Income-related reporting heterogeneity inself-assessed health: Evidence from France

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Income-related reporting heterogeneity in subjective health: evidence from France

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Abstract

This paper tests for income-related reporting heterogeneity in self-assessed health (SAH). It also constructs a synthetic measure of clinical health to decompose the effect of income on SAH into an effect on clinical health (which is called a health production effect) and a reporting heterogeneity effect. We find health production effects essentially for the low-income individuals, and reporting heterogeneity for the choice between the medium labels i.e. "fair" vs. "good" and for the high-income individuals. As such, SAH should be used cautiously for the assessment of income-related health inequalities in France. It is however possible to minimize the reporting heterogeneity bias by dichotomizing the SAH variable into a poor health / other health statuses distinction.

1 Introduction

Inequalities in terms of health outcomes, payment and access have been the subject of a lively literature in Economics (Wagstaff and van Doorslaer, 2000). The calculation of health outcome inequality requires a good measure of individuals' state of health. This paper assumes that the key variable of interest for the design of public policies is **clinical health**[1] Suppose now that Health Authorities need a tool for monitoring income-related health inequalities. Such a tool should enjoy the following properties: on the one hand the measure of clinical health should be reliable, on the other hand the data should be collected at a low cost. The latter is especially important for Health Authorities that operate at a local level, because they may not have a lot of resources to devote to the follow-up of health inequalities. In this perspective, self-assessed health measures, which

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[1] By "clinical health", we mean health as it is defined by health institutions.

are subjective measures of health, may be interesting. However, it has become apparent in recent years that their reliability is questionable, because different sociodemographic groups tend to perceive their health differently even when their clinical health is the same. The term “reporting heterogeneity” is often used to qualify this phenomenon, as in Shmueli (2003), but this heterogeneity may be considered as a bias in the sense that subjective health is a biased measure of clinical health.[2] The presence of reporting heterogeneity.in self-assessed health in France is the key concern of this methodological paper. More specifically, we ask whether there is income-related reporting heterogeneity, since this point is crucial for the measurement of health inequalities.

We suppose that clinical health is a random variable $\tilde{H}_i$ (i is an index for the individual), and consider a reporting device $T(.)$, such that the level of health reported for the agent, H_i, may be written as:

$$H_i = T[\tilde{H}_i; Q_i] \tag{1}$$

where $T(.)$ is a monotone transformation of $\tilde{H}_i$, for a given set Q_i of individual- and method-specific factors, observable or unobservable, affecting reporting at the time of the survey. When the reporting device $T(.)$ is designed so as to be independent of individual characteristics, one can claim to have an objective measure of clinical health. An important benefit of objective health measure is their inter-personal comparability: for two individuals i and j we have $H_i > H_j \Longrightarrow \tilde{H}_i > \tilde{H}_j$. However, there are a number of costs associated to the use of any objective health measure. First, there are expensive to collect, since the construction of a synthetic measure requires that a number of health conditions be observed. Data collection can be based either on a costly device of medical check-ups, which may induce a strong selection bias, or on the information that the agent has available. In the latter case, since information results from the individual's choice to collect information (*via* preventative health consultations for example), the evaluation of health capital is potentially polluted by individual preferences. Second, any synthetic health measure requires the weighting of diverse medical criteria, and thus incorporates the individual preferences of a sub-sample of the population (Gerdtham *et al.*, 1999, Dolan, 2000). However, as Wagstaff and van Doorslaer (2000) note, what is important is not that such a synthetic health measure include preference factors, but rather that it should be as independent as possible of vested interests.

Measuring subjective health is much more cheaper. One widespread measure of subjective health is obtained by asking individuals to evaluate their health on an ordinal scale. This self-assessed health measure is easy to collect and is strongly correlated with a number of measures of morbidity and mortality (see

[2] Other articles evoke “state-dependent reporting bias” (Kerkhofs and Lindeboom, 1995), and “scale of reference bias” (Groot, 2000). The epidemiological literature uses the more technical term of “response category cut-point shift” (Sadana *et al.*, 2000 and Murray *et al.*, 2001; also used by Lindeboom and van Doorslaer, 2004).

Idler and Benyamini, 1997, and van Doorslaer and Gerdtham, 2003). However, Kerkhofs and Lindeboom (1995) emphasise that the responses to such questions, which translate underlying clinical health into a subjective measure, are subject to considerable heterogeneity: individuals may have different reference points for this evaluation, which may also change over time. There are indeed a number of reasons why individual preferences may affect subjective health evaluations. Individuals may differ in their reaction to physiological symptoms according to their social status, which then affects their decision to consult a doctor (Boltanski, 1971, Murray *et al.*, 2001). A given clinical health status will be appreciated differently according to both the cultural and historical context, and the phenomenon of habituation which plays on individual expectations with respect to health (Johansson, 1991, Heyink, 1993, Wu, 2001).[3] Last, the survey itself may introduce systematic measurement biases.[4] When the transformation function $T(.)$ is dependent of individual Q_i variables we do not have ordinal interpersonal comparability of reported health. This problem becomes crucial for the measurement of income-related inequalities in clinical health when $T(.)$ depends on income. For instance, the strong positive correlation between income and subjective health, could just as well reflect an optimism bias which rises with income as a positive effect of income on the production of clinical health. Then, the clinical health-income relationship is confounded by reporting heterogeneity, and the methods developed *inter alia* by Wagstaff and van Doorslaer (1994) or Kakwani *et al.* (1997) are no longer valid.

A number of papers in Health Economics have already considered income-related reporting heterogeneity in subjective health. Current results are mixed. For instance, Humphries and van Doorslaer (2000), using Canadian data, report some results, which indicate that there is a pessimism reporting bias for lower income individuals. On the same data set, Lindeboom and van Doorslaer (2004) find reporting heterogeneity linked to income for young men with lower education. Last, Hernandez-Quevedo *et al.* (2004), using British data, find optimism bias amongst better-off respondents. Hence, the magnitude and the sign of reporting bias seem to be country-specific. In the perspective of international comparisons, it is worth testing if there are also income-related reporting bias in France. By concentrating on reporting heterogeneity linked to income, we underline the inherent problems in relating health inequality to income inequality when only subjective measures of health are available.

This article uses French data from the 2001 Conditions de Vie des ménages survey to test reporting heterogeneity in subjective health. Our measure of H_i is an individual judgement, whereby the respondent classifies her health using ordered qualitative labels such as "very good ", "good" and so on: H_i is thus an ordered qualitative variable with M levels. Using specific identifying assumption, we are able to test for reporting heterogeneity. However, we would also like to assess the magnitude of reporting heterogeneity, which is quite difficult

[3] Sadana *et al.* (2000) note that, in European Community Household Panel data from 1994, 53% of the Danish say they are in very good health, as compared to only 8% of the Portugese.

[4] Crossley and Kennedy (2002)

in the absence of any exact measure of objective health. As such, the correlation between income and subjective health is composed of the effect of income on objective health, and the effect of income on judgement, *i.e.* the choice of a qualitative verbal label that the individual uses to describe her objective state of health. In the current paper, we follow Kerkhofs and Lindeboom (1995) and Lindeboom and van Doorslaer (2004) by using a proxy measure of clinical health to identify reporting heterogeneity. While the papers cited above use pre-defined measures (the Hopkins Symptom Checklist and the Health utility Index respectively), we construct a synthetic index based on a classification of individuals resulting from a latent class analysis of a number of clinical health conditions self-reported in our data. We then attempt to decompose the effect of income on H_i into an effect on $\hat{H}_i$ and an effect on the transformation $T[.;Q]$ of $\hat{H}_i$ into H_i. This decomposition allows us to assess the magnitude of reporting heterogeneity.

Our main finding is that there is substantial income-related reporting heterogeneity in subjective health in France. Our estimates also reveal that the "effect" of a rise in income on subjective health varies according to the individual's initial income and initial subjective health level.[5] Three results should be emphasised. First, for individuals at the bottom of the income distribution reporting a poor subjective health, income affects significantly subjective health *via* clinical health. Furthermore, a fall in income has a strong negative reporting effect on the richest reporting a good or a very good health. Last, it is the choice between the medium labels ("fair" *vs.* "good") which seems to be the most affected by reporting heterogeneity, whatever the income level. Hence, the utilisation of subjective health information may bias the measure of health inequality, except if one is willing to dichotomize appropriately the subjective health measure, the bottom category ("poor") being taken as a reference.

The paper is organised as follows. Section two explains the method. Section three presents the data. The results are found in Section four, and are discussed in Section five. Section six concludes.

2 Models and Methods

2.1 Specification

We suppose that clinical health $\hat{H}_i$ is linked to the information set X_i by a linear index equation :

$$\hat{H}_i = \alpha_0 + X_i\alpha + \varepsilon_i \tag{2}$$

[5] The rest of the paper uses the term "effect" somewhat abusively, since income is potentially endogenous: health influences productivity, and unobservable factors such as time preference may affect simultaneously investment in health and career choices. See Adams *et al.* (2003) for a thorough treatment of this question.

where α is a vector of parameters and e_i is an error term capturing inobservable terms. To measure the effect of income on $\tilde{H}_i$, we have to identify α in equation (2). The reporting equation linking the observable variables is:

$$H_i = T[\alpha_0 + X_i\alpha + \mathsf{e}_i; Q_i] \tag{3}$$

The function $T(.;.)$ and the error term e are thus nuisance parameters.

When there is common agreement regarding evaluation of subjective health, i.e. when everyone agrees on what it means to be in very good/good/.../poor health, the interpersonal comparability of health is assured. The relation (3) reduces to $H_i = T[\alpha_0 + X_i\alpha + \mathsf{e}_i]$. We can then suppose that there exist cutpoints $s_0, s_1..., s_M$ such that

$$\begin{aligned} s_0 &= -\infty, s_M = \infty, \\ \forall m &= 1, ..., M, \quad H_i = m \iff s_{m-1} \leq \tilde{H}_i \leq s_m \end{aligned}$$

with the identification restriction $\alpha_0 = 0$: when e_i is distributed normally, this relation defines the ordered probit model.

