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 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.

Codes JEL: C25, D63, I12, I31.

Keywords: reporting, heterogeneity, self-assessed, subjective, health.

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. 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.

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An objective measure of clinical health is usually expensive to collect, since data collection has to be based on a costly device of medical check-ups, which may further induce a strong 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 incorporates the individual preferences of a sub-sample of the population (Gerdtham *et al.*, 1999, Dolan, 2000).

Given these arguments, a subjective health measure may be interesting. A 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, the individual social status and the individual health history (Boltanski, 1971; Butler *et al.*, 1987; Johansson, 1991; Heyink, 1993; Kerkhofs and Lindeboom, 1995; Sadana *et al.*, 2000; Wu, 2001; Murray *et al.*, 2001). This reporting heterogeneity may be considered as a bias in the sense that self-assessed health (SAH) is a biased measure of clinical health.[1]

The presence of reporting heterogeneity in self-assessed health in France is the key concern of this paper. 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, 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 biases in France.

This article uses French data from the 2001 Conditions de Vie des ménages survey to address this question. Using specific identifying assumption, we are able to test for reporting heterogeneity. We also construct a synthetic proxy

[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).

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. We then use this proxy to decompose the effect of income on H_i into an effect on clinical health, which is a random variable $\tilde{H}_i$, and an effect on the transformation $T[.;Q_i]$ of $\tilde{H}_i$ into H_i, where Q_i is the set of variables that affect reporting: $H_i = T[\tilde{H}_i; Q_i]$. This allows us to assess the magnitude of reporting heterogeneity.

Our main finding is that there is substantial 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 a poor SAH, income affects significantly SAH 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 SAH 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 The generalised ordered probit model

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

$$\tilde{H}_i = \alpha_0 + X_i \alpha + \mathbf{e}_i \tag{1}$$

where α is a vector of parameters, α_0 is a constant, and $\mathbf{e}_i$ is an error term capturing unobservable factors. The reporting equation linking the observable variables is:

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

The function $T(.;.)$ and the error term $\mathbf{e}$ 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: for two individuals i and

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

j we have $H_i > H_j \Longrightarrow \tilde{H}_i > \tilde{H}_j$, and H_i can be used to assess income-related inequalities in clinical health. The relation (2) reduces to $H_i = T[\alpha_0 + X_i\alpha + \varepsilon_i]$. We can then suppose that there exist cut-points $s_0, s_1 ..., s_M$ such that

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

with the identification restriction $\alpha_0 = 0$: when ε_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

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

where β_m are additional parameters, and Q includes a constant. Reported health H_i then depends on the way in which clinical health $\tilde{H}_i$ is translated by the cut-points $(s_{i0}, s_{i1} ..., s_{iM})$. In this case interpersonal comparability of health may no be assured.

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 Testing for reporting heterogeneity

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

$$\tilde{H}_i = \alpha X_i + \varepsilon_i^A$$

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

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 $\tilde{H}_i$ 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:

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

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

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

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

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

The structural models associated with these probabilities differ with respect to the specification of the cut-points s_{im} and the modelisation of $\tilde{H}_i$. For the models associated with equation (6) we have $\tilde{H}_i = X_i(\alpha + \delta) + \mathbf{e}_i$ and $s_{im} = X_i(\beta_m + \delta)$; for those associated with (7) we have $\tilde{H}_i = X_i\alpha_2 + \mathbf{e}_i$ and $s_{im} = X_i(\beta_m - \alpha_1)$. Hence equation (1) is not identified, because any variable which has an effect on $\tilde{H}_i$ 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 $\tilde{H}_i$ (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 cut-points.[3] Indeed, Specification **(A)** identifies $\gamma_m = (\beta_m - \alpha)$ for $m = 1, ..., M-1$. A variable has a homogeneous effect on the cut-points if the coefficients β_m associated with this variable does not vary from one cut-point to another. Such a restriction 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**.

