*
	(0.31)	(-1.57)	(0.77)	(-1.69)
Thin	-0.11	-0.11	-0.27*	-0.036
	(-1.01)	(-1.01)	(-1.81)	(-0.55)
Waist-hip ratio	-0.042	0.028	-0.13	-0.031
	(-0.49)	(0.25)	(-1.29)	(-0.34)
IMR	-0.17*	-0.30**	-0.25***	-0.090
	(-1.94)	(-2.46)	(-3.00)	(-1.19)
N	11925	7791	13546	13230
adj R^2	0.282	0.233	0.282	0.336
Gender	Men	Women	Men	Women
Sample	Fully employed		Employed	

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Other controls are age, age squared, years of education, marital status, work-hours per week, work-category, work posture and indicator for shift-work.

Introducing some control for non-random samples we see that the impact is the strongest on the sample with fully employed. Of the former significant proxies, no chronic disease is the only one that still matters using standard inference rules. I addition no muscular problems emerges as a determinant of annual income. Comparing with the corresponding estimates in Table 7 we observe that the effects of chronic health are reduced when we introduce the IMRs, but are still significant in 3 out of four specifications. Chronic health problems are not important to women's income when we use the fully employed sample, but significant in the employed sample. One interpretation is that the presence of chronic conditions does represent an obstacle related to holding a full position, but women with such health-problems do not receive lower income. The specification that stands out from the rest is the analysis of women's income based on the employed sample. In this specification the IMR is not significantly different from zero and SAH, chronic health and mental health are significant determinants. This could mean that health is less important to work-force participation for women and that health works directly on income. An alternative explanation is that we are not sufficiently capturing the time-fraction of the women's work. We are able to control for the number of work-hours per week, but not the number of weeks worked during a whole year.[13] As above the effects of height and doctor-certified absence are highly significant and untouched by the controls for selection bias. A 10 % increase in height represents income-premiums worth between 3 and 4 percent.

The samples selected for the analyses reflect an ambition that any indications of health-effects are due to differences in productivity (or perhaps discrimination). We have established some effects, but the causal interpretations of these still are in doubt. Some effects most certainly make no sense interpreted as causality. This particularly relates to the effects of absence and height. Leaning on the works of Case and Paxson (2008) we need to consider that the effect of height may be due to some correlation of ability, which is not controlled for in other ways than education in our samples. During the last decades Norway has experienced a rapid growth in the number of university- and college-graduates. This is mainly a supply-effect and not a reflection of an increase in ability within the population. So signalling ability through higher education is a luxury of the later generations, making the unmerited older respondents a much more heterogeneous group with respect to ability. We have tried specifications which controlled for education using deviations from the mean years of education by age, but these specifications did not significantly alter the model fit, or the effects of other variables[14]. Still, the main purpose of this study is to identify health-based income-differences. We have established some systematic differences in income by health, but do they survive a test of endogeneity?

Endogenous health?

Until now we have estimated the effects of one health-proxy conditional on the other proxies. When we start assessing the potential endogenous nature of these health-proxies we choose to assess the effects with restrictions imposed on the effects on all other health proxies. This is done primarily to simplify the estimation of our models, but we do not go down this path without convincing the reader that; conditional or not on other proxies, it really does not make much of a difference. Table 9 contains estimates without and with these restrictions imposed. It seems that these assumptions do not have strong impacts on the estimates, *i.e.* the effect of a health-proxy does not change much if

[13] The quality of reported work-hours per week in this context depends on whether respondents report average work-hours or work-hours for the weeks they actually work.

[14] We also specified health as deviations from means by age and gender, without changing anything. It is a fact that the average height has increase during the last decades. In our data that average height of a 67 year old man is 174 centimeters, compared to an average of 180 centimeters for 19 year old men.

we omit the all other health-proxies. The same goes for the significance levels. For the fully employed sample no chronic and no muscular / skeletal problems are the only ones that matter, regardless of controlling for other health proxies or not. In the table we have reported the confidence intervals for all health proxies. We see that the unconditional estimates are well within the 5 % confidence intervals of the conditional estimates.

The results reported in Table 9 work to defend the simplified approach which models income against only one health proxy at the time. At least when we assume that the health-proxies are exogenous we can defend this simplification. We embrace this result when we allow for endogeneity of the health-proxies.

Table 9 The effect of health on annual income. Health-proxies estimated with and without restrictions on other health-proxies. Both men and women.

Sample:	**Fully employed**							
	Conditional estimate	Confidence intervals	Unconditional estimates					
SAH	-0.0072	(-0.031 - 0.017)	-0.0018					
CHRONIC	0.024***	(0.0066 - 0.0420)		0.026***				
MENTAL (HAD)	0.0097	(-0.018 - 0.037)			0.0083			
MUSCLE	0.015**	(0.0019 - 0.0272)				0.017***		
HEART DIS	-0.0088	(-0.062 - 0.044)					-0.017	
SYS BP(ln)	0.00033	(-0.052 - 0.053)						-0.0018
IMR	-0.29***		-0.34***	-0.30***	-0.32***	-0.32***	-0.34***	-0.33***
N	19716		19716	19716	19716	19716	19716	19716
adj R^2	0.308		0.307	0.308	0.307	0.308	0.307	0.307
Sample:	**Employed**							
	Conditional estimate	Confidence intervals	Unconditional estimates					
SAH	0.021*	(-0.0035 - 0.0453)	0.017					
CHRONIC	0.040***	(0.022 - 0.058)		0.037***				
MENTAL (HAD)	0.031**	(0.0049 - 0.0566)			0.023*			
MUSCLE	0.010	(-0.0027 - 0.0237)				0.017***		
HEART DIS	0.042	(-0.015 - 0.098)					0.022	
SYS BP(ln)	-0.016	(-0.070 - 0.037)						-0.015
IMR	-0.16***		-0.28***	-0.26***	-0.30***	-0.31***	-0.31***	-0.32***
N	26776		26776	26776	26776	26776	26776	26776
adj R^2	0.376		0.376	0.376	0.376	0.376	0.375	0.375

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Other controls are gender, age, age squared, years of education, marital status, work-hours per week, work-category, work posture and indicator for shift-work.