We can relax the hypothesis of common agreement by supposing that the cutpoints are idiosyncratic $s_{i0}, s_{i1}..., s_{iM}$ such that

$$\begin{aligned} s_{i0} &= -\infty, s_{iM} = \infty, \\ \forall m &= 1, ..., M-1, \quad s_{im} = Q_i\beta_m \\ \forall m &= 1, ..., M, \quad H_i = m \iff s_{im-1} \leq \tilde{H}_i \leq s_{im} \end{aligned} \tag{4}$$

where β_m are additional parameters, and Q includes a constant (Terza, 1985; Kerkhofs and Lindeboom, 1995; Groot, 2000; Lindeboom and van Doorslaer, 2003; Hernandez-Quevedio et al., 2004). The model defined by equations (2) and (4) is a generalised ordered probit (Pudney and Shields, 2000). Reported health H_i then depends on the way in which clinical health $\tilde{H}_i$ is translated by the cutpoints $(s_{i0}, s_{i1}..., s_{iM})$. This model, in which the cutpoints depend on observable variables, is particularly well-suited to cross-section data. In panel data, it is possible to estimate semi-parametric ordered logit models in which the cutpoints are individual nuisance parameters (Ferrer-i-Carbonell and Frijters, 2004).

2.2 Testing for reporting heterogeneity

The generalised ordered probit model poses substantial interpretation problems when Q_i and X_i overlap. In this case, a movement in income can affect both reporting (i.e. the transformation of $\tilde{H}_i$ into H_i) and clinical health $\tilde{H}_i$. The specification we use renders the separation of these two effects impossible. To illustrate the problem, note that the probability of observing reply m can be written as:

$$\Pr(H_i = m) = F[Q_i\beta_m - X_i\alpha] - F[Q_i\beta_{m-1} - X_i\alpha] \quad (5)$$

where $F(.)$ is the distribution function of the unobservable $\mathbf{e}_i$. This probability can also be written for any vector of parameters δ as:

$$\Pr(H_i = m) = F[Q_i(\beta_m+\delta)-(X_i\alpha+Q_i\delta)]-F[Q_i(\beta_{m-1}+\delta)-(X_i\alpha+Q_i\delta)] \quad (6)$$

or again for any couple of vectors α_1 and α_2 such that $\alpha = \alpha_1 + \alpha_2$ as:

$$\Pr(H_i = m) = F[(Q_i\beta_m - X_i\alpha_1) - X_i\alpha_2] - F[(Q_i\beta_{m-1} - X_i\alpha_1) - X_i\alpha_2)] \quad (7)$$

The structural models associated with these probabilities differ with respect to the specification of the cutpoints s_{im} and the modelisation of $\hat{H}_i$. For the models associated with equation (6) we have $\hat{H}_i = X_i\alpha + Q_i\delta + \mathbf{e}_i$ and $s_{im} = Q_i(\beta_m + \delta)$; for those associated with (7) we have $\hat{H}_i = X_i\alpha_2 + \mathbf{e}_i$ and $s_{im} = Q_i\beta_m - X_i\alpha_1$. Hence equation (2) is only identified if Q_i and X_i are orthogonal to each other. The results from the literature show that it is difficult to classify *a priori* variables as belonging exclusively to X_i or Q_i. The model does not yield an *a posteriori* classification either. Any variable which has an effect on $\hat{H}_i$ also potentially influences the cutpoints (see the equivalence between equations (5) and (7)). Consequently the hypothesis of interpersonal comparability is not testable. Analogously, any variable playing a role in the determination of the cutpoints may equally affect $\hat{H}_i$ (see the equivalence between equations (5) and (6)).

The generalised ordered probit model does however allow us to conclude that a variable affects individual reporting if it has a heterogeneous effect on the different cutpoints. A variable has a heterogeneous effect on the cutpoints if the coefficients β_m associated with this variable vary according to the cutpoint m, which can be shown by a Hausman test of the equality of coefficients of the cutpoints (Pudney and Shields, 2000). In the rest of this article, we shall call this test **Test 1**.

Focusing on income-related reporting heterogeneity, **Test 1** may reject homogeneity of income effects, and thus accept reporting heterogeneity, because the link between income and $\hat{H}_i$ is badly specified. Let Y_i denote income and Z_i the other variables, and $X_i = (Y_i, Z_i)$. Suppose for example that this relationship is actually concave (for example $\hat{H}_i = \alpha_1 \log(Y_i) + \alpha_2 Z_i + \mathbf{e}_i^1$). In this case, we will certainly find a heterogeneous effect of income on the cutpoints, corresponding, at least in part, to variations in the effect of income on clinical health $\hat{H}_i$ in the region of the cutpoints (*cf.* Figure 1).

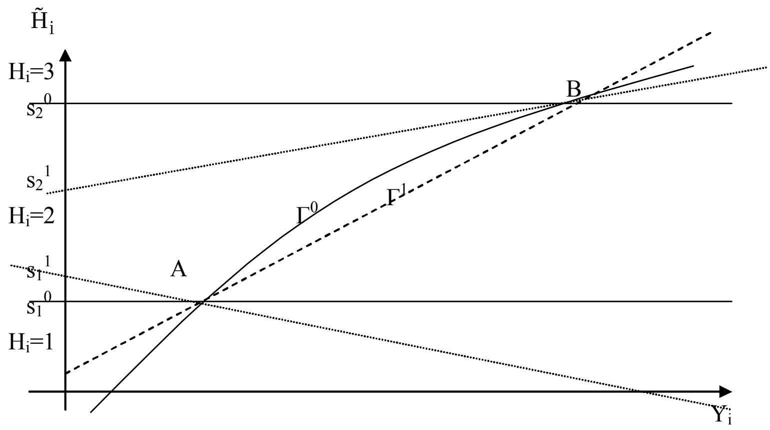

Figure 1. Specification error and estimation bias.

In Figure 1, the real model is shown by a continuous fine line. The real relation between income Y_i and clinical health $\tilde{H}_i$ is concave (the curve Γ^0). The cutpoints are represented by horizontal lines which are independent of income (the horizontal lines s_1^0 and s_2^0). The identification of the model depends crucially on the information brought by individuals who are close to the intersection of the cutpoints and the health production curve (points A and B). The curve Γ^1 corresponds to a model specifying a linear health production function. The effect of income actually only works through the production of clinical health, an effect which differs according to whether we are close to point A or to point B. With a linear specification of health production, this effect can be decomposed into an effect on clinical health which is identical at points A and B, and a different effect on each cutpoint, which effects will depend on income. Hence, close to A, the real impact of income on clinical health is greater than the slope of Γ^1: there is therefore a compensation via a negative effect of income on the cutpoint. As such, we will find a heterogeneous effect of income on the cutpoints. We are thus fully aware that we identify reporting heterogeneity only under the following assumption:

Hypothesis 1 The relationship between income and clinical health $\tilde{H}_i$ is correctly specified.

To guard against a potential specification bias, we use a set of eight dummy variables measuring household income: the relationship between income and clinical health is thus specified in a very flexible manner.

2.3 Assessing the existence of reporting heterogeneity

Using the generalised ordered probit model, we first test for the presence of income-related reporting heterogeneity. For this, as emphasized previously, we rely on the assumption that the variables with a heterogeneous effect on the cut-points affect the reporting of clinical health.

Suppose that (2) is a reduced form equation for health capital production: X_i only includes prices and resources (financial, educational, social) affecting health investment. This is the approach taken by van Doorslaer and Jones (2003) and Hernandez-Quevedo et al. (2004). It allows us to show that some variables including income has a heterogeneous effect on the cutpoints. We hence estimate specification **(A)**, which satisfies **Hypothesis 1**:

$$\hat{H}_i = \alpha_1 Y_i + \alpha_2 Z_i + \varepsilon_i^1 = \alpha X_i + \varepsilon_i^1$$

$$\begin{aligned} s_{i0} &= -\infty, s_{iM} = \infty, \\ \forall m &= 1, ..., M-1, \quad s_{im} = \beta_m^1 Y_i + \beta_m^2 Z_i = \beta_m X_i \\ \forall m &= 1, ..., M, \quad H_i = m \iff s_{im-1} \leq \hat{H}_i \leq s_{im} \end{aligned} \tag{8}$$

All of the variables here potentially influence both the cutpoints and clinical health. By supposing that ε_i is distributed normally with variance σ_ϵ^1, the probability of observing reply m can be written:

$$\Pr(H_i = m) = \Phi\left(\frac{(\beta_m - \alpha)}{\sigma_\epsilon^1} X_i\right) - \Phi\left(\frac{(\beta_{m-1} - \alpha)}{\sigma_\epsilon^1} X_i\right) \tag{9}$$

As the variance σ_ϵ^1 of the residuals is normalised to 1 for estimation, this specification allows us to identify $\gamma_m = \frac{(\beta_m - \alpha)}{\sigma_\epsilon^1} \forall m = 1, ..., M-1$ (including, for the income, $\gamma_m^1 = \frac{(\beta_m^1 - \alpha^1)}{\sigma_\epsilon^1}$), and to carry out **Test 1** of the equality of the cut-points. Specification **(A)** will thus help us to test for reporting heterogeneity, by determining the variables that have an heterogeneous effect on the cutpoints. However, it is impossible to identify the variables that have an homogeneous effect on the cut-points.

Without additional hypotheses it is difficult to interpret the effect of a variable for which the coefficients β_m are not identical for each m: such a variable has a non-linear effect on the cutpoints (a reporting effect) but could also have a linear effect on clinical health. A number of different strategies can be imagined to overcome these difficulties of interpretation. Groot (2000) supposes that for all individuals $s_{i1} = 0$: one of the two extreme subjective health categories constitutes a common anchoring point. This hypothesis allows us to identify separately α and a part of the β_m. van Dooslaer and Jones (2003) appeal to the correspondance, for any sub-group of the population, between the distribution of subjective health and the distribution of a synthetic measure of clinical health, the Health Utility Index.[6]

In the current paper, we are interested in both the identification of the effect of variables including income on $\tilde{H}_i$ as well as the income effect on the cutpoints. To achieve this goal, we adopt a third strategy proposed by Kerkhofs and Lindeboom (1995) and Lindeboom and van Doorslaer (2004): the use of a proxy measure of clinical health.

