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Health status over the life cycle*

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Abstract

We construct a health measurement model which combines panel data on self-reported health with a rich set of health measures from administrative medical records. Our estimated health model allows us to predict health status for the population at large. We account both for unobserved heterogeneity and for the persistence in unobserved health shocks. To account for inconsistent reporting in self-reported health we propose a 'corrected' health measure. We show that this 'corrected' measure substantially increases the estimated persistence in health status. We use predicted health status to study the evolution of health as individuals age. Moreover, we analyze how health interacts with economic variables and education. We find a strong gradient in education; the age at which health starts to decline at a greater rate differs by education and gender.

Keywords: self-reported health; administrative data, health dynamics; health index; socio-economic status
JEL classification: C42, I12

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1 Introduction

Health is a very important asset: if you are healthy you are able to work or produce goods at home; health also plays an important role in financial planning and in consumption and saving decisions. Most people probably have a good sense what the word 'health' means; it is, however, difficult to capture health in a single measure. To measure 'true' health we preferably like to combine different sources of information, or dimensions of health, which could explain a person's latent health status. Many studies in this field use self-reported health status (SRH) as a summary measure of health. The SRH variable is typically based on a question in which people are asked to rate their own health on a five-point ordinal scale ranging from 'excellent health' to 'poor health'.

The SRH measure has proven to be a very useful measure of health but is sometimes criticized because it involves some biases. For example Crossley and Kennedy (2002) show that many persons tend to change their self-reported health status within the same survey. Inconsistent reporting makes it difficult to analyze the evolution of health of a person over time as it reduces the persistence in health. Psychological factors, such as a person's mood might also influence the reported health status between waves. In addition to reporting bias, two persons with the same underlying health problems might report a different SRH, due to a difference in health perception; e.g. Lindeboom and van Doorslaer (2004). Differences in health perception among age groups result in a biased life cycle health profile. In addition to measurement error and heterogeneity in health perception, SRH seems also sensitive to justification bias as was first mentioned by Bound et al. (1999); people outside of the labor market tend to justify their labor market status by reporting worse health in a survey.

Another disadvantage, at least from our perspective, is that SRH is only available for a relatively small sample of the population. As administrative data from medical registers become more widely available, there is a growing interest to use these data. Important benefits of large administrative data are the possibility to focus on very specific groups in the population and the absence of survey attrition—which is often related to a deterioration in health (Jones et al., 2006).

In this paper, we estimate a health measurement model where we link survey data on SRH to a rich set of objective health conditions from medical records. Relying on objective health measures, instead of self-reported health conditions in survey data, has several advantages.

Objective health conditions do not suffer from justification bias and are less prone to reporting bias (Baker et al., 2004). Even though the questions to measure health outcomes in the Health and Retirement Study (HRS) and other similar surveys such as SHARE, PSID and ELSA are very specific there is ample evidence that self-reported health outcomes in survey data are sensitive to reporting bias. Johnston et al. (2009) show that the large majority of individuals in the UK who are diagnosed with hypertension, which is a very common disease, do not report this in a health questionnaire, though the question is very clear.[1] Also measures like ADL, which are often used as 'objective' measures in health measurement models, may be prone to reporting bias. Shulman et al. (2006), for example, find discrepancies between patients subjective reporting of ADL and IADL and their objective ratings.

On the other hand, SRH might contain information on 'true' health not being captured by the objective health conditions. It is important to take these unobserved individual differences in health into account, otherwise the persistence in health status might be underestimated. We account for unobserved individual differences in health as well as the persistence in unobserved health shocks by exploiting the panel dimension of our data.

One problem is that inconsistent reporting in SRH (i.e. measurement error) will reduce the estimated persistence in unobserved health. The Longitudinal Internet Study in the Social Sciences (LISS) panel, administered by CentERdata in the Netherlands, allows us to examine the existence of possible inconsistent reporting patterns. In addition to the standard SRH question, respondents are asked to report the change in their health compared to last year. For some respondents we notice inconsistent reporting by comparing the SRH measure and the self-reported change in health (SRCH) measure. For instance, some respondents state that their health did not deteriorate over the last year while they report being in worse health compared to last year, or vice versa. These inconsistencies cannot be explained by phenomena such as learning about health status over time, a change in social perception about certain health conditions, or medical innovations, since this would probably result in an up- or downward trend in SRH. We use both measures of SRH to construct a 'corrected' measure of SRH which accounts for these inconsistencies. We show that this corrected measure substantially increases the estimated persistence in health.

Several methods have been put forward to construct a health index using survey data on

[1] The wording of such a question in a survey is typically as follows: "Has a doctor ever told you that you have high blood pressure or hypertension?"

SRH and on a vector of variables $\boldsymbol{x}$, which measure objective health conditions. A useful overview of the different approaches proposed in the literature is provided by Kapteyn and Meijer (2013), Lindeboom and van Doorslaer (2004) and Cutler et al. (1997). Our method is closely related to the method proposed by Jürges (2007) which boils down to estimating an extended ordered probit model with SRH as dependent variable and objective health measures as explanatory variables. We will extend the approach of Jürges in three directions. First, we exploit the fact that we have panel data on SRH at our disposal. This allows us to take into account unobserved heterogeneity and the persistence in unobserved health shocks. Second, we are able to enrich the LISS survey data with a large set of health indicators stemming from administrative sources. This set of health indicators is very similar to the variables used in the latent health index developed by Poterba et al. (2010) who use measures collected in the HRS. Their latent health index is widely used in recent research, and well able to explain saving and retirement behavior as shown by Kapteyn and Meijer (2013). Related studies to our work by Lange and McKee (2012) and Heiss et al. (2014) also emphasize the importance of using multiple 'objective' measures of health to construct a single index and to account for unobserved heterogeneity in health. Third, we account for inconsistent reporting in SRH which, not taking into account, reduces the estimated persistence in health. A good understanding of the persistence in health status is crucial for explaining saving behavior and designing health and long-term care insurance, among other things; see e.g. De Nardi et al. (2010).

The estimated health model allows us to predict health status for the population at large. We account for the stochastic properties of unobserved differences in health. The advantage of using administrative data is that we can focus on specific subgroups that are usually small in surveys–such as the oldest-old—and that we overcome health related attrition in survey data. We use the predicted objective health status for the large administrative data to study the evolution of health as individuals age. This allows us to answer important questions such as: What is the likelihood of a deterioration in health at different stages in life and how persistent is this health shock? Does the evolution of health differ by socio-economic status and by gender? Do education and economic variables reduce the risk to get in poor health and how does this differ by gender?

Many studies, such as Case and Deaton (2005) for the US show, that women report a lower SRH than men and that the health status of men deteriorates at a faster rate than women. A recent study by Ross et al. (2012) for the US reports that the relationship between education and

health is stronger for women than for men. One explanation for this gender gap is a difference in health perception rather than a difference in the prevalence of chronic disease between men and women. Another explanation could be that women are more inclined to mention health problems then men in a survey. Our health measurement model deals with both measurement problems. Contoyannis et al. (2004) analyze the dynamics of health status among British men using SRH, they do not find clear differences in the health persistence by education and income.

Our main results are as follows: First, using both the corrected and uncorrected measure of SRH shows significant differences in the estimated persistence in health. For both measures of SRH, objective medical conditions, such as having diabetes, affect SRH in a similar way; using the corrected SRH measure, however, substantially increases the persistence in health. Second, we find that people of low socio-economic status are more likely to stay in poor health —independent from the measure we use. The age at which health starts to decline at a greater rate arrives earlier for males and persons with a lower level of education. Finally, we show that women on average are in worse health than men due to a higher prevalence of chronic diseases which have a relative detrimental effect on health. Woman's health seems to benefit more from having higher education than men. We also provide evidence that income and wealth are protective of health over and above education.

The outline of the paper is as follows. Section 2 explains the health measurement model. Section 3 extensively discusses the survey data set and administrative data. Section 4 discusses the estimation results of the health measurement model and the ability to explain the empirical patterns in for example SRH. Section 5 presents descriptive statistics on the persistence in health and the evolution of health over the life cycle. The final section concludes.

