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Income-related reporting heterogeneity in self-assessed 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 low-income individuals, and reporting heterogeneity for the choice between the medium labels *i.e.* "fair" vs. "good" and for 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 converting SAH into a binary variable for poor health versus other health statuses.

1 Introduction

Health inequalities have been the subject of a lively literature in Economics (Wagstaff and van Doorslaer, 2000). Their calculation requires a good measure of individual health. In this perspective, this paper assumes that the key variable of interest for the design of public policies is **clinical health**. Suppose now that Health Authorities need a tool for monitoring income-related health inequalities in the general population. Such a tool should have 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, as they may not have many resources to devote to the follow-up of health inequalities.

An objective measure of clinical health is usually expensive to collect, since data collection has to be based on a costly array of medical check-ups, which

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may induce a significant selection bias. An alternative might be to use self-reported clinical conditions, but the information that the agent has available results from her choice to collect information (*via* preventative health consultations for example). Moreover, constructing a synthetic health measure requires the weighting of diverse clinical health conditions, and thus often embodies the individual preferences of a sub-sample of the population (Gerdtham *et al.*, 1999, Dolan, 2000).

Given these arguments, a self-assessed health measure may be interesting. One widespread measure that we use in this paper is obtained by asking individuals to classify their health using ordered qualitative labels such as "very good", "good", "fair" and "poor": subjective health H_i is then an ordered qualitative variable with M levels. This self-assessed health measure is cheap and easy to collect, is synthetic by construction, and is strongly correlated with a number of clinical health conditions (see Idler and Benyamini, 1997, and van Doorslaer and Gerdtham, 2003). However, its reliability is questionable, because a given clinical health condition is appreciated differently according to individual characteristics and more particularly the cultural and historical context, individual social status and individual health history (Boltanski, 1971; Johansson, 1991; Heyink, 1993; Kerkhofs and Lindeboom, 1995; Sadana *et al.*, 2000; Wu, 2001; Murray *et al.*, 2001). Reporting heterogeneity does not matter if one believes that subjective health contains valid information on health beyond all potentially available clinical health measures. However, this position may have untenable consequences in terms of public health policy. A striking example from Murray and Chen (1992), and Sen (1993) shows that self-reported health is much lower in the U.S. than in the Indian state of Kerala, although the mortality rate is higher in the latter (for another example see Case and Deaton, 2005). As far as possible, we would certainly prefer to invest more in Kerala than in the U.S. We therefore assume that clinical health is the target outcome for public health policies. From this position, reporting heterogeneity may be considered as a bias in the sense that self-assessed health (SAH) is a biased measure of clinical health.[1]

This paper considers the presence of reporting heterogeneity in self-assessed health in France. More specifically, we ask whether this reporting heterogeneity is related to income, since this point is crucial for the measurement of health inequalities.

A number of papers in Health Economics have already considered income-related reporting heterogeneity in SAH. Current results are mixed. For instance, Humphries and van Doorslaer (2000), using Canadian data, as well as Hernandez-Quevedo *et al.* (2004), in British data, report results indicating that, for a given level of clinical health, lower income individuals are more likely to report a poor level of SAH than higher income groups. On the contrary, Jürgens (2006) finds in German data that richer respondents tend to understate

[1] Shmueli (2003) uses the term "reporting heterogeneity". Other articles evoke "state-dependent reporting bias" (Kerkhofs and Lindeboom, 1995), and "scale of reference bias" (Groot, 2000).

their clinical health in their SAH assessment. Hence, the magnitude and the sign of reporting heterogeneity seem to be country-specific. In the perspective of international comparisons, it is worth testing if there are also income-related reporting heterogeneities in France.

This article uses French data from the 2001 Conditions de Vie des Ménages survey to address this question. Conceptually, the effect of income on H_i can be decomposed into an effect on clinical health, which is a random (unobserved) variable $\widetilde{H}_i$, and an effect on the transformation $T[.;Q]$ of $\widetilde{H}_i$ into H_i, where Q_i is the set of variables that affect reporting. Two methods are proposed to test for income-related reporting heterogeneity. The first method identifies the presence of reporting heterogeneity using specific and arguably strong parametric assumptions (this is our Test 1). The second method relies on a synthetic proxy measure of clinical health based on a classification of individuals, which results from a latent class analysis of a number of clinical health conditions self-reported in our data. This second method allows us to assess the sign and the magnitude of reporting heterogeneity (this is our Test 2).

Our main finding is that there is some income-related reporting heterogeneity in SAH in France. Our estimates also reveal that the "effect" of a rise in income on SAH varies according to the individual's initial income and initial SAH level.[2] Three results should be emphasised. First, for individuals at the bottom of the income distribution reporting poor SAH, income significantly affects SAH *via* clinical health. Second, a fall in income has a strong negative reporting effect on the richest reporting good or very good health. Third, 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 SAH information may bias the measure of health inequality, except if we use a dichotomous measure of SAH distinguishing between the bottom category ("poor") and the other categories.

The paper is organised as follows. Section two explains the methods. 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 The generalised ordered probit model

We suppose that clinical health $\widetilde{H}_i$ is linked to a set of variables X_i by a linear index equation:

$$\widetilde{H}_i = \alpha_0 + X_i\alpha + \widetilde{\epsilon}_i \tag{1}$$

where α is a vector of parameters, α_0 is a constant, and $\widetilde{\epsilon}_i$ is an error term capturing unobservable terms. To measure the effect of income on $\widetilde{H}_i$, we have

[2] The rest of the paper uses the term "effect" somewhat abusively, since income is potentially endogenous.

to identify α in equation (1). The reporting equation linking the observable variables is:

$$H_i = T[\alpha_0 + X_i\alpha + \widetilde{\epsilon}_i; Q_i] \tag{2}$$

The function $T(.;.)$ and the error term $\widetilde{\epsilon}$ are thus nuisance parameters.

When there is common agreement regarding evaluation of SAH, *i.e.* when everyone agrees on what it means to be in very good/good/fair/poor health, the interpersonal comparability of health is assured. The relation (2) reduces to $H_i = T[\alpha_0 + X_i\alpha + \widetilde{\epsilon}_i]$. We can then suppose that there exist cut-points $s_0, s_1..., s_M$ such that

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

with the identification restriction $\alpha_0 = 0$: when $\widetilde{\epsilon}_i$ is distributed normally, this relation defines the ordered probit model.

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

$$\begin{aligned} s_{i0} &= -\infty, s_{iM} = \infty, \\ \forall m &= 1, ..., M-1, \quad s_{im} = Q_i\beta_m \\ \forall m &= 1, ..., M, \quad H_i = m \iff s_{im-1} \leq \widetilde{H}_i \leq s_{im} \end{aligned} \tag{3}$$

where β_m are additional parameters, and Q includes a constant. Reported health H_i then depends on the way in which clinical health $\widetilde{H}_i$ is translated by the cut-points $(s_{i0}, s_{i1}..., s_{iM})$. This model, in which the cut-points depend on observable variables, is a generalised ordered probit model (Terza, 1985). It is particularly well-suited to cross-section data. In panel data, it is possible to estimate semi-parametric ordered logit models in which the cut-points are individual nuisance parameters (Ferrer-i-Carbonell and Frijters, 2004).