2.4 Assessing the magnitude of reporting heterogeneity

Now imagine that (2) is a measurement equation. Including in X_i a synthetic measure of clinical health that has by assumption no effect on the cut-points will help us to isolate the income-related reporting heterogeneity. In this line, Kerkhofs and Lindeboom (1995) use the Hopkins Symptom Checklist and Lindeboom and van Doorslaer (2004) use the Health Utility Index. As we do not have a ready-made measure available, we construct our own by a latent class analysis of a number of self-reported clinical health conditions. One may argue that, instead of using a synthetic measurement index constructed from a set of clinical health measures,we could drop directly all these clinical measures in equation (2). However, a number of findings suggest that some clinical health conditions may have a specific impact on the way the individuals perceive their health (see, for instance, Wu, 2001). Using a synthetic proxie measure of clinical health yields two benefits here. First, it keeps the model parsimonious. Second, we can detect the clinical health conditions that have a heterogeneous effect on the cut-points and, as such, are likely to affect reporting.

Let H^0 be this synthetic measure of clinical health for which the following conditional mean independence condition holds:[7]

Hypothesis 2

$$E(\tilde{H}|H^0, Y, Z) = E(\tilde{H}|H^0, Z)$$

Specification **(B)** then consists of the following equations:

$$\tilde{H}_i = \delta_1 H^0 + \delta_2 Z_i + \varepsilon_i^2$$

$$\begin{aligned} s_{i0} &= -\infty, s_{iM} = \infty, \\ \forall m &= 1, ..., M-1, \quad s_{im} = \beta_m^1 Y_i + \beta_m^2 Z_i = \beta_m X_i \\ \forall m &= 1, ..., M, \quad H_i = m \iff s_{im-1} \leq \tilde{H}_i \leq s_{im} \end{aligned} \tag{10}$$

[6] They investigate the effect of age, sex and disabilities on reporting heterogeneity. To achieve this objective, they define appropriate sub-groups by crossing indicators for age, sex and/or disabilities. If, for instance, 25% of individuals in a sub-group report a poor health, then the 25th percentile of the empirical distribution function of the health utility index in the subgroup is the threshold for the choice between the "poor" and the "fair" labels.

[7] Note that hypothesis 2 may be replaced by a more stringent assumption (see Kerkhofs and Lindeboom, 1995): $\text{p.d.f.}(\tilde{H}_i | H^0, Y_i, Z_i) = \text{p.d.f.}(\tilde{H}_i | H^0, Z_i)$

Here, we assume for the sake of parsimony that H^0 picks up only the effect of income on clinical health. This is why we keep the Z_i variables in the health production equation.

Letting β_m^1 be the coefficient associated with the income variable for the cutpoint (i.e. $s_{im} = Y_i\beta_m^1 + Z_i\beta_m^2$), this second specification allows us to identify $\gamma_m'^1 = \frac{\beta_m^1}{\sigma_2^2}$. The variance σ_ϵ^2 of the residual $\hat{e}_i^2$ being *a priori* different from one specification to another, the direct comparison of the coefficients γ_m^1 and $\gamma_m'^1$ resulting from the estimation of **(A)** and **(B)** does not permit us to identify the effect of income on $\hat{H}_i$. Indeed, H^0 contains certainly more information on $\hat{H}_i$ than does income, for, in this case, $\sigma_\epsilon^2 < \sigma_\epsilon^1$. The hypothesis of equality of variance being strong, we compare the marginal effects of income between specifications **(A)** and **(B)**. Under **Hypothesis 2**, specification **(B)** identifies the effect of reporting heterogeneity on income, and comparing marginal effects between the two specifications enables us to evaluate the impact of income on the production of clinical health at different levels of income and subjective health.

3 Data

We test for reporting heterogeneity in subjective health in France, by using data from the "Enquête Permanente sur les Conditions de Vie des Ménages" survey, carried out by the INSEE in 2001. This survey contains informations at both the household and the individual level. In particular, we have various household indicators (housing and financial situation amongst others) and the usual socio-demographic informations on three household members drawn randomly in each household. Last, one randomly-drawn individual in each household answers a health questionnaire. The final sample consists of 5194 individuals in the same number of households.

It is difficult to construct clinical health indicators which are valid for both younger and older adults, due to the natural depreciation of health with age, as is suggested by the existence of specific health measures for the elderly. This is why respondents aged over 65 were dropped.We analyse the sub-sample of respondents having finished their schooling and under 65 years of age at the time of the interview, so as to use the variables referring to education and household structure. Given the missing values, this leaves us with a sample of 2956 individuals.

This section presents descriptive statistics regarding the key variables, as well as the method that we use to construct a synthetic indicator of clinical health.

3.1 Subjective Health and Income

Subjective health is measured by the question "Would you say that your current health status is very good, good, fair, poor, bad, very bad ". The last three ordered response categories have been grouped together due to small cell sizes. The subjective health variable thus consists of four ordered categories: very good, good, fair, poor.

In the estimation sample, 52% of respondents say that they are in good health, and only 6% in poor health. Women are more likely to say that they are in poor health than men: 7.1% vs. 4.5% respectively. There are two distinct periods in the evolution of subjective health with age: up to the age of 40, health is good, and the variance of self-reported health decreases with age; afterwards there is a gradual degradation of self-reported health with age, with increasing variance.

We tested variables such as social class, debt, and labour market status to capture individuals' economic and financial status. Preliminary analyses reveal that the variables which were the most strongly correlated with clinical and subjective health were education and income.

Education is measured by four dummy variables for: no qualifications, CEP or Brevet des collèges (QUAL1); a short or long technical qualification (CAP, BEP, Technical or Vocational Baccalauréat: QUAL2); a general Baccalauréat (QUAL3 equivalent to a A-level); or higher education (QUAL4). Subjective health is positively correlated with education. In particular, the least-educated individuals are more likely to say that they are in "poor" health than the other respondents (11.3 against 4 respectively).[8] This correlation probably reveals an age effect, with older respondents likely being on average less well-educated due to the increasing access to secondary and higher education over the past thirty years. However, older respondents are also richer. Multivariate analyses in the following section allow us to distinguish between the two explanations.

Income is defined at the **household** level. It is a a yearly income, net from social contributions, and not equivalized. It is measured by nine categorical variables: under 9,000 Euros/year (noted as INCOME1), from 9,000 to 12,000 (INCOME2), from 12,000 to 15,000 (INCOME3), from 15,000 to 18,000 (INCOME4), from 18,000 to 22,500 (INCOME5), from 22,500 to 27,000 (INCOME6), from 27,000 to 36,000 (INCOME7), from 36,000 to 45,000 (INCOME8), over 45,000 (INCOME9). A higher level of household income is associated with a better level of subjective health (see Figure A2, Appendix A).

The correlation between income and subjective health may reflect two different kinds of effects. First, higher income is associated with a better clinical health, via greater investment in health. Second, for a given clinical health status, perceived health status may rise with income, perhaps because the individual feels more secure. This paper proposes a test of the two explanations.

[8] The 2001 reform of health coverage, which afforded everyone the same health coverage regardless of their income only came into effect at the time the survey was carried out, and is unlikely to affect the socio-economic gradient.

3.2 Clinical Health Measures

The estimation of specification **(B)** requires a measure of clinical health. The PCV 2001 survey includes a number of different questions regarding individual physical and psychological health.

We know about the serious or chronic illnesses from which the individual suffers. Subjective health is worse when the individual suffers, or has suffered, from one of the more common serious illnesses: "nervous" illnesses, problems of the digestive system, paralyses, cancers, cardio-vascular problems, or musculo-skeletic troubles. Nervous illness and paralyses are the most strongly associated with lower levels of subjective health.[9] Other clinical health variables are used: teeth and eyesight problems, being currently treated for an illness, having had a fever of over $39°c$ in the past year, four dummy variables for weight (thin, normal, overweight, obese).As these measures are self-declared, we may worry that they reflect income-related heterogeneity in individual access to health, and therefore the information that individuals possess. Indeed, a number of these variables are strongly correlated with income, which determines access to healthcare. Replies to these questions could indicate both clinical health problems and inequities in the access to health care.[10] In France, everyone is covered by Social Security with a reimbursement rate of 75%, and 92% of the French population have additional health insurance. Finally, the most costly diseases are treated in hospital, which reduces drastically the individual cost of health. Only teeth and eyesight cares are poorly reimbursed by social security.

The use of psychological health variables (feelings of loneliness, self-reported stress, psychiatric treatment) is also open to criticism. However, the mental well-being is an important dimension of health, and several measures of clinical health, such as the Health Utility Index, include psychological measures in their construction, as well as other self-reported health conditions.[11]

Last, we use several indicators that link clinical health to every day living, such as not being able to exercise, to work or to give blood, or having a limited mobility.

We use these self-reported clinical health conditions to build a synthetic index H^0. Alternatively, we could introduce all self-reported clinical health conditions in the vector X_i, in order not to loose information. But, first, our approach is more parsimonious in that we do not overload the model with too many parameters. Second, we test whether each self-reported condition has a specific impact on the thresholds, which we interpret as an evidence of adaptation or mis-adapatation to illness.

[9] Wu (2001) shows that ischemic illnesses affect not only clinical health, but also the perception that the individual has of her health. Those who have experienced heart attacks become more optimistic about their health, *ceteris paribus*. We will test for this result in our data.

[10] Poorer respondents experience health problems younger and may not be well-diagnosed by the health care system (Jougla *et al.* 2000).

[11] More generally, we propose here a "partial equilibrium" analysis that excludes feedbacks. For instance, self-reported health conditions are diagnosed by the medical institutions only if the individual visits a doctor. But visits to doctors are determined by income and the subjective perceptions of one's own health.