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

[3] 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).

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 to measure income: the relationship between income and clinical health is thus specified in a very flexible manner.

Using Specification **(A)**, we will test for reporting heterogeneity, by determining the variables that have a heterogeneous effect on the cut-points. However, these variables may also have a linear effect on clinical health, so that Specification **(A)** does not allow us to draw conclusions regarding the magnitude of reporting heterogeneity. A number of different strategies can be imagined to overcome this difficulty of interpretation. Groot (2000) supposes that for all individuals $s_{i1} = 0$: one of the two extreme SAH categories constitutes a common anchoring point. This hypothesis allows to identify 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.

In the current paper, we are interested in both the identification of the income effect on $\tilde{H}_i$ as well as 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

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. In this perspective, 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 we could introduce all self-reported clinical health conditions in the vector X_i, in order not to loose information. Using a synthetic proxie measure of clinical health yields two benefits here. First, our approach is more parsimonious in that we do not overload the model with too many parameters. Second, we can test whether each self-reported condition has a specific impact (a heterogeneous effect) on the thresholds, which we interpret as an evidence of adaptation or mis-adaptation to illness.

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

Hypothesis 2

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

where Y is the income and Z denotes the other right hand side variables ($X = (Y, Z)$).

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

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

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

Here, we assume for the sake of parsimony that H^0 picks up only the effect of income on clinical health, because Specification **(B)** focuses more specifically on income-related reporting heterogeneity. This is why we keep the Z_i variables in the health production equation. Under **Hypothesis 2**, specification **(B)** identifies the effect of reporting heterogeneity on income. 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 $\tilde{H}_i$, since the variances of both ε_i^A and ε_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, by using data from the "Enquête Permanente sur les Conditions de Vie des Ménages" survey (EPCV2001), carried out by the INSEE 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 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 SAH and Income

SAH 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 are grouped together due to small cell sizes. The SAH 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 SAH 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 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 a 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).[4] This correlation may result from 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.

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 SAH (see Figure A2, Appendix A).

The correlation between income and SAH 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.

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.

[4] 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.

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 musculo-skeletic troubles. Nervous illness 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 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.[5] 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.[6]

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}. 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; 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 conditionally to 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 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.

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

[6] 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.

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).[7] 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 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.

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

This section presents the results of generalised ordered probit estimation of specifications **(A)** and **(B)**.

[7] 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.

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 different 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 SAH 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, measures the correlations between the socioeconomic variables and SAH. Sex, age (measured as a three-order polynomial),[8] education, and type of residential area have the same effect on the cut-points. However, family situation, region and income have a heterogeneous effect on the cut-points.

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 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 B1). In particular, amongst the variables which do not affect the cut-points (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). 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 cut-point 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.

[8] 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.

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 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. 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 cut-points is rejected in favour of heterogeneous correlations (**Test 1**, P-value=0.020). Hence, under **Hypothesis 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 **Hypothesis 2** income-related reporting heterogeneity.

The results from specification **(B)** 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)). 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 cut-points, 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 cut-points.

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 cut-points. Having stayed in hospital, regular examinations due to an illness or being advised against certain sporting activities increase the probability of reporting a poor or fair health, but not 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 SAH, 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 cut-points (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 SAH and income, paying particular attention to 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 clinical health is to compare the marginal effects between the two specifications. 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. On this basis, we describe how reporting heterogeneity affects the predicted distributions of SAH, and we provide some evidence in favour of non-linearities in income effects by initial level of SAH.

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 SAH 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 2**, these variations represent the way reporting heterogeneity affects the distribution of SAH for the average individual. Tables C1 in Appendix C 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 SAH (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.

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 at the 5% level.

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 $j+1$. 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.[9] These mean effects are represented, with the difference between them, in Figures C1 to C3 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. 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 1. 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 SAH 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 an 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.