2 A longitudinal health measurement model

2.1 Different approaches to model health

Several methods have been put forward to construct a health index using survey data on SRH and on a vector of variables $\boldsymbol{x}$, which measure health conditions or difficulties with activities of daily living.

Our method is closely related to the method proposed by Jürges (2007) who estimates an extended ordered probit model with SRH as dependent variable and objective health measures $\boldsymbol{x}$ as explanatory variables. The extended ordered probit model assumes the existence of a single

latent health index y^* which is equal to $\boldsymbol{x}'\boldsymbol{\beta}$. The value of the health index is predicted as follows: $\hat{y}^* = \boldsymbol{x}'\hat{\boldsymbol{\beta}}$. Notice that self-reported health is only used in the construction of the index but not in the predication of the index. Poterba et al. (2010) use a somewhat different approach: in their model latent health status not only directly influences self-reported health but also all other health measurements. This results in a factor analysis model from which they derive the first principal component as their health index. In the empirical analysis Jürges uses the first wave of the SHARE survey, which includes information of 22,000 individuals aged 50 and above from ten European countries. Like many others the author stresses that the SRH measure is not comparable across countries because of differences in reporting style. For this reason he does not use the standard ordered probit model in his analysis but an extended version of it which allows the threshold parameters to be different across countries, which is known as a 'cut-point shift'. Lindeboom and van Doorslaer (2004) point out that heterogeneity in reporting behavior could not only lead to a cut-point shift but also to a so-called 'index shift' in the β parameters of the latent health index. They propose some likelihood ratio tests to check whether cut-point shifting and index shifting are relevant phenomena. Jürges deliberately does not allow for a country specific $\boldsymbol{\beta}$ vector so that he does not need to choose a 'reference country' in the cross-country comparison of general health.[2]

Lindeboom and van Doorslaer (2004) show that reporting not only varies across countries. They present evidence for both 'cut-point shifts' and 'index shifts' across age groups and gender: females and older persons are more likely to understate their health status compared to males and younger individuals.[3] A possible explanation is that persons compare their health status relative to another person of the same age and gender—in some surveys respondents are actually asked to report their health status relative to another person of the same age. This implies that there is a flattened out age profile in SRH. Since we are interested in modelling 'true' health status over the life cycle it is important to take this difference in reporting style into consideration. Lindeboom and van Doorslaer (2004) find no clear evidence that reporting differs by socio-economic status; which is also shown by McFadden et al. (2009).

[2]To be more precise, Jürges divides the estimated coefficients $\hat{\boldsymbol{\beta}}$ by the difference between the highest and lowest predicted health level to come up with a predicted health index which takes a value between zero and one. These scaled coefficients are referred to as 'implicit disability weights'. Poterba et al. (2010) ranks the predicted health status in percentile scores.

[3]The authors use cross-sectional data from Canada. It is well-known that in a cross-section study we cannot distinguish age effects from cohort effects. In other words the age effect could also be interpreted as a generation effect. In our study we use panel data to allow the threshold parameters to be cohort specific and not age specific.

2.2 Constructing a health index

In this section we introduce our longitudinal ordered response model in more formal terms. This model should enable us to predict a single latent true health index for individual i in period t by means of a set of health indicators $\boldsymbol{x}_{it}$ from administrative sources. The ordered response model assumes a linear relationship between a latent health index y_{it}^* and $\boldsymbol{x}_{it}$:

$$y_{it}^* = \boldsymbol{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it},\ t = 1, \ldots, T, \tag{1}$$

where ε_{it} represent unobserved factors influencing SRH which are not captured by the explanatory variables, such as lifestyle. We assume that this error term is standard normal distributed conditional upon $\boldsymbol{x}_{it}$: $\varepsilon_{it}|\boldsymbol{x}_{it} \sim N(0,1)$. Notice that the $\boldsymbol{\beta}$ parameter vector may vary across demographic groups. However, we do not allow for index shifting to keep the model parsimonious.

Since we are interested in the evolution of health over the life cycle, it is important to model the persistence in the random effect ε_{it}. Persistence in health can be the result of (1) persistence in observed medical conditions, (2) serial correlation in the error term—for example the experience of recurring health problems after the diagnosis of a chronic diseases such as diabetes—or (3) because of unobserved heterogeneity, for example if unhealthy lifestyle increases the probability of experiencing health problems and this is not captured by the observed variables. In light of these considerations, we assume that the error term ε_{it} can be decomposed into a random individual effect c_i and an idiosyncratic error term u_{it} which represent unobserved health shocks:

$$\begin{aligned} \varepsilon_{it} &= c_i + u_{it} \\ c_i &\sim NID(0, \sigma_c^2) \\ u_{it} &\sim N(0, \sigma_u^2) \\ \operatorname{cov}(c_i, u_{it}) &= 0,\ t = 1, \ldots, T. \end{aligned}$$

Given these assumptions, $\sigma_u^2 = 1 - \sigma_c^2$ because $\operatorname{var}(\varepsilon_{it}) = 1$. As we said above, the unobserved health shocks u_{it} are likely to be rather persistent. We therefore model u_{it} by means of an AR(1)

process:

$$u_{it} = \gamma u_{it-1} + \zeta_{it}$$

$$\zeta_{it} \sim NID(0, \sigma_\zeta^2).$$

Since $\text{var}(\varepsilon_{it}) = 1$, it holds that $\sigma_\zeta^2 = \sigma_u^2 \cdot (1 - \gamma^2) = (1 - \sigma_c^2) \cdot (1 - \gamma^2)$.

As we said before SRH is measured on a 5-point scale. We assume the following relationship between SRH_{it} and the latent health index y_{it}^*:

$$SRH_{it} = L \text{ if } \lambda_{L-1}^g < y_{it}^* \leqslant \lambda_L^g,\ L = 1, \cdots, 5;\ g = 1, \ldots, G, \tag{2}$$

where $\boldsymbol{\lambda}^g = (\lambda_1^g, \lambda_2^g, \lambda_3^g, \lambda_4^g)'$ are the threshold parameters for demographic group g ($\lambda_0^g = -\infty$ and $\lambda_5^g = \infty$). We allow the thresholds to differ by demographic group g to account for reporting heterogeneity in health ('cut-point' shifting). Based on earlier empirical work by Lindeboom and van Doorslaer, 2004 we distinguish on the basis of the variables 'gender' and 'year-of-birth cohort'.[4]

We further assume that the thresholds as well as the β parameters are constant over time. The β parameters may change over time if medical innovations reduces the impact of certain medical conditions on SRH. In the empirical analysis we will formally test this assumption. We also test for 'index-shifting', the AR(1) structure of the error term and whether the autocorrelation of the error term and the random effect differs between gender and year of birth cohort.

2.3 Estimation of the health index model

In this subsection we explain how we estimate the 'structural' parameter vector $\boldsymbol{\theta} = (\boldsymbol{\beta}', \sigma_c^2, \gamma)'$. For the explanation of the estimation procedure it is relevant to know that our survey data consists of four waves (see the data description in the next section). Estimation is done in several steps. First, we estimate for each demographic group g the multivariate ordered probit model where the dependent variables are SRH in waves 1 till 4.[5] Obviously, the vectors of threshold parameters $\boldsymbol{\lambda}_t^g,\ t = 1, \ldots, 4$ are also wave specific. The multivariate ordered probit model assumes the following relationships between the latent health indices and the explanatory

[4] We create five different demographic groups ($G = 5$): males born before 1945, females born before 1945, males born between 1945 and 1965, females born between 1945 and 1965 and individuals born after 1965.