A number of different techniques can be used to sum up the information contained in these clinical health measures. The best-known are factor analysis, latent class analysis (LCA, see Bandeen-Roche *et al.*, 1997) and the Grade of Membership method (GoM, see Portrait *et al.*, 1999). The LCA and GoM approaches split the population up into classes, in such a way that the clinical health indicators are independent conditionally to class membership (Goodman, 1974, McLachlan and Peel, 2000). The LCA method supposes that probabilities of class membership are equal across individuals, contrary to the GoM approach. However, the asymptotic properties of the GoM method are unknown (there are more parameters than observations). Moreover, the only sure way of using GoM techniques is to hypothesise that the probabilities of class membership follow a certain distribution, which imposes parametric restrictions (Erasheva, 2002). This is one reason why we appeal to LCA analysis, which is presented in Appendix B.

We choose to classify the sample into 6 latent classes, which can be considered as ordered with reference to the mean values of the clinical health variables in each class. The first two classes, which represent 40.7% and 15.2% of the sample, are characterised by the absence of serious health problems. However, individuals in the second group are all overweight. The large percentage figure of those with no chronic disease is explained by the absence of individuals aged over 65. The third class accounts for 13.7% of the sample, with members who are not ill, but are more likely to spend time in hospital, see their doctor and take medicines regularly, take more time off of work, and are more likely to suffer psychologically (feeling alone or stressed). The fourth class covers 17.6% of the population, and is similar to the third class, but more so. Restrictions on giving blood and ischemic illnesses are more frequent. The third and fourth classes consist of individuals with pathologies that are treated *via* preventative actions. The last two classes include individuals who are most likely to report the health problems we consider, with a slight difference between the two groups. In the fifth class (6.5% of the sample), the probability of psychological problems is higher, while in the sixth class (6.3% of the sample), physical health problems are more prevalent: difficulties in walking, not being able to take part in sporting activities, a diminished ability to work, needing help (see Table A.2. in Appendix A).

In the regressions, we introduce the estimated probabilities that the individual belongs to each one of the six classes. The omitted category is the first class, that of individuals with no serious health problems.

3.3 Other control variables

It is possible that local cultural effects explain both differences in clinical health and the degree of optimism that the individual expresses about her health. The health Atlas in France shows sharp differences in mortality rates between regions (Salem *et al.*, 1999). We include as explanatory variables the region and classification of residential area: rural (STRATA1), urban with under 20 000 inhabitants (STRATA2), urban with between 20 000 and 100 000 inhabitants (STRATA3), and urban with over 100 000 inhabitants (STRATA4). Paris is considered separately as living in Paris induces very specific living conditions in comparison to the rest of Ile de France. For instance, while commuting times are lower for Parisians, they face very specific environmental conditions (more pollution and more noise), housing is much more expensive, etc.. In addition, we introduce controls for the individual's family situation.

4 Estimation results

In this section we present in turn the results of generalised ordered probit estimation of specifications **(A)** and **(B)**. We then consider the robustness of our results, and decompose the marginal effect of income into an effect on clinical health and reporting heterogeneity.

Tables C1 and C2 in Appendix C show the estimation results. Table C1 presents the results for the variables which, in specification **(A)**, have a homogeneous effect on the cutpoints, according to **Test 1**, which is applied to each group of variables separately, i.e. we test regional dummies, then sex, then age etc. Table C2 shows the results with respect to the variables which do have different effects on the different cutpoints. For each specification, the first column shows, for comparison purposes, the results from simple ordered probit estimation with common cutpoints. The second column shows estimation results from generalised ordered probit models. In Table C2, for each specification, columns 2 to 4 show the results for the three cutpoints with a sign reversal to ease the interpretation in terms of health effects (i.e. coefficients $-\beta_1, -\beta_2, -\beta_3$).

4.1 The socioeconomic determinants of health

Specification **(A)**, which does not include informations on clinical health, allows us to measure the correlations between our socioeconomic variables and subjective health. Sex, age (measured as a three-order polynomial)[12], education, and type of residential area have the same effect on cutpoints. However, family situation, region and income have a heterogeneous effect on the cutpoints.

The results of a simple ordered probit, which does not take into account reporting heterogeneity, are fairly standard (the first column of Table C1): male has a positive estimated coefficient on reported health, as does income or living in the West of France. On the other hand, lower levels of education attract negative coefficients. The results of the generalised ordered probit are more judicious (second column of Table C1). In particular, amongst the variables which

[12] We tested for a break in the age trend at age 40, as indicated by our descriptive analysis of the age/self-assessed correlation. It turns out that, everything else being equal, there is no significant break. Other econometric specifications of the age effect were tested with no significant improvement.

do not affect the cutpoints, only sex and being unqualified are significant: males are more likely to say that they are in good health. Having no education has a negative effect and, as we are controlling for income, this result is consistent with a basic assumption of the demand for health model: the efficiency of health production rises with education (Grossman, 1972). However, age is insignificant at the ten per cent level. This may result from the exclusion of those aged over 65.

While the two variables best characterising household structure have no significant effect on individual perceptions of health, this is not true for the region dummies. The omitted category is living in Paris. Living in the Ile-de-France (outside of Paris) is associated with a smaller cutpoint between poor and fair health, showing a lesser tendency to declare oneself in poor health. Those living in the West, as opposed to those living in the East or the North, are also less likely to say that they are in poor or fair health.

There is a positive correlation between subjective health and income. Being poor (income categories 1 to 3 out of 9) is negatively correlated with the declared level of health, the estimated coefficients being significant for all of the cutpoints. While poverty increases the probability of being in poor health, those in middle or higher income classes are not significatively more or less likely to report a poor health: income does not protect against poor health, it is rather poverty that is a risk factor for poor health. There is also a significant difference between the effect of being in the medium income categories (4 to 6) and the high income classes (categories 7 to 9) on the probability of reporting a very good health. In sum, the hypothesis of a homogeneous correlation of income with the cutpoints is rejected in favour of heterogeneous correlations (**Test 1**, P-value=0.020). Hence, under **Hypothesis 1**, there is income-related reporting heterogeneity in subjective health.

4.2 Clinical and Subjective Health

Specification **(B)** introduces the clinical health measure constructed in subsection (3.2), which allow us under **Hypothesis 2** to identify income-related reporting heterogeneity.

The results from specification **(B)** are presented on the right-hand side of Tables C1 and C2 in Appendix C. Following Kerkhofs and Lindeboom (1995) and Lindeboom and van Doorslaer (2004), we introduce our synthetic measures of clinical health into the index only (equation (2)). As a number of articles have evoked the phenomenon of habituation to health problems (or coping), we also test the impact of clinical health conditions on the cutpoints, so as to identify any potential heterogeneous effects. We only retain in specification **(B)** the variables for which we have identified such a heterogeneous effect on the cutpoints.

The coefficients on the different classes of clinical health exhibit the expected negative relationship, given the description of these classes above: the relationship between clinical and subjective health is monotone positive. While low education is associated with poorer health, sex no longer has an impact on health. Living in the West of France or in Greater Paris is associated with a probability of declaring oneself in poor or fair health, but no effect on the probability of declaring oneself in very good health.

Five measures of health conditions have a heterogeneous effect on the cutpoints. Having stayed in hospital, regular examinations due to an illness or being advised against certain sporting activities affect the probability of reporting a poor or fair health, but not the the probability of declaring oneself in very good health. Having heart problems reduces the probability of declaring oneself in poor health, without affecting the probability of declaring oneself in good or very good health. This recalls the results in Wu (2001) regarding hedonic adaption to cardio-vascular health problems. Last, feelings of stress have a negative effect on subjective health, but more so on the probability of the respondent saying that they are in fair or poor health.

In this specification, income always has a positive but heterogeneous effect on the cutpoints (with a $P-value$ of 0.023 for **Test 1**). This result is of interest because it differs from that in Lindeboom and van Doorslaer (2004) on Canadian data, who find heterogenous effects for age and sex, but not for income. The difference in results between countries might be interpreted as reflecting heterogeneity in reporting between countries. The following section considers in more detail the relationship between subjective health and income, paying particular attention to the the distinction between reporting heterogeneity and health production effects.

5 Health production *vs.* reporting

The only way to have an idea of the effect of income on health production is to compare the marginal effects between the two specifications. Specification **(A)** shows the total marginal effect of income on subjective health, while specification **(B)** indicates the marginal effect of income *via* reporting heterogeneity. The difference between the two yields the effect of income on the production of clinical health. On this basis, we describe how reporting heterogeneity affects the predicted distributions of subjective health, and we provide some evidence in favour of non-linearities in income effects by initial level of health.

5.1 Reporting heterogeneity

Using specification (B), we compare the distributions of predicted health level for an individual with the average sample characteristics including the mean sample clinical health. For each level of subjective health m, we compute the following changes in the probability of reporting health greater than m :

$$\Pr(H > m|Y = j+1, H^0 = \overline{H^0}, Z = \overline{Z}) - \Pr(H > m|Y = j, H^0 = \overline{H^0}, Z = \overline{Z})$$

Under **Hypothesis 1**, these variations represent the way reporting heterogeneity affects the distribution of subjective health for the average individual. Figures D.1. to D.3. in Appendix D report these probability changes for different values of m and j.

If we consider the changes greater than 1% in absolute values, one clearly note that reporting heterogeneity affects crucially the middle of the distribution of subjective health (fair and good). Reporting heterogeneity is also more important at the extremes of the income distribution. Whereas there is almost no income-related reporting heterogeneity for those reporting a poor health, we observe a strong reporting bias for the more affluent in very good health. This may be due to the specificity of the subjective health distributions in the right tail of the income distribution. As shown in Figure A.1., those in the 9^{th} income range (INCOME9=1) are less likely to report a good level of health and much more likely to report a very good level of health than those in the 8^{th} income range (i.e. with INCOME8=1). This peculiarity of our data explains that the gradient in the coefficients of the income dummies is fairly flat when one moves from INCOME2 to INCOME8 (between -0.567 and -0.369, see Table C.2. last column), but the coefficient of INCOME8 is itself quite high (-0.429). Hence, the marginal change of moving from INCOME8 to INCOME9 is very important in the right tail of the health distribution.

In the end, our estimates provide clear evidence in favour of the existence of income-related reporting heterogeneity. However, although a number of marginal effects are fairly large, our estimates are somewhat imprecise. Confidence intervals for these changes were calculated using the delta-method, at the level of 95% and 22 changes out of 24 are unsignificant for Specification **(B)**, 19 out of 24 for Specification **(A)**.

5.2 Decomposing the income effect

We now decompose the health-income total correlation in a health production effect and a reporting bias. The individual marginal effect is calculated as the impact of the transition from income category j to income category $j+1$ on the probability of declaring health greater than m. For specification **(A)**, it is:

$$\Delta_i^{(A)} = \Pr(H > m|Y = j+1, Z = Z_i) - \Pr(H > m|Y = j, Z = Z_i)$$

and for specification **(B)**, the individual effect is:

$$\Delta_i^{(B)} = \Pr(H > m|Y = j+1, H^0 = H_i^0, Z = Z_i) - \Pr(H > m|Y = j, H^0 = H_i^0, Z = Z_i)$$

These can be interpreted as the probability of leaving the health categories inferior or equal to m as the individual changes from income category j to $j+1$.

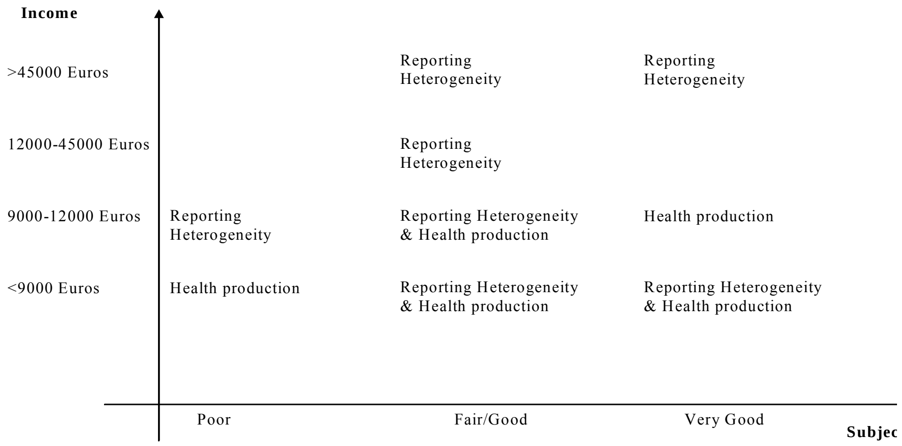

Figure 1: Summary of the results.

These marginal effects are calculated for each individual i and for specifications **(A)** and **(B).** For each j, we then average these individual effects over the sub-sample of those who are in income range j.[13] These mean effects are represented, with the difference between them, in Figures D.4. to D.6. in Appendix D, which correspond to the three health states in which the individual may initially find herself ($m = 1$, $m = 2$, and $m = 3$). The graphical representation of specification **(A)**, given by the dotted line, shows the total effect of income on health. The effect due to reporting heterogeneity results from specification **(B)**, and is shown by the thick black line. The thin line, which is the difference between these two, shows the effect of income on health production. For each individual, we are able to compute confidence intervals for the total marginal effects and the reporting heterogeneity effect.

Two important conclusions can be drawn from our estimates and are summarized in Figure 2. First, the health production effect of a rise in income seems particularly important for those in the lowest income range (under 12000 Euros), whatever the subjective health level m we consider. This is consistent with standard results of the literature on the health production effect of income among the poorest (Deaton, 2003). Second, computing mean marginal effects instead of marginal changes for the mean individual does not change our conclusion regarding reporting heterogeneity: the latter plays a very important role for transitions from a fair to a good health level, but a minor role for exits from a poor health level or transitions to a very good health level (except for the more affluent). This reporting heterogeneity is somewhat convex in income.

[13] The results are about the same when one averages the marginal effects over the whole sample rather than over the sub-sample of individuals in the "treated" income category.

Figures D7 and D8 report the percentage of individuals in each income category for which the reporting heterogeneity and the total effect of income are significant at the 5% level. It clearly shows that reporting heterogeneity is quite important for those in fair or good health whatever the income level, but also for those in poor health. The pattern is less easy to interpret for those in good or very good health, and in the middle of the income distribution (especially income categories 4 to 7).

6 Conclusion

This article has demonstrated the existence of substantial reporting heterogeneity in subjective health in France. Our estimates reveal that the reporting bais is convex in income and can be interpreted as an optimism bias. However, this result relies heavily on the assumption that all of the health production effect of income is captured by the introduction of the self-reported clinical health conditions available in the survey. The validity of this hypothesis may be questionable, since we may not capture all relevant income-related dimensions of clinical health. If there is a pro-rich bias in access to health cares as one may suppose, then the health production effect of income is underestimated, and the income-related reporting biases are over-estimated for the low-income individuals. In some sense, our work provides an upper-bound evaluation of income-related reporting heterogeneity for the poorest.

Saying it, this paper shows the existence of substantial income-reporting heterogeneity in subjective health, which are correlated with initial levels of both health and income. In particular, we find that, for those in the middle of the subjective health distribution, a rise in income seems to affect subjective health mainly *via* reporting (a noticeable exception being the poors).We also uncover some empirical evidence that, for the less well-off in poor health, a rise in income has a real effect on clinical health, which we have called a health production effect although this term might be excessive. Indeed, we are fully aware that we identify correlation rather than causalities, given that subjective health determines the demand for health which, in turn, has an effect on income (see Adams *et al.*, 2003).

It is worth noting that we did not find any connection between sex, age or education and reporting heterogeneity, while such connections have been found for other countries in previous studies. However, this may be specific to the methodology we use, which enables us to identify reporting heterogeneity only in the case of heterogeneous cut-points shifts. Further, this may also be explained by the very specific nature of our sample, which excludes the elderly.

Last, the starting point and the limits of our exercise are clear: we focus on subjective health as a cheap measure of clinical health, which is the true objective of public health policies. First, one would not base a major change in health policies on subjective health alone. Second, an alternative view is that subjective health should be the target because any change in the same physical function (functionings) has an idiosyncratic impact on the individual's capacity for enjoying life (Sen, 2003). Our results just call for cautiousness in the use of subjective health measures for assessing income-related health inequalities in French data. Binary indicators constructed from self-reported health may however be used, if the "poor health" category is taken as a reference.

The reporting heterogeneity that we have identified for the well-off in good health should be followed up in future work, in particular with respect to medical care and prevention. It would be interesting to consider a joint model of health demand and evaluation of subjective health, given that the information used by the individual to evaluate her health depends on the consumption of medical services.

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APPENDIX A. DESCRIPTIVE STATISTICS.

Table A1. Variable definitions and main statistics

	Definition	Mean	Std-error
Male	=1 if male	43.1%	
Age	Age	43.1	11.6
STRATA1	Urban area = rural	24.8%	
STRATA2	Urban with less than 20,000 inh.	16.3%	
STRATA3	Urban, between 20,000 and 100,000 inh.	13.8%	
STRATA4	Urban more than 100,000 including Paris	45.1%	
Income1	Household income <9,000 Euros /yr (converted from French Francs to Euros)	8.3%	
Income2	9,000-11,999 Euros/yr	8.3%	
Income3	12,000-15,000 Euros/yr	10.9%	
Income4	15,000-18,000 Euros/yr	10.2%	
Income5	18,000-22,500 Euros/yr	14.2%	
Income6	22,500-27,000 Euros/yr	14.2%	
Income7	27,000-36,000 Euros/yr	16.3%	
Income8	36,000-45,000 Euros/yr	9.1%	
Income9	>45,000 Euros/yr	8.5%	
Qual4	=1 if education over the Baccalaureat (A-level)	27.3%	
Qual3	=1 if Baccalaureat achieved	34.2%	
Qual2	=1 if has a degree under the Baccalaureat	12.3%	
Qual1	=1 if no education	26.2%	
Single parent	=1 if is a single parent	8.1%	
Live alone	=1 if lives alone and aged over 30.	19.5%	