2.2 Assessing the presence of reporting heterogeneity: Test 1

Suppose that (1) is a reduced form equation for health capital production: X_i only includes prices and resources, especially income, that affect health investment. We will first estimate specification **(A)**:

$$\widetilde{H}_i = \alpha X_i + \widetilde{\epsilon}_i^A$$

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

All of the variables here potentially influence both the cut-points and clinical health, *i.e.* $Q_i = X_i$. 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 $\widetilde{H}_i$ into H_i) and clinical health $\widetilde{H}_i$. The specification we use renders the separation of these two effects impossible *a priori*. To illustrate the problem, note that the probability of observing reply m can be written as:

$$\begin{aligned} \Pr(H_i &= m) = \Phi[X_i\beta_m - X_i\alpha] - \Phi[X_i\beta_{m-1} - X_i\alpha] \\ &= \Phi[X_i(\beta_m - \alpha)] - \Phi[X_i(\beta_{m-1} - \alpha)] \end{aligned} \tag{5}$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal residuals $\widetilde{\epsilon}_i^A$ (their variance has to be normalised to 1 as usual).[3] This probability can also be written for any vector of parameters δ as:

$$\begin{aligned} \Pr(H_i &= m) = \Phi[X_i(\beta_m + \delta) - X_i(\alpha + \delta)] - \Phi[X_i(\beta_{m-1} + \delta) - X_i(\alpha + \delta)] \\ &= \Phi[X_i(\beta_m - \alpha)] - \Phi[X_i(\beta_{m-1} - \alpha)] \end{aligned} \tag{6}$$

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

$$\begin{aligned} \Pr(H_i &= m) = \Phi[X_i(\beta_m - \alpha_1) - X_i\alpha_2] - \Phi[X_i(\beta_{m-1} - \alpha_1) - X_i\alpha_2)] \\ &= \Phi[X_i(\beta_m - \alpha)] - \Phi[X_i(\beta_{m-1} - \alpha)] \end{aligned} \tag{7}$$

The structural models associated with these probabilities differ with respect to the specification of the cut-points s_{im} and the modelisation of $\widetilde{H}_i$. For the models associated with equation (6) we have $\widetilde{H}_i = X_i(\alpha + \delta) + \widetilde{\epsilon}_i$ and $s_{im} = Q_i(\beta_m + \delta)$; for those associated with (7) we have $\widetilde{H}_i = X_i\alpha_2 + \widetilde{\epsilon}_i$ and $s_{im} = X_i(\beta_m - \alpha_1)$. Hence equation (1) is not identified, because any variable which has an effect on $\widetilde{H}_i$ also potentially influences the cut-points (see the equivalence between equations (5) and (7)), and any variable playing a role in the determination of the cut-points may equally affect $\widetilde{H}_i$ (see the equivalence between equations (5) and (6)).

Following Hernandez-Quevedo *et al.* (2004), a first approach to test for the presence of income-related reporting heterogeneity assumes that a variable affects individual reporting if it has a heterogeneous effect on the different cut-points of the generalised ordered probit model.[4] Indeed, Specification **(A)** identifies $\gamma_m = (\beta_m - \alpha)$ for $m = 1, ..., M-1$. A variable then has a heterogeneous

[3] The model thus identifies coefficients scaled by the variance. Homoscedasticity is assumed throughout the paper.

[4] The epidemiological literature uses the 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).

effect on the cut-points if the coefficients β_m associated with this variable vary according to the cut-point m. This can be tested by a Hausman test of the equality of the coefficients γ_m (Pudney and Shields, 2000). In the rest of this article, we shall call this test **Test 1**.

What are the main drawbacks of this approach? Some variables may not have a heterogeneous effect on the cut-points, but a homogeneous effect *i.e.* they do not affect differentially the cut-points. This is an index-shift effect, as the literature calls it, and may be interpreted in terms of reporting heterogeneity or in terms of production of "clinical health". This point has two major consequences. First, **Test 1** can detect some kinds of reporting heterogeneity, but not a reporting heterogeneity that involves a common effect on all the cut-points. Second, **Test 1** does not allow us to draw conclusions about either the magnitude of reporting heterogeneity or the effect of income on clinical health.

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 $\widetilde{H}_i$ is badly specified. Hence, estimating Specification **(A)** may identify reporting heterogeneity, but only under the following assumption:

Assumption 1 The relationship between income and clinical health $\widetilde{H}_i$ 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. However, this does not remove out the possibility that the marginal effect of income may vary at different points in the clinical health distribution.[5]

The first approach thus hinges on a strong assumption and is unable to identify reporting heterogeneity to its full extent. A number of different strategies can be imagined to overcome this difficulty of identification. Groot (2000) supposes for instance that $s_{i1} = 0$ for all individuals: one of the two extreme SAH categories constitutes a common anchoring point. This hypothesis identifies separately α and a part of the β_m. van Doorslaer and Jones (2003) appeal to the correspondence, for any sub-group of the population, between the distribution of SAH and the distribution of a synthetic measure of clinical health, the Health Utility Index.

[5] A key implication of assumption 1 is that there is no slope heterogeneity in the relationship between income and clinical health. To understand this point, imagine that subjective health is a continuous variable. We would then run quantile regressions instead of estimating a generalized ordered probit model. Slope heterogeneity between quantiles could be interpreted as expressing merely differences in the marginal effect of income on clinical health between different points of the clinical health distribution, instead of reflecting some kind of reporting bias. However, this interpretation would hold only if individuals are ordered in the same manner according to their subjective health or to their clinical health. That orderings differ according to clinical health or to subjective health, is precisely what we appeal to for the identification of reporting heterogeneity.

In the current paper, we are interested in the identification of the income effect on the cut-points. 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.

2.3 Assessing the magnitude of reporting heterogeneity: Test 2

Including in X_i a synthetic measure of clinical health that has, *by assumption*, no effect on the cut-points helps to isolate the income-related reporting heterogeneity. Let H^0 be a synthetic measure of clinical health for which the following conditional mean independence condition holds:

Assumption 2

$$E(\widetilde{H}|H^0, Y, Z) = E(\widetilde{H}|H^0, Z) \tag{8}$$

where Y is income and Z denotes the other right hand side variables ($X = (Y, Z)$). Our second approach does not require that clinical health be perfectly measured, but that there exists a proxy measure of clinical health, which captures all the components of clinical health that are affected by income. One can arguably consider that Assumption 2 is weaker than Assumption 1.

Having this proxy measure in hand, we will estimate specification **(B)**, which consists of the following equations:

$$\widetilde{H}_i = \delta_1 H^0 + \delta_2 Z_i + \widetilde{\epsilon}_i^B \tag{9}$$

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

Since we assume for the sake of parsimony that H^0 picks up only the effect of income on clinical health, we keep the Z_i variables in the health production equation. Under Assumption 2, specification **(B)** identifies the effect of reporting heterogeneity on income. Hence, our second test (**Test 2**) for the presence of income-related reporting heterogeneity is whether income has a significant effect on SAH in specification **(B)**.

The main requirement of **Test 2** is the existence of a proxy measure of clinical health that captures the effect of income on the various dimensions of clinical effect. In this perspective, Kerkhofs and Lindeboom (1995) use the Hopkins Symptom Checklist and Lindeboom and van Doorslaer (2004) rely on 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 introducing all self-reported clinical health conditions in the vector X_i avoids any loss of information. However,

constructing a synthetic proxy measure of clinical health yields two benefits. First, our approach is more parsimonious in that we do not overload the model with too many parameters. Second, using a synthetic measure minimizes the impact that random or systematic measurement errors on each indicator may have on the estimates (this is discussed in the "Data" section hereafter).

By comparing estimation results from specification (A) and (B), one can decompose the effect of income on SAH into a reporting and a "clinical health" production effect. However, the direct comparison of the income coefficients resulting from the estimation of (A) and (B) does not permit us to identify the effect of income on $\widetilde{H}_i$, since the variances of both $\widetilde{\epsilon}_i^A$ and $\widetilde{\epsilon}_i^B$ are normalised to 1. We therefore compare the marginal effects of income between specifications (A) and (B), to evaluate the impact of income on the production of clinical health.