In general OLS-estimates, in the absence of omitted variables, unobserved heterogeneity and measurement biases, approximate average effects on the respondents in the sample. A binary regressor can be looked upon as a “treatment”, even if it in nature is not a matter of choice. The literature separates between average treatment effects (ATE) and local average treatment effects

(LATE), see Imbens and Angrist (1994)[15]. The latter is relevant in cases where instruments are used to increases the validity of causal inference. Even though the literature on instrumental variables (IV) is clear in terms of the properties instruments need to satisfy, the interpretation of the effect vary depending on the instruments used. The local effects of treatment constrict any causal interpretation to the part of the sample that reacts to the instruments used. For instance, when we use self-reported health-information about family-members as instruments in the IV analysis. In this context a LATE represents the effect of health-problems for the part of the sample that have inherited health-problems (or have similar problems by chance or through common environmental factors). In other words we do not estimates causal effects which are universal to the sample with the endogeneity problems. When we utilize IV in addition to sample-selection bias we really acknowledge that there are two different sources of endogeneity, one based on selection bias and another one potentially caused by reverse causation (or other omitted variables). The fact that we deal with variables which may have relationships which are reciprocal has some bearing on how we address sample selection bias. Wooldridge (2002) suggests an approach where we replace the suspected endogenous regressors with their instruments in the selection equation. This approach has been adopted in the following analysis.

We use 3 different sets of instruments, which in the context of LATE allow for 3 different interpretations of the health-proxies:

- IV1: Self-reported health-information about family-members and parental smoking-habits
- IV2: Respondent has been admitted to hospital during last five years
- IV3: Respondent has utilized privately supplied medical care last year, contingent on not being hospitalized during last 5 years. In the case of hospitalization such treatment would probably be free as it is an extension/follow-up to the treatment in hospital. This definition increases the probability that the respondents' actively maintain their health. The type of medical care in question is care provided by physiotherapists, chiropractors and homeopaths. Self-reported.

The information that these sets of instruments are based on is self-reported. The grounds on which the reports build on may depend both on necessity and circumstance. The first set of instruments partly controls for genetically transferred health problems and, perhaps even more important, contextual influences which have affected both parents and offspring. The first part of the argument serves as an excellent instrument, while the other does not. Which of the explanations seem to

[15] Not exclusively as other identification-strategies allow for the estimation of average treatment effects on the treatment (ATT) and average treatment effects on the untreatment (ATUT).

matter the most is an empirical question that will be addressed when assessing the validity of the instruments. The second set of instruments may be interpreted as an exogenous shock to health. Or, at the other end of the scale of interpretation, it may represent elective surgery promoting to income. Again, the validity is an empirical question. Finally, the consumption of health-services may be important to health, but not necessarily for income. We have chosen to control for consumption of such services given that no hospital-admittance was reported during the last five years. This highlights both treatment of minor health-problems and a general awareness related to maintaining health.

In Table 10 we have reported IV-estimates for all health-proxies individually, together with a standard battery of first-step diagnostics and endogeneity-tests. In columns (b) through (d) and (f) through (h) we have indications that the instruments used are both relevant and valid using standard inference rules. For SAH and no chronic conditions we can safely say that the first step equations are identified, even if we apply critical values from Stock and Yogo (2002) for identification rather than the traditional rule of thumb. For the other health-proxies we do find mixed results with respect to identification and validity but the overall picture is that we are able to pick a set of instruments which both agree to the criteria of identification- and validity thresholds traditionally applied. The tests for endogeneity point in the direction of health as an exogenous regressor. We therefore have indications that the specifications in Table 8 still hold. The fact that we can not reject the exogeneity of the health proxies has (at least) two interpretations One is that the health proxies really are exogenous to annual income. Another is that the IMRs work as control-functions for the endogeneity of health, so the correlation between the error term and health is already accounted for through the IMRs.

The main result of the above analysis is that the effects of health in general are taken into account through the controls for sample selection. Some health-proxies still determine annual income directly though. For the fully employed men the absence of chronic problems is associated with higher income, while fully employed women gain from no musculoskeletal problems. Testing for the endogeneity of health supported the exogeneity assumptions. That is, we are right in treating the health as exogenous variables to income as there is no obvious channel from income on health in our model specifications.

Table 10 Exploring the exogeneity of health proxies. Both genders pooled.

		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
		OLS	IV1	IV2	IV3	OLS	IV1	IV2	IV3
SAH	Estimate	-0.0018	0.14	-0.12	-0.10	0.017	0.24**	0.19	-0.11
	Identification (F-value)		16.2	38.1	31.6		21.7	51.3	42.0
	Overidentification (p-value)		0.22	0.13	0.62		0.17	0.047	0.84
	Exogeneity test (p-value)		0.36	0.26	0.096		0.082	0.37	0.042
CHRONIC	Estimate	0.026***	0.086	-0.20	-0.11	0.037***	0.076	0.14	-0.12
	Identification (F-value)		26.3	21.4	13.7		34.9	25.4	26.2
	Overidentification (p-value)		0.22	0.24	0.46		0.041	0.022	0.69
	Exogeneity test (p-value)		0.51	0.13	0.24		0.81	0.74	0.095
MENTAL	Estimate	0.0083	0.14	-0.48	-0.40	0.023*	0.22**	0.25	-0.45
	Identification (F-value)		19.5	4.51	3.84		27.5	7.93	3.97
	Overidentification (p-value)		0.22	0.17	0.79		0.13	0.020	0.81
	Exogeneity test (p-value)		0.36	0.30	0.15		0.092	0.73	0.17
MUSCLE	Estimate	0.017***	0.12	-0.38	-0.023	0.017***	0.14*	-0.030	-0.032
	Identification (F-value)		12.6	8.17	256		18.9	21.7	325
	Overidentification (p-value)		0.26	0.68	0.43		0.085	0.018	0.64
	Exogeneity test (p-value)		0.21	0.078	0.12		0.13	0.66	0.054
HEART DIS	Estimate	-0.017	-0.15	-0.28	0.38	0.022	-0.054	0.28	0.52
	Identification (F-value)		3.64	63.8	60.7		5.53	52.5	24.9
	Overidentification (p-value)		0.14	0.23	0.42		0.027	0.026	0.62
	Exogeneity test (p-value)		0.59	0.18	0.55		0.73	0.48	0.40
SYS BP(ln)	Estimate	-0.0018	0.47	-0.61	-1.14	-0.015	0.15	0.85	-0.13
	Identification (F-value)		5.57	18.8	1.68		10.3	24.3	2.27
	Overidentification (p-value)		0.17	0.13	0.48		0.022	0.038	0.39
	Exogeneity test (p-value)		0.37	0.35	0.47		0.85	0.21	0.98
	Observations	~19716				~26776			
	Sample	Fully employed				Employed			