[5] We use the Stata module CMP developed by Roodman (2011) for the estimation of the multivariate ordered probit model.

variables:

$$y_{i1}^* = \boldsymbol{x}_{i1}'\boldsymbol{\beta}_1^g + \varepsilon_{i1}$$
$$y_{i2}^* = \boldsymbol{x}_{i2}'\boldsymbol{\beta}_2^g + \varepsilon_{i2}$$
$$y_{i3}^* = \boldsymbol{x}_{i3}'\boldsymbol{\beta}_3^g + \varepsilon_{i3}$$
$$y_{i4}^* = \boldsymbol{x}_{i4}'\boldsymbol{\beta}_4^g + \varepsilon_{i4},$$

where the vector $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}, \varepsilon_{i4})'$ is normally distributed conditional upon $\boldsymbol{x}_i = (\boldsymbol{x}_{i1}, \boldsymbol{x}_{i2}, \boldsymbol{x}_{i3}, \boldsymbol{x}_{i4})'$:

$$\boldsymbol{\varepsilon}_i|\boldsymbol{x}_i \sim NID\left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{21}^g & \rho_{31}^g & \rho_{41}^g \\ \rho_{21}^g & 1 & \rho_{32}^g & \rho_{42}^g \\ \rho_{31}^g & \rho_{32}^g & 1 & \rho_{43}^g \\ \rho_{31}^g & \rho_{32}^g & \rho_{43}^g & 1 \end{pmatrix}\right).$$

The first step of the estimation procedure yields for each demographic group g an estimate of the following vector of 'auxiliary' parameters $\boldsymbol{\xi}^g = (\boldsymbol{\eta}_1^{g'}, \ldots, \boldsymbol{\eta}_4^{g'}, \boldsymbol{\rho}^{g'})'$ where $\boldsymbol{\eta}_t^g = (\boldsymbol{\beta}_t^{g'}, \boldsymbol{\lambda}_t^{g'})',\ t = 1, \ldots, 4$ and $\boldsymbol{\rho}^g = (\rho_{21}^g, \rho_{31}^g, \rho_{41}^g, \rho_{32}^g, \rho_{42}^g, \rho_{43}^g)'$. In the second step we apply a minimum distance estimation procedure in which we impose the restriction that the parameters of the index functions and the threshold parameters are not wave specific, i.e. $\boldsymbol{\eta}_1^g = \ldots = \boldsymbol{\eta}_4^g = \boldsymbol{\eta}^g = (\boldsymbol{\beta}^{g'}, \boldsymbol{\lambda}^{g'})'$.[6] This second step yields consistent estimates of the vector: $\boldsymbol{\theta}^{*g} = (\boldsymbol{\beta}^{g'}, \boldsymbol{\lambda}^{g'}, \boldsymbol{\rho}^{g'})'$. In the third step we follow Jürges (2007) and apply a minimum distance step in which we impose the restriction that there is no 'index shifting'. In other words, we assume that $\boldsymbol{\beta}^g = \boldsymbol{\beta}$ and $\boldsymbol{\rho}^g = \boldsymbol{\rho}$. In the fourth and final step of the estimation procedure we impose the restriction that the error term ε_{it} can be decomposed into a random individual effect c_i and an AR(1) distributed idiosyncratic term u_{it}. These restrictions imply the following relation between the 'auxiliary' parameter vector $\boldsymbol{\rho}$ and the 'deep' parameters σ_c^2 and γ:

$$\rho_{21} = \rho_{32} = \rho_{43} = (1-\gamma)\sigma_c^2 + \gamma \tag{4a}$$
$$\rho_{31} = \rho_{42} = (1-\gamma^2)\sigma_c^2 + \gamma^2 \tag{4b}$$
$$\rho_{41} = (1-\gamma^3)\sigma_c^2 + \gamma^3. \tag{4c}$$

[6] See e.g. Cameron and Trivedi (2005) for more information about the minimum distance estimation procedure.

2.4 Prediction of the health index in a large administrative data set

Next, we use the estimated parameters γ, σ_c^2 and $\boldsymbol{\beta}$ to construct a health index for a large random sample of the Dutch population. The health index is a linear prediction of true health status

$$\hat{y}_{it}^* = \boldsymbol{x}_{it}'\hat{\boldsymbol{\beta}} + \tilde{c}_i + \tilde{u}_{it}. \tag{5}$$

where $\boldsymbol{x}_{it}'\hat{\boldsymbol{\beta}}$ is the estimated conditional expectation of true health status given observed health indicators. As mentioned before, SRH is only used in the construction of the index but not in the prediction of the index. To correct for the stochastic properties of the error term we add a simulated composite residual $\tilde{c}_i + \tilde{u}_{it}$ to $\boldsymbol{x}_{it}'\hat{\boldsymbol{\beta}}$, similar to stochastic regression imputation to restore lost variability in the data (Little et al., 2002).

For the simulation of the composite error term we first assign each person an individual random effect $\tilde{c}_i$ by drawing it from a normal distribution with zero mean and variance $\hat{\sigma}_c^2$. Next, we impute a value of the idiosyncratic error term in the first period $\tilde{u}_{i1}$ by performing a random draw from a normal distribution with zero mean and variance $1 - \hat{\sigma}_c^2$. Finally we draw $\tilde{\zeta}_{it},\ t = 2, \cdots, T$ from a zero mean normal distribution with variance $(1 - \hat{\gamma}^2)(1 - \hat{\sigma}_c^2)$ to simulate $\tilde{u}_{it}$ for subsequent periods exploiting that u_{it} follows an AR(1) process.

3 Data

We distinguish between two samples. The first sample contains survey data on SRH from the Longitudinal Internet Study in the Social Sciences (LISS) between 2007 and 2010. We link this 'LISS sample' to administrative medical data. In addition, we use a large sample of 200,000 individuals on 1 January 2006 from the Dutch municipal population register for which we predict the health index. This sample is linked to administrative medical data and administrative data which contain socio-economic and demographic measures.

3.1 LISS

Survey data are taken from the LISS panel, gathered by CentERdata. This panel is recruited through address-based sampling (no self-selection). Households without a computer and/or internet connection receive an internet connection and computer for free. Residents of institutions

and nursing homes are excluded from the survey. This roughly nationally representative household panel (Van der Laan, 2009) receives online questionnaires each month, on different topics. When respondents complete a questionnaire they receive a monthly incentive. A variety of data is available from studies conducted in the LISS panel.[7] In this paper we use the yearly survey on health.

In the LISS panel we select all respondent of the yearly survey on health from 2007 to 2010. This data set consists of 24,486 individual-year observations. To link administrative data to the panel members, an opt-out consent method was used. In September 2011 all panel members received an email asking whether they objected against matching their survey responses with administrative resources (Das and Couper, 2014). A small minority objects against linkage. Unfortunately, not all of our respondents were still participating in September 2011. For these people we have no consent and because of ethical considerations we could not link their survey answers to the administrative data. Administrative records can be retrieved for 17,114 of the 24,486 observations (70%). Nonetheless, in 2007 SRH among those who can be linked to administrative data is not significantly different from the SRH among those who cannot be linked. This suggests that the loss of observations due to linking with administrative data does not yield an endogenous sample selection.[8] When we pool the data for all years (2007-2010), SRH is significantly different at the 5 percent level for those who can and cannot be linked to administrative records.[9] The differences, however, are not substantial as can be seen in table 1. Since we are interested in the working age population, we select all individuals of age 15 and older. The resulting sample consists of 16,720 observations.

Table 1: Self-reported health for observations which can and cannot be linked to administrative records, $N = 24,486$

Self-reported health	Linked data	No linkage
Poor	0.9	1.4
Moderate	14.0	14.4
Good	60.1	59.6
Very good	19.5	18.9
Excellent	5.4	5.8

To measure SRH, we use the following two questions in the LISS questionnaire.

[7] For more information, see http://www.lissdata.nl/lissdata/.
[8] The p-value corresponding to the null hypothesis of no difference is equal to 0.733
[9] The p-value corresponding to the null hypothesis of no difference is equal to 0.011

How would you describe your health in general? With response options: Poor, Moderate, Good, Very Good and Excellent.

Can you indicate whether your health is poorer or better, compared to last year? With response options: considerably poorer, somewhat poorer, the same, somewhat better and considerably better.