3 Data

We test for reporting heterogeneity in SAH in France, using data from the "Enquête Permanente sur les Conditions de Vie des Ménages" survey (EPCV2001), carried out by the INSEE (the French National Statistical Agency) in 2001. This survey contains information at both the household and the individual level, and one randomly-drawn individual in each household answered a health questionnaire. The starting sample thus consists of 5194 individuals in the same number of households. In the perspective of estimating Specification **(B)**, it is difficult to construct clinical health indicators that are valid for both younger and older adults, due to the natural depreciation of health with age, as suggested by the existence of specific health measures for the elderly that are not available in our data.[6] 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. Given 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 the synthetic indicator of clinical health.

3.1 SAH and Income

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

[6] A number of limitations that are fairly specific to the older populations are not measured in the survey: reading skills, writing skills, memory skills, being able to pursue activities that require moderate levels of energy (going for a walk, climbing the stairs, washing oneself), etc. Such variables are present for instance in the Survey of Health, Ageing and Retirement in Europe (SHARE) data.

In the estimation sample, 52% of respondents say that they are in good health and only 6% are 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 SAH with age: up to age 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 health and SAH 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 an A-level); or higher education (*QUAL4*). SAH 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).[7] This correlation may result from an age effect, with older respondents likely being on average less well-educated due to increasing access to secondary and higher education over the past thirty years. However, older respondents are also richer.

Income is defined at the household level. This is yearly income, net of social contributions, and not equivalised. 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 SAH (see Figure A2, Appendix A).

The correlation between income and SAH may reflect two different 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.

3.2 Clinical Health Measures

The estimation of specification **(B)** requires a measure of clinical health. The EPCV 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. SAH is worse when the individual suffers from one of the more common serious illnesses: nervous illnesses, problems of the digestive system, paralyses, cancers, cardio-vascular problems, or

[7] 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.

musculoskeletal troubles. Nervous illnesses and paralyses are the most strongly associated with lower levels of SAH. Other clinical health variables are used: teeth and eyesight problems, being currently treated for an illness, having a psychiatric treatment, having had a fever of over $39°c$ in the past year, four dummy variables for the body mass (thin, normal, overweight, obese). 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, having a limited mobility, reporting some stress or a feeling of loneliness.

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. A number of these variables are actually 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. 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.[8] The use of psychological health variables (feelings of loneliness, self-reported stress, and 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.[9]

We use these self-reported clinical health conditions to build a synthetic index H^0. 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 Goodman, 1974; Bandeen-Roche *et alii*, 1997; McLachlan and Peel, 2000, chap. 5.12) 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 conditional on class membership. 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, and the only sure way of using GoM techniques is to assume that the probabilities of class membership follow a certain distribution, which imposes parametric restrictions (Erosheva, 2002). This is one reason why we appeal to

[8] 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. For instance, it is known that poorer respondents experience health problems younger and may not be well-diagnosed by the health care system (Jougla *et al.* 2000).

[9] We tested the robustness of our results by dropping the "suspect" health variables (psychological health, teeth, and eyesight) and re-estimating the full model. The results did not change significantly.

LCA analysis.[10]

On the basis of the Integrated Laplace Criterion, 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 (see Table A.2. in Appendix A).[11] 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 medicine 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 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. Table A.3. in Appendix A also reports the distribution of SAH by class of "clinical health": it clearly shows that there is positive correlation between these two synthetic measures of health. Tables A.4. to A.6. illustrate the central idea of this paper. They decompose the SAH distribution by income category and clinical health class, and clearly reveal a positive correlation between SAH and income conditional on clinical health. For instance, the rate of respondents who are in excellent clinical health (Class 1) and in good or very good SAH rises from 91% to 97.2% between income categories 5 and 9. Under **Assumption 2**, this difference might reflect the presence of reporting heterogeneity. Specification **(B)** tests this explanation in a multivariate regression setting.

In the regressions, we introduce linearly the estimated probabilities that the individual belongs to each one of the six classes, since they represent expected values of class memberships. The omitted category is the first class, that of

[10] The latent class model treats the "clinical health" variables as manifest indicators of a latent variable: "clinical health". As such, these observable indicators are considered as different measures of a same unobservable construct: following the terminology of the structural modelling literature, this is a measurement model (Bollen, 1989). Bandeen-Roche *et alii* (1997) propose a nice application of LCA to the relationship between a set of covariates and a set of indicators for clinical health. Using measurement models minimizes the impact that random or systematic measurement errors on each self-reported indicator may have on the estimates of specification **(B)**. In the context of the current paper, applying a latent class model also offers several advantages over factor analysis. First, factor analysis can not be applied to qualitative indicators. Second, the results of a factor analysis are not unique, since the factors need to be rotated to be interpretable. Third, factor analysis assumes multivariate normality.

[11] The Integrated Laplace Criterion balances the gain in information from adding one class with the loss in the precision of the classification (McLachlan and Peel, 2000). More details on the LCA are available upon request from the authors.

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*). In addition, we introduce controls for the individual's marital status.

4 Estimation results

This section presents the results of generalised ordered probit estimation of specifications **(A)** and **(B)**. Tables B1 and B2 in Appendix B show the estimation results. Table B1 presents the results for the variables which, in specification **(A)**, have a homogeneous effect on the cut-points, 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 B2 shows the results with respect to the variables which do have differential effects on the different cut-points. For each specification, the first column shows, for comparison purposes, the results from simple ordered probit estimation with common cut-points. The second column shows estimation results from generalised ordered probit models. In Table B2, for each specification, columns 2 to 4 show the results for the three cut-points 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 SAH

Specification **(A)**, which does not include information on clinical health, measures the correlations between the socioeconomic variables and SAH. Sex, age (measured as a second-order polynomial), education, marital status and type of residential area have a homogeneous effect on the cut-points.[12] However, region and income have a heterogeneous effect on the cut-points. Under Assumption 1, this means that there is some region- and income-related reporting heterogeneity in SAH.

The results of a simple ordered probit, which does not take into account reporting heterogeneity, are fairly standard (the first column of Table B1): male

[12] We tested for a break in the age trend at age 40, as indicated by our descriptive analysis of the age/self-assessed health 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.

has a positive estimated coefficient on reported health, as does income or living in the West of France; age has a negative effect. 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 B1). In particular, amongst the variables which do not affect the cut-points differentially (according to **Test 1**), 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). Age has a decreasing convex effect on SAH.

Region dummies have a significant effect on individual perceptions of health. The omitted category is living in Paris. Those living in the West or the Ile-de-France are less likely to say that they are in poor health.

There is a positive correlation between SAH 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 cut-points. While poverty increases the probability of being in poor health, those in middle or higher income classes are not significantly more or less likely to report poor health: income does not protect against poor health, it is rather poverty that is a risk factor. There is also a significant difference between the effect of being in the medium to high income categories (3 to 8) and the highest income class (category 9) on the probability of reporting very good health. In sum, the hypothesis of a homogeneous correlation of income with the cut-points is rejected in favour of heterogeneous correlations (**Test 1**, *P-value=0.005*). Hence, under **Assumption 1**, there is income-related reporting heterogeneity in SAH.

4.2 Clinical and self-Assessed Health

Specification **(B)** introduces the clinical health measure constructed in subsection (3.2), which identifies under **Assumption 2** income-related reporting heterogeneity.The results are presented on the right-hand side of Tables B1 and B2 in Appendix B. Following Kerkhofs and Lindeboom (1995) and Lindeboom and van Doorslaer (2004), we introduce our synthetic measures of clinical health into the index only (equation (9)). 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 self-assessed health is monotone positive. Sex no longer has an impact on health and being divorced is associated (somewhat surprisingly) with better health. The effects of education and regions are not different from those in specification **(A)**.

In this specification, income has still a positive, significant and heterogeneous effect on the cut-points. Hence, under **Assumption 2**, that income is significant provides some evidence that there is income-related reporting heterogeneity in SAH. This result is of interest because it differs from that in Lindeboom and van Doorslaer (2004) on Canadian data, who find heterogeneous 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 SAH and income, paying particular attention to the magnitude of reporting heterogeneity.

5 The magnitude of reporting heterogeneity

This section describe how reporting heterogeneity affects the predicted distributions of SAH, and provide some evidence in favour of non-linearity in income effects by initial level of SAH. It also compares the marginal effects between the two specifications to demonstrate the effect of income on clinical health. Since specification **(A)** shows the total marginal effect of income on SAH, 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.

5.1 Marginal effects

Using estimates from specification **(B)**, we can estimate the effect of an income increase on the SAH through reporting heterogeneity. The size of this effect will help determine the usefulness of SAH as a potential indicator for income-related health inequalities. Marginal effects for a discrete choice model depend crucially on the choice of values for the explanatory variables (see Greene, 2003, p. 668). A first and widely used solution is to use average sample values including the sample mean of clinical health. For each level of SAH m, the change in the probability of reporting health greater than m when the individual moves from the income category j to $j+1$ is:

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

Under **Assumption 2**, these differentials represent the way in which reporting heterogeneity affects the distribution of SAH for the average individual. Table C.1. in Appendix C reports these probability changes for different values of m and j. If we consider changes greater than 1% in absolute values, we see that reporting heterogeneity affects the middle of the distribution of SAH (fair and good), and is also larger at the extremes of the income distribution. Whereas there is almost no income-related reporting heterogeneity for those reporting poor health, we observe greater reporting heterogeneity for the more affluent in very good health. 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. It turns out that 22 changes out of 24 are insignificant at the 5% level.[13] Hence, the marginal effects computed

[13] As pointed out by a referee, the probability that 2 out of 24 estimates are significantly different from 0 at the 5% level - even if the true value is 0 - is about 35%.

at the sample mean show that income-related reporting heterogeneity has a negligible effect on the clinical health/subjective health gap.

However, a second approach to computing marginal effects is to estimate for each individual 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 **(B)**, the individual effect is then:

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

These marginal effects 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 $j{+}1$. They are calculated for each individual i. For each j**,** we compute these individual effects over the sub-sample of those individuals who are in income range j only, and the individual confidence interval at the 5% level. This can be interpreted as an "effect on the treated". Figure C1 reports the percentage of individuals in each income category for whom the reporting heterogeneity is significant at the 5% level. Here, the picture is somewhat different from that obtained for the average individual. We clearly see that reporting heterogeneity is quite large 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, or in the middle of the income distribution (especially income categories 4 to 7). Hence, computing individual marginal effects instead of marginal effects for the average individual changes our conclusion regarding reporting heterogeneity: the latter plays a fairly important role for transitions from fair to good health level, but a minor role for exits from a poor health level or transitions to very good health (except for the more affluent). This reporting heterogeneity is to an extent convex in income.

5.2 Reporting heterogeneity vs. health production

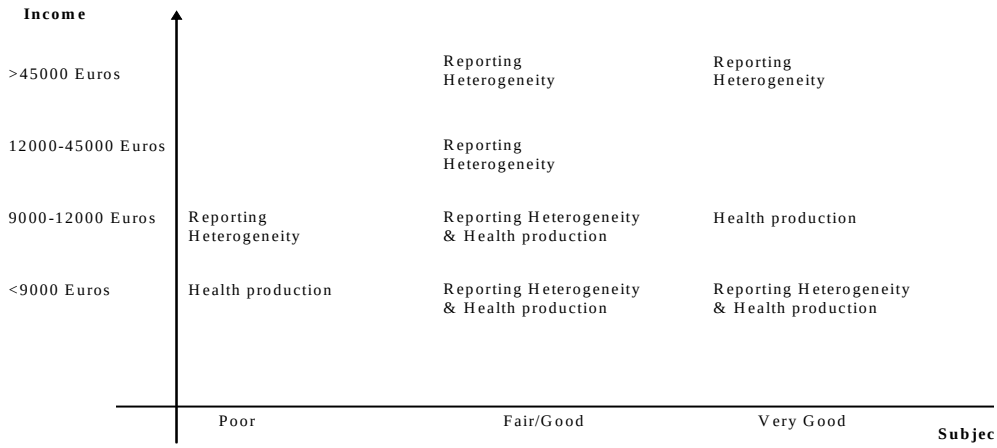
We now decompose the total health-income correlation in to a health production effect and reporting **heterogeneity**. Individual marginal effects are calculated for specification **(A)** as follows:

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

These individual effects represent the total impact of an income change on the individual predicted distribution of SAH. Figure C2 in Appendix A displays the proportion of respondents in each income category for whom the total income effect is significant at the 5% level. Income clearly affects the distribution of SAH for individuals in low-income households. For each j**,** we average the individual effects for specifications **(A)** and **(B)** over the sub-sample of those who are in income range j. These average individual marginal effects are represented, with the difference between them, in Figures C.3. to C.5. in Appendix C, 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.

Two major conclusions can be drawn from our estimates and are summarized in Figure 1. First, the health production effect of a rise in income seems particularly large for those in the lowest income range (under 12000 Euros), whatever the SAH level m we consider. This implies that income has declining marginal productivity in health production, and is consistent with standard results in the literature on the health production effect of income among the poorest (Deaton, 2003). This income gradient in health production is also found when one models the probabilities of membership of "clinical health" classes as a function of income and other covariates. The regression results that are reported in Table C.2. in Appendix C show however that income does not influence the probability of membership of all "unhealthy" classes. For instance, income plays a major role for membership of class 3 but not membership of class 4. This could reflect differences in equality of access to health care according to the pathologies. Indeed, class 4 attracts more individuals with ischemic problems, who are eligible for Social Security, while individuals in class 3 declare more often problems or health conditions that are not eligible (teeth, migraines, assistance at home).



Summary of the results.

6 Conclusion

This article has proposed and implemented two different appraoches to testing for the existence of reporting heterogeneity in SAH. The first relies essentially on the assumption that the marginal effect of income on clinical health does not vary with the position in the clinical health distribution. Hence, heterogeneous

income effects on the different cut-points are interpreted as evidence of income-related reporting heterogeneity: this is our **Test 1**. The second approach uses a proxy measure of clinical health to control for the effect of income on clinical health, and interprets any remaining impact of income on SAH as reporting heterogeneity. This is our Test 2, which is based on arguably weaker identifying assumptions than **Test 1**. Further, **Test 1** does not enable us to detect reporting heterogeneity, when the latter has a homogeneous effect on the cut-points, while this is not the case for Test 2. Both approaches produce some support for the existence of income-related reporting heterogeneity.

Using the proxy-based approach (**Test 2** and **Specification B**), our estimates reveal that reporting heterogeneity is convex in income, which can be interpreted as an optimism bias for the rich and a pessimism bias for the poor. However, this result relies heavily on the assumption that all of the clinical 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 assumption may be questionable if we do not capture all of the relevant income-related dimensions of clinical health. For instance, if there is a pro-rich bias in access to health care, as one may suppose *a priori*, then the effect of income on clinical health is underestimated, and income-related reporting heterogeneity is over-estimated for low-income individuals. In some sense, our work provides an upper-bound evaluation of income-related reporting heterogeneity for the less well-off, and a lower bound evaluation of the effect of income on their clinical health, which we have called a clinical health production effect although this term might be excessive. Indeed, we are fully aware that we identify correlations rather than causalities, given that SAH determines the demand for health which, in turn, affects income (see Adams *et al.*, 2003).

The starting point and the limits of our exercise are clear: we focus on SAH as a cheap measure of clinical health, which is considered as the true objective of public health policies, even if one would not base a major change in health policies on SAH alone. Our results call for caution in the use of SAH measures for assessing income-related health inequalities in French data. In particular, we find that, for those in the middle of the SAH distribution, a rise in income seems to affect SAH mainly *via* reporting (a noticeable exception being individuals in low-income households). As a consequence, binary indicators constructed from self-reported health may be used, but only if the "poor health" category is taken as a reference. The results provided here could be checked by a fairly new and promising third method: that of vignettes (King *et al.*, 2004).

Last, 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 SAH, 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
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 inhabitants	16.3%
STRATA3	Urban, between 20,000 and 100,000 inhabitants	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/year	8.3%
Income3	12,000-15,000 Euros/ year	10.9%
Income4	15,000-18,000 Euros/ year	10.2%
Income5	18,000-22,500 Euros/ year	14.2%
Income6	22,500-27,000 Euros/ year	14.2%
Income7	27,000-36,000 Euros/ year	16.3%
Income8	36,000-45,000 Euros/ year	9.1%
Income9	>45,000 Euros/ year	8.5%
Qual4	=1 if education over the Baccalaureat (A-level)	27.3%
Qual3	=1 if Baccalaureat passed	34.2%
Qual2	=1 if has a degree under the Baccalaureat	12.3%
Qual1	=1 if no education	26.2%
SINGLE	=1 if single	30.6%
WIDOWED	=1 if widowed.	3.7%
DIVORCED	=1 if divorced	12.1%
MARRIED	=1 if married	53.6%

Figure A1. Distribution of subjective health by household income category

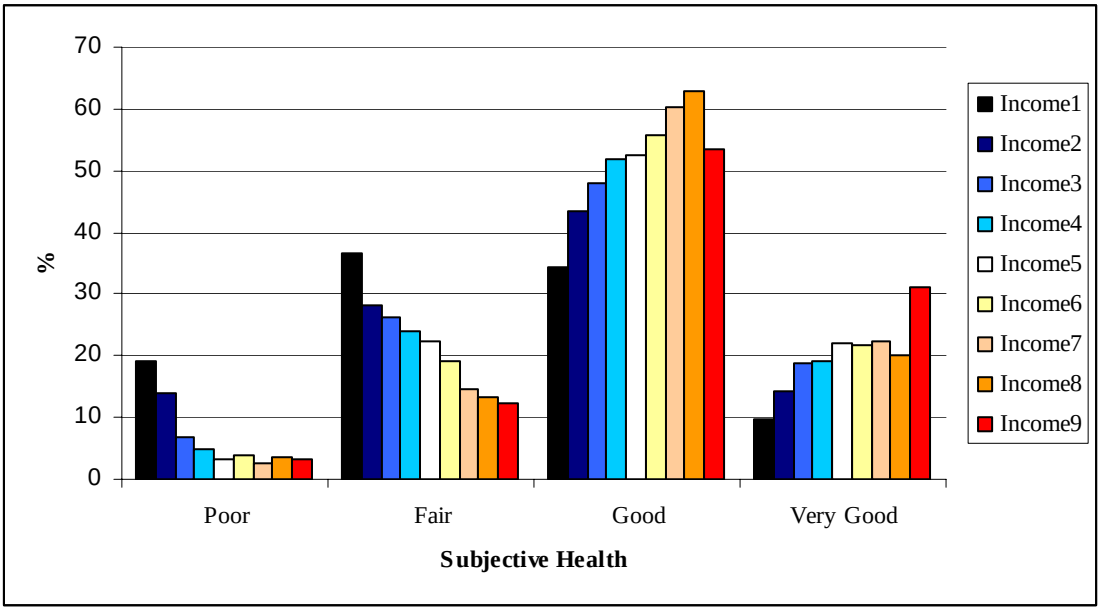


Table A.2. Objective health conditions by class of clinical health

Class	**1**	**2**	**3**	**4**	**5**	**6**
% of the sample (N=2956)	**40.7%**	**15.2%**	**13.7%**	**17.6%**	**6.5%**	**6.3%**
Immunity						
Has had a fever over 39°c in the past year	3%	3%	6%	3%	6%	16%
Use of health care						
Follows psychiatric treatment	1%	1%	8%	5%	69%	54%
Has regular check-ups for chronic disease	0%	0%	26%	79%	59%	96%
Has to take medicines regularly	9%	17%	38%	93%	95%	100%
Has had a 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 pain moderate (ref: none)	26%	25%	32%	17%	32%	27%
Teeth pain 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%

Table A.3. Distribution of subjective health by class of clinical health

Class	**1**	**2**	**3**	**4**	**5**	**6**
Subjective health = poor	0.5%	0.5%	5.0%	5.7%	16.9%	46.5%
Subjective health = fair	8.5%	10.8%	27.9%	35.3%	50.5%	45.1%
Subjective health = good	58.8%	64.4%	54.7%	50.6%	29.0%	6.8%
Subjective health = very good	32.2%	24.4%	12.4%	8.4%	3.7%	1.7%

Table A.4. Percentage of respondents reporting very good SAH by income category and class of clinical health (in %)

Class	**1**	**2**	**3**	**4**	**5**	**6**
Income1	17.8	18.1	8.1	3.7	2.9	4.5
Income2	24.3	28.8	2.6	5.2	8.2	3.6
Income3	32.6	25.0	8.1	4.2	0.1	0
Income4	26.9	31.2	11.3	11.2	3.7	0
Income5	35.3	25.2	11.7	7.8	4.8	0.3
Income6	34.5	17.4	17.1	12.0	0.6	0.0
Income7	32.1	24.2	16.1	5.9	2.9	0.0
Income8	32.9	16.5	13.4	4.9	0.2	0.0
Income9	43.9	37.4	22.1	16.5	10.0	0.3

Table A.5. Percentage of respondents reporting good or very good SAH by income category and class of clinical health (in %)

Class	**1**	**2**	**3**	**4**	**5**	**6**
Income1	78.7	61.9	53.6	30.7	11.3	8.4
Income2	81.9	84.4	55.4	43.9	28.2	7.4
Income3	90.0	80.9	61.7	46.6	29.1	0.8
Income4	88.5	97.9	61.1	55.7	36.1	1.3
Income5	91.0	88.9	66.4	57.5	44.6	8.8
Income6	92.6	90.5	70.8	65.2	39.2	5.8
Income7	94.9	90.5	74.9	69.5	30.1	14.3
Income8	93.5	94.2	77.0	65.2	44.8	51.1
Income9	97.2	93.1	82.8	73.0	56.1	6.5

Table A.6. Percentage of respondents reporting good or very good SAH by income category and class of clinical health (in %)

Class	**1**	**2**	**3**	**4**	**5**	**6**
Income1	3.7	4.6	10.9	17.1	35.5	47.3
Income2	0.2	0.0	16.1	10.1	19.1	67.6
Income3	0.0	0.3	4.0	12.1	18.5	39.3
Income4	0.8	0.0	3.8	4.9	14.8	35.1
Income5	0.2	0.0	3.1	1.3	4.7	45.5
Income6	0.0	0.0	2.1	3.1	13.2	46.4
Income7	0.4	1.1	2.2	4.4	11.9	23.8
Income8	1.1	0.0	4.6	5.3	16.9	31.2
Income9	0.0	0.0	3.7	2.8	2.5	80.5

APPENDIX B. RESULTS.

Table B1. Variables that do not have a differential effect on the thresholds

Specification	**A**		**B**	
Statistical model	*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	-0.127*	-0.126*
			(0.068)	(0.068)
Objective Health: class 3	No	No	-0.997***	-1.003***
			(0.074)	(0.075)
Objective Health: class 4	No	No	-1.153***	-1.153***
			(0.092)	(0.093)
Objective Health: class 5	No	No	-1.754***	-1.769***
			(0.113)	(0.114)
Objective Health: class 6	No	No	-2.720***	-2.753***
			(0.116)	(0.119)
Male	0.153***	0.151***	0.043	0.043
	(0.042)	(0.042)	(0.044)	(0.044)
STRATA1	0.050	0.049	-0.035	-0.032
	(0.057)	(0.057)	(0.059)	(0.059)
STRATA2	-0.058	-0.060	-0.048	-0.052
	(0.063)	(0.063)	(0.065)	(0.065)
STRATA3	-0.008	-0.011	0.025	0.022
	(0.066)	(0.066)	(0.068)	(0.068)
STRATA4	Reference	Reference	Reference	Reference
QUAL1	-0.209***	-0.214***	-0.175***	-0.181***
	(0.065)	(0.065)	(0.067)	(0.068)
QUAL2	-0.064	-0.070	-0.034	-0.039
	(0.058)	(0.058)	(0.060)	(0.060)
QUAL3	0.054	0.052	0.096	0.097
	(0.073)	(0.073)	(0.075)	(0.076)
QUAL4	Reference	Reference	Reference	Reference
AGE/10	-0.641***	-0.614***	-0.645***	-0.627***
	(0.144)	(0.144)	(0.149)	(0.150)
$(AGE/10)^2$	0.042**	0.039**	0.059***	0.057***
	(0.016)	(0.016)	(0.017)	(0.017)
SINGLE	-0.002	-0.006	0.029	0.026
	(0.054)	(0.054)	(0.056)	(0.056)
WIDOWED	-0.163	-0.143	-0.044	-0.033
	(0.114)	(0.115)	(0.120)	(0.121)
DIVORCED	0.047	0.052	0.147**	0.154**
	(0.069)	(0.069)	(0.071)	(0.072)
MARRIED	Reference	Reference	Reference	Reference
Threshold intercepts. ordered probit model only				
Threshold 1: s_1	-4.088***	No	-4.814***	No
	(0.324)		(0.338)	
Threshold 2: s_2	-3.008***	No	-3.353***	No
	(0.321)		(0.334)	
Threshold 3: s_3	-1.420***	No	-1.504***	No
	(0.318)		(0.329)	

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

Table B2. Variables that have a differential effect on the thresholds

Specification	**A**				**B**			
Model	*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	0.070	0.325**	0.024	0.055	0.116	0.358**	0.087	0.095
	(0.076)	(0.148)	(0.096)	(0.096)	(0.079)	(0.175)	(0.104)	(0.100)
West	0.134*	0.486***	0.163	0.021	0.224***	0.716***	0.304***	0.063
	(0.080)	(0.167)	(0.103)	(0.103)	(0.083)	(0.204)	(0.115)	(0.107)
East	-0.056	0.171	-0.185*	0.015	-0.002	0.276	-0.143	0.067
	(0.084)	(0.164)	(0.105)	(0.107)	(0.086)	(0.200)	(0.115)	(0.112)
North	-0.099	0.105	-0.180	-0.071	-0.009	0.357*	-0.084	-0.037
	(0.091)	(0.171)	(0.115)	(0.125)	(0.095)	(0.211)	(0.128)	(0.131)
Center	-0.022	-0.089	-0.016	0.004	0.079	0.014	0.112	0.085
	(0.079)	(0.142)	(0.101)	(0.103)	(0.082)	(0.173)	(0.112)	(0.108)
Southwest	-0.028	0.191	-0.074	-0.056	0.022	0.208	-0.011	0.002
	(0.082)	(0.153)	(0.103)	(0.108)	(0.085)	(0.179)	(0.112)	(0.112)
Mediterranean	0.048	0.101	-0.013	0.107	0.001	0.168	-0.048	0.007
	(0.080)	(0.145)	(0.101)	(0.105)	(0.083)	(0.180)	(0.112)	(0.110)
INCOME1	-1.099***	-1.014***	-1.174***	-0.876***	-0.884***	-0.734***	-0.987***	-0.664***
	(0.113)	(0.197)	(0.140)	(0.152)	(0.118)	(0.238)	(0.155)	(0.161)
INCOME2	-0.798***	-0.813***	-0.849***	-0.623***	-0.713***	-0.698***	-0.790***	-0.531***
	(0.111)	(0.200)	(0.138)	(0.142)	(0.115)	(0.244)	(0.151)	(0.149)
INCOME3	-0.548***	-0.382*	-0.628***	-0.472***	-0.542***	-0.239	-0.628***	-0.510***
	(0.103)	(0.203)	(0.131)	(0.126)	(0.106)	(0.249)	(0.145)	(0.133)
INCOME4	-0.479***	-0.260	-0.515***	-0.479***	-0.448***	-0.072	-0.491***	-0.468***
	(0.103)	(0.211)	(0.133)	(0.127)	(0.106)	(0.260)	(0.147)	(0.133)
INCOME5	-0.386***	-0.065	-0.444***	-0.384***	-0.384***	0.042	-0.462***	-0.389***
	(0.095)	(0.211)	(0.125)	(0.114)	(0.098)	(0.262)	(0.137)	(0.120)
INCOME6	-0.301***	-0.134	-0.296**	-0.326***	-0.318***	-0.015	-0.325**	-0.349***
	(0.093)	(0.203)	(0.124)	(0.113)	(0.096)	(0.253)	(0.137)	(0.118)
INCOME7	-0.238***	0.021	-0.133	-0.355***	-0.313***	-0.074	-0.204	-0.422***
	(0.090)	(0.206)	(0.123)	(0.109)	(0.093)	(0.249)	(0.136)	(0.113)
INCOME8	-0.232**	-0.138	-0.077	-0.368***	-0.309***	-0.285	-0.132	-0.440***
	(0.099)	(0.217)	(0.136)	(0.123)	(0.102)	(0.259)	(0.149)	(0.129)
INCOME9	Reference	Reference			Reference	Reference		
Intercept	No	3.754***	3.003***	1.384***	No	4.395***	3.359***	1.507***
		(0.353)	(0.329)	(0.324)		(0.385)	(0.344)	(0.336)

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

APPENDIX C. MARGINAL EFFECTS.

*Table C1. Reporting bias (in percentage points) at the sample mean – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.3%	7.5%	2.4%
Between 9 000 and 12 000€: *INCOME2*	**2.8%**	5.8%	0.4%
Between 12 000 and 15 000€: *INCOME3*	0.5%	4.5%	0.9%
Between 15 000 and 18 000€: *INCOME4*	0.3%	0.9%	1.7%
Between 18 000 and 22 500€: *INCOME5*	-0.1%	4.0%	0.9%
Between 22 500 and 27 000€: *INCOME6*	-0.1%	3.2%	-1.7%
Between 27 000 and 36 000€: *INCOME7*	-0.7%	1.7%	-0.4%
Between 36 000 and 45 000€: *INCOME8*	0.9%	2.8%	**11.7%**

Ref: over 45 000 €. *INCOME9*

Note: Marginal effects computed at the sample mean for all characteristics. These effects represent changes in the probability of declaring a health status over the figure indicated in the top of the column. The changes 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 shown on the left. The figures in bold are significant at the 5% level.

Table C2. Relative risk of membership of "clinical health" classes by income category.

Class of "clinical health"	**2**	**3**	**4**	**5**	**6**
Income category					
Less than 9 000 €/year: *INCOME1*	1.022	**2.171**	0.976	**2.158**	**9.956**
Between 9 000 and 12 000€: *INCOME2*	1.134	**1.972**	1.045	1.322	**5.502**
Between 12 000 and 15 000€: *INCOME3*	1.260	1.495	0.721	1.011	**3.197**
Between 15 000 and 18 000€: *INCOME4*	1.258	**1.910**	0.879	0.780	**3.162**
Between 18 000 and 22 500€: *INCOME5*	1.169	**1.634**	0.891	0.870	**2.108**
Between 22 500 and 27 000€: *INCOME6*	1.211	1.362	0.922	0.671	**2.055**
Between 27 000 and 36 000€: *INCOME7*	1.078	1.201	0.735	0.545	1.054
Between 36 000 and 45 000€: *INCOME8*	1.172	1.262	0.751	0.511	1.180

Note: These figures represent the relative risk of being in the "clinical health" class *j* over the first "clinical health" class when the individual is in income category *k* instead of being in the top income category (*INCOME9*). These relative risk ratios are computed by supposing that the class membership probabilities follow a multinomial distribution conditional on income and the other control variables in Tables B1 and B2 (see Etilé, 2006, for more details on this technique). The relative risk ratios in bold are significant at the 5% level.

Figure C1. Specification B – Significance of the individual marginal income effects.

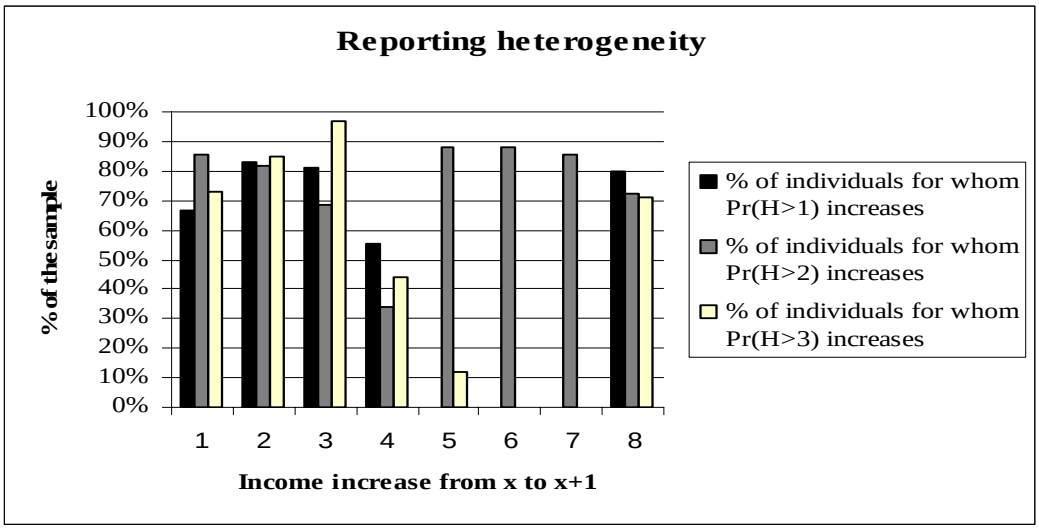
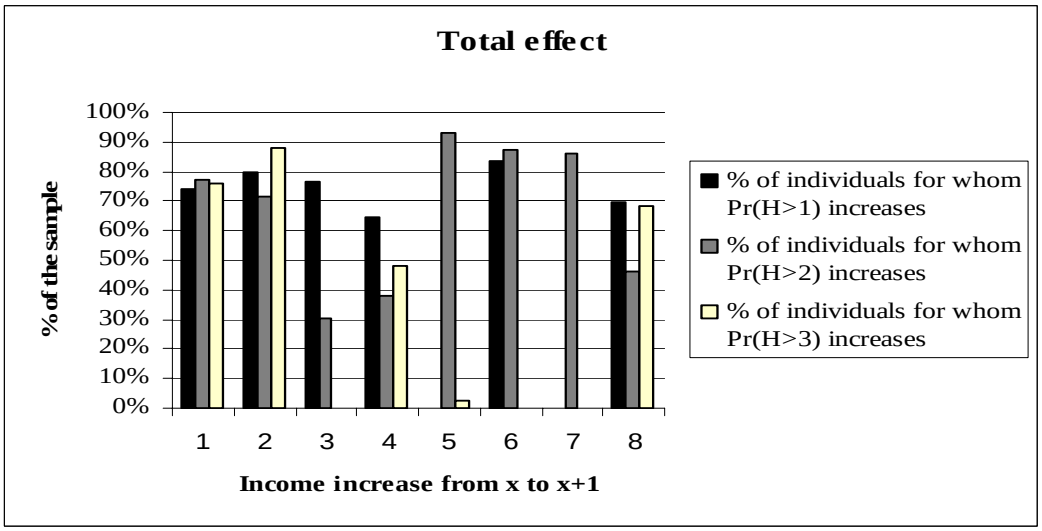
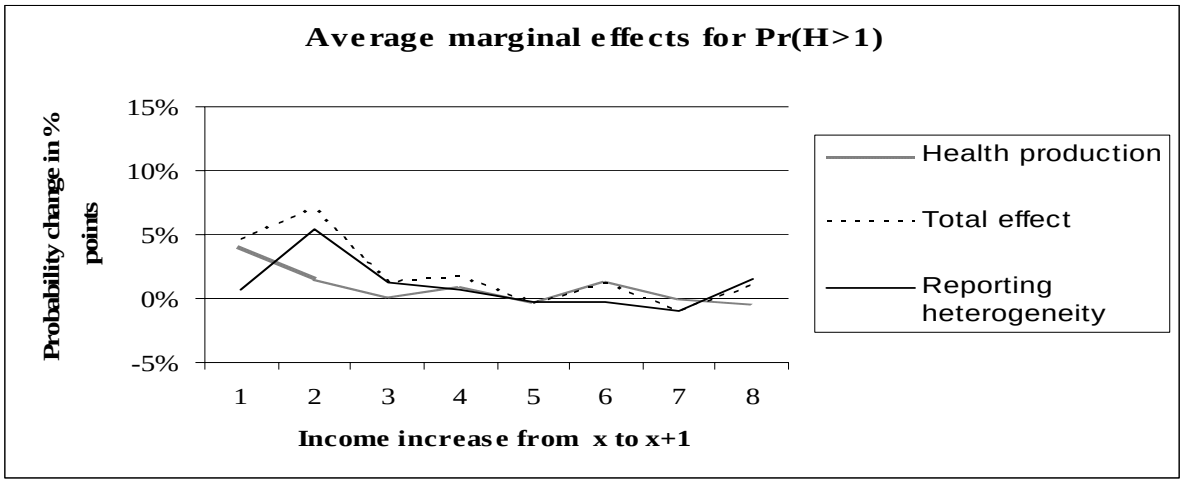


Figure C2. Specification A – Significance of the individual marginal income effects.



Note: Figures C1 and C2 show for each income category the % of individuals for whom a given marginal effect is significant at the 5% level.

Figure C3. Probability of reporting SAH greater than poor.



Note: Figures C3 to C5 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 from specification **(B)**, and the "total effect" line using estimates from specification **(A)**. The "health production" line is simply the average of differences between marginal effects from **(A)** and from **(B)**.

Figure C4. Probability of reporting SAH greater than fair.

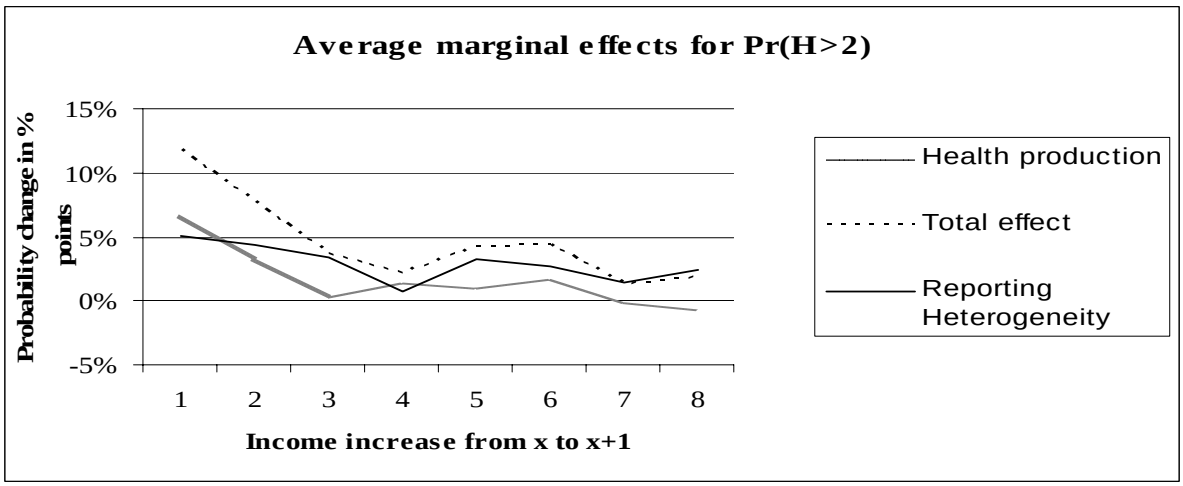
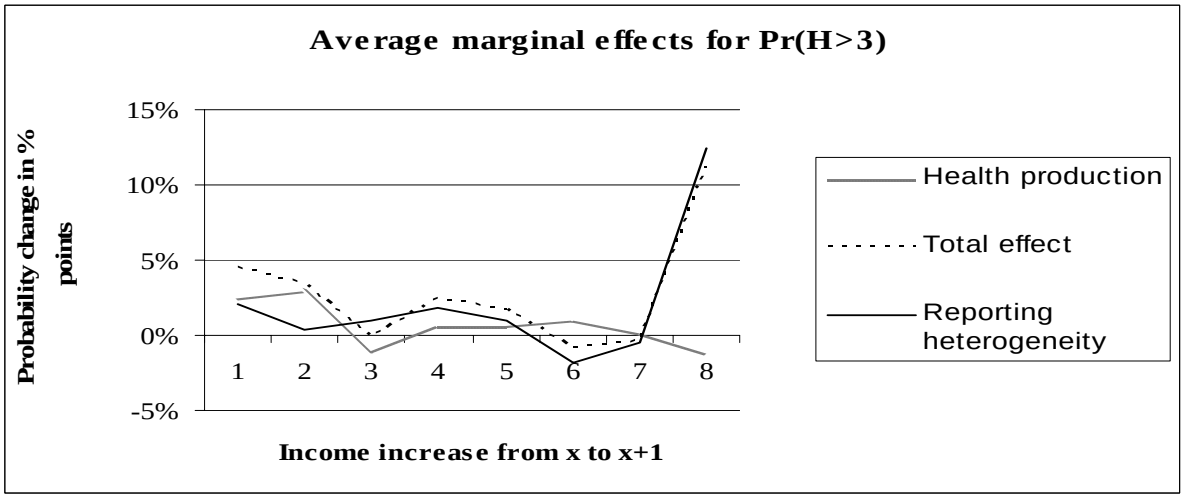


Figure C5. Probability of reporting SAH greater than good.



ALTERNATIVE SPECIFICATIONS: MAIN RESULTS.

1/ Separate regressions.

Individuals in households with 1.5 consumption units or less.

*Table C1. Reporting bias effect (percentage in points) – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.3%	**13.6%**	2.9%
Between 9 000 and 12 000€: *INCOME2*	**3.1%**	2.0%	0.4%
Between 12 000 and 15 000€: *INCOME3*	1.2%	5.4%	0.5%
Between 15 000 and 18 000€: *INCOME4*	0.3%	2.5%	2.2%
Between 18 000 and 22 500€: *INCOME5*	0.1%	4.1%	0.1%
Between 22 500 and 27 000€: *INCOME6*	0.2%	4.8%	-0.6%
Between 27 000 and 36 000€: *INCOME7*	**-3.6%**	0.6%	-0.6%
Between 36 000 and 45 000€: *INCOME8*	**3.3%**	2.6%	**9.1%**

Ref: over 45 000 €. *INCOME9*

Individuals in households with more than 1.5 consumption units.

*Table C1. Reporting bias effect (percentage in points) – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.5%	-19.2%	-2.9%
Between 9 000 and 12 000€: *INCOME2*	1.5%	**21.7%**	3.4%
Between 12 000 and 15 000€: *INCOME3*	-0.3%	3.6%	3.1%
Between 15 000 and 18 000€: *INCOME4*	0.2%	-1.0%	2.7%
Between 18 000 and 22 500€: *INCOME5*	-0.2%	4.0%	1.7%
Between 22 500 and 27 000€: *INCOME6*	-0.4%	2.4%	-1.8%
Between 27 000 and 36 000€: *INCOME7*	0.7%	1.8%	-0.8%
Between 36 000 and 45 000€: *INCOME8*	-0.4%	2.9%	**14.5%**

Ref: over 45 000 €. *INCOME9*

Test threshold heterogeneity – P-value = 0.604 (specification A)

2/ Dropping teeth, eyesight and psychological variables from the list of indicators

*Table C1. Reporting bias effect (percentage in points) – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.8%	6.3%	2.5%
Between 9 000 and 12 000€: *INCOME2*	**2.7%**	6.0%	1.4%
Between 12 000 and 15 000€: *INCOME3*	0.5%	4.9%	0.3%
Between 15 000 and 18 000€: *INCOME4*	0.1%	0.9%	2.0%
Between 18 000 and 22 500€: *INCOME5*	0.0%	**5.7%**	1.5%
Between 22 500 and 27 000€: *INCOME6*	-0.1%	2.6%	-1.5%
Between 27 000 and 36 000€: *INCOME7*	-0.3%	3.4%	0.1%
Between 36 000 and 45 000€: *INCOME8*	0.6%	1.4%	**12.2%**

Ref: over 45 000 €. *INCOME9*

3/ Controlling for the number of consumption units (ln(uc) is included as a regressor in the cut-points).

*Table C1. Reporting bias effect (percentage in points) – specification **(B)***

Initial income	ΔPr(H>1)	ΔPr(H>2)	ΔPr(H>3)
Less than 9 000 €/year: *INCOME1*	0.3%	-4.2%	0.0%
Between 9 000 and 12 000€: *INCOME2*	**2.7%**	0.3%	-1.4%
Between 12 000 and 15 000€: *INCOME3*	0.5%	0.4%	0.1%
Between 15 000 and 18 000€: *INCOME4*	0.2%	0.5%	0.0%
Between 18 000 and 22 500€: *INCOME5*	-0.1%	0.1%	0.1%
Between 22 500 and 27 000€: *INCOME6*	-0.1%	0.7%	0.1%
Between 27 000 and 36 000€: *INCOME7*	-0.6%	0.8%	0.1%
Between 36 000 and 45 000€: *INCOME8*	0.9%	1.9%	0.9%

Ref: over 45 000 €. *INCOME9*
Test of threshold heterogeneity (specification A) – P-value = 0.066

But there is no health production effect if we compute the latter by the difference between the results of specification (A) and specification (B).

Table C2. Relative risk of membership of "clinical health" classes by income category.

Class of "clinical health"	**2**	**3**	**4**	**5**	**6**
Income category					
Less than 9 000 €/year: *INCOME1*	0.950	**1.971**	0.898	1.608	**10.107**
Between 9 000 and 12 000€: *INCOME2*	1.044	**1.776**	0.955	1.000	**5.513**
Between 12 000 and 15 000€: *INCOME3*	1.181	1.373	0.672	0.810	**3.190**
Between 15 000 and 18 000€: *INCOME4*	1.194	**1.787**	0.830	0.649	**3.194**
Between 18 000 and 22 500€: *INCOME5*	1.126	**1.554**	0.854	0.744	2.140
Between 22 500 and 27 000€: *INCOME6*	1.181	1.316	0.897	0.624	2.046
Between 27 000 and 36 000€: *INCOME7*	1.057	1.172	0.719	**0.510**	1.058
Between 36 000 and 45 000€: *INCOME8*	1.156	1.238	0.740	**0.489**	1.179

Note: These figures represent the relative risk of being in the "clinical health" class *j* over the first "clinical health" class when the individual is in income category *k* instead of being in the top income category (*INCOME9*). These relative risk ratios are computed by supposing that the class membership probabilities follow a multinomial distribution conditional on income and the other control variables in Tables B1 and B2 (see Etilé, 2006, for more details on this technique). The relative risk ratios in bold are significant at the 5% level.