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Other controls are gender, age, age squared, years of education, marital status, work-hours per week, occupational category, work posture and indicator for shift-work.

4. Extensions

Selection into occupational categories?

What we have established so far is that chronic and muscular / skeletal health issues seem to be associated with on average lower income. The exogenous nature of these effects has been argued, leaving us with the option of treating the variables as independently determined outside of the empirical framework. Health as an input into production depends on the process of turning inputs into assets. I have a set of work categories available which allows us to explore this further. Every health-proxy is allowed to interact with work-category to partially control for selection into different occupational categories, which ultimately represent different requirements with respect to health. I do this to check if the above results really just reflect sorting into occupations.

Table 11 The effects of health-proxies if interacted with work-category[16]. Fully employed respondents only. Controlled for selection bias. t-values in parenthesis.

VARIABLES	SAH	CHRONIC	MENTAL (HAD)	MUSCLE	HEART DIS	SYS BP(ln)
health measure	0.0090	0.041*	-0.016	-0.0069	-0.00096	0.067
	(0.34)	(1.79)	(-0.56)	(-0.41)	(-0.015)	(0.85)
Interactions (reference:unskilled)						
Skilled	0.0070	-0.011	0.027	0.040**	0.037	-0.13
	(0.24)	(-0.41)	(0.75)	(2.03)	(0.55)	(-1.39)
Low white collar	-0.013	-0.040	0.053	0.013	-0.096	0.0039
	(-0.37)	(-1.42)	(1.25)	(0.61)	(-1.31)	(0.042)
White collar	-0.037	-0.022	0.011	0.018	0.076	-0.12
	(-1.26)	(-0.84)	(0.28)	(0.92)	(0.63)	(-1.41)
Executive	0.0030	-0.028	0.032	0.026	-0.013	-0.022
	(0.083)	(-1.00)	(0.98)	(1.20)	(-0.16)	(-0.21)
Chauffeur	-0.049	-0.073	0.018	-0.030	0.10	-0.10
	(-1.08)	(-1.39)	(0.20)	(-0.71)	(0.84)	(-0.67)
Farmer	0.057	0.033	-0.0020	0.057	-0.18	-0.25*
	(1.02)	(0.69)	(-0.035)	(1.60)	(-1.60)	(-1.80)
Fisher	0.052	-0.13	0.67	0.32*	-0.035	0.76
	(0.18)	(-0.76)	(0.98)	(1.71)	(-0.13)	(0.61)
Self-employed academic	-0.11	0.043	0.27	0.29**	0.58	0.82
	(-0.70)	(0.27)	(1.41)	(2.49)	(0.87)	(1.64)
Self-employed	-0.14**	0.092	-0.018	0.017	-0.34***	-0.20
	(-2.20)	(1.25)	(-0.21)	(0.33)	(-2.90)	(-0.97)
IMR	-0.33***	-0.29***	-0.32***	-0.32***	-0.34***	-0.33***
	(-6.47)	(-6.19)	(-6.86)	(-7.30)	(-7.66)	(-7.66)
N	19716	19716	19716	19716	19716	19716
adj R^2	0.309	0.309	0.309	0.310	0.309	0.309

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Other controls are gender, age, age squared, years of education, marital status, work-hours per week, work posture, anthropometric features, and indicators for absence and shift-work.

The results in Table 11 represent the effect of health on income if allowed to vary between occupational categories. The reference effect is the health-premium for the unskilled workers, while the other estimates indicate deviations from that effect. The sample is fully employed men and women and all specifications control for selection bias. Allowing for interactions reveal that chronic conditions still seems to have independent effects on income. The impact of all other health-proxies is not significantly different from zero. We do identify some significant interaction-effects. We see that no muscular / skeletal problems are associated with income premiums among the self-employed

[16] Refer to **Appendix table 4** for corresponding results for employed sample.

academics[17], fishermen and skilled employees. The self-employed have significantly lower payoffs compared to the control-group which consist of unskilled employees. All in all the results provide little evidence that good health is a more important asset in some occupations that others. At least not given the covariates included in the models. Chronic health is a significant factor for the reference category and no other occupational category differs substantially. This indicates that chronic health has an effect on annual income across all categories.

Blinder-Oaxaca-decompositions

Blinder-Oaxaca-decompositions have traditionally been used to study discrimination (Blinder, 1973; Oaxaca, 1973). These decompositions give additional insight into the source of income-differences, allowing the observed differences in income to be explained by two components. What is a caveat using health to separate the individuals is that we can not claim health to be exogenous to income given the observables in the model. This is really a violation on the ignorability-assumption. I have to consider that health probably works to affect income through channels I am unable to control for. Still, the decomposition provides some, although potentially biased, information of the sources of income-differences. Below I maintain Blinder and Oaxaca's terminology labelling the unexplained variation as discrimination.

Within this tradition we can decompose the differences into endowment- and coefficient-effects (and the interaction between them), or a simple two-fold decomposition into explained and unexplained effects. We will present the former version which allows for interactions between the unexplained and explained components. For a thorough presentation of the decomposition and information on the technical procedure used see Jann (2008)[18].