Figures C4 and C5 report the percentage of individuals in each income category for which the reporting heterogeneity and the total effect of income are

[9] 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.

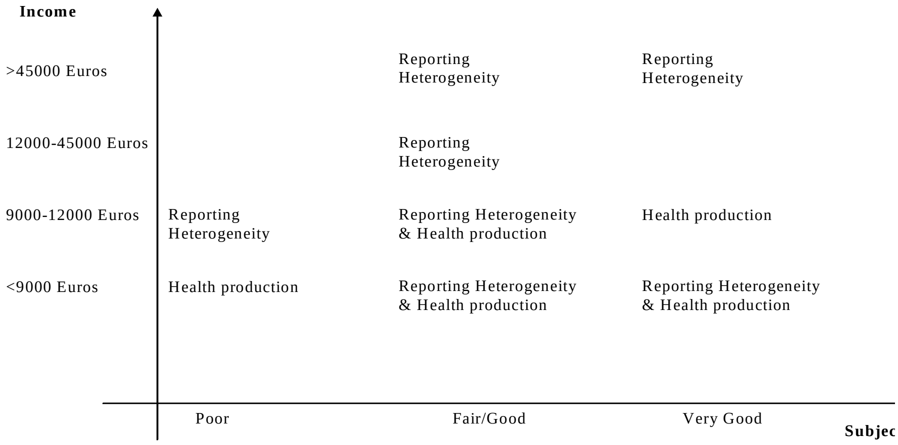

Figure 1: Summary of the results.

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 SAH in France.

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-point shifts. Further, this may also be explained by the very peculiar nature of our sample, which excludes the elderly.

Our estimates reveal that the reporting bias is convex in income and 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 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 *a priori*, then the effect of income on clinical health 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 less well-off. And a lower bound evaluation of the effect of a rise in income on their 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).

Last, the starting point and the limits of our exercise are clear: we focus on SAH as a cheap measure of clinical health. If clinical health is the true objective of public health policies, then one would not base a major change in health policies on SAH alone. However, an alternative view is that SAH 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 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 the poors). 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 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 subjective evaluation of 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

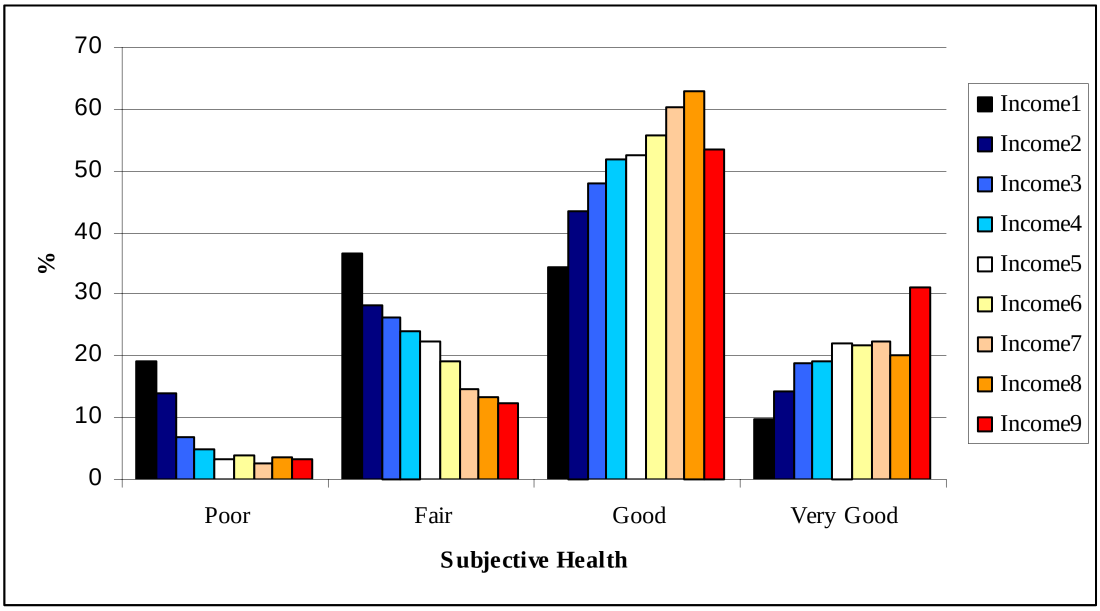


Table A.2. Objective health conditions

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%

APPENDIX B. RESULTS.