The first question gives us what we call the 'uncorrected SRH'. The latter question is used to construct what we call the 'corrected SRH'. By using the second question we account for inconsistencies in individual response pattern of health status over time. For the construction of the corrected measure of SRH status we use the following steps: first, we assume that in the first period we observe a persons' 'true health status'. Next, we assess whether the health status of the same persons improves, stays the same, or degenerates in the subsequent period. We compare this change in the level of SRH with the self-reported change in health status (SRCH), which can be either "poorer", "the same", or "better". If the change in the reported level of health does not correspond with the reported change in health, we will modify this measure as follows: (1) if the level improves or degenerates and no change is reported we assume that true health status remains the same; we adjust the level of health in the subsequent period by reducing/increasing the level of SRH by one unit.[10]

Table 2 shows that the distribution of corrected and uncorrected SRH is almost the same. Most people have a good health status (60%). Transitions, however, occur less often when using corrected SRH. The diagonals in table 3 present the percentage of people with unchanged health status. Most of the people in good health are also in good health in the next period (79% and 88% for uncorrected and corrected SRH, respectively). With the uncorrected measure of self-reported health about 40-55% of the people in excellent of very good health end up in a worse health status in the next period. For the corrected health measure this is about 18-22%.

Table 2: Uncorrected and corrected self-reported health, $N = 16,720$

Self-reported health	Uncorrected	Corrected
Poor	0.9	1.1
Moderate	14.2	14.7
Good	60.4	59.8
Very good	19.2	19.1
Excellent	5.2	5.3

[10] A more detailed description of the adjustment is available upon request.

Table 3: Transition probabilities uncorrected and corrected self-reported health, $N = 16,720$

Panel A: Uncorrected health measure					
$t-1 \setminus t$	Poor	Moderate	Good	Very good	Excellent
Poor	46.8	46.8	6.4	0.0	0.0
Moderate	3.3	59.5	36.3	0.9	0.1
Good	0.2	8.3	78.6	11.7	1.3
Very good	0.1	1.6	37.3	51.6	9.5
Excellent	0.2	0.7	17.6	37.1	44.5

Panel B: Corrected health measure					
$t-1 \setminus t$	Poor	Moderate	Good	Very good	Excellent
Poor	70.6	25.7	3.7	0.0	0.0
Moderate	2.5	74.0	22.7	0.9	0.0
Good	0.2	5.7	88.4	5.3	0.5
Very good	0.1	1.3	16.6	78.4	3.6
Excellent	0.2	0.7	6.8	14.3	78.1

3.2 Administrative sample

From the Municipal Population Register (in Dutch: Gemeentelijke Basisregistratie) we draw a random sample of 200.000 Dutch residents for whom educational attainment is available. This register contains demographic information on age, gender, marital status, among others.

For the sample to be representative, we sample with a higher probability from the older age groups. That is because for middle aged and older individuals, educational attainment is not available in educational registers. For a large part of the older population—approximately 10 percent of the population—educational attainment is registered in the Labor Force Survey (LFS). The LFS is a representative large scale rotating panel which started in 1996. Once a person participates in the LFS, educational attainment is registered. Furthermore, it is updated if a higher educational level is registered in a subsequent survey. The LFS does not sample institutionalized persons, such as individuals in nursing homes. However, educational attainment is available for this group if observed in the LFS before a person permanently moves to a nursing home. As a result, educational attainment is also available for many persons who stay in a nursing home (although these people are not included in the analysis).

We link administrative health records (which we describe in the next paragraph) and records on income, wealth and education to the Municipal Population Register on the basis of a unique personal identifier. Wealth and income data are based on the national tax register and on data from banks, which are available for the whole population.

For a small number of individuals we are unable to link the data records on income (0.77%

of the sample). We have checked whether this is related to the person's age or health status (i.e. proximity to death), but this seems not to be the case. We drop these observations from our sample.

From the administrative records on income and wealth we create a variable measuring total household wealth (net worth), a variable measuring net household income, a dummy for home ownership, variable measuring household size and dummy variables for labor market status. Educational attainment refers to the highest level of completed education, according to the Standard Classification of Education (SOI). In the analysis we distinguish between three groups: lower education (primary education or first stage secondary education), intermediate education (second stage secondary education) and higher education (University Bachelor or University Master or higher).

Again, we select all individuals age 15 and older since we are interested in the working age population. In addition we exclude persons from the year of entering a nursing home to make the sample comparable with the LISS survey. Table 4 shows the sample statistics.

Table 4: Summary statistics, 2006, $N = 163,695$

	mean	sd	
Age	45.167	18.716	
Married	0.492	0.500	
Female	0.505	0.500	
Household size	2.709	1.400	
Primary education	0.032	0.176	
Secondary education, 1st stage	0.185	0.389	
Secondary education, 2nd stage	0.338	0.473	
University bachelor	0.278	0.448	
University master	0.167	0.373	
Owner occupied house	0.642	0.480	
Employed	0.579	0.494	
Job seeker	0.015	0.120	
Exempted from job seeking	0.020	0.139	
(Partial) disabled	0.031	0.172	
Retired	0.179	0.383	
Student	0.092	0.289	
No paid work	0.085	0.279	
Yearly net household income	35,395	25,829	
Total household wealth	202,004	673,287	
Distribution	p25	p50	p75
Yearly net household income	20,994	32,371	44,792
Total household wealth	9,724	90,494	244,892

3.3 Administrative medical data

In the analysis we use dichotomous indicators of having a medical condition in a specific year. We derive these medical conditions from two sources: (1) the use of prescription medication, and

(2) the main diagnosis responsible for hospitalization. The data about prescription medication is administered by the National Health Care Institute (in Dutch: Zorginstituut Nederland). In the data set the dispensed drugs is classified by the Anatomical therapeutic chemical (ATC) code. With this code we identify the presence of specific medical conditions. We use the same mapping between a specific substance and medical condition as Lamers and van Vliet (2004) and Chini et al. (2011). For example, the ATC-code for insulin is 'A10A' which is used medically to treat (some forms) of diabetes.[11] The derived conditions are mainly chronical.

The main diagnosis responsible for hospitalization is based on the Tenth edition of the International Classification of Diseases, ICD10, derived from the hospital discharge register (in Dutch: Landelijke Medische Registratie, LMR). The LMR contains data about hospital admission (inpatient stays) and covers all general and university hospitals and most specialized hospitals.[12] We use the data from 2007-2010 and identify the same group of medical conditions as the group of conditions derived from prescription medication.[13] In addition to the indicators of having a medical condition we create three indicator variables of medical utilization: (1) hospital admission (2) prescription drug use, and (3) receiving care at home. The data set on the use of long-term care is provided by CAK (in Dutch: Centraal Administratie Kantoor).

Table 5 provides an overview of the prevalence of medical utilization and the prevalence of medical conditions in both the LISS survey and the administrative sample. We distinguish between men and women in the LISS sample and the administrative sample. The prevalence of medical utilization and medical conditions is about the same in the two samples, as we would expect given that the LISS panel is a representative sample of the Dutch population. The LISS survey asks respondents, in addition to SRH, whether they are currently taking medicine at least once a week for a specified condition and whether the physician has told them that they suffer from a specific disease last year. We use this information to create an indicator variable of having a 'self-reported' medical conditions.

Column three of table 5 reports the self-reported prevalence of medical condition based on both questions. Comparing the self-reports to administrative records suggests that respondents tend to underreport medical conditions such as mental problems while for cardiac diseases and diabetes the prevalence is about the same. Bharadwaj et al. (2015) report similar discrepancies

[11] Table 12 in the appendix describes the exact mapping of diseases to chronical conditions.

[12] The LMR covers approximately 88% of all inpatient hospital stays (Van der Laan, 2013).

[13] The analysis is primarily based on the prescription medication data. We use the hospital data as a sensitivity check. In that case we classify a person as having a disease if a condition is observed in either one of both sources.

in the US which they contribute to stigma about mental illness.