Following Jann (2008) the two components can be expressed in the following framework:

$$(1.3)\;\; R = E(Y_A) - E(Y_B)$$

For two groups A and B the outcome difference R is the differences between, in this case, the expected income for the two groups. Given the linear model $Y_\eta = X_\eta^{'}\beta_\eta + \varepsilon_\eta,\;\; \eta \in \{A, B\}$, this can be written as $R = E(Y_A)'\beta_A - E(Y_B)'\beta_B$ where β_X's are the estimated coefficients for both intercepts and slopes. Further this can be written as:

[17] This category probably consists of dentists, medical doctors with private practice and self-employed consultants / advisors.

[18] Estimated using the package *oaxaca* using Stata 10.1

$$(1.4)\ R = \underbrace{\left[E(X_A) - E(X_B)\right]'\beta_B}_{E} + \underbrace{E(X_B)'(\beta_A - \beta_B)}_{C} + \underbrace{\left[E(X_A) - E(X_B)\right]'(\beta_A - \beta_B)}_{I}$$

The income-gap is decomposed according to equation (1.4) into endowments (E), differences in coefficients (C) and the interaction between them (I). The endowment-effect is based on predicting the outcome gap between the two groups using the estimated coefficients for one group only. For instance this would measure the effect of education keeping the return from education equal for both groups (equal to the effect on group B). The difference in endowments (years of education) is thus the only source of differences in outcome. The second component (C) sets the level of the predictors equal for both groups but allow the coefficients (*e.g.* returns to education) to vary between the two groups. The last component (I) is the final source of differences in income allowing for interaction-effects between the two components defined above.

What we have learned from the analysis above is that correction of selection bias renders most of the health-proxies irrelevant to health. In this approach we will disregard this bias and pursue what components (seemingly) cause income-differences. This may provide some insight into the channels of health at the expense of out-of-sample validity of our results, but on the other hand this exaggerates the relevant effects. Of the three components in equation (1.4) the purely "discriminatory" component is differences due to coefficients. This allows return to education and other determinants to differ between the healthy and the non-healthy. We could have done this based on traditional regression analysis, but one of the advantages of the implementation of this particular Oaxaca-Blinder decomposition is that variances are readily calculated[19]. In this literature several studies have relied on point-estimates only to determine differences between groups, leaving inference pending on "sufficiently" large income / wage differences.

[19] With the assistance of Jann's procedure we are able to make qualified assessments of inference.

Table 12 Three-fold decomposition of predicted income-differences. Fully employed sample.

	Good health (SAH)		Good health (chronic)		Good health (mental)		Good health (muscle)	
Differential								
Pred income good health	21.2***	16.0***	21.3***	16.0***	21.1***	16.1***	21.1***	15.9***
	(677)	(441)	(665)	(421)	(700)	(456)	(557)	(335)
Pred income poor health	20.2***	15.7***	20.3***	15.8***	20.4***	15.1***	21.1***	16.1***
	(258)	(158)	(288)	(200)	(188)	(116)	(465)	(329)
Ratio	1.05***	1.02	1.05***	1.01	1.03**	1.06**	1.00	0.99
	(3.77)	(1.06)	(4.07)	(0.70)	(2.05)	(2.49)	(-0.26)	(-1.09)
Decomposition of ratio								
Endowments	1.01	0.91***	1.00	0.95***	0.98	1.00	0.99***	0.96***
	(0.79)	(-5.97)	(-0.66)	(-5.04)	(-1.55)	(-0.097)	(-2.87)	(-6.29)
Coefficients	1.04***	1.06***	1.05***	1.05***	1.05***	1.05**	1.02**	1.04***
	(3.53)	(3.16)	(4.79)	(3.63)	(3.02)	(2.24)	(2.01)	(3.16)
Interaction	1.00	1.06***	1.00	1.01	1.00	1.01	1.00	1.00
	(-0.34)	(4.21)	(0.79)	(1.16)	(0.62)	(1.09)	(-0.71)	(-0.57)
Gender	Men	Women	Men	Women	Men	Women	Men	Women
Observations	11942	7796	11942	7796	11942	7796	11942	7796

*** p<0.01, ** p<0.05, * p<0.1.

We start by establishing the differences in pay between the healthy and unhealthy, decomposing the differences into the components described above. In Table 12 we report estimates stratified by gender, with the predictions and differences exponentiated for easy interpretation. The estimates on differences are reported as the ratio between the predicted incomes for the healthy and the unhealthy. A coefficient > 1 favours the healthy. The raw differences in annual income range from 0 to 6 % in favour of the healthy. Differences in coefficients are significant along most health-proxies. An exception is muscular- and skeletal-problems which do not seem to be a source of net income-differences, even though we observe that both components are significant, but with opposite signs. Self-assessed health and chronic-health problems for women also have no net effect, but for both groups the explained component offsets the unexplained. The results in Table 12 give us indications on aggregate differences based on the covariates used in the models. Differences in coefficients are the most important source of differences. Whether this result is due to differences in productivity, discrimination or other characteristics depends on the specific source of the differences.

Detailed report on the differences in coefficients

Looking behind the results in Table 12 we can assess every coefficient individually. We do not regard differences due to endowments as discrimination, even if one could argue that differences in work-experience and tenure might represent some form of discrimination. What is clear from the decomposed results of endowments (see Appendix table 5 for differences in endowments) is that the healthy respondents are consistently more educated and younger. In addition, there is no systematic relationship between the hours worked per week and health-status. What is crucial to our assessments of discrimination is that differences in coefficients reported in Table 13. Are the returns from age, education and other characteristics higher for the healthy compared to the unhealthy?

Table 13 A detailed account on the differences in coefficients. Fully employed respondents only.