Table B1. 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 B2. 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 C. MARGINAL EFFECTS.

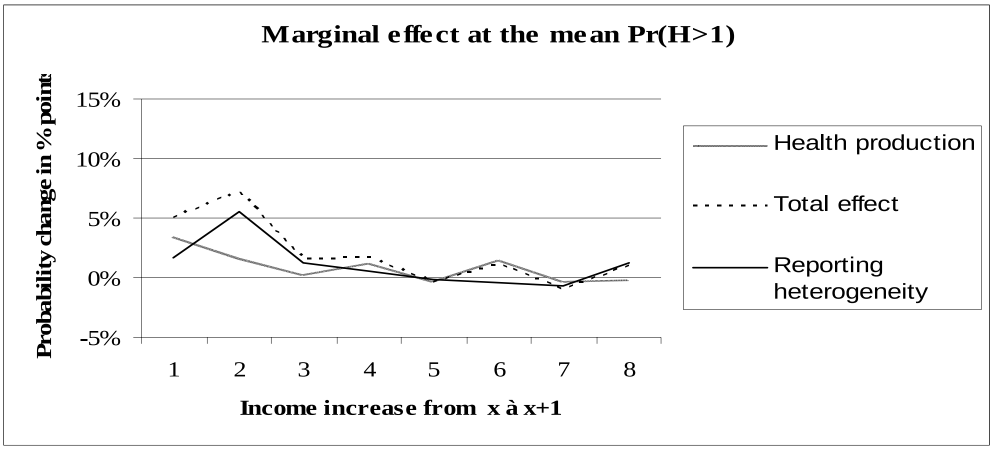
Table C1. Reporting bias effect (in points of probability) – specification ***(B)***

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*

Note: Marginal effects computed at the sample mean for all characteristics. 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.

Figure C1. Probability of reporting SAH greater than poor.



Note: Figures C1 to C3 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 C2. Probability of reporting SAH greater than fair.

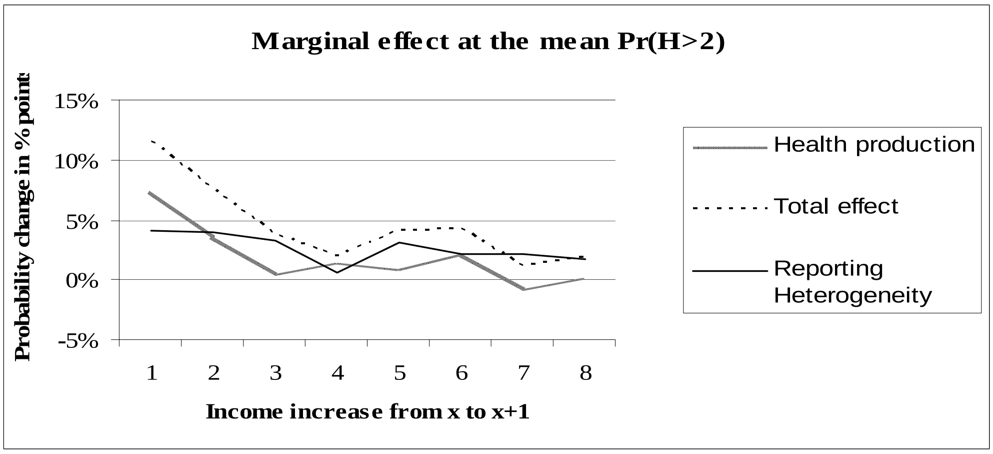


Figure C3. Probability of reporting SAH greater than good.

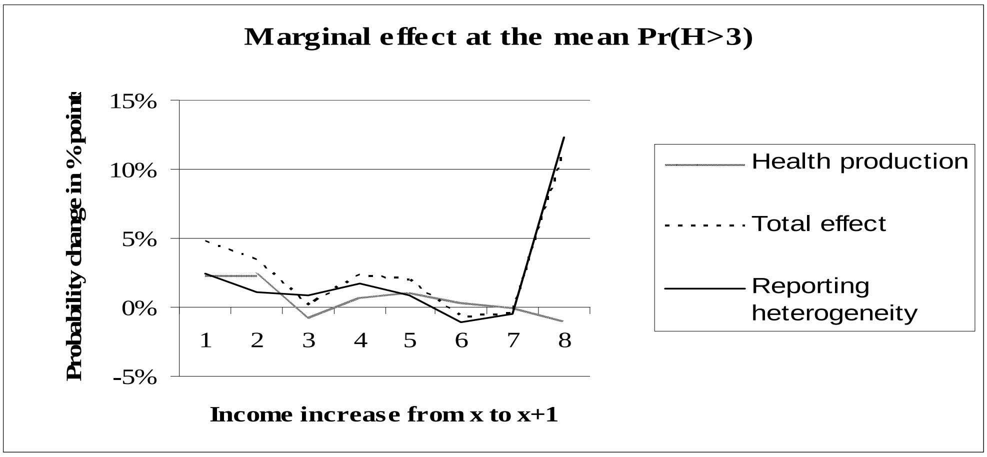
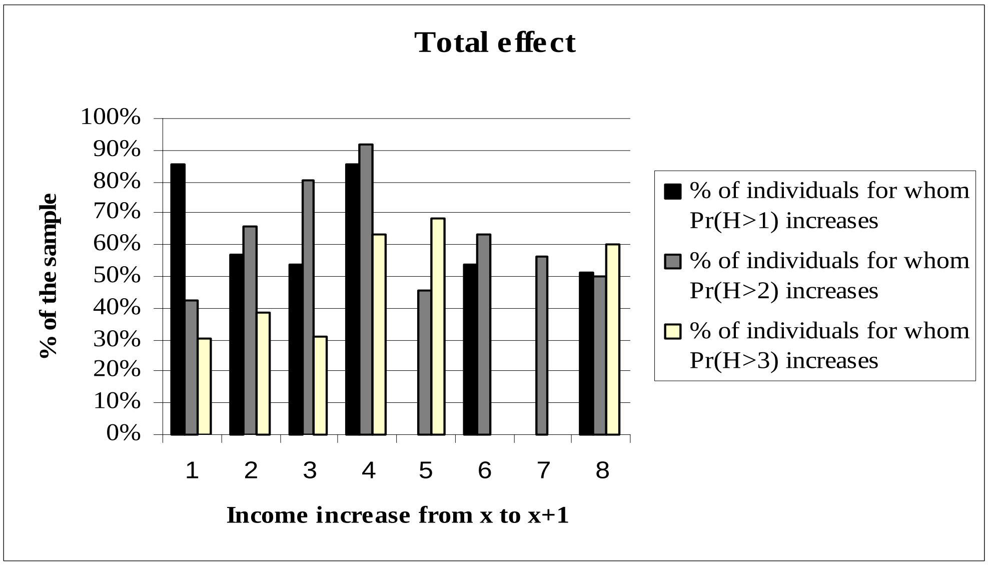


Figure C4. Specification A – Significance of the individual marginal income effect.



Note: Figures C4 and C5 represent for each income category the % of individuals for whom a given marginal effect is significant at the 5% level.

Figure C5. Specification B – Significance of the individual marginal income effect.