Table 5: Prevalence of hospital care, homecare, prescription drug use and chronic conditions (based on prescription drug information)

	Men			Women		
	LISS Objective	Admin Objective	LISS Self-reported	LISS Objective	Admin Objective	LISS Self-reported
Hospital care	15.72	14.24	9.37	19.59	19.30	11.61
Homecare	0.75	1.85	1.87	0.77	3.45	3.45
Prescription drug use	66.56	62.03	43.95	84.08	81.37	48.41
Coronary disease	12.45	11.43		7.26		
Epilepsy	1.54	1.41		1.88		
Cardiac disease	19.28	16.62	20.29	18.05	19.45	17.04
Inflammation and rheumatism	20.16	18.20	4.48	26.69	23.31	9.15
Hyperlipidemia	14.83	11.13	13.72	8.24	8.76	7.65
Malignancies	0.67	0.43		0.47		
Parkinson disease	0.64	0.45		0.56		
Diabetes	5.10	4.41	4.85	3.22	4.22	3.02
Glaucoma	1.53	1.41	1.53	1.11	1.35	1.11
Peptic acid disease	14.37	11.91	6.72	16.77	15.40	6.84
Respiratory illness, asthma	7.85	7.53	4.80	9.37	9.23	5.29
Thyroid disorders	1.00	0.86		4.66		
Crohn	0.49	0.51		0.68		
Pain	4.09	3.23		5.08		
Depression, anxiety	7.54	7.32	3.12	11.68	12.78	4.70

This table shows the prevalence of hospital care, homecare, prescription drug use and chronic conditions (based on prescription drug information). We distinguish between men and women in the LISS sample and the large random administrative sample. 'Objective' indicates the objective health measures in the administrative data and 'Self-reported' indicates the self-reported health measures in the LISS survey.

4 Results

4.1 Health index

Table 6 shows the estimation results of the health index model. As we explained in section 2 these estimates are obtained by first estimating for each demographic group a multivariate ordered probit model in order to obtain estimates for some auxiliary parameters and then perform sequentially some minimum distance estimation (MDE) steps. In the first MDE step we impose for each demographic group the restriction that the β and threshold parameters are constant over time. The results of the goodness of fit tests indicate that it is allowed to impose these restrictions.

The second MDE step hinges on the hypothesis that all parameters of the health index model except the threshold parameters do not vary across the demographic groups which we consider in this study. The goodness-of-fit test statistic indicates that this hypothesis should be rejected

at any reasonable significance level. Nonetheless, we choose to impose these restrictions because we can then construct a 'unique' health index which does not depend on a chosen reference group. In the last MDE step we estimate the parameters γ and σ_c^2 from the autocorrelation coefficients (cf. the system of equations 4). The goodness of fit test indicates that the stochastic part of the health index model can be effectively modeled by means of a random individual effect and an AR(1) distributed idiosyncratic error term.

We first consider the model using only information on chronic diseases and do not consider inpatient treatment for the same chronical condition. In the first column of table 6 the 'uncorrected' SRH measure is the dependent variable. The estimated coefficients, of the impact of a disease on SRH, are displayed in order. All coefficients have the expected negative sign and are highly significant except for tuberculosis, which has the wrong sign but is insignificant, and glaucoma, which is insignificant but has the correct sign. It is informative to compare our results with other studies to interpret the magnitude of the effect of specific chronic illnesses on subjective health. In line with earlier clinical studies (see e.g. Sprangers et al., 2000 and Gilliam, 2003) we find that neurologic conditions, such as epilepsy and Parkinson's disease, have a sizeable negative association with perceived health. For diabetes, we find a relative large negative effect in comparison with other studies, and for rheumatic conditions a relative small association. For the other conditions we find a similar ranking of the coefficients.

The lower part of table 6 reports the estimated threshold parameters. The estimates of the threshold parameters suggest that reporting behavior differs significantly across the five demographic groups which we distinguish in this study (cut-point shifts). If we only compare males and females born before 1945 with the same health index y_{it}^* it turns out that males are more positive about their health status than females: for instance, elderly females are more likely to report 'moderate' or 'poor' health than elderly males. There does not seem to exist large gender-specific differences in the reporting behavior of the 'middle' generation (born between 1945 and 1965). The youngest generation (born after 1965) has a higher tendency to report that their health is 'very good' or 'excellent' than other generations. It should be stressed again that all the findings on reporting behavior hinges on the assumption that the β-parameters of the health index (cf. equation 1) do not differ across demographic groups.

The estimates of the parameters σ_c^2 and γ imply that correlation between y_{it}^* and y_{it-1}^* is equal to $(1-\gamma)\cdot\sigma_c^2+\gamma = 0.70$. This first autocorrelation coefficient is not that large: if we use these estimates to impute values of the health index in the administrative data set (cf. equation

5) we find that health evolves over the life cycle in a rather erratic way (i.e. big upward and downward shocks in the value of the health index). That is the reason that we also constructed a 'corrected health' measure to account for reporting error. Column two of table 6 reports the estimates of health index model with the corrected health measure as the dependent variable. It turns out that in this case the estimates of σ_c^2 and γ are completely different: $\hat{\sigma}_c^2 = 0.161$ and $\hat{\gamma} = 0.856$. We obtain a larger estimate for the first order autocorrelation coefficient of the health index y_{it}^*: 0.88 versus 0.70. For both measures of SRH, objective medical conditions, such as having diabetes, affect SRH in a similar way. Overall, the estimates of the β and threshold coefficients become slightly smaller in absolute value if we take the corrected SRH measure as dependent variable in the health index model instead of the uncorrected one.

In the previous estimations we did not account for inpatient treatment for the sam e chronical condition, which might influence the results. Inpatient treatment can either be interpreted as a health shock (first occurrence of the disease) or a treatment to cure someone's health. Column 3 shows the results when we combine the medical information on chronical conditions based on prescription drug use and hospitalization. We classify a person as having a disease if a medical condition is observed in either the hospital data or prescription drug data. We have excluded the insignificant disease groups glaucoma and tuberculosis and include the disease groups: Alzheimer, dementia and psychosis; osteoporosis and Paget disease; and migraine to the specification. The results are very similar to the results which only use the prescription drug data. For the added variables we find that both having Alzheimer, dementia or psychosis and having osteoporosis and Paget disease has a large negative influence on health.

Next, we analyze whether the results change if we estimate the index 'solely' on the basis of self-reported medical conditions as reported in the LISS survey. We therefore substitute the disease groups as observed in the administrative data (column 3 of table 6) by self-reported medical conditions in the LISS survey. The variables of which no self-reported information is available are indicated in the table.[14] Column 4 of the table shows that there are noteworthy differences. For most diseases we find significantly lower coefficients. The coefficients of diabetes and cardiac diseases for which there seems little underreporting in the LISS data remain very similar in magnitude. This suggests that we should take measurement error issues seriously.

To examine the fit of the health measurement model we use the estimated coefficients to

[14]For the following variables no self-reported information is available: Parkinson's disease, Alzheimer, dementia and psychosis; Epilepsy; Thyroid disorders; Chronic pain and Migraine.

Table 6: Estimation results of the health index model, $N = 16,720$

	(1)		(2)		(3)		(4)	
	Chronic				Chronic and inpatient treatment			
	Uncorrected		Corrected		Uncorrected		Uncorrected	
Parkinson's disease *	-0.589	0.060	-0.645	0.052	-0.563	0.059	-0.361	0.055
Diabetes	-0.578	0.029	-0.534	0.028	-0.588	0.029	-0.562	0.061
Osteoporosis and Paget disease					-0.437	0.040	-0.288	0.019
Alzheimer, dementia and psychosis *					-0.429	0.048	-0.365	0.060
Epilepsy *	-0.436	0.034	-0.416	0.028	-0.350	0.029	-0.414	0.034
Anxiety and depression	-0.337	0.014	-0.288	0.012	-0.313	0.014	-0.187	0.032
Malignancies	-0.288	0.054	-0.181	0.045	-0.210	0.037	-0.076	0.019
Cardiac disease	-0.282	0.015	-0.244	0.013	-0.272	0.015	-0.214	0.016
Respiratory illness, asthma	-0.274	0.016	-0.198	0.014	-0.273	0.016	0.009	0.044
Thyroid disorders *	-0.269	0.031	-0.258	0.030	-0.244	0.031	-0.248	0.019
Chronic pain *	-0.250	0.019	-0.239	0.016	-0.256	0.019	-0.248	0.023
Stomach Ulcers	-0.218	0.013	-0.154	0.011	-0.216	0.012	-0.598	0.030
Coronary disease	-0.163	0.020	-0.171	0.018	-0.177	0.019	-0.169	0.020
High blood cholesterol	-0.137	0.019	-0.127	0.018	-0.127	0.019	-0.506	0.019
Migraine *					-0.121	0.033	-0.357	0.024
Rheumatic conditions	-0.062	0.009	-0.051	0.008	-0.044	0.010	0.027	0.044
Glaucoma	-0.027	0.043	-0.110	0.039				
Tuberculosis	0.062	0.043	0.062	0.036				
Hospital use	-0.121	0.011	-0.091	0.010	-0.095	0.011	-0.194	0.012
Home care	-0.150	0.046	-0.142	0.038	-0.161	0.045	-0.124	0.024
Prescription drugs use	-0.153	0.010	-0.090	0.008	-0.158	0.010	-0.401	0.012
$\lambda_{g1,1}$	-3.382	0.061	-3.109	0.057	-3.367	0.060	-3.492	0.060
$\lambda_{g1,2}$	-1.721	0.027	-1.566	0.027	-1.717	0.027	-1.821	0.026
$\lambda_{g1,3}$	0.392	0.024	0.508	0.025	0.396	0.024	0.339	0.024
$\lambda_{g1,4}$	1.347	0.033	1.556	0.036	1.351	0.033	1.320	0.033
$\lambda_{g2,1}$	-2.903	0.035	-2.590	0.032	-2.900	0.035	-3.025	0.036
$\lambda_{g2,2}$	-1.447	0.018	-1.312	0.018	-1.445	0.018	-1.510	0.018
$\lambda_{g2,3}$	0.434	0.016	0.484	0.016	0.435	0.016	0.428	0.015
$\lambda_{g2,4}$	1.445	0.021	1.559	0.022	1.445	0.021	1.458	0.021
$\lambda_{g3,1}$	-2.902	0.032	-2.703	0.031	-2.895	0.033	-2.989	0.033
$\lambda_{g3,2}$	-1.556	0.015	-1.428	0.014	-1.553	0.015	-1.566	0.014
$\lambda_{g3,3}$	0.272	0.012	0.323	0.011	0.273	0.012	0.312	0.010
$\lambda_{g3,4}$	1.276	0.014	1.335	0.014	1.276	0.014	1.327	0.013
$\lambda_{g4,1}$	-3.734	0.093	-3.453	0.092	-3.803	0.090	-3.865	0.097
$\lambda_{g4,2}$	-1.507	0.026	-1.264	0.026	-1.534	0.026	-1.618	0.026
$\lambda_{g4,3}$	0.449	0.025	0.515	0.026	0.433	0.025	0.398	0.025
$\lambda_{g4,4}$	1.463	0.038	1.500	0.038	1.452	0.038	1.446	0.038
$\lambda_{g5,1}$	-3.059	0.037	-2.773	0.035	-3.055	0.037	-3.223	0.038
$\lambda_{g5,2}$	-1.440	0.018	-1.273	0.017	-1.440	0.018	-1.533	0.017
$\lambda_{g5,3}$	0.521	0.016	0.577	0.016	0.519	0.016	0.519	0.015
$\lambda_{g5,4}$	1.412	0.021	1.494	0.022	1.409	0.021	1.432	0.020
γ	0.253	0.018	0.856	0.020	0.248	0.018	0.256	0.018
σ_c^2	0.602	0.009	0.161	0.112	0.607	0.008	0.581	0.009

For the threshold parameters we distinguish on basis of the variables 'gender' and 'year-of-birth' five different demographic groups ($G = 5$): (1) males born before 1945, (2) males born between 1945 and 1965, (3) individuals born after 1965, (4) females born before 1945, (5) females born between 1945 and 1965.

* In column (4) we do not replace the indicated variables (*) by self-reported medical conditions because there is no information on these medical conditions in the LISS data.

predict the transition probabilities for the LISS sample. We calculate these in-sample predictions as follows:

$$\Pr\left(SRH_{it} = l | SRH_{it-1} = k, x_{it}, x_{it-1}\right) =$$
$$\Pr\left(\hat{\lambda}^g_{l-1} - x^{'}_{it}\hat{\beta} < \varepsilon_{it} < \hat{\lambda}^g_{l} - x^{'}_{it}\hat{\beta} | \hat{\lambda}^g_{k-1} - x^{'}_{it-1}\hat{\beta} < \varepsilon_{it-1} < \hat{\lambda}^g_{k} - x^{'}_{it-1}\hat{\beta}\right) =$$
$$\frac{P(\hat{\lambda}^g_{l-1} - x^{'}_{it}\hat{\beta} < \varepsilon_{it} < \hat{\lambda}^g_{l} - x^{'}_{it}\hat{\beta}, \hat{\lambda}^g_{k-1} - x^{'}_{it-1}\hat{\beta} < \varepsilon_{it-1} < \hat{\lambda}^g_{k} - x^{'}_{it-1}\hat{\beta}, \hat{\rho}_{12})}{P(\hat{\lambda}^g_{k-1} - x^{'}_{it-1}\hat{\beta} < \varepsilon_{it-1} < \hat{\lambda}^g_{k} - x^{'}_{it-1}\hat{\beta})}, \; k, l = 1, \ldots, 5$$

where the first-order autocorrelation coefficient equals $\hat{\rho}_{12} = (1 - \hat{\gamma})\,\hat{\sigma}^2_c + \hat{\gamma}$. Table 7 shows the in-sample predictions. A comparison of table 3 and table 7 shows that for both the uncorrected and uncorrected health measures the predicted and empirical transition probabilities agree reasonably well although the health measurement model assigns somewhat higher probabilities to the off-diagonal elements of the transition matrix.

Table 7: In-sample predictions: 'uncorrected' and 'corrected' SRH, $N = 16,720$

	Poor	Moderate	Good	Very good	Excellent
Poor	36.2	56.3	7.5	0.0	0.0
Moderate	4.4	52.5	42.5	0.5	0.0
Good	0.1	10.7	74.3	13.7	1.2
Very good	0.0	0.4	43.9	43.3	12.4
Excellent	0.0	0.0	14.4	43.6	41.9
Poor	58.3	41.0	0.7	0.0	0.0
Moderate	4.5	66.7	28.8	0.0	0.0
Good	0.0	8.0	81.9	9.9	0.2
Very good	0.0	0.0	30.1	60.1	9.8
Excellent	0.0	0.0	1.9	37.0	61.1

4.2 Persistence in health

Table 8 shows transition probabilities for predicted health in the administrative sample by educational attainment. We construct predicted health status on the basis of the estimated thresholds. We use the thresholds of middle-aged males as a reference group for all individuals in the sample.

The table shows that lower educated people are much more likely to stay in poor health than higher educated people (university bachelor or master). This does (by construction) not depend on using either the uncorrected measure or corrected measure. Table 9 shows the transition matrix by income quintile (only for the uncorrected measure). We observe a higher persistence

Table 8: Health persistence by Educational Attainment, N=163,695

	$t \setminus t+1$	Very poor	Poor	Fair	Good	Very good
Panel A: Uncorrected health measure						
Lower	Very poor	36.7	55.6	7.6	0.0	0.0
	Poor	5.1	50.5	43.8	0.6	0.0
	Fair	0.2	12.0	74.2	12.5	1.2
	Good	0.0	0.7	48.3	39.9	11.1
	Very good	0.0	0.1	18.5	43.9	37.6
Higher	Very poor	31.2	60.4	8.5	0.0	0.0
	Poor	3.1	47.7	48.7	0.6	0.0
	Fair	0.1	10.0	74.9	13.7	1.3
	Good	0.0	0.5	46.8	40.8	11.9
	Very good	0.0	0.0	16.8	44.6	38.6
Panel B: Corrected health measure						
Lower	Very poor	50.1	47.7	2.2	0.0	0.0
	Poor	4.8	60.2	35.0	0.1	0.0
	Fair	0.1	10.2	78.9	10.6	0.3
	Good	0.0	0.1	38.6	51.6	9.7
	Very good	0.0	0.0	6.1	43.6	50.3
Higher	Very poor	39.9	58.1	2.0	0.0	0.0
	Poor	3.5	58.4	38.0	0.1	0.0
	Fair	0.1	8.6	79.5	11.5	0.4
	Good	0.0	0.1	37.1	52.8	10.0
	Very good	0.0	0.0	5.4	44.2	50.4

of staying in poor health for low income households than for their high income counterparts. We do not observe important differences in health persistence if we stratify the sample by wealth quintile (Table 9).[15]

4.3 Evolution of health status over the life-cycle

To describe the evolution of health over the life cycle we estimate fixed effects models on the administrative sample. The fixed effect captures unobserved time-invariant individual effects, such as cohort effects. The model contains a dummy for every age and is estimated separately by gender and educational level. We present the results for the linear prediction of health since the (un)corrected measure generates a somewhat erratic pattern for the highest age groups. As we estimate a fixed effect model we can only interpret the slope, or the evolution, in health status as people age, and not the difference in the (initial) level of health. For an easier comparison we let all figures start at zero.

Figure 1 reports the estimated age pattern for both males and females. Health deteriorates with age; as from age 50 we observe that health starts to decline at a faster rate for both males and females. For both males and females we observe that health declines at a similar pace up to

[15] We notice that the level of income and wealth also differs by age-group.

Table 9: Health persistence by 2006 Income quintile, Uncorrected health measure, N=163,695

	$t \setminus t+1$	Very poor	Poor	Fair	Good	Very good
Q1	Very poor	39.5	53.0	7.5	0.0	0.0
	Poor	6.1	51.8	41.6	0.5	0.0
	Fair	0.3	13.2	73.6	11.9	1.1
	Good	0.0	0.9	48.4	39.9	10.9
	Very good	0.0	0.1	18.2	44.1	37.6
Q2	Very poor	36.9	55.9	7.2	0.1	0.0
	Poor	5.1	50.8	43.5	0.6	0.0
	Fair	0.2	12.4	74.2	12.1	1.1
	Good	0.0	0.7	49.2	39.2	10.9
	Very good	0.0	0.1	18.9	43.9	37.2
Q3	Very poor	33.3	57.7	8.8	0.1	0.0
	Poor	3.9	49.1	46.4	0.6	0.0
	Fair	0.1	10.9	74.7	13.0	1.2
	Good	0.0	0.5	47.2	40.6	11.7
	Very good	0.0	0.0	17.4	45.1	37.5
Q4	Very poor	32.9	60.0	7.2	0.0	0.0
	Poor	3.6	47.5	48.3	0.6	0.0
	Fair	0.1	10.3	74.6	13.7	1.4
	Good	0.0	0.6	47.5	40.4	11.6
	Very good	0.0	0.1	17.8	44.0	38.1
Q5	Very poor	28.1	62.5	9.4	0.0	0.0
	Poor	3.1	48.2	48.1	0.6	0.0
	Fair	0.1	10.0	75.0	13.6	1.3
	Good	0.0	0.5	46.8	40.8	11.9
	Very good	0.0	0.0	17.1	43.7	39.1

Table 10: Health persistence by 2006 Wealth quintile, Uncorrected health measure, N=163,695

	$t \setminus t+1$	Very poor	Poor	Fair	Good	Very good
Q1	Very poor	36.5	54.7	8.8	0.0	0.0
	Poor	4.6	49.0	45.8	0.7	0.0
	Fair	0.2	11.0	74.5	13.1	1.2
	Good	0.0	0.6	47.3	40.7	11.4
	Very good	0.0	0.0	17.5	44.5	38.0
Q2	Very poor	39.3	54.0	6.7	0.1	0.0
	Poor	5.2	50.4	43.8	0.6	0.0
	Fair	0.2	11.9	74.2	12.5	1.3
	Good	0.0	0.7	47.2	40.4	11.7
	Very good	0.0	0.1	17.7	44.3	38.0
Q3	Very poor	29.9	61.1	8.9	0.1	0.0
	Poor	3.9	49.0	46.6	0.5	0.0
	Fair	0.1	10.7	74.4	13.5	1.3
	Good	0.0	0.6	47.7	40.2	11.5
	Very good	0.0	0.0	18.0	45.2	36.8
Q4	Very poor	35.5	55.7	8.8	0.0	0.0
	Poor	4.2	49.6	45.7	0.5	0.0
	Fair	0.2	11.4	74.6	12.6	1.3
	Good	0.0	0.6	48.1	39.9	11.4
	Very good	0.0	0.1	18.1	44.9	36.9
Q5	Very poor	34.4	59.2	6.4	0.0	0.0
	Poor	4.4	50.1	44.9	0.6	0.0
	Fair	0.2	11.5	74.5	12.7	1.2
	Good	0.0	0.6	48.5	40.0	11.0
	Very good	0.0	0.1	17.7	42.0	40.2

about age 60. For men, we observe a further increase in the rate of deterioration in health as from age 60. As a results, there is about a 0.3 standard deviation difference in health between men and women at age 95, which corresponds to having cardiac disease.

Figure 2 reports the health pattern for different levels of education for males. We observe strong differences in the age gradient by level of education. For lower educated males we observe a relative high gradient already from age 25 onwards; as from age 50 the level of health starts to decline at an even faster rate. For males with an intermediate level of education, the level of health declines slowly up to age 55, after that age the deterioration in health steadily start to accelerate. For highly educated males we also observe a relatively flat age gradient, after age 55 health starts to decline more rapidly. The gradient is however flatter than for males with an intermediate level of education.

Figure 3 stratifies the health profile for females by education. There are three important differences compared to the health profiles for males: First, for lower educated women, the gradient is less steep than for men. Second, for higher and intermediate levels of education the gradient is very similar to men, but the gradient stays relatively linear up to age 70; thereafter health starts to decline at a somewhat faster rate (but not as fast as for men). Finally, also for lower educated women, the increase in the deterioration of health starts at a later age and the gradient is less steep than for men.

These figures show two broad patterns. First, there is a strong gradient in education. Second, we observe a gender and education difference in the timing when the rate of worsening in health speeds-up. This moment arrives earlier for males and persons with a lower level of education.

Do education and economic resources reduce the risk to get in poor health and how does this differ by gender? Table 11 gives results from a regression of health estimated separately for men and women. The different models include dummies for the level of educational attainment (the reference category is lower education), income and wealth quantiles (the bottom quantile is the reference category), a homeowner dummy, a dummy variable for being married and a variable measuring household size. All estimated models account for age as well.

Women are on average in worse health than men. Woman's health advantages more from higher education than men. This even holds after controlling for economic resources. The results also suggests that economic variables as income and wealth are more protective for women's health than for men's health. A possible explanation is that poor health is in particular detrimental for household income when this affects the earning capacity of the main earner;

women more often work part-time than men. Indeed when we account for labor market status the association between income and health disappears for men.

Table 11: Estimation results, dependent variable: predicted health, N=163,695

	Men	Women	Men	Women	Men	Women
Intermediate education	0.083 ***	0.098 ***	0.064 ***	0.070 ***	0.056 ***	0.068 ***
Higher education	0.124 ***	0.175 ***	0.093 ***	0.126 ***	0.084 ***	0.121 ***
Married	-0.002	0.013 *	-0.011	-0.015 **	-0.013 *	-0.017 *
Household size	0.003	0.012	-0.005	-0.002	-0.004	-0.001
Homeowner			0.026 ***	0.010	0.022 **	0.005
2nd income quintile			0.018 *	0.048 ***	0.012	0.039 ***
3th income quintile			0.019 *	0.037 ***	0.006	0.025 **
4th income quintile			0.028 **	0.053 ***	0.011	0.038 ***
5th income quintile			0.022 *	0.080 ***	0.000	0.060 ***
2nd wealth quintile			0.032 ***	0.046 ***	0.026 ***	0.038 ***
3th wealth quintile			0.045 ***	0.045 ***	0.040 ***	0.038 ***
4th wealth quintile			0.069 ***	0.095 ***	0.064 ***	0.089 ***
5th wealth quintile			0.094 ***	0.137 ***	0.088 ***	0.130 ***
Retired					-0.056 ***	-0.065 ***
Unemployed					-0.045 **	-0.085 ***
Disabled					-0.348 ***	-0.314 ***
Self-employed					0.010	0.018
Other					0.020	-0.011
Constant	-0.169 ***	-0.369 ***	-0.195 ***	-0.384 ***	-0.183 ***	-0.359 ***

5 Conclusions

We construct a health measurement model where we combine survey data on SRH linked to a rich set of health measures from medical records. The estimated health model allows us to predict health for the population at large. We thereby account for unobserved heterogeneity and the persistence in unobserved health shocks by exploiting that we have panel data on SRH at our disposal. To account for inconsistent reporting patterns in SRH we introduce a 'corrected' health measure. We show that this 'corrected' measure substantially increases the estimated persistence in health.

We use predicted health to study the evolution of health as individuals age and the interaction with economic variables and education. We find that people of low socio-economic status are more likely to stay in poor health —independent from the measure we use. Studies using SRH usually find a weaker pattern.

The age at which health starts to decline at a greater rate arrives earlier for males and persons with a lower level of education. Finally, we show that women on average are in worse health than men due to a higher prevalence of chronic diseases that have a relative detrimental effect on health. Women's health seems to benefit more from having higher education than

men. We also provide evidence that income and wealth are protective of health over and above education. Since a woman's health deteriorates at a lower rate over the life-cycle then the health of men, their health status will converge.

These stylized facts are able to explain the variation in the decline in health status for different socio-economic groups which is also reported in other studies using SRH (e.g. Case and Deaton, 2005). However, we believe we find a somewhat higher level of decay for older persons than usually observed in studies using SRH.

In future research, we will use the health index in a structural life cycle model to explain the observed interaction between health, economic variables and education.

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Table 12: Mapping prescription drugs to chronic conditions

Chronic disease	ATC-code in medical reg.	Matching variable LISS survey
Coronary disease	B01A, C04A	
Epilepsy	N03A	
Cardiac disease	C01, C03C	Heart or brain infarction, other heart diseases
Hypertension	C02, C03A, C07, C08, C09A,B	High blood pressure
Tuberculosis	J04A	
Rheumatic conditions	H02, M01, M02	Joint pain or joint infection
High blood cholesterol	C10A	High blood cholesterol
Malignancies	L01	
Parkinson's disease	N04B, N04A	
Diabetes	A10A, A10B	Diabetes
Glaucoma	S01E	
Stomach Ulcers	A02A, A02B	Heartburn
Respiratory illness, asthma	R03	Chronic bronchitis, asthma
Thyroid disorders	H03A, H03B	
Chronic pain	N02A	
Anxiety and depression	N05B, N06A	Anxiety or depression
Alzheimer, dementia, psychotic illness	N06D, N05A	
Osteoporosis and Paget's disease	M05	Osteoporosis (non-hormonal)
Migraine	N02C	Other pains (such as headache, backache)

Figure 1: Predicted health by age and gender

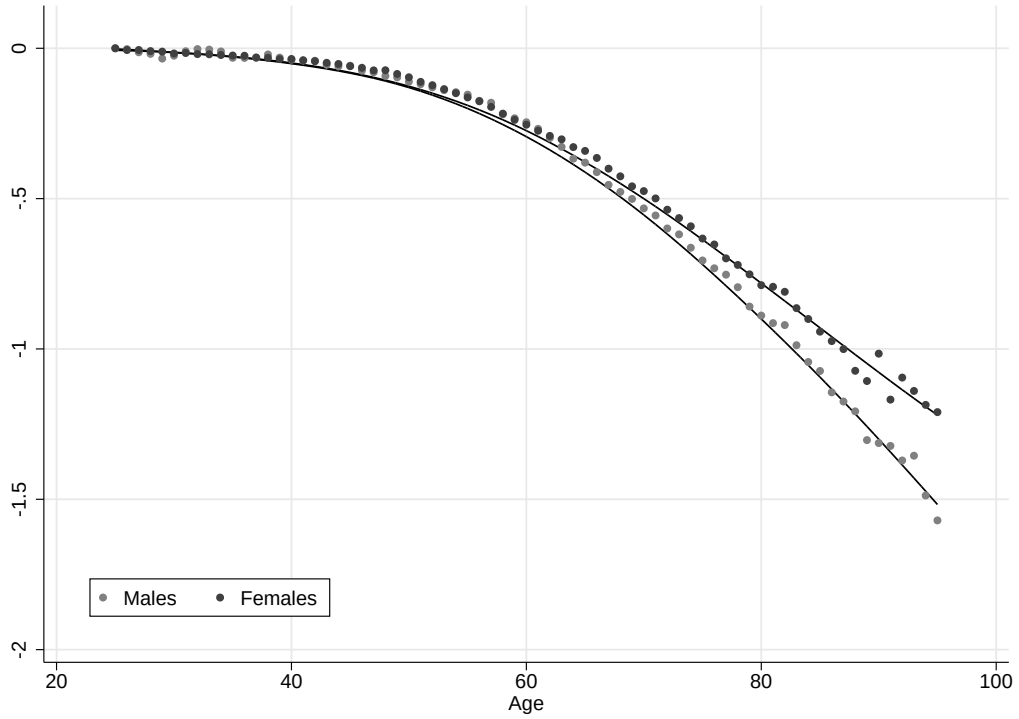

Figure 2: Predicted health by age and education - males

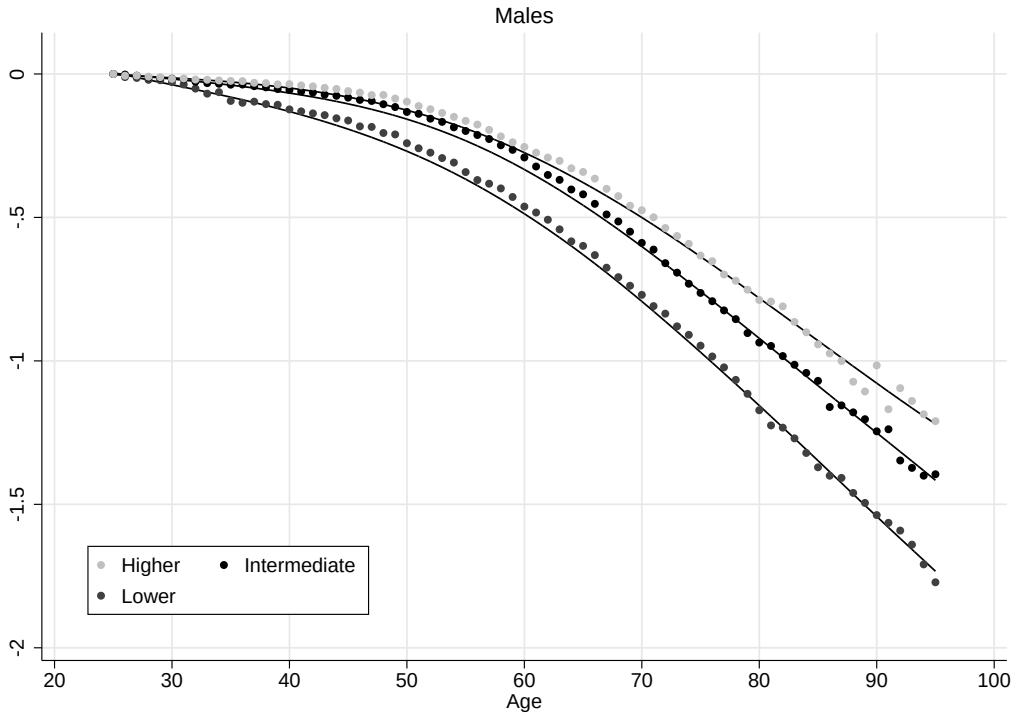

Figure 3: Predicted health by age and education - females