Coefficients	Good health (SAH)		Good health (chronic)		Good health (mental)		Good health (muscle)	
Yrs of education	0.98	1.03	0.99	1.01	1.07	1.00	1.03	1.03
Age	14.1***	0.41	1.75*	1.42	1.09	0.35	2.40***	3.88***
Age^2	0.26***	1.39	0.74*	0.81	1.01	1.52	0.63***	0.51***
Work hours per week	1.57***	1.05	1.04	0.99	1.20	1.19	1.13	1.19
Shift worker	1.00	1.00	0.99	1.00	1.00	0.98	1.01*	1.01
Frequent walking	1.00	1.00	1.01	0.99	0.99	1.02	1.00	0.98**
Walking and lifting	1.00	0.99	1.00	1.01	1.00	1.02	1.00	0.99
Heavy lifting	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00
Married	0.94***	0.93**	0.95***	0.98	0.97	0.96	1.00	0.96**
Widow(er)	1.00	0.99*	1.00	1.01**	1.00	1.00	1.00	1.00**
Divorced	0.99	0.99	1.00	1.00	1.00	1.00	1.00	0.99*
Separated	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00*
Skilled	1.00	0.99	0.99	1.00	0.99	1.00	1.01**	1.00
Low white collar	1.00	0.98	1.00	0.99	1.00	1.04	1.00	0.99
White collar	1.00	0.97*	1.00	1.00	0.99	1.01	1.00	0.99
Executive	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00
Chauffeur	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Farmer	1.01**	1.00	1.00	1.00	0.99	1.01	1.01**	1.00
Fisher	1.00	1.00	1.00	1.00	1.00*	1	1.00***	1.00
Selfemp academic	1.00	1.00	1.00	1.00	1.00	1.00	1.00**	1.00*
Self-employed	0.99*	0.99**	1.00	1.01***	1.00	1.00	1.00	1.00
Certified absence	0.99	0.95***	1.00	0.98	1.00	1.01	0.99	1.00
Height (ln)	1.25	0.76	6.91	0.34	0.51	0.44	0.35	0.33
Obese	1.00	0.99	1.00	1.00	1.01	0.98	1.00	0.99
Thin	1.00	1.00	1.00	1.00*	1.00	1.00	1.00	1.00
Waist-hip ratio	0.77	1.30	1.04	1.23	0.63	1.50	1.07	1.19
Total	1.04***	1.06***	1.05***	1.05***	1.05***	1.05**	1.02**	1.04***
Observations	11942	7796	11942	7796	11942	7796	11942	7796
Gender	Men	Women	Men	Women	Men	Women	Men	Women

*** p<0.01, ** p<0.05, * p<0.1.

A short comment on interpretation. The estimates in Table 13 are the exponentiated differences in marginal effects between the healthy and the unhealthy. A coefficient > 1 favours the healthy. We have already observed that the total effect of differences in coefficients is positive and significantly different from zero. The determinant driving this net difference seems to be age. The healthy have marginally a “higher” return to their age, or work-experience as this variable is a proxy for. This may be an indication of discrimination, but we cannot separate the health-effect on real experience from an income-penalty based on health. There are no differences related to the return to education, and only one indication that the return to work-hours differ. If SAH is used to separate the respondents' health-wise, healthy men have a significantly higher return from their hours worked. The effects of anthropometric features are the same for healthy and unhealthy, so being tall is as rewarding in terms of income for both healthy and unhealthy respondents. There are other effects which are significantly different from zero. For instance we observe that within occupations that traditionally require physical strength (farmer, fisher, self-employed academics) respondents without muscular / skeletal problems have on average higher annual income.

The general interpretation based on the decomposition, which does not control for selection bias, is that there is a difference in income between the healthy and the unhealthy. The returns from age represent most of this effect. As age is not experience we may capture differences in actual tenure / experience that should affect income. In the end we are not able to establish health-discrimination based on our data. There may be an effect from health to work-experience, which could be related to discrimination at some level, but our analysis is not able to provide useful information on that.

5. Discussion and final words

In this paper I have studied if health has a systematic effect on annual income. The findings suggest that health is important to income only if we fail to consider selection bias.

Ideally, different health stocks should mean different work task, a perfect sorting from ability to occupation. Given the different demands of occupations most should find one that suits their physical stature and health. Such differences in health stocks may be established early in life and consequently pave the way for a labour-force career. Different careers inherently have different payoffs. We do not choose our pay; we choose what we do professionally, depending on interests, skills, regional supply and coincidences. Within these choices we differ in ambition, ability, training and formal education creating an income-distribution that reflects these choices and abilities.

We have tried to estimate potential income-premiums associated with good health using several proxies of heath. What we find is that health matters, but only as a prerequisite to entering either the labour-force or full employment. It is difficult to pass judgment on these findings as occupational attachment may be a function of physical abilities. And perhaps it should be, if it is a matter of choice. An employee offered a part-time position rather than being ousted into early retirement represents a win-win situation for both individual and society. Using the data available we cannot identify involuntary part-time work as a function of health. Controlling for selection into either employment or full employment cancels out several of the health proxies used in this study. Two survive; those are the absence of chronic, muscular and skeletal diseases.

Anthropometric features matter, but not necessarily through productivity or discrimination. Height has consistently been an important factor in all model specification but the Blinder-Oaxaca decomposition. This effect may reflect employer preferences, but we feel that height also proxies for other individual qualities. Being thin, obese or having a high waist to hip-ratio seems to be unimportant to annual income.

A puzzle encountered in this analysis is the effects of absence. In the empirical analysis I have used reports of doctor-certified absence as a control variable. The effect of this variable has consistently been positive and significantly different from zero. Replacing this with self-certified absence does little to change the direction and importance of this variable. However, using reports on long-terms absence changes the effect. So, those who report spells of long-term absence are worse off on average, and those reporting short-term absences are better off.

Allowing the required health capital to vary with occupational category rendered muscular / skeletal health unimportant with respect to annual income. This result may also have normative consequences but our analysis does not warrant this. Selection of occupational category based on health does not necessarily represent discrimination; it is potentially based on individual preferences and regional supply effects. To address such issues we need explicit conformation on the voluntary nature of unemployment / part-time employment. The effects of chronic health problems did not vanish when we allow health to interact with occupational category.