Figure A1. Distribution of subjective health by household's income category

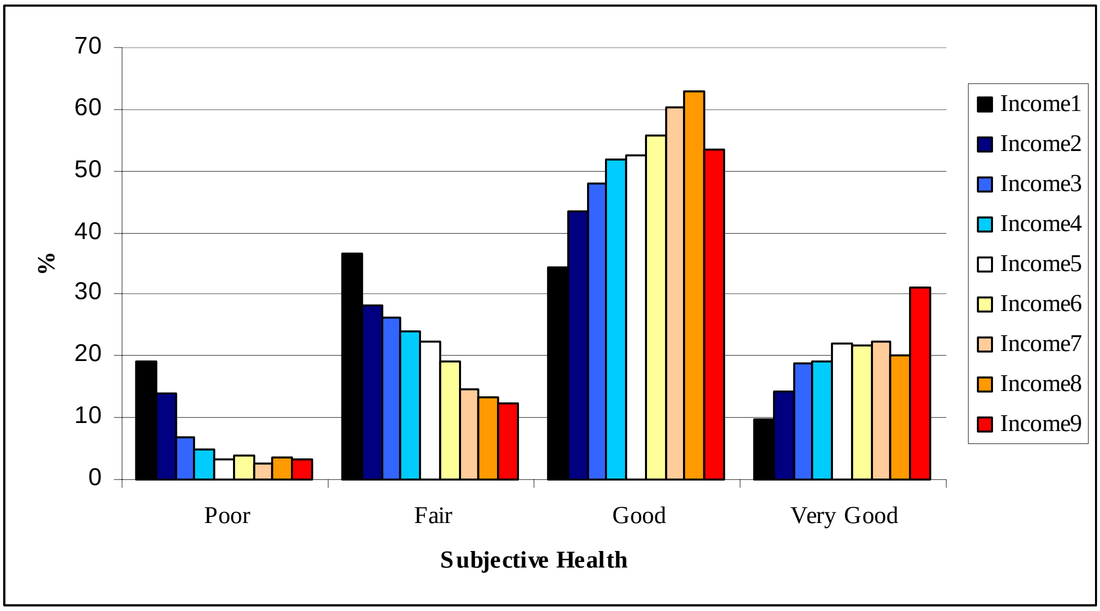


Table A.2. Objective health conditions

Class	**1**	**2**	**3**	**4**	**5**	**6**
Immunity						
Has had a fever over 39°c in the past year	3%	3%	6%	3%	6%	16%
Use of health care						
Follows a psychiatric treatment	1%	1%	8%	5%	69%	54%
Has regular check-ups for a chronic disease	0%	0%	26%	79%	59%	96%
Has to take medicines regularly	9%	17%	38%	93%	95%	100%
Had had an hospital stay in the past year	7%	7%	22%	15%	23%	53%
Has been assisted at home for medical reasons more than 3 months in the last year	0%	0%	11%	1%	4%	30%
Chronic illnesses that have been diagnosed						
Nervous system	0%	0%	1%	2%	3%	5%
Digestive system	1%	2%	11%	8%	20%	25%
Strain injury	0%	0%	5%	2%	0%	18%
Cancer	0%	0%	1%	4%	0%	11%
Heart	1%	3%	2%	41%	23%	32%
Joints	3%	5%	24%	21%	32%	47%
Other illnesses	3%	3%	21%	43%	24%	45%
Frequent migraines	2%	2%	10%	5%	14%	17%
Psychological troubles	1%	1%	10%	1%	52%	46%
Mental well-being						
Feels sometimes stressed (ref: no stress)	33%	36%	28%	32%	13%	18%
Feels often stressed (ref: no stress)	23%	20%	37%	21%	35%	31%
Feels very often stressed (ref: no stress)	10%	9%	22%	11%	52%	40%
Feeling of loneliness	7%	7%	18%	8%	47%	39%
Limitations to capabilities						
Medical restrictions for blood donations	5%	4%	14%	39%	32%	68%
Medical restrictions for sport	0%	2%	11%	10%	3%	64%
Medical conditions limit working capabilities	0%	1%	16%	10%	24%	74%
Mobility limited	0%	0%	12%	1%	4%	36%
Teeth pains moderate (ref: none)	26%	25%	32%	17%	32%	27%
Teeth pains severe (ref: none)	5%	6%	12%	6%	9%	12%
Eyesight problems	56%	67%	68%	85%	89%	89%
Thin (BMI<18.5)	7%	0%	3%	2%	6%	4%
Overweight (25<BMI<30)	0%	100%	19%	34%	38%	20%
Obese (BMI>30)	9%	0%	5%	17%	7%	22%

B Constructing a measure of clinical health.

Consider a set of J qualitative objective indicators of health. Each indicator W_{ij} can take L_j values w_{ij} in $\{1, 2, .., L_j\}$. We construct from each W_{ij} a set of L_j dummies w_{ijl} such that $w_{ijl} = 1\{w_{ij} = l\}$. We suppose that the distribution of objective health in the population is a mixture of K single-valued distributions, whereby we define K latent classes. Each individual has a probability g_k of belonging to class k. We note $\lambda_{kjl} = \Pr(w_{ijl} = 1 | i \in k)$ the conditional probability of having characteristic l for the variable W_{ij} conditionaly to membership of class k. Latent Class Analysis (LCA) assumes that the health indicators are independent conditionally to class membership. Therefore, the individual contribution to the likelihood is (asssuming an i.i.d. sample):

$$
\begin{aligned}
L^{LCA} &= \sum_{k=1}^{K} g_k \prod_{j=1}^{J} \prod_{l=1}^{L_j} (\lambda_{kjl})^{w_{ijl}} \\
u.c. \forall j, \quad \sum_{l=1}^{L_j} \lambda_{kjl} &= 1 \\
\sum_{k} g_k &= 1 \\
\forall k, j, l, \quad \lambda_{kjl} &\in [0, 1], g_k \in [0, 1]
\end{aligned}
$$

This clustering model is estimated by an Expected-Maximisation (E-M) algorithm, as membership of class k is missing (Dempster et al., 1977). The basic idea is to work iteratively on the best prediction of the likelihood. Suppose that, at iteration $r-1$, one has an initial value for the parameters $\hat{\Theta}^{r-1} = \{\forall k, j, l, \quad \hat{g}_k^{r-1}, \hat{\lambda}_{kjl}^{r-1}\}$, then in the E-step of the rth itération, one computes:

$$
E(L | W_{ij}, \hat{\Theta}^{r-1}) = \sum_{k=1}^{K} E(g_k | W_{ij}, \hat{\Theta}^{r-1}) \prod_{j=1}^{J} \prod_{l=1}^{L_j} (\lambda_{kjl})^{w_{ijl}}
$$

where by Bayes law:

$$
\begin{aligned}
E(g_k | W_{ij}, \hat{\Theta}^{r-1}) &= \Pr(g_k = 1 | W_{ij}, \hat{\Theta}^{r-1}) \\
&= \frac{\Pr(W_j | \hat{\Theta}^{r-1}, g_k = 1) \Pr(g_k = 1 | \hat{\Theta}^{r-1})}{\Pr(W_j | \hat{\Theta}^{r-1})} \\
&= \frac{\hat{g}_k^{r-1} \prod_{j=1}^{J} \prod_{l=1}^{L_j} (\hat{\lambda}_{kjl}^{r-1})^{w_{ijl}}}{\hat{L}^{r-1}}
\end{aligned}
$$

In the M-step, this expected likelihood is maximised. The E-M algorithm is monotonically increasing and converge for any starting value to a local maximum. To detect the global maximum, we used several starting values and

Number of classes	**BIC**	**ICL-BIC**
2	-27143	-27399
3	-26735	-27257
4	-26551	-27377
5	-26450	-27465
6	-26372	-27309
7	-26308	-27479
8	-26230	-27382

a simulated annealing procedure (Celeux et al., 1995). After convergence, we get the best estimates of individual probabilities of membership conditionally on available information on objective health conditions : $E(g_k|W_{ij}, \hat{\Theta}^{\infty})$. The latent classes can be ranked in terms of objective health, by comparing the within-class distributions of the health indicators W_{ij}. We then use the set of probabilities $E(g_k|W_{ij}, \hat{\Theta}^{\infty})$ as a more objective measure of health. The optimal number of classes is determined by the comparison of several information criteria (AIC, BIC) with a potential penalty for the quality of the clustering (for instance the Integrated Laplace Criterion, see McLachlan et Peel, 2000). The analysis was undertaken on the sub-sample we use for the estimation of the generalised ordered probit models : 2956 individuals aged under 65.

The Table B1 reports a number of criteria to choose the optimal number of classes. McLachlan et Peel (2000) show on the basis of Monte-Carlo experiments that the ICL-BIC criterion is better suited to the detection of latent structures that pure information criteria such as the BIC. So, we may opt for 3 classes. However,the quality of the clustering improves again when one goes from 5 classes to 6 classes (the ICL-BIC strongly increases), and the information criteria are better for 6 classes than for 4 classes. In the end, we decided to keep a 6-classes structure. In the regressions, we introduce five probabilities of membership $E(g_k|W_j, \hat{\Theta}^{\infty})$ (one of the probability has to be omitted since they sum up to one).

APPENDIX C. RESULTS.

Table C1. Variables that do not have a differential effect on the thresholds

Subjective Health	Specification A		Specification B	
	Ordered Probit (α)	*Generalized Ordered Probit (α)*	*Ordered Probit (α)*	*Generalized Ordered Probit (α)*
Observable variables independent of the thresholds				
Objective Health: class 1	No	No	Reference	Reference
Objective Health: class 2	No	No	-0.134** (0.068)	-0.146** (0.069)
Objective Health: class 3	No	No	-1.375*** (0.134)	-0.887*** (0.104)
Objective Health: class 4	No	No	-0.831*** (0.102)	-0.941*** (0.128)
Objective Health: class 5	No	No	-0.889*** (0.124)	-1.337*** (0.138)
Objective Health: class 6	No	No	-2.124*** (0.179)	-2.100*** (0.187)
Male	0.154*** (0.042)	0.149*** (0.042)	0.027 (0.045)	0.029 (0.045)
STRATA1	0.051 (0.057)	0.054 (0.057)	-0.049 (0.059)	-0.043 (0.060)
STRATA2	-0.060 (0.063)	-0.060 (0.063)	-0.066 (0.065)	-0.072 (0.066)
STRATA3	-0.005 (0.066)	-0.008 (0.066)	0.013 (0.068)	0.017 (0.069)
STRATA4	Reference	Reference	Reference	Reference
QUAL1	-0.209*** (0.065)	-0.214*** (0.066)	-0.161** (0.068)	-0.166** (0.069)
QUAL2	-0.059 (0.058)	-0.065 (0.058)	-0.001 (0.060)	-0.003 (0.060)
QUAL3	0.055 (0.073)	0.052 (0.073)	0.111 (0.075)	0.114 (0.076)
QUAL4	Reference	Reference	Reference	Reference
AGE/10	-1.117 (0.720)	-0.932 (0.724)	-1.939** (0.749)	-1.732** (0.756)
$(AGE/10)^2$	0.160 (0.173)	0.117 (0.173)	0.383** (0.179)	0.335* (0.181)
$(AGE/10)^3$	-0.009 (0.013)	-0.006 (0.013)	-0.026* (0.014)	-0.023 (0.014)
Threshold intercepts. ordered probit model only				
Threshold 1: s_1	-4.700*** (0.969)	No	-6.727*** (1.010)	No
Threshold 2: s_2	-3.622*** (0.968)	No	-5.230*** (1.008)	No
Threshold 3: s_3	-2.034** (0.967)	No	-3.355*** (1.006)	No

Notes: *Std. Error in parentheses. *** significant at the 1% level. ** significant at the 5% level. * significant at the 10% level.*

Table C2. Variables that have a differential effect on the thresholds

Subjective Health	**Specification A**				**Specification B**			
	Ordered Probit	*Generalized Ordered Probit*			*Ordered Probit*	*Generalized Ordered Probit*		
Thresholds	None (linear index: α)	Poor / Fair:-β_1	Fair / Good : -β_2	Good / Very good : -β_3	None (linear index: α)	Poor / Fair : -β_1	Fair / Good : -β_2	Good / Very good: -β_3
Paris	Reference	Reference			Reference	Reference		
Ile-de-France	0.067 (0.076)	0.318** (0.148)	0.007 (0.096)	0.060 (0.096)	0.129 (0.079)	0.383** (0.180)	0.113 (0.107)	0.105 (0.100)
West	0.135* (0.080)	0.473*** (0.167)	0.154 (0.103)	0.027 (0.103)	0.213** (0.083)	0.633*** (0.206)	0.294** (0.117)	0.059 (0.107)
East	-0.056 (0.084)	0.194 (0.166)	-0.198* (0.105)	0.017 (0.107)	-0.005 (0.087)	0.303 (0.207)	-0.150 (0.117)	0.065 (0.111)
North	-0.104 (0.091)	0.096 (0.170)	-0.201* (0.115)	-0.061 (0.125)	-0.002 (0.095)	0.323 (0.214)	-0.072 (0.131)	-0.016 (0.131)
Center	-0.023 (0.079)	-0.092 (0.142)	-0.027 (0.102)	0.007 (0.103)	0.099 (0.082)	0.032 (0.178)	0.151 (0.115)	0.085 (0.108)
Southwest	-0.028 (0.082)	0.194 (0.153)	-0.086 (0.103)	-0.054 (0.108)	0.030 (0.085)	0.214 (0.184)	0.002 (0.114)	-0.004 (0.112)
Mediterranean	0.052 (0.080)	0.107 (0.146)	-0.016 (0.101)	0.111 (0.105)	0.034 (0.083)	0.235 (0.188)	-0.015 (0.115)	0.051 (0.110)
INCOME1	-1.115*** (0.116)	-1.098*** (0.206)	-1.145*** (0.144)	-0.909*** (0.156)	-0.898*** (0.121)	-0.815*** (0.261)	-0.964*** (0.162)	-0.723*** (0.164)
INCOME2	-0.810*** (0.113)	-0.880*** (0.205)	-0.828*** (0.141)	-0.650*** (0.145)	-0.730*** (0.118)	-0.723*** (0.262)	-0.796*** (0.158)	-0.567*** (0.153)
INCOME3	-0.558*** (0.104)	-0.431** (0.205)	-0.612*** (0.133)	-0.497*** (0.128)	-0.549*** (0.108)	-0.231 (0.262)	-0.634*** (0.150)	-0.510*** (0.134)
INCOME4	-0.481*** (0.103)	-0.287 (0.213)	-0.497*** (0.134)	-0.490*** (0.128)	-0.456*** (0.107)	-0.050 (0.271)	-0.489*** (0.151)	-0.472*** (0.134)
INCOME5	-0.387*** (0.095)	-0.079 (0.212)	-0.431*** (0.126)	-0.400*** (0.115)	-0.396*** (0.099)	0.033 (0.272)	-0.461*** (0.140)	-0.402*** (0.121)
INCOME6	-0.302*** (0.093)	-0.139 (0.203)	-0.289** (0.124)	-0.333*** (0.113)	-0.331*** (0.097)	-0.002 (0.259)	-0.319** (0.139)	-0.369*** (0.118)
INCOME7	-0.239*** (0.090)	0.013 (0.206)	-0.131 (0.123)	-0.357*** (0.109)	-0.316*** (0.093)	-0.087 (0.256)	-0.212 (0.138)	-0.411*** (0.113)
INCOME8	-0.235** (0.099)	-0.137 (0.217)	-0.080 (0.136)	-0.374*** (0.123)	-0.301*** (0.102)	-0.230 (0.268)	-0.095 (0.152)	-0.429*** (0.128)
INCOME9	Reference	Reference			Reference	Reference		
Live alone and aged over 30	0.032 (0.060)	0.092 (0.105)	0.051 (0.072)	0.124 (0.080)	0.068 (0.063)	0.111 (0.131)	0.004 (0.082)	0.146* (0.085)
Single parent	-0.032 (0.081)	0.169 (0.160)	0.062 (0.099)	-0.078 (0.112)	-0.031 (0.085)	0.184 (0.194)	-0.056 (0.112)	-0.095 (0.118)
Hospital stay	No	No			-0.135** (0.066)	-0.274** (0.114)	-0.167** (0.085)	0.019 (0.097)
Sport trouble	No	No			-0.307*** (0.101)	-0.323** (0.139)	-0.407*** (0.125)	0.077 (0.176)
Chronic diseases	No	No			-0.186** (0.090)	-0.188 (0.130)	-0.257*** (0.098)	0.052 (0.121)
Ischemic diseases	No	No			0.161** (0.080)	0.407*** (0.132)	0.040 (0.097)	0.151 (0.131)
Subjective stress	No	No			-0.180*** (0.023)	0.229*** (0.050)	0.236*** (0.031)	-0.121*** (0.030)
Intercept		4.160*** (0.982)	3.431*** (0.974)	1.789** (0.973)		6.102*** (1.037)	5.148*** (1.020)	3.006*** (1.017)

Notes: Std. Error in parentheses. *** significant at the 1% level. ** significant at the 5% level. * significant at the 10% level.

APPENDIX D. MARGINAL EFFECTS.

Figure D1. Probability of reporting SAH greater than poor.

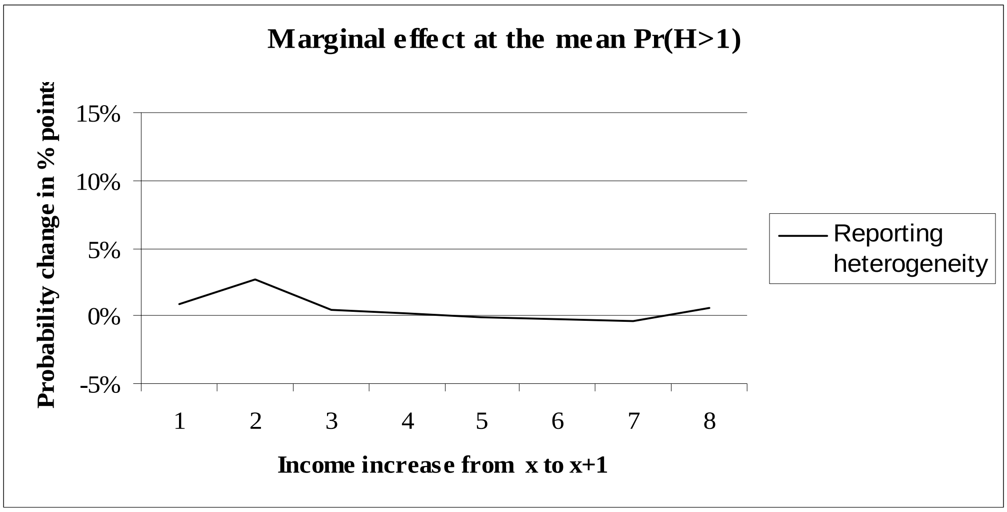


Figure D2. Probability of reporting SAH greater than fair.

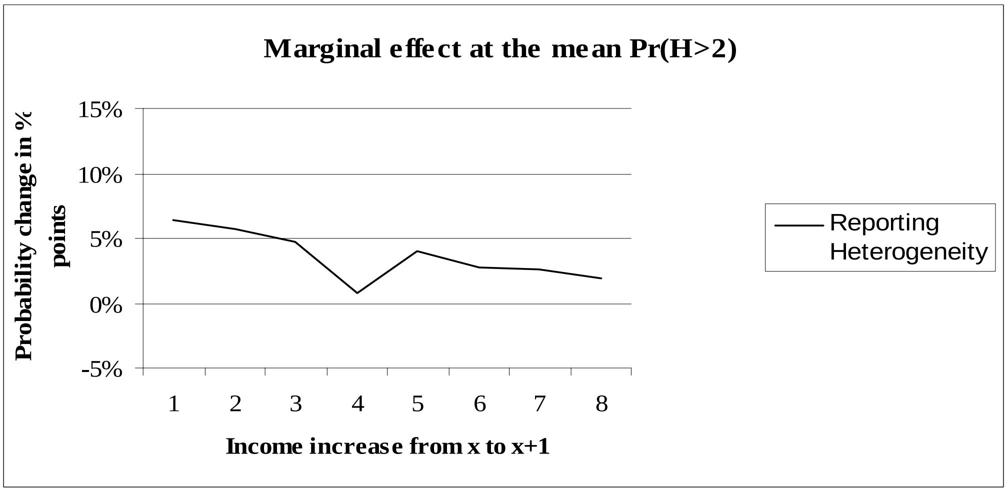


Figure D3. Probability of reporting SAH greater than good.

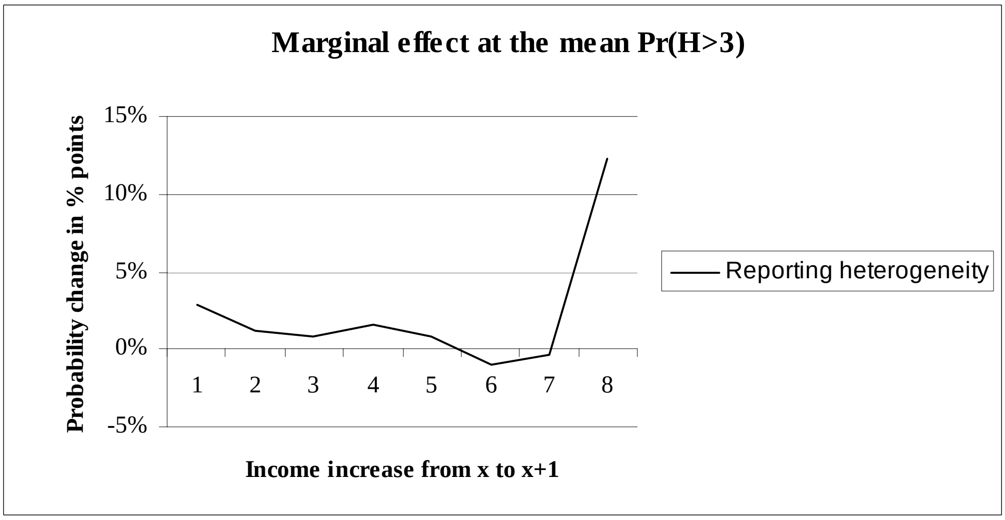


*Table D1. Total effect (in points of probability) – specification **(A)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	4.9%	**12.5%**	*4.7%*
Between 9 000 and 12 000€: *INCOME2*	**6.7%**	*8.0%*	3.5%
Between 12 000 and 15 000€: *INCOME3*	1.4%	4.0%	0.2%
Between 15 000 and 18 000€: *INCOME4*	1.4%	2.2%	2.4%
Between 18 000 and 22 500€: *INCOME5*	-0.4%	4.3%	1.9%
Between 22 500 and 27 000€: *INCOME6*	0.8%	4.3%	-0.7%
Between 27 000 and 36 000€: *INCOME7*	-0.8%	1.3%	-0.5%
Between 36 000 and 45 000€: *INCOME8*	0.8%	1.8%	**11.9%**

Ref: over 45 000 €. *INCOME9*

Note: Marginal effects computed at the sample mean for all characteristics (including objective health in Table D2). These effects represent variations of probability of declaring an health status over the figure indicated in the top of the column. Variations are in percentage points. They are generated by an income increase such that the individual changes from income category k to income category k+1 where the initial income category k is reported on the left.Effects in bold are significant at the 5% level, in bold and italic at the 10% level.

*Table D2. Reporting bias effect (in points of probability) – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.9%	6.4%	2.9%
Between 9 000 and 12 000€: *INCOME2*	**2.8%**	5.7%	1.2%
Between 12 000 and 15 000€: *INCOME3*	0.5%	4.7%	0.8%
Between 15 000 and 18 000€: *INCOME4*	0.2%	0.8%	1.6%
Between 18 000 and 22 500€: *INCOME5*	-0.1%	4.1%	0.8%
Between 22 500 and 27 000€: *INCOME6*	-0.2%	2.7%	-1.0%
Between 27 000 and 36 000€: *INCOME7*	-0.4%	2.7%	-0.4%
Between 36 000 and 45 000€: *INCOME8*	0.6%	1.9%	**12.2%**

Ref: over 45 000 €. *INCOME9*

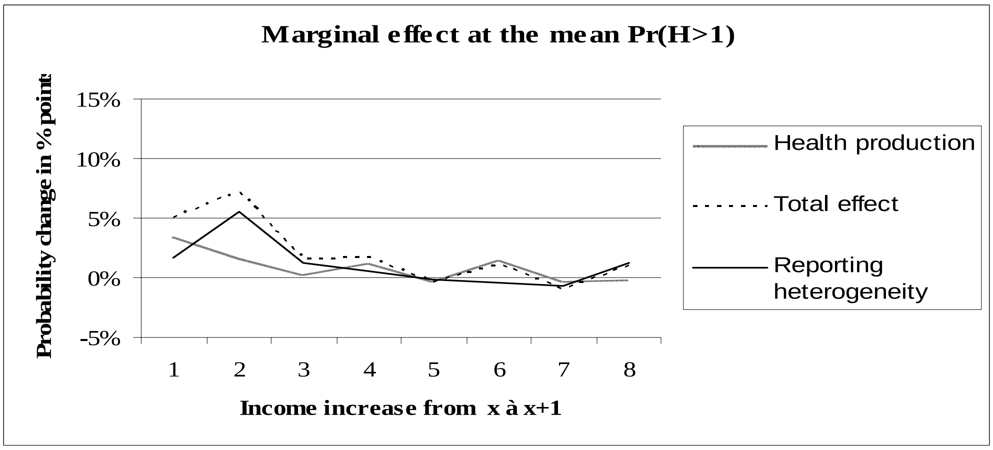
*Table D3. Health production effect (in points of probability) – **(A)-(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	4.1%	6.2%	1.9%
Between 9 000 and 12 000€: *INCOME2*	4.0%	2.4%	2.3%
Between 12 000 and 15 000€: *INCOME3*	0.9%	-0.7%	-0.7%
Between 15 000 and 18 000€: *INCOME4*	1.3%	1.3%	0.7%
Between 18 000 and 22 500€: *INCOME5*	-0.3%	0.3%	1.1%
Between 22 500 and 27 000€: *INCOME6*	1.0%	1.6%	0.3%
Between 27 000 and 36 000€: *INCOME7*	-0.4%	-1.4%	-0.1%
Between 36 000 and 45 000€: *INCOME8*	0.2%	-0.1%	-0.3%

Ref: over 45 000 €. *INCOME9*

Note: Figures in this table are computed by withdrawing those of table D2 from those of table D1

Figure D4. Probability of reporting SAH greater than poor.



Note: Figures D4 to D6 represent average individual marginal effects of income on the probability of reporting health greater than 1, 2 or 3. The individual effects are averaged over individuals who are actually in the specific income categories. The "reporting heterogeneity" line is computed using estimates of specification **(B)**, and the "total effect" line using estimates of specification **(A)**. The "health production" line is simply the average of differences between marginal effects from **(A)** and from **(B)**.

Figure D5. Probability of reporting SAH greater than fair.

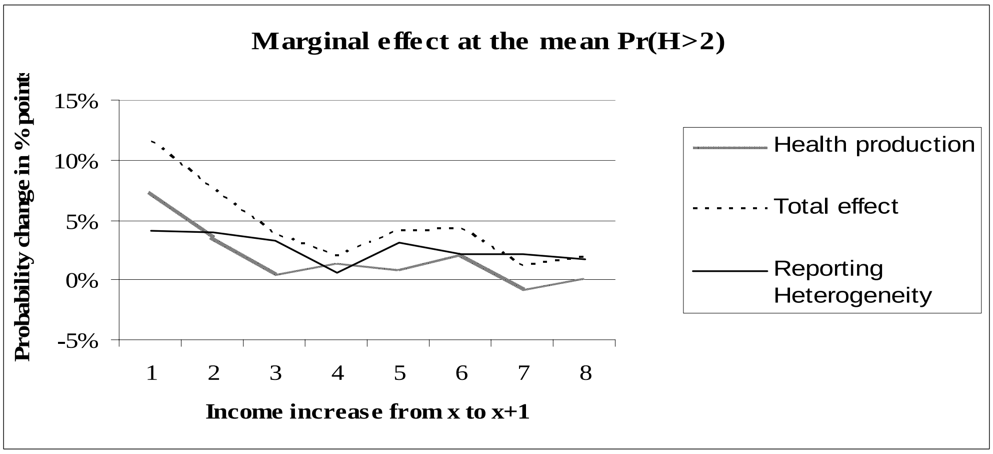


Figure D6. Probability of reporting SAH greater than good.

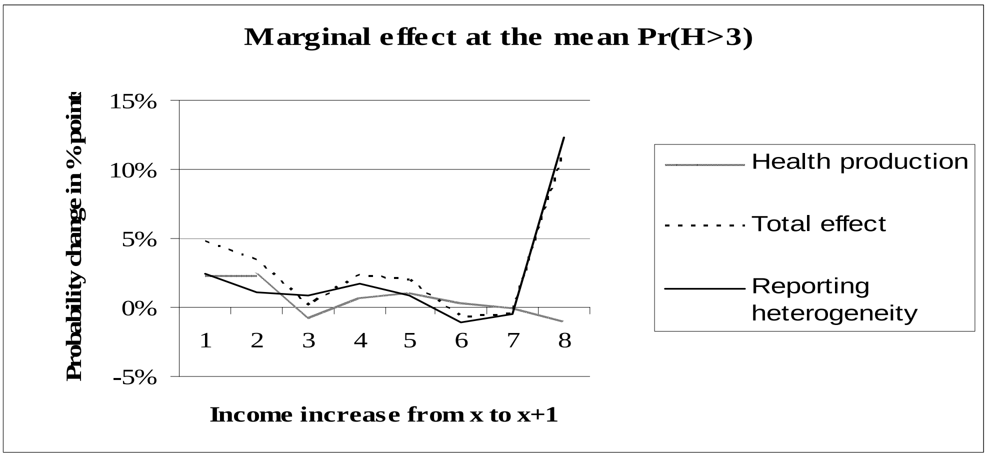
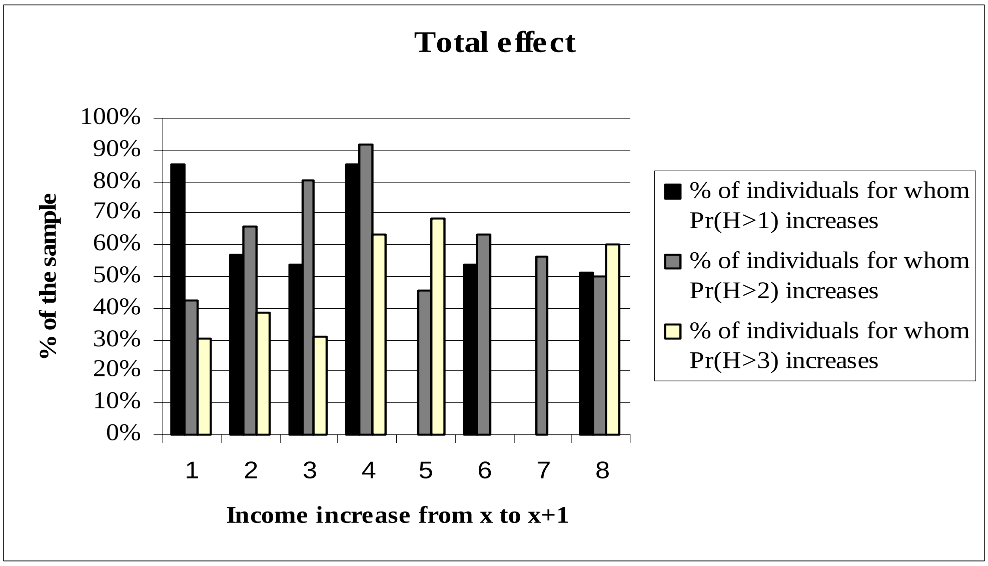


Figure D7. Specification A – Significance of the individual marginal income effect.



Note: Figures D7 and D8 represent for each income category the % of individuals for whom a given marginal effect is significant at the 5% level.

Figure D8. Specification B – Significance of the individual marginal income effect.