In general we cannot conclude that health-differences systematically create differences in income in Norway. Even if the initial results suggest there is a relationship, we have empirically established results which do not warrant this conclusion. Yes, there is a difference related to different labour-market attachments, and yes there is a difference between those working full time or not. Based on the data we have there is no way we can pass any normative judgement on these results. Part-time work may be a result of loss of work-capacity or individual choice. It is wrong to pass judgement based on the basis of data not explicitly expressing desired work-scheduled related to actual. Not being employed at all also may depend on a number of individual and contextual characteristics. We feel we have shed some light on of the pathways health could work through; the next step would be to highlight labour-force-attachment related to health and free choice.

A question that arises in such a study is how to interpret health-based income differences; are they signs of discrimination, differences in productivity or both? Future extensions could focus on the separating differences in productivity from discrimination. One way of doing this would be to extend controls for selection. If we controlled for selection into health-stature, this would narrow the gap between the estimated effects on income-differences and estimates on discriminations.

Either way the results do help in shaping the understanding of the correlation between health and income. The contribution from this study is that the channel *from* health *to* income is modest. This result may be useful in interpreting the reverse relationship, namely the effect of income on health. The identification of an income-effect on health has proven to be difficult. One interpretation of the results in this analysis is that reverse causality is not the primary concern when estimating the effect of income on health.

References

Bartel, Ann and Paul Taubman. 1979. "Health and Labor Market Success: The Role of Various Diseases." *The Review of Economics and Statistics*, 61:1, pp. 1-8.

Becker, G.S. 1964. *Human Capital.* New York: Columbia University Press for the National Bureau of Economic Research.

Ben-Porath, Y. 1967. "The production of human capital and the life cycle of earnings." *Journal of Political Economy*, 75, pp. 353-67.

Bjelland, Ingvar, Alv A. Dahl, Tone Tangen Haug, and Dag Neckelmann. 2002. "The validity of the Hospital Anxiety and Depression Scale: An updated literature review." *Journal of Psychosomatic Research*, 52:2, pp. 69-77.

Blinder, Alan S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of human resources*, 8:4, pp. 436-55.

Case, Anne and Christina Paxson. 2008. "Stature and Status: Height, Ability, and Labor Market Outcomes." *Journal of Political Economy*, 116:3, pp. 499-532.

Cawley, John and Richard V. Burkhauser. 2006. "Beyond BMI: The Value of More Accurate Measures of Fatness and Obesity in Social Science Research." National Bureau of Economic Research, Inc.

Chowdhury, Gopa and Stephen Nickell. 1985. "Hourly Earnings in the United States: Another Look at Unionization, Schooling, Sickness, and Unemployment Using PSID Data." *Journal of Labor Economics*, 3:1, pp. 38-69.

Contoyannis, Paul and Nigel Rice. 2001. "The impact of health on wages: Evidence from the British Household Panel Survey." *Empirical Economics*, 26:4, pp. 599-622.

Currie, J. and B. C. Madrian. 1999. "Health, Health Insurance and Labor Market." *Handbook of Labour Economics*, 3C.

Deaton, Angus S. and Christina H. Paxson. 1998. "Aging and Inequality in Income and Health." *The American Economic Review*, 88:2, pp. 248-53.

Edwards, J. H. and A. W. F. Edwards. 1984. "Approximating the Tetrachoric Correlation Coefficient." *Biometrics*, 40:2, pp. 563.

French, Michael T. and Laura J. Dunlap. 1998. "Compensating wage differentials for job stress." *Applied Economics*, 30:8, pp. 1067 - 75.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy*, 80:2, pp. 223-55.

Hamermesh, Daniel S. and Jeff E. Biddle. 1994. "Beauty and the Labor Market." *The American Economic Review*, 84:5, pp. 1174-94.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica*, 47:1, pp. 153-61.

Imbens, Guido W. and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica*, 62:2, pp. 467-75.

Jann, Ben. 2008. "A Stata implementation of the Blinder-Oaxaca decomposition." ETH Zurich, Chair of Sociology.

Jäckle, Robert. 2007. "Health and Wages - Panel data estimates considering selection and endogeneity." *Ifo Working Paper, No 43*. Ifo Institute for Economic Research at the University of Munich.

Mincer, Jacob. 1974. *Schooling, experience and earnings*. New York: Colombia University Press.

Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, 14:3, pp. 693-709.

Ose, Solveig Osborg. 2005. "Working conditions, compensation and absenteeism." *Journal of Health Economics*, 24:1, pp. 161-88.

Raaum, Oddbjørn. 1999. "Inntektseffekter av utdannning i Norge – en litteraturoversikt." *Arbeidsnotat*. Frischsenteret.

Rosenzweig, Mark R. and Jack Morgan. 1976. "Wage Discrimination: A Comment." *The Journal of Human Resources*, 11:1, pp. 3-7.

Schou, Morten Brix, Steinar Krokstad, and Steinar Westin. 2006. "Hva betyr selvopplevd helse for dødeligheten?" *Tidsskr Nor Lægeforen*:126, pp. 2644-7.

Smith, Adam. 1904. *An Inquiry into the Nature and Causes of the Wealth of Nations.*: Library of Economics and Liberty.

Stern, Steven. 1996. "Semiparametric estimates of the supply and demand effects of disability on labor force participation." *Journal of Econometrics*, 71:1-2, pp. 49-70.

Stock, James H. and Motohiro Yogo. 2002. "Testing For Weak Instruments In Linear IV Regression." Technical Working Paper 284, National Bureau Of Economic Research.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*: The MIT Press.

Appendix

Appendix table 1 Full set of covariates

Variable	Type	Source	Comment
Woman	Binary	Self-reported	
Year of education	Semi-continuous	Self-reported	5 ordinal categories are recoded into years.
Age	Continuous	Official registers	
Age squared	Continuous	Official registers	
Work hours per week	Continuous	Self-reported	Fully working if >30 hours per week
Certified absence	Binary	Self-reported	Doctor-certified. At least once during last 12 months.
Unskilled (reference)	Binary	Self-reported	
Skilled	Binary	Self-reported	
Low white collar	Binary	Self-reported	
White collar	Binary	Self-reported	
Executive	Binary	Self-reported	
Chauffeur	Binary	Self-reported	
Farmer	Binary	Self-reported	
Fisher	Binary	Self-reported	
Self-employed academic	Binary	Self-reported	
Self-employed	Binary	Self-reported	
Good health (SAH)	Binary	Self-reported	Equals 1 if health is assessed very good or good
Good health (chronic)	Binary	Self-reported	Equals 1 if no chronic diseases are reported
Good health (mental)	Binary	Self-reported	Equals 1 if HAD-score is below 15
Good health (muscle)	Binary	Self-reported	Equals 1 if no musculoskeletal problems are
No heart disease	Binary	Self-reported	Equals 1 if no heart-problems are reported
Continuous	Continuous	Medical examination	Blood pressure. Systolic (in logs)
Height (ln)	Continuous	Medical examination	Height (in logs)
Obese	Binary	Medical examination	Body mass index > 30
Thin	Binary	Medical examination	Body mass index < 18
Waist-hip ratio	Continuous	Medical examination	The ratio between waist- and hip-circumference
Shift worker	Binary	Self-reported	Shift worker
Mostly sitting (reference)	Binary	Self-reported	
Frequent walking	Binary	Self-reported	
Walking and lifting	Binary	Self-reported	
Heavy lifting	Binary	Self-reported	
Unmarried (reference)	Binary	Self-reported	
Married	Binary	Self-reported	
Widow(er)	Binary	Self-reported	
Divorced	Binary	Self-reported	
Separated	Binary	Self-reported	
IMR	Continuous		Inverse Mill's ratio

Appendix table 2 Selection equations. Probit-estimates.

	IMR (fully employed)	IMR (fully employed endog h)	IMR (employed)	IMR (employed endog h)
woman	-0.85***	-0.86***	-0.36***	-0.39***
educ_yrs	0.026***	0.028***	0.055***	0.057***
age	0.16***	0.16***	0.28***	0.27***
age_sq	-0.19***	-0.19***	-0.33***	-0.33***
wcat2	0.41***	0.41***		
wcat3	0.050*	0.062**		
wcat4	0.13***	0.14***		
wcat5	0.35***	0.36***		
wcat6	-0.12**	-0.11**		
wcat7	-0.79***	-0.78***		
wcat8	-0.82***	-0.84***		
wcat9	-0.56***	-0.54***		
wcat10	-0.54***	-0.53***		
lnheight	0.25	0.29	0.84***	0.86***
obese	-0.029	-0.039*	-0.061***	-0.095***
thin	-0.31***	-0.35***	-0.32***	-0.39***
whratio	-0.82***	-0.91***	-1.10***	-1.36***
risk_shift	0.0099	0.0082		
wpost2	-0.23***	-0.22***		
wpost3	-0.22***	-0.21***		
wpost4	-0.46***	-0.45***		
married	-0.076***	-0.072***	0.20***	0.20***
divorced	-0.19***	-0.16***	0.18***	0.20***
widow	-0.0033	-0.028	-0.077**	-0.12***
sep	0.14**	0.10	0.019	-0.042
SAH	0.23***		0.41***	
no_chron	0.11***		0.24***	
no_ment	0.18***		0.25***	
no_musc	-0.021		-0.028*	
no_hdis	0.24***		0.26***	
ln_bpsys	0.16**		0.023	
par_no_stroke		-0.043**		-0.041*
par_no_heartd		-0.0085		0.019
par_no_asth		0.041**		0.12***
par_no_allergy		0.022		0.000082
par_no_cancer		0.021		0.021
par_no_mental		0.057***		0.11***
par_no_oste		-0.010		0.0082
par_no_diab		0.032		0.013
par_smoke		-0.015		0.057***
const	-4.43***	-3.15***	-9.31***	-8.17***
Identifying variables:				
fam_size1	-0.019	-0.014	0.072**	0.080***
fam_size2	0.054***	0.057***	0.081***	0.096***
nkids_home	-0.14***	-0.14***	-0.068***	-0.042*
mover	0.014	0.013	-0.10***	-0.085***
spouse_nowork	0.13***	0.12**	0.20***	0.16***
N	34025	33924	54080	53413
Ident F-val	57.6	54.0	70.7	44.1

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors.

Appendix table 3 Naïve mincer-regressions. Sample: employed respondents. OLS-estimates.

	Dependent variable: ln annual income									
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
educ_yrs	0.035***	0.040***	0.015***	0.023***	0.015***	0.023***	0.015***	0.023***	0.014***	0.023***
	(27.5)	(30.2)	(10.2)	(12.7)	(9.75)	(12.4)	(9.76)	(12.5)	(9.53)	(12.5)
age	0.12***	0.10***	0.085***	0.095***	0.085***	0.093***	0.085***	0.094***	0.086***	0.095***
	(31.5)	(28.4)	(21.2)	(22.7)	(21.2)	(22.5)	(21.3)	(22.8)	(21.4)	(22.3)
age_sq	-0.12***	-0.10***	-0.089***	-0.094***	-0.089***	-0.092***	-0.089***	-0.092***	-0.089***	-
	(-28.9)	(-25.6)	(-20.5)	(-20.6)	(-20.4)	(-20.1)	(-20.5)	(-20.3)	(-20.5)	(-19.9)
whours	0.010***	0.024***	0.0085***	0.021***	0.0083***	0.021***	0.0083***	0.021***	0.0083***	0.021***
	(14.0)	(37.2)	(11.9)	(31.2)	(11.7)	(31.1)	(11.7)	(30.9)	(11.6)	(30.4)
SAH					0.039***	0.035**	0.048***	0.057***	0.047***	0.052***
					(2.85)	(2.43)	(3.50)	(3.85)	(3.36)	(3.59)
no_chron					0.061***	0.039***	0.063***	0.047***	0.063***	0.043***
					(5.41)	(3.29)	(5.63)	(3.92)	(5.54)	(3.58)
no_ment					0.034**	0.047***	0.036**	0.051***	0.034**	0.051***
					(2.04)	(2.65)	(2.16)	(2.87)	(2.08)	(2.84)
no_musc					0.013	-0.0068	0.016*	0.0031	0.016*	0.0028
					(1.42)	(-0.71)	(1.78)	(0.33)	(1.78)	(0.29)
no_hdis					0.079**	-0.019	0.088**	-0.0057	0.085**	-0.013
					(2.32)	(-0.39)	(2.58)	(-0.12)	(2.49)	(-0.28)
ln_bpsys					0.034	-0.10***	0.038	-0.094***	0.046	-0.064*
					(0.90)	(-2.83)	(0.99)	(-2.59)	(1.19)	(-1.71)
abs_doc							0.044***	0.092***	0.045***	0.092***
							(4.60)	(9.73)	(4.65)	(9.64)
lnheight									0.30**	0.40***
									(2.39)	(2.88)
obese									0.0066	-0.029*
									(0.48)	(-1.84)
thin									-0.29**	-0.048
									(-1.99)	(-0.76)
whratio									-0.20**	-0.069
									(-2.02)	(-0.79)
Gender	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*
Other ctrls	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	17153	17092	13584	13482	13566	13473	13566	13473	13546	13230
adj R^2	0.210	0.306	0.275	0.327	0.280	0.330	0.281	0.334	0.282	0.336

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors.

Appendix table 4 The effects of health-proxies if allowed to interact with work-category. Employed respondents. Controlled for selection bias. OLS-estimates.

VARIABLES	SAH	CHRONIC	MENTAL (HAD)	MUSCLE	HEART DIS	SYS BP(ln)
health measure	0.0029	0.033	-0.017	-0.014	-0.0091	0.050
	(0.11)	(1.54)	(-0.58)	(-0.84)	(-0.17)	(0.68)
Interactions (reference:unskilled)						
Skilled	0.032	0.030	0.025	0.052**	0.10	-0.059
	(1.10)	(1.08)	(0.67)	(2.53)	(1.56)	(-0.62)
Low white collar	0.0027	-0.030	0.059	-0.0053	-0.023	-0.016
	(0.091)	(-1.16)	(1.54)	(-0.26)	(-0.32)	(-0.18)
White collar	-0.027	-0.016	0.035	0.024	0.035	-0.15*
	(-1.01)	(-0.63)	(0.94)	(1.21)	(0.36)	(-1.89)
Executive	0.0072	-0.025	0.027	0.024	-0.035	-0.11
	(0.21)	(-0.93)	(0.77)	(1.08)	(-0.48)	(-1.08)
Chauffeur	-0.087*	-0.080	-0.032	-0.035	-0.045	-0.17
	(-1.94)	(-1.63)	(-0.37)	(-0.87)	(-0.40)	(-1.10)
Farmer	0.030	0.014	0.057	0.055	0.023	-0.19
	(0.60)	(0.33)	(0.98)	(1.60)	(0.12)	(-1.48)
Fisher	0.034	0.024	0.25	0.24	0.40	0.34
	(0.15)	(0.14)	(0.51)	(1.44)	(1.22)	(0.31)
Self-employed academic	-0.093	-0.025	0.31	0.24**	0.61	0.31
	(-0.42)	(-0.19)	(1.56)	(2.14)	(0.92)	(0.65)
Self-employed	-0.10*	0.14**	0.059	0.033	-0.068	-0.081
	(-1.85)	(2.23)	(0.83)	(0.75)	(-0.47)	(-0.47)
IMR	-0.27***	-0.22***	-0.25***	-0.27***	-0.27***	-0.27***
	(-6.06)	(-5.71)	(-6.74)	(-7.56)	(-7.76)	(-7.86)
N	26776	26776	26776	26776	26776	26776
adj R^2	0.374	0.375	0.374	0.375	0.374	0.374

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Other controls are gender, age, age squared, years of education, marital status, work-hours per week, work posture, anthropometric features, and indicators for absence and shift-work.

Appendix table 5 Differences in endowments. Fully employed respondents only.

	Good health (SAH)		Good health (chronic)		Good health (mental)		Good health (muscle)	
Coefficients								
Yrs of education	1.02***	1.02***	1.01***	1.01***	1.01*	1.02***	1.01***	1.01***
Age	0.90***	0.58***	0.86***	0.74***	0.87***	0.84***	0.80***	0.74***
Age^2	1.09**	1.56***	1.14***	1.29***	1.13***	1.14***	1.20***	1.26***
Work hours per week	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shift worker	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00**
Frequent walking	1.00	1.00*	1.00	1.00	1.00	1.00	1.00	1.00*
Walking and lifting	1.00*	1.00	1.00*	1.00	1.00	1.00	1.00***	1.00**
Heavy lifting	1.00*	1.00	1.00	1.00	1.00	1.00	1.00***	1.00**
Married	0.99***	1.00	0.99***	1.00	1.00	1.00	0.99***	1.00
Widow(er)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Divorced	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Separated	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Skilled	1.00*	1.00	1.00	1.00	1.00	1.00	1.00***	1.00
Low white collar	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
White collar	1.00**	1.02***	1.00*	1.00	1.00	1.01	1.00***	1.01***
Executive	1.01***	1.00	1.00	1.00	1.00	1.00	1.01***	1.00
Chauffeur	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Farmer	1.00**	1.00	1.00	1.00*	1.00	1.00	1.00	1.00
Fisher	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Selfemp academic	1.00	1.00	1.00	1.00	1.00	1.00	1.00*	1.00
Self-employed	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00**
Certified absence	0.99	0.96***	1.00	0.98***	1.00	1.00	1.00*	0.99***
Height (ln)	1.00	1.00	1.00	1.00	1.00	1.00	1.00**	1.00*
Obese	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Thin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Waist-hip ratio	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00*
Total	1.01	0.91***	1.00	0.95***	0.98	1.00	0.99***	0.96***
Observations	11942	7796	11942	7796	11942	7796	11942	7796
Gender	Men	Women	Men	Women	Men	Women	Men	Women

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors.