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Decomposing the causes of health care use inequalities: a micro-simulations approach

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Abstract

We propose an innovative method of the decomposition of health care use inequalities by factors. We run analyses on individual data and make use of microsimulations in order to evaluate the effects of the heterogeneity of individual behaviors on inequality in access to care. We build on previous literature in order to improve the standard decomposition method where these effects cannot be disentangled. We propose an application of this method: a decomposition of inequality by factors for France, year 1998. We show that half of the inequity in access to care is due to the heterogeneity of behaviors relative to the rank of individuals in the income distribution.

Keywords: Health care consumption - Econometrics - Microsimulations - Inequalities
JEL codes: C15 - C34 - D63 - I11 - I18

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1 Introduction

The issue of inequalities in health and health care use is regularly part of the public agenda. In the European countries, the goal of public policies is not only to globally improve the health status of the population, but also to ensure equality in access to care. In most of these countries, the main conception of the health care system is egalitarian: health care is allocated following individual *need*[1], and is dissociated from the ability to pay for health care. The French system of *Sécurité Sociale* and the *National Health Service* in Britain, although quite dissimilar, share these basic principles. In the United States, despite the presence of *Medicare* and *Medicaid*, equality of access to care is a far less prominent issue in the health care system organization. For Wagstaff and VanDoorslaer (2000), the research literature concerning equality and equity in access to care is strongly related to the political agenda, which could explain the great amount of European literature on this theme. The relative scarcity of American research papers came to an end at the time of the Clinton administration's reforms, whose goal was to improve equity in the American health care system (Wagstaff and VanDoorslaer 2000). For the authors, equity of the health care system is conceived as a fundamental objective, even more important than its efficiency.

While the French health care system is conceived as egalitarian, covering 99% of the population *(Régime Général)* and with mostly regulated fees, there still exist inequalities in health, at the expense of the most disadvantaged (Jusot 2003, VanDoorslaer and Masseria 2004, Couffinhal, Dourgnon, and Tubeuf 2004). This situation could be due to the apparent correlation between hardness of work and low wages (Cribier 1997). Nevertheless, if health care use is thought to influence individual health status, one could question the effective access to care, and whether it is equitable or not. In France, the *Régime Général* does not cover the whole population. Even for those covered, there still exists financial barriers to care, notably the absence of complementary insurance, or the presence of excess fees (in excess of the regulated fee amount) that some medical doctors are allowed to demand.

The *CMU (Couverture Maladie Universelle)* was implemented in France on January 1st, 2000, as a way to correct for what was conceived as unjustifiable financial barriers to care. The *CMU* provides basic coverage to every individual who does not have the right to *Régime Général*. Furthermore, the *CMU* complementary system (*CMU-C*) provides low-income households with free complementary insurance. The *CMU-C* beneficiaries enjoy free care[2]. The income limit is slightly lower than the minimum elderly revenue: people age 65 and more are thus excluded from this system.

[1] A discussion of the notion of *need* for care can be found in Wagstaff and VanDoorslaer (2000).
[2] Source: `www.cmu.fr`

However, if all the financial barriers to care were done away with, the health care distribution would not necessarily become totally equitable. Equity in health care use can be defined through two dimensions: horizontal and vertical equity (Wagstaff and VanDoorslaer 2000). Horizontal equity is defined by a situation where on average, people in the same need of treatment receive a similar treatment, irrespective of their other characteristics (notably income). Vertical equity is defined by a situation where people in different need for care receive appropriately dissimilar treatments. The issue of equity in health care use usually resorts to horizontal equity, while vertical equity is often neglected[3].

A great number of factors can make the distribution of health care use apparently inequitable. One can think for example of the differences in the agents' preferences: some can give more importance to health than others would. Individuals can also disagree on the benefit supplied by health care use, or disagree on the evaluation of this benefit. Heterogeneity of preferences on the one hand, and the trade-off between costs and benefit on the other, could explain the apparent income dependent inequity of health care use, for a given health status. The observed inequity would then result from rational choices.

Equal health care use for a given health status (in other words, horizontal equity) is a benevolent goal, which could lead to a reduction in health inequalities. However, such a goal neglects individual preferences. A more appropriate goal would be ensuring equal access to care, but access is largely unobserved. The only observed variable is effective use. For Wagstaff and VanDoorslaer (2000), an equitable health care distribution should exactly reflect health care need in the population[4]. Any deviation from this *need-expected* distribution is conceived as inequitable. Health care use inequalities can be decomposed into a justifiable part, due to the distribution of need, and an unjustifiable part, due to other factors than need. A measure of health care use inequality (often its *concentration index* with respect to individual income) is thus decomposed into the sum of the different factors which have led to this inequality, labeled justifiable (such as differences in health care need) or unjustifiable (such as differences in income).

In this article we propose an original method of decomposition of inequalities in health care use. We pin on previous literature, particularly the studies led by the ECUITY group, based on the concentration index of health care use with respect to individual income. This way of measuring inequality is very common in the literature. The main contribution of this work is to extend the standard method, proposing a decomposition that allows for the evaluation of individual preferences

[3]See Wagstaff and VanDoorslaer (2000). The notion of vertical equity is prominent on the issue of health care *financing*: in a great number of health care systems, individuals contribute in accordance with their ability to pay, and the progressivity of contributions is a crucial issue of the literature.

[4]From this point of view, health inequalities are described as given, while one should keep in mind that the distribution of health is likely to be influenced by health care use.

on inequalities in access to care.

We first describe the method we propose and then present an application on French data, dedicated to the decomposition by factors of health care use inequality for the year 1998.

The data we use is the *Appariement*, built by IRDES[5]. It is built on the *SPS* survey *(Santé Protection Sociale)* that is led every other year on a subsample of *EPAS (Echantillon Permanent d'Assurés Sociaux)* of the CNAMTS (the main health care fund in France), for the year 1998. More than 4,000 individuals are available for the analysis. The data provide detailed health care use of every individual, as well as personal characteristics such as age, household size and household income. A great number of morbidity indicators are available, synthetic indicators (e.g. level of disability) as well as detailed indicators corresponding to diseases (e.g. presence of diabetes). All values are converted to Euros.

2 The decomposition of health care use inequalities: the standard method and its limitations

A great number of studies (VanDoorslaer and Masseria 2004, VanDoorslaer, Wagstaff, Burg, Christiansen, Graeve, Duchesne, Gerdtham, Gerfin, Geurts, Gross, Hakkinen, John, Klavus, Leu, Nolan, O'Donnell, Propper, Puffer, Schellhorn, Sundberg, and Winkelhake 2000, VanDoorslaer, Koolman, and Jones 2004) show that the individual rank in the income distribution is highly correlated to the rank in the health distribution: the rich are (proportionnally) in better health than the poor. This fact is observed in developing countries as well as in developed countries. These studies also show that for some types of expenditures (especially for specialist visits), the rich spend proportionnally more than the poor (which is not the case for general practitioner visits). This can be described as inequitable: health care needs would be concentrated among the poor, and health care use would be concentrated among the rich. This particular feature of specialists visits use can be found in many European countries (VanDoorslaer and Masseria 2004).

2.1 The concentration index

An index measuring inequality in health care use with respect to income must be able to describe observed inequality, while disentangling the part of this inequality that is due to the differences in need (labeled "justifiable") from the part due to the other individual characteristics (labeled "unjustifiable"). This distinction between justifiable and unjustifiable inequality is widely used in the literature (see Wagstaff and VanDoorslaer (2000) for example). The index of inequality we

[5]Institute for Research and Information in Health Economics, Paris (`www.irdes.fr`). A thorough description of the data can be found in Dormont, Grignon, and Huber (2006)

use here is the concentration index of health care use, relative to income. This index is widely used, and has nice properties (Wagstaff and VanDoorslaer 2000). In particular, it can be easily decomposed in a linear way (see next section). It is used in particular by the studies led by the ECUITY group[6] devoted to international comparisons in health and health care use inequalities.

The concentration index of a variable y (for example, the number of physician visits) relative to income I can be defined using the concentration curve of y with respect to I. This concentration curve links the cumulative proportion of individuals, ranked by income, to the corresponding proportion of y used by them, with respect to the total amount of y. Within this framework, a measure of inequality in health care use is given by the concentration index, i.e. twice the area between the concentration curve and the line of equality. Let there be a population of n individuals i ($i \in [1..n]$), each having a health consumption y_i and whose fractional rank[7] in the income distribution is R_i. Let $\overline{y}$ be the mean health care use. The concentration index of health care use in this population can be defined as (Wagstaff, VanDoorslaer, and Watanabe 2003):

$$C = \frac{2}{n\overline{y}} \sum_{i=1}^{n} y_i R_i - 1 \tag{1}$$

The concentration index of y with respect to I can be computed by estimating the following regression (WorldBank 2005a):

$$2\sigma_R^2 \frac{y_i}{\overline{y}} = \alpha + \beta R_i + v_i \tag{2}$$

where R_i is the fractional rank of individual i in the income distribution and σ_R^2 its variance. The estimator $\widehat{\beta}$ is equal to the concentration index of y with respect to income, and the standard error of $\widehat{\beta}$ gives the standard error of the concentration index. The estimation is computed with the method of Newey and West (1994) so as to correct for autocorrelation or heteroscedasticity that could be present in the data.

The concentration index is meant to be a synthetic measure of the degree of inequality in health care use in a population. It has a certain number of limitations though. These limitations are analog to the limitations of the Gini index, from wich the concentration index is derived. The concentration index depends from the rank of individuals in the income distribution, but not on their level of income. Furthermore, this index gives the same importance to inequality among the rich than inequality among the poor (Gourieroux 1999). The most severe limitation of the concentration index is that it is unable to rank all possible health care use distributions. Let

[6] European project whose goal is to study inequality in health, health care use and health care financing: `http://www2.eur.nl/bmg/ecuity/`. Research teams come from the following countries: Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Spain, Sweden, U-K, Norway, Switzerland, USA.

[7] Let r_i be the rank of individual i in the income distribution. The fractional rank R_i is defined as $R_i = r_i/n$.

$(x_i), 1 \leq i \leq n$ be a distribution whose concentration index is smaller than the one of another distribution $(y_i), 1 \leq i \leq m$: (x_i) does not necessarily dominates (y_i) from the inequality point of view. Indeed, the concentration curves (from which the concentration indices are defined) can cross. In this case, one distribution will show greater health care use equality in large incomes, while the other will show greater equality in low incomes. In the same way, two distributions showing the same concentration index are not necessarily equal, and a distribution with a concentration index equal to zero is not necessarily egalitarian (the concentration curve can cross the line of equality). The concentration index is an imperfect measure of inequality, but we will use it so as to ba able to compare our results to the existing literature. We should emphasize here that since our analyses are based on simulated distributions whose degree of inequality is computed, it is possible to measure the degree of inequality with other tools than with the concentration index[8].

2.2 The decomposition by factor of the concentration index: the standard method

Let's suppose here that health care use can be explained by factors $(x_k), k \in [1..K]$ within a standard linear model (Wagstaff, VanDoorslaer, and Watanabe 2003), which is a relatively strong assumption:

$$\forall i \in [1..n], y_i = \alpha + \sum_{k=1}^{K} \beta_k x_{k,i} + \varepsilon_i \tag{3}$$

This implies the following decomposition (Wagstaff, VanDoorslaer, and Watanabe 2003)[9]:

$$C = \sum_{k=1}^{K} \frac{\beta_k \overline{x_k}}{\overline{y}} C_k + \frac{GC_\varepsilon}{\overline{y}} \tag{4}$$

Where $\overline{x_k}$ is the mean of the $x_{k,i}$, $\overline{y}$ the mean of y_i, C_k the concentration index of x_k with respect to income, and GC_ε the generalized concentration index of ε_i ($GC_\varepsilon = \frac{2}{n} \sum_{i=1}^{n} \varepsilon_i R_i$).

In order to study changes in inequality between two given periods of time (ΔC), Wagstaff, VanDoorslaer, and Watanabe (2003) propose the following decomposition, directly derived from linear decomposition (4):

$$\Delta C \approx dC = -\frac{C}{\overline{y}} d\alpha + \sum_{k=1}^{K} \frac{\overline{x_k}}{\overline{y}} (C_k - C) d\beta_k + \sum_{k=1}^{K} \frac{\beta_k}{\overline{y}} (C_k - C) d\overline{x_k} + \sum_{k=1}^{K} \frac{\beta_k \overline{x_k}}{\overline{y}} dC_k + d\frac{GC_\varepsilon}{\overline{y}} \tag{5}$$

[8] In fact, the concentration index is widely used because it can be decomposed easily. Since we do not use the standard decomposition method when disentangling the various factors leading to inequality, the exclusive use of the concentration index is no longer necessary.

[9] Originally, Wagstaff, VanDoorslaer, and Watanabe (2003) had developed this decomposition for *health* inequality and not *health care use* inequality, but their method is suitable for the decomposition of inequality of any variable y (see VanDoorslaer and Masseria (2004)).

The observed changes in the health care use concentration index is a function of the changes in the concentration indices of every factor explaining health care use.

2.3 A definition of inequity: the Horizontal Inequity Index

Inequality in health care use with respect to income could totally be explained by differing needs: if the distribution of health care use perfectly reflects the distribution of need, the distribution of health care use can be inegalitarian *but* equitable. A way of measuring inequity that is often found in the literature is the *Horizontal Inequity Index*, built by Wagstaff and VanDoorslaer (2000). Inequity in health care use is defined as the fraction of inequality that is not explained by need: in other words, it is the part of inequality that is unjustifiable. Looking back at expression (4), labeling M the need variables and Z all the other variables, and labeling δ et γ their vectors of coefficients, we get :

$$C = \sum_{k=1}^{K} \frac{\delta_k \overline{m_k}}{\mu} C_k + \sum_{k=1}^{K} \frac{\gamma_k \overline{z_k}}{\mu} C_k + \frac{GC_\varepsilon}{\mu}. \tag{6}$$

The first element of expression (6) represents justifiable inequality, coming from inequality in need. The second element represents unjustifiable inequality, coming from factors other than need: it is the Horizontal Inequity Index. Calling *Need* the justifiable part and *HI* the Horizontal Inequity Index, we get:

$$Need = \sum_{k=1}^{K} \frac{\delta_k \overline{m_k}}{\mu} C_k \tag{7}$$

and

$$HI = \sum_{k=1}^{K} \frac{\gamma_k \overline{z_k}}{\mu} C_k + \frac{GC_\varepsilon}{\mu}. \tag{8}$$

2.4 A decomposition that is necessarily linear

According to expression (4), the decomposition of the concentration index of variable y is a function of the sum of the concentration indices C_k of factors x_k, weighted by the elasticity of y with respect to x_k, evaluated at the mean individual of the sample. This expression also comprises a residual element, that takes into account the amount of inequality unexplained by the model. When estimating this decomposition, the β are replaced by their estimated counterpart $\hat{\beta}$ and the redidual term is computed with the estimated residuals $\hat{\varepsilon}$.

A first drawback of this decomposition is the fact that it is necessarily linear. A great number of explanatory models of health care use are non linear though. In order to model a number of physician visits, one can use a count data model of the following form:

$$E(y_i) = h(\alpha + \sum_{k=1}^{K} \beta_k x_{k,i}) \tag{9}$$

Where h is a non linear function (often, the exponential function) and y follows a Poisson or a Gamma distribution. Parameters β_k are estimated by maximum likelihood.

In this case, the non linear form of expression (9) does not allow to disentangle the effects of the various factors x_k. We thus have to linearize expression (9). The following decomposition is thus used:

$$C = \sum_{k=1}^{K} \frac{\beta_k^m \overline{x_k}}{\mu} C_k + \frac{GC_\varepsilon}{\mu} \tag{10}$$

where the β_k^m are the marginal effects evaluated at the mean (WorldBank 2005b). The decomposition is then an approximation. VanDoorslaer and Masseria (2004) recommend the use of a standard linear model such as (3) for y, even when the estimated model does not suit the variable (for example, a number of visits, necessarily non-negative). Even though quite practical, this solution is conceptually unsatisfactory.

2.5 The interpretation of the C_k

The presence in expressions (4), (5) and (10) of concentration indices of every explanatory factor imply that these indices make sense. Among other variables, indicators of health status are present in the explanatory model of health care use (models (3) or (9)). Standard decompositions must thus compute and interpret the concentration indices of these indicators of health status.

Let's take a health measurement index such as the Health Utility Index *(HUI)*. The concentration index of *HUI* makes sense: individual *HUI* represents individual health, and the sum of every individual's *HUI* gives the total stock of health available in the population[10].

While the universality of the *HUI* might seem questionable, the surveys that are necessary to compute it are not always available. The French data we work on does not provide enough information to compute individual *HUI*'s. However, the *Appariement* provides a great number of indicators of health status, such as the presence of certain diseases, and general synthetic indicators such as the level of disability. These indicators are categorical, and are coded with integers. For example, the indicator of death risk varies from 0 (zero death risk) to 5 (highest death risk), and the indicator of disability varies from 0 to 6 (see appendix B for a description of the variables). Using decomposition (4) with categorical explanatory factors means we have to interpret their concentration index C_k. The concentration index of a categorical health indicator is not easily

[10]See the website of the Health Utility Group of McMaster University `http://www.fhs.mcmaster.ca/hug/`

interpretable. Computing the concentration index on the health variable taken as continuous means considering it as an "ill-health stock", that could be aggregated into a total stock of ill-health at the population level. This is obviously not the case for a categorical variable. To avoid such a misuse of the variable, one can compute a concentration index for every category of the health indicator considered (each category being coded with a dummy variable: 0/1). This option is chosen by the ECUITY group. The main drawback of such a method is that describing the distribution of an indicator of ill-health according to income becomes uneasy, as there are as many concentration indices to analyze as there are categories within this indicator. A way to sidestep this lack of synthesis would be the use of a health score, that could be built using the health indicators available in the survey. For example, Perronnin, Rochaix, and Tubeuf (2006) propose to built a synthetic health indicator incorporating the level of disability and the level of death risk. Research on synthetic indicators of health is indeed very promising. FOr the purpose of studying health care use, the method we propose here avoids the computation of such indicators, which leads to a much lesser loss of information.

Apart from the issue concerning health indicators, let us notice that since income is often introduced as logged in the explanatory models, the standard decomposition leads to the computation and interpretation of the concentration index of the log of income with respect to income, whose interpretation is difficult as well.

2.6 Taking preferences into account

Disentangling inequality into its justifiable and unjustifiable parts using expression (6) assumes that an equitable distribution of health care use is the one that we would observe if every individual in the population were treated as the average individual is treated, according to his/her health status. Indeed, in order to implement decompositions (4) then (6), the estimation of model (3) is made on the whole sample: parameters δ_k relative to the need variables M reflect the *mean* relationship between need and health care, observed in the whole sample. Any deviation from this mean relationship is taken into account by the variables Z and their coefficients γ. One cannot distinguish different δ_k by income level, and presumably different preferences according to income level. Decomposition (6) only takes into account the distribution of explanatory variables with respect to income, and does not take into account the potential heterogeneity of coefficients with respect to income. For any indicator of health care need Z_k, the estimated coefficient $\hat{\delta_k}$ represents what amount of health care society as a whole allocates *on average* for that need. In the works of the ECUITY group, this average behavior is taken as a norm, whose relevance is yet a topic of discussion.

2.7 The limitation to a single explanatory equation of health care consumption

Explanatory models of health care consumption can be highly non-linear. The most relevant - and usual - model specifications are two-part models, explaining the decision to consume (*probit* or *logit*) and the level of consumption conditional on the participation to the health care system (*GLM* truncated at zero). Another way of modeling health care consumption is the use of single equation zero-inflated models. These models are much less used though.

Whatever explanatory model is chosen ((3) or (9)), the decomposition of inequality by factor (expressions (4) and (10), respectively) can only be computed for one single equation of a model. In the works of Ecuity, we thus get separately:

- a decomposition of the probability of use (*logit* or *probit* model)
- a decomposition of the conditional consumption (*GLM* or *OLS*...)
- a decomposition of unconditional consumption (*zero-inflated* model).

A first problem arises, as the standard decomposition needs a linear approximation of the model. Furthermore, the coherence between the different steps of the reasoning is not guaranteed: two-part models and zero-inflated models are conceptually different, and do not at all model the same type of phenomena. Thus, such a method does not ensure that the fraction of inequity due to a certain factor can be relevantly partitioned into a part due to participation behaviors and another due to conditional consumption behaviors.

3 A new method using microsimulations

The new decomposition method proposed here provides a way of overcoming the difficulties of the standard approach that were underlined in section 2. We chose to keep the concentration index as the way of measuring inequity, mainly in order to be able to compare our results to the ones of the ECUITY group. Our analyses are based on distributions of health care use simulated under various hypotheses. We use convenient estimation methods of health care use first on the whole sample, then on the different income quantiles of the sample. For all theses simulated distributions, we compute the concentration index of health care use with respect to income; we are thus able to identify the impact of each hypothesis on the value of the concentration index. This original method provides several advantages: it avoids the linear approximation that is imposed by the standard decomposition approach even when the explanatory model is non-linear; it avoids the limitation to one single equation; it permits the identification of the impact of heterogeneity of behaviors on the observed inequality in health care use.

While the standard decomposition expresses the health care use concentration index as a function of the concentration indices of all the explanatory factors of the model (see expressions (4) and (10)), the method we propose here does not impose the use of explanatory factors of health care use whose concentration index makes sense.

Using simulated health care use distributions from which we compute the concentration index *instead of* decomposing the concentration index of an observed distribution let us disentangle the effects of participation and conditional consumption. Indeed, with the standard decomposition, it is necessary to decompose the concentration index of participation, conditional consumption, and unconditional consumption, with no guarantee of the coherence of results. With the method we propose, health care use distributions are simulated using two-part models. The relative importance of explanatory factors with respect to participation or conditional consumption can thus be disentangled within one single explanatory model of total health care consumption.

The most innovative feature of our method is the possibility to estimate a model of health care use by income quintile. In the standard method, estimating the explanatory model on the whole sample leads to neglect individual preferences that could depend on the rank of individuals in the income distribution. Our goal here is to improve the standard decomposition method by proposing a horizontal inequity index that depends on the distribution of variables Z according to income *and* on the heterogeneity of parameters γ with respect to income. We believe that this method provides a way of identifying individual preferences, which is not possible with the standard decomposition described in section 2.

3.1 The choice of an explanatory model of health care use

Let y_i be the variable representing individual i's health care use, belonging to a population of N individuals. In this paper, y_i will be the number of GP visits, the number of specialist visits, and the total number of visits. We chose here to use a two-part model (*Logit* and *GLM*). The *GLM* is a zero-truncated negative binomial with a *log* link, which is a very common way to model a number of visits. The explanatory model is the following:

(1) $P_i = I_{P_i^*>0}$ and $E(P_i^*) = G(Z_1\gamma_1)$ with $G(p) = \dfrac{1}{1+e^{-p}}$

(2) $y_i = I_{P_i=1} y_i^*$ and $E(y_i^*/P_i = 1) = F(Z_2\gamma_2)$ with $F(p) = e^p$ and y_i following a zero-truncated negative binomial distribution.

We thus have $E(y_i) = E(P_i^*) * E(y_i^*/P_i = 1)$

Let C be the concentration index of health care use in the observed population. According to our model, health care use is a function of variables Z_1 and Z_2: our goal here is to determine the respective contribution of each variable to the observed concentration index C. As is common in the literature, we will distinguish two sub-group of variables: *need* and *non-need* variables, whose importance in the concentration index will be computed. We should keep in mind though that this decomposition can be computed with any group of variables.

The vectors of explanatory variables Z_1 et Z_2 are subdivided into 2 groups of variables: need variables (M_1 and M_2 respectively) and non-need variables (X_1 and X_2 respectively). The objective here is to decompose the value of C into the sum of the contributions of each group of variables, using simulated distributions of health care use.

The model can be rewritten in the following way:

(1) $E(P_i) = G(X_1 b + M_1 d)$

(2) $E(y_i/P_i = 1) = F(X_2\beta + M_2\delta)$

And a prediction of the model would be the following, for every individual i:

$$\widehat{y_i} = \underbrace{G(X_{1,i}\widehat{b} + M_{1,i}\widehat{d})}_{participation} * \underbrace{F(X_{2,i}\widehat{\beta} + M_{2,i}\widehat{\delta})}_{conditional\ consumption} \tag{11}$$

3.2 Parameter estimation

The model is estimated on the whole sample: parameters $\widehat{b}$, $\widehat{d}$, $\widehat{\beta}$ are $\widehat{\delta}$ are thus computed. The sample is then split into Q quantiles of income. The model is estimated on each quantile, and the following parameters are computed: $(\widehat{b_q})$, $(\widehat{d_q})$, $(\widehat{\beta_q})$ and $(\widehat{\delta_q}), q \in [1..Q]$. Parameters $\widehat{\beta_q}$ can differ, which would indicate the presence of different practices for a given morbidity, according to the income quantile the individual belongs to. Parameters $\widehat{\delta_q}$ can differ as well, which would indicate a heterogenous effect of socio-economic variables on health care consumption, with respect to income level. This estimation of coefficients specific to distinct subgroups of population can be found in studies inspired from Oaxaca (1973).

For each estimated equation, the estimated parameters represent individual behaviors. Among these, parameters b and β (as well as their equivalents b_q and β_q for each income quantile q) represent the observed practices for a given level of morbidity, all other things equal. In the rest of the article, we will indeed call these parameters *practices*: the value of a parameter estimate represents the response in terms of health care to a given health status. These *practices* are individual behaviors, and can originate from the demand or supply of health goods. Parameters b correspond to practices linked to participation, which can be related to demand. Parameters β correspond to practices linked to conditional consumption, mainly related to the supply side.

3.3 The simulation of distributions and the computation of their concentration indices

Once the parameters are estimated, we simulate health care use distributions. In order to understand the role of each factor in total observed health care use inequality, we start from a perfectly egalitarian distribution of health care use (the distribution that would be observed if everyone in the sample had the same characteristics and the same consumption behavior), then we vary one by one each explanatory factor of health care use in order to identify its contribution to the degree of inequality that is observed for variable y_i. The different steps of simulations are described hereafter (we label $\overline{X_1}$, $\overline{M_1}$, $\overline{X_2}$ and $\overline{M_2}$ the variables corresponding to the mean sample).

The baseline of our microsimulations is a distribution of health care use that is perfectly egalitarian. As mentioned before, it corresponds to a situation where all the individuals would share the same characteristics ($\forall i,\ \forall j \in 1, 2, X_{j,i} = \overline{X_j}$ and $M_{j,i} = \overline{M_j}$) and where the impact of these characteristics would be the same, whatever the income quantile the individual belongs to ($\forall q, b_q = b$ and $d_q = d$ et $\forall q, \beta_q = \beta$ and $\delta_q = \delta$). This egalitarian distribution of health care use can be expressed the following way:

$$\forall i, \widehat{y_i^0} = G(\overline{X_1}\widehat{b} + \overline{M_1}\widehat{d}) * F(\overline{X_2}\widehat{\beta} + \overline{M_2}\widehat{\delta}) = Constant \tag{12}$$

As the simulated health care use is by definition the same for everyone, its concentration index is necessarily equal to 0: $CI_0 = 0$.

The successive steps of simulation are the following:

1) The taking into account of the heterogeneity of morbidity among individuals (with homogenous behaviors) can be done while simulating the following health care use distribution:

$$\forall i, \widehat{y_i^1} = G(\overline{X_1}\widehat{b} + M_{1,i}\widehat{d}) * F(\overline{X_2}\widehat{\beta} + M_{2,i}\widehat{\delta}) \tag{13}$$

Where $\overline{M_1}$ was replaced by $M_{1,i}$ and $\overline{M_2}$ by $M_{2,i}$ in expression (12). The concentration index CI_1 computed on distribution $\widehat{y^1}$ (with the method using regression (2)) gives the degree of inequality due to inequality in morbidity. It is close to the *Need* index, mentioned in section 2.3, because it is the part of the index of inequality that is due to diffences in need with respect to income.

2) The taking into account of the heterogeneity of practices corresponding to participation can be written the following way (labeling i the individual and q the income quantile he/she belongs to):

$$\forall i, q, \widehat{y_{i,q}^2} = G(\overline{X_1}\widehat{b} + M_{1,i}\widehat{d_q}) * F(\overline{X_2}\widehat{\beta} + M_{2,i}\widehat{\delta}) \tag{14}$$

Where $\widehat{d}$ was replaced by $\widehat{d_q}$ in expression (13). The difference between concentration index CI_2 computed on distribution $\widehat{y^2}$ and concentration index CI_1 computed on the preceding distribution give the degree of inequality due to the heterogeneity of practices corresponding to participation, for a given morbidity.

2bis) The taking into account of the heterogeneity of practices corresponding to the conditional consumption can be written in the following manner, with the same notations than before:

$$\forall i, q, \widehat{y_{i,q}^{2bis}} = G(\overline{X_1}\widehat{b} + M_{1,i}\widehat{d_q}) * F(\overline{X_2}\widehat{\beta} + M_{2,i}\widehat{\delta_q}) \tag{15}$$

Where $\widehat{\delta}$ was replaced by $\widehat{\delta_q}$ in expression (14). The difference between concentration index

CI_{2bis} computed on distribution $\widehat{y^{2bis}}$ the concentration index CI_2 computed before gives the degree of inequality due to the heterogeneity of practices corresponding to conditional consumption, for a given morbidity.

3) The taking into account of the distribution of socio-economic variables among the population can be done with the following simulated distribution:

$$\forall i, q, \widehat{y^3_{i,q}} = G(X_{1,i}\widehat{b} + M_{1,i}\widehat{d_q}) * F(X_{2,i}\widehat{\beta} + M_{2,i}\widehat{\delta_q}) \tag{16}$$

Where $\overline{X_1}$ was replaced by $X_{1,i}$ and $\overline{X_2}$ by $X_{2,i}$ in expression (15). The difference between CI_3 computed on distribution $\widehat{y^3}$ and index CI_2 gives the degree of inequality due to inequalities in socio-economic variables.

4) The taking into account of the heterogeneity of the impact of socio-economic variables on health care use is done with the following simulated distribution:

$$\forall i, q, \widehat{y^4_{i,q}} = G(X_{1,i}\widehat{b_q} + M_{1,i}\widehat{d_q}) * F(X_{2,i}\widehat{\beta_q} + M_{2,i}\widehat{\delta_q}) \tag{17}$$

Where $\widehat{\beta}$ was replaced by $\widehat{\beta_q}$ and $\widehat{b}$ by $\widehat{b_q}$ in expression 16. The difference between CI_4 and CI_3 gives the degree of inequality due to the heterogebeity of the impact of socio-economic variables on health care use, with respect to income.

5) Last, the difference between CI_4 and the observed concentration index C gives the degree of inequality due to factors that are not present in the model (in other words, unobserved heterogeneity).

To sum up, C can be decomposed into the sum of the following 6 elements:

- $\Delta_1 = CI_1 - CI_0$ $(= CI_1 - 0 = CI_1)$ is the contribution of the inequalities in morbidity
- $\Delta_2 = CI_2 - CI_1$ is the contribution of the heterogeneity of practices corresponding to participation
- $\Delta_{2bis} = CI_{2bis} - CI_2$ is the contribution of the heterogeneity of practices corresponding to the conditional consumption
- $\Delta_3 = CI_3 - C_{2bis}$ is the contribution of socio-economic inequalities

- $\Delta_4 = CI_4 - CI_3$ is the contribution of the heterogeneity of behaviors linked to the socio-economic variables
- $\Delta_5 = C - CI_4$ is the contribution of unobserved heterogeneity

And we of course have: $C = \Delta_1 + \Delta_2 + \Delta_{2bis} + \Delta_3 + \Delta_4 + \Delta_5$.

3.4 Interpretation

The part of C due to the heterogeneoty of needs is equal to Δ_1, that we will call *Need* in what follows, mainly in order to compare our results with the existing literature (see equation (6)):

$$Need = \Delta_1. \tag{18}$$

The part of C due to other factors than need, labeled HI still in order to compare it to the existing literature, is equal to $\Delta_2 + \Delta_{2bis} + \Delta_3 + \Delta_4 + \Delta_5$:

$$HI = \Delta_2 + \Delta_{2bis} + \Delta_3 + \Delta_4 + \Delta_5. \tag{19}$$

We should emphasize that the effect of unobserved heterogeneity is part of HI, which is a common usage (see VanDoorslaer and Masseria (2004)).

The decomposition that we propose here let us know the global effect of morbidity on the degree of inequality observed (the *Need* indicator), without facing the problem of the computation and interpretation of the C_k that are found in expression (4). Moreover, while the heterogeneity of practices is not modeled in the standard approach, it is explicitly modeled here with the estimated parameters $\widehat{b_q}$ and $\widehat{\beta_q}$, $q \in [1..Q]$. As was mentioned earlier, the groups of variables we chose reflect the common distinction between need and non-need variables. However, our method is able to compute the contribution to inequality of any group of variables or even any isolated variable.

The index HI as defined by expression (19) can be decomposed between its part due to the distribution of the variables in the sample and its part due to the heterogeneity of the coefficients corresponding to these variables. The part of inequality due ti the variables si thus defined by the following expression:

$$Variables = \Delta_3 + \Delta_6 \tag{20}$$

While the part of HI due to the heterogeneity of behaviors can be written as:

$$Behaviors = \Delta_2 + \Delta_{2bis} + \Delta_4 \tag{21}$$

The degree of inequality due to the heterogeneity of behaviors with respect to income can be decomposed into three effects:

- Δ_2: practices corresponding to participation, that can be linked to the demand side
- Δ_{2bis}: practices corresponding to the conditional consumption, that can be linked mainly to the supply side
- Δ_4: parameters corresponding to non-need variables (socio-economic variables), that can be linked to the demand side

This decomposition enables us to distinguish the degree of inequality that is due to the supply and demand of health care through the analysis of Δ_2 and Δ_{2bis}, and through this to identify precisely the agents' preferences.

4 The analysis of health care use inequality in France: an application

We use the *Appariement* which is a survey conducted by IRDES. We use year 1998 of the survey, restricted to people age 15 and more. The data comprise 4,336 individuals. Health care use is observed as the number of visits, divided into the number of GP visits and the number of specialist visits. The difference in recourse to each kind of physician can easily be seen with the table below:

	Total	GP's	Specialists
1998	8,3	4,8	3,5

Table 1: Mean number of visits per person, year 1998

We propose here a decomposition of health care use inequality for the year 1998, using the new method we outlined earlier, and compare our results to the existing literature on the subject.

4.1 Method

We use the method described in section 3: we choose an explanatory model, define the number of income quantiles q, estimate the model parameters, simulate health care use distributions, and compute concentration indice on these distributions.

4.1.1 The choice of a model for health care use

We use here a two-part model, which explain participation to the health care system and conditional consumption for users with two independent equations. The dependent variable is the number of visits. We chose to model the number of visits instead of the cost of visits, in order to facilitate the interpretation of results and make them comparable to the previous literature (notably the ECUITY project). The fees are mostly regulated in France, so studying both the cost and number of visits seemed redundant to us. We study three variables: the total number of physician visits, the number of GP visits, and the number of specialist visits. The explanatory variables of health care use are selected according to their degree of significancy in a regression explaining the total number of visits. We chose not to select the variables differently for GP and specialist visits, in order to easily compare the results for these three types of variables. The synthetic indicators of morbidity as well as the presence of complementary insurance are likely to be endogenous in the estimated equations: they are tested, and only exogenous variables are kept in the analysis. This selection of variables is done on the whole sample of individuals age 15 and more. The list of the selected variables is available in appendix B.

The participation equation We model the probability of participation to consultations, using a *Logit* model. We select the explanatory variables according to their degree of significancy (global

nullity test) and only exogenous variables are kept (following a methodology inspired by Rivers and Vuong (1988)). Indeed, as individuals are observed on a one year period, some morbidity variables can be non-exogenous: for example, the amount of health care use can influence the degree of disability. Using instrumental variables in the estimation would make the simulations too complicated with such non-linear models. We thus chose to omit the endogenous variables from the model. We should emphasize that omitting these variables do not lead to an omitted variable bias, since the tests we implement test the exogeneity of all the variables we keep in the analysis.

Modeling the number of physician visits In order to model the number of visits conditionnally to participation, we chose a *GLM* (Generalized Linear Model) using a log link and a Zero-Truncated Negative Binomial as the distribution. Indeed, the data show overdispersion: the variance of the dependent variable is greater than its expectancy. This can often be found in the literature (see for example VanDoorslaer, Koolman, and Jones (2004)). The Poisson distribution characterized by a variance equal to the mean is not appropriate in this context (see Grogger and Carson (1991)). The way of calculating the predicted number of visits is detailed in appendix A.

The choice of the number Q of income quantiles For the sample covering individuals age 15 and more, a natural choice consists in choosing income quintiles, since the number of individuals is sufficient here. Individuals are thus ranked according to their income (more precisely, their income by consumption unit), and for each individual we define his/her belonging to the corresponding quintile q, $q \in [1..Q]$, with $Q = 5$.

4.2 The analysis of inequalities in health care use in France, year 1998

The results are presented here as tables synthesizing total inequality, decomposed into various elements. The degree of total inequality, called *CI*, is presented as the sum of two elements: the degree of inequality due to the heterogeneity of need[11] (the *Need* index) and the degree of inequality due to other factors than need (the inequity index *HI*). The inequity index *HI* is in turn decomposed into a part due to the distribution of variables with respect to income, and the part due to the heterogeneity of behaviors (represented by the heterogeneity of coefficients with respect to income). This part due to behaviors comes from the heterogeneity of three types of coefficients, whose different effects are presented in the tables:

- the heterogeneity of practices corresponding to participation (linked to morbidity),
- the heterogeneity of practices corresponding to the conditional consumption (linked to morbidity),
- the heterogeneity of other behaviors (linked to the other non-need variables).

[11] In other words, due to morbidity and age.

The table presented hereafter gives the decomposition by factor of inequality observed on our sample, year 1998.

	GP's	Specialists	All physicians
CI	**-0,0219**	**0,0884**	**0,0252**
Need	-0,0047	-0,0078	-0,0065
HI	-0,0172	0,0962	0,0317
HI	**-0,0172**	**0,0962**	**0,0317**
Variables	-0,0097	0,0450	0,0135
Behaviors	-0,0075	0,0512	0,0182
Behaviors	**-0,0075**	**0,0512**	**0,0182**
Participation	0,0004	0,0381	0,0257
Other	0,0281	0,0481	0,0047
Cond. consumption	-0,0361	-0,0351	-0,0122

Table 2: Decomposition of the inequality observed in 1998 in France

Let us underline that "participation" and "other" behaviors can be linked to the demand side, while "conditional consumption" behaviors can be linked to the supply side.

The contribution of each factor was computed using the concentration indices of the various simulated distributions of health care use. We made available in appendix C the concentration indices of each simulated distribution and the way we computed the values presented in table 2. An analysis of reliability with respect to the order of introduction of the various effects is presented as well in this appendix. The order of introduction of the various effects in the simulated distributions described in section 3.3 does not modify the computed value of these effects.

4.2.1 Comparability with the previous literature

The order of magnitude of the indices of total inequality *CI* is rather close to what can be found in the literature. As an example, table 3 presents the decomposition by factor of inequality observed on GP visits on French data, by VanDoorslaer and Masseria (2004), using the same survey as us (*Appariement*) but for year 2000. The authors use the method described in section 2. In this analysis, the concentration index of GP visits is equal to $-0,0275$ for the year 2000, while we find a value of $-0,0219$ on our data for the year 1998. The total index of inequality *CI* is decomposed into the sum of one part due to need (*Need*) and another part due to all the non-need factors (*HI*). *HI* is itself decomposed into different factors. The line *Residual*, that we added, represents the difference between the observed concentration index *CI* and the sum of all the various effects that are identified by the authors. For VanDoorslaer and Masseria (2004), this residual is implicitly part of *HI*.

	Decomposition
CI	-0,0275
Need	-0,0227
HI	-0,0047
Income	-0,0031
Education	-0,0077
Activity status	0,0087
Region	-0,0073
Insurance	0,0181
CMU	-0,0185
Residual	-0,0177

Table 3: Decomposition of the inequality in GP visits, year 2000, by ECUITY

The *Need* index found with our method differs largely from what has been found by Van-Doorslaer and Masseria (2004). For GP visits, the authors get $Need = -0,0227$, which amounts to almost the total value of CI, while we get $Need = -0,0047$. The need variables retained are indeed not at all the same. The goal of the study by VanDoorslaer and Masseria (2004) is international comparisons: the authors use self-assessed health variables, along with variables indicating the degree of impairment in everyday life. These variables are indeed present in most of the surveys the authors have access to, at the international level. We work on the same survey as VanDoorslaer and Masseria (2004) as regards France, and self-assessed health was part of the potential health status indicators that could be used in our analyses. However, the selection of variables that we implemented showed that self-assessed health was non-significant for the participation equation, and non-exogenous for the conditional consumption equation: it was thus removed from the analysis. For comparison purposes, we implemented our analysis using self assessed health as the sole indicator of health (in order to get close to the study led by VanDoorslaer and Masseria (2004)): the *Need* indicator that we found is in that case very close to what is found by VanDoorslaer and Masseria (2004) for the year 2000 ($-0,0254$ vs. $-0,0227$).

This shows that our method leads to results that are coherent with the previous literature, *but* that the rigorous selection of variables that we implemented led to a decomposition which is largely different. To sum up, in our results, the part of inequality due to differences in need is much smaller, and the part due to non-need variables (the unjustifiable part) is much bigger, than in previous literature. The main conclusion here is that we observe a great instability of the evaluation of the *Need* index with respect to the choice of regressors.

4.2.2 Our results: the importance of the heterogeneity of behaviors in the observed inequality

The signs of indices CI differ with respect to the variable considered: $CI < 0$ for GP visits, and $CI > 0$ for specialist visits and the total number of visits. GP visits are thus concentrated among the poor, while specialist visits are concentrated among the rich. The *Need* index is negative for

the three variables: this shows that needs are concentrated in the lowest part of the income distribution. Let us emphasize that the *Need* indices are not equal, although all three of them represent an indication of the need distribution with respect to income. The *Need* index represents the concentration index of the distribution of health care use that would be observed if everyone were treated the same way, and independently of their other characteristics. This distribution reflects the distribution of need with respect to income, but depends on the mean relationship between need and health care use, estimated on the whole sample. This relationship differs according to the type of care considered (GP, specialists, all physicians): the simulated distributions differ, as well as their corresponding concentration indices. The results are nevertheless coherent, whatever type of care is considered, and indicate that the poor are globally in poorer health than the rich.

The *HI* index, that represents the degree of horizontal inequity, is negative for the number of GP visits and positive for the number of specialist visits and the total number of visits. This means that for GP visits, the poor receive more in proportion than the rich, for a given need. Conversely, for specialists visits, the rich receive more in proportion than the poor, for a given need. To sum up, for the total number of visits, the *HI* index is positive, indicating that the rich use a greater number of visits than the poor, for a given need.

The *HI* index is divided into a part due to the distribution of variables and a part due to the heterogeneity of behaviors. The goal of our method is precisely to put emphasis on this part due to the heterogeneity of behaviors. We observe that inequality due to the heterogeneity of behaviors are far from being negligible: for all type of care, it amounts to nearly half of the *HI* index. With having estimated the model on each one of the income quintiles, we have shown that half of the horizontal inequity index is due to the heterogeneity of behaviors with respect to income. This feature cannot be identified in the studies using the standard methodology. In these studies (see for example table 3), the *HI* index is decomposed into the sum of the effects of the distribution of the explanatory variables but does not take into account the potential heterogeneity of the impact of these variables on health care use, with respect to income. Following expression (4) (section 2), the inequality index is decomposed into the sum of the concentration indices of the various explanatory variables of the model, weighted by the coefficient of each variable, estimated on the whole sample. The heterogeneity of behaviors with respect to income cannot be identified. Our method enables us to show that this heterogeneity amounts to half of the observed horizontal inequity index.

The part of *HI* due to behaviors is decomposed into the sum of various factors. The effect of behaviors is globally pro-poor in the case of GP visits and pro-rich in the case of specialists visits. However, each one of the three components of *HI* have the same sign for each type of care. The heterogeneity of practices linked to participation is clearly pro-rich: for a given morbidity and

given other characteristics, the poor resort less to physician care (GP or specialists) than the rich. However, the heterogeneity of behaviors linked to conditional consumption is pro-poor. Once the decision to consume is made, the poor receive more in proportion than the rich, for an equivalent morbidity.

For the three types of health care use we study, the heterogeneity of practices linked to participation appears to be pro-rich. Participation behaviors for a given morbidity have a strong link to demand behaviors. This results shows the presence of an heterogeneity of access linked to the rank in the income distribution. This heterogeneity could be the sign of the poor's lesser preference for health. Indeed, the coefficients capturing practices for a given morbidity are estimated with a model where income is present, as well as many other individual characteristics. The influence of income level is thus taken into account in the explanatory model of health care use.

The heterogeneity of practices linked to conditional consumption appear to be pro-poor, for all types of health care use. Conditional consumption can be linked to the supply side. The suppliers' pro-poor behavior could compensate the pro-rich behaviors of individuals: the health care system would support equality of treatment. However, the poor's lesser participation to the health care system can induce a late taking into account of their illness, and thus a degradation of health. This can lead to more health care use for the poor once participation has been decided, but to less favorable outcomes. Dormont and Huber (2006) have shown on French data that when estimating a model of health care use using the *Sample selection model* specification (Heckman 1979), the estimated coefficient of correlation between the residuals of the two equations was negative. For a given health status, a smaller probability of participation induces a greater conditional consumption, once participation has been decided. We believe what we observe here is close to this phenomenon, that is indeed well-known in Public Health.

The total number of physician visits is globally inequitable, and in favor of the rich ($HI = 0,0317$). Half of this inequity is due to the heterogeneity of behaviors ($0,0182$). This pro-rich inequity of behaviors is mainly due to the pro-rich heterogeneity of practices linked to participation, that correspond to the demand side. The interpretation of results can be questioned: they can be interpreted as the poor's lesser preference for health, or as an indication of a problem in access to care for the poor. In the case of a lesser preference for health, should these preferences be followed?

As a matter of fact, the results we outline here can be strongly linked to the social epidemiology literature. The link between inequality in health and inequality in income has largely been underlined: according to (Wilkinson 1992), the absolute level of income is less important that the relatve position of individuals in the society. From an economic point of view, this position can in

some way be assessed by the rank of the individual in the income distribution. Our results showed heterogenous behaviors with respect to the individual rank in the income distribution in an model where the level of income is controlled for. Following the social epidemiology literature, it indicates that when explaining individual behaviors, the relative place in the society is as important as the observed level of income. Within a public policy perspective, these results might indicate that in order to reduce inequity in health care use, one should reduce income inequality but also influence behaviors of underconsumption that can be observed in the lower part of the income distribution. Solely reducing inequality will indeed reduce health care use inequity, but if behaviors are linked to the relative position in the society (which in our study is represented by the rank in the income distribution), an important source of inequity will remain. This source of inequity, the heterogeneity of behaviors with respect to income, cannot be identified in the standard decompositions, and its effect is unjustly attributed to inequality of income (as in expression (4)). Using the standard decomposition for policy purposes might be misleading, in the sense that it leads to neglecting an important source of inequity.

5 Conclusion

The method we propose for the analysis of inequality provides a synthetic analysis of the various factors leading to the observed inequality in health care use. The micro-simulation approach avoids the computation and calculation of indices whose interpretation might be questionable, as in the standard decomposition. The estimation by income quantile provides the identification of heterogeneity of behaviors linked to the rank in the income distribution, which is impossible with the standard decompositions. While the standard way of testing for health care use inequity is usually done by comparing behaviors relative to various income quantiles (see Wagstaff and VanDoorslaer (2000)), this feature is absent from the standard decompositions of health care use. The decomposition we propose here provides a link between the Oaxaca (1973) style counterfactual analyses and the inequity decomposition methods.

The application we proposed enabled us to analyze the sources of inequity in physician visits use in France, for the year 1998. We find results that are coherent with the previous literature: for a given morbidity, GP use is concentrated among the poor, and specialist use is concentrated among the rich.

We sticked to the common use in the literature, that distinguishes justifiable and unjustifiable inequality. The index of horizontal inequity that we built (HI) was decomposed into the part due to behaviors and the part due to individual characteristics; we showed that the heterogeneity of behaviors represents nearly half of the HI index. In the course of the analysis, we showed that the results were highly dependent on the choice of health indicators, suggesting that the selection of health variables is an issue that cannot be neglected in a decomposition of inequality. Taking into account the heterogeneity of behaviors appears to be fundamental when trying to explain the sources of inequity in health care use. This heterogeneity of behaviors can be linked to the heterogeneity of individual preferences. The link with the social epidemiology literature is an improvement upon the standard decomposition that is commonly used, and the question of the interpretation of the heterogeneity of behaviors seems promising.

A Calculation of the conditional number of visits

A negative binomial distribution of mean μ has the following density function (Grogger and Carson 1991):

$$f(y) = P[Y = y] = \frac{\Gamma(y+\theta)}{\Gamma(y+1)\Gamma(\theta)}(\frac{\mu}{\theta})^y(1+\frac{\mu}{\theta})^{-\theta(y+1)} \tag{22}$$

With:

$$E[Y] = \mu \tag{23}$$

$$V[Y] = \mu(1+\frac{\mu}{\theta}) \tag{24}$$

Where θ is the overdispersion parameter, and where function Γ is defined by $\forall\alpha$, $\Gamma(\alpha) = \int_0^{+\infty} t^{\alpha-1}e^{-t}dt$.

From (22), we get (since $\Gamma(1) = 1$):

$$P(Y > 0) = 1 - P(Y = 0) \tag{25}$$

$$= \frac{\Gamma(\theta)}{\Gamma(1)\Gamma(\theta)}(\frac{\mu}{\theta})^0(1+\frac{\mu}{\theta})^{-\theta} \tag{26}$$

$$= 1 - (\frac{\theta}{\theta+\mu})^\theta \tag{27}$$

Using (27), the zero-truncated negative binomial has the following density function:

$$h(y) = P[Y = y|Y > 0] = \frac{P[Y=y]}{P[Y>0]}\frac{\Gamma(y+\theta)}{\Gamma(y+1)\Gamma(\theta)}(\frac{\mu}{\theta})^y(1+\frac{\mu}{\theta})^{-\theta(y+1)}\frac{1}{1-(\frac{\theta}{\theta+\mu})^\theta} \tag{28}$$

The *GLM* approach models μ:

$$\mu = \exp(Xb) \tag{29}$$

Parameters b as well as the overdispersion parameter θ are estimated by maximum likelihood, where the likelihood of the model is written using expression 28.

We have:

$$E[Y|Y > 0] = \frac{\mu}{P(Y > 0)} \tag{30}$$

The mean of a negative binomial of mean μ and parameter of overdispersion θ but truncated at zero can be written as:

$$E(Y|Y>0) = \frac{\mu}{1 - \frac{\theta}{(\theta+\mu)^{\theta}}}. \tag{31}$$

The conditional expectancy of y can be expressed the following way:

$$E(y_i|P_i = 1) = \frac{\exp(Xb)}{1 - \frac{\theta}{(\theta + \exp(Xb))^{\theta}}} \tag{32}$$

And this expression is estimated by the following expression, that is used when implementing the simulations:

$$\hat{E}(y_i|P_i = 1) = \frac{\exp(Xb)}{1 - \frac{\hat{\theta}}{(\hat{\theta} + \exp(Xb))^{\hat{\theta}}}} \tag{33}$$

With θ the overdispersion parameter, and $\hat{\theta}$ an estimator of θ found by the estimation. When simulating the distributions, the $\hat{\theta}$ used for the computations is the one estimated on the whole sample (and not on income quantiles), for comparability reasons.

B Variables used

B.1 Variables potentially used in the estimations

- Age
- PCS of the head of household
- Education level
- Income
- Complementary coverage
- Number of people in household
- Living in a couple
- Female
- Unemployed
- Widow / widower
- Death risk
- Disability
- Self-assessed health (grade from 0 to 10)
- Diabetes
- Chronic obstructive pulmonary disease and related diseases (COPD)
- Ischemic heart disease
- Hypertension
- Circulatory disease
- Cancer
- Trouble of lipid metabolism
- Mental disorder
- Depression
- Sleeping disorder
- Cataract

- Arthropathy, arthritis, back pain
- Kidney failure
- Number of diseases

Age is taken into account through dummies coding decades (10-19 years old, 20-29 years old...), until age 70 years old and more. The PCS of the head of household is coded with the usual INSEE classification, grouping PCS's 1 and 2, 4 and 5, and 6 and 7. The level of disability is coded through 3 dummies, grouping levels 0 and 1, 2 and 3, and 4 and more. Death risk is coded with 3 dummies as well, grouping levels 0 and 1, 2 and 3, and 4 and more. The number of diseases is coded through 3 dummies, corresponding to a number of diseases 0 to 3, 4 to 7, and 8 or more. Self-assessed health is coded with 3 dummies: 0-5 (low self-assessed health), 6-7 (average), 8 and more (high). The variables that chode for chronic diseases are dummies coding for the presence of at least one disease among the family of diseases they represent.

The level of disability:

- 0: no difficulty
- 1: very small level of difficulty
- 2: small level of difficulty
- 3: experiences difficulties but lives normally
- 4: must diminish his/her domestic or professional activity
- 5: diminished activity
- 6: no domestic autonomy
- 7: confined to bed

The death risk (DR):

- 0: level zero of death risk
- 1: very low negative prognosis
- 2: low negative prognosis
- 3: possible risk
- 4: probably negative prognosis
- 5: surely negative prognosis

The level of death risk (probability of death within the following 5 years) is elaborated by the IRDES physicians who recode the survey.

The number of illnesses (nbpath) is calculated from the list of illnesses declared by the respondent, coupled with the ones found out by the physicians recoding the survey, on the basis of other elements of the survey, such as the type of medication taken.

The self-assessed health (SAH) is captured through a grade declared by the surveyed individual who rates his/her health from 0 (poorest) to 10 (highest).

Social and occupational group (INSEE classification)

- 1 : farmers
- 2 : independent workers
- 3 : intellectual professions
- 4 : intermediary professions
- 5 : clerks
- 6 : qualified workers
- 7 : non-qualified workers

B.2 Selected variables for the estimations

B.2.1 Participation equation:

- Age
- Female
- Pcs of head of household
- Income (Euros)
- Living in a couple
- Complementary coverage
- Hypertension
- Mental disorder

- Level of disability
- Number of diseases

B.2.2 Conditional consumption equation:

- Age
- Female
- Income (Euros)
- Number of people in household
- Living in a couple
- Unemployed
- Widow / widower
- Diabetes
- Chronic obstructive pulmonary disease and related diseases (COPD)
- Ischemic heart disease
- Cancer
- Mental disorder
- Depression
- Cataract
- Level of disability
- Number of diseases

C The simulated distributions

C.1 Identification of the sources of inequality in heath care use: a microsimulations approach

This appendix presents the results of the application proposed, i.e. the analysis of the sources of health care use inequality in France for the year 1998, for people age 15+. Since this appendix is devoted to the explanation of the detailed procedure of simulation, we limit ourselves to the GP case (the calculations are the same for the number of specialist visits and the total number of visits).

C.1.1 The concentration indices of the simulated distributions

The way we simulate distributions is explained in section 3.3. The concentration indices are computed on each one of these simulated distributions. Results are presented in table 4.

	1998	
	0	
CI0 (egalitarian)		
IC (95%)	-	-
CI1 (morbidity)	-0,0056	
IC (95%)	-0,0139	0,0027
CI2 (age)	-0,0047	
IC (95%)	-0,0139	0,0045
CI3 (prat part)	-0,0043	
IC (95%)	-0,0147	0,0062
CI4 (prat cond)	-0,0403	
IC (95%)	-0,0506	-0,03
CI5 (socio)	-0,0509	
IC (95%)	-0,0617	-0,04
CI6 (coef socio)	-0,0227	
IC (95%)	-0,0326	-0,0128
CI7 (cmu)	-0,0227	
IC (95%)	-0,0326	-0,0128
CI observé	-0,0219	
IC (95%)	-0,0403	-0,0036

Table 4: Concentration indices of the simulated distributions - GP visits, 15+

The concentration indices are computed using regression (2) presented in the article. The confidence intervals are computed from this regression: they are computed as if the distributions

were certain. However, they are simulated: the confidence intervals do not take into account the variability due to the simulations.

C.1.2 Computation of the different sources of inequality

	Δ 98
Morbidity	-0,0056
Age	0,0009
Prat part	0,0004
Prat cond	-0,0361
Socio	-0,0105
Coef socio	0,0281
Heterog	0,0008

The different Δ's are calculated as presented in section 3.3.

C.2 Analysis of the stability of the decomposition with respect to the order of introduction of the various effects

The following table presents the concentration indices of simulated distributions for specialist visits (France, year 1998).

	1998	
CI0 (egalitarian)	0	
IC (95%)	-	-
CI1 (morbidity)	-0,0034	
IC (95%)	-0,0092	0,0024
CI2 (age)	-0,0078	
IC (95%)	-0,0126	-0,0029
CI3 (prat part)	0,0303	
IC (95%)	0,0239	0,0367
CI4 (prat cond)	-0,0047	
IC (95%)	-0,0148	0,0054
CI5 (socio)	0,049	
IC (95%)	0,035	0,063
CI6 (coef socio)	0,0971	
IC (95%)	0,0882	0,1061
CI (observed)	0,0884	
IC (95%)	0,0661	0,1107

The following table presents the concentration indices of the simulated distributions, where

the order of the introduction of effects has been modified: we first introduce the heterogeneity of practices, then the heterogeneity of health status.

	1998	
CI0 (egalitarian)	0	
IC (95%)	-	-
CI1 (prat cond)	-0,0436	
IC (95%)	-0,0459	-0,0414
CI2 (prat part)	-0,0217	
IC (95%)	-0,0235	-0,0199
CI3 (age)	-0,0255	
IC (95%)	-0,0293	-0,0217
CI4 (morbidity)	-0,0277	
IC (95%)	-0,0342	-0,0211
CI5 (socio)	0,0357	
IC (95%)	0,0228	0,0486
CI6 (coef socio)	0,0999	
IC (95%)	0,0912	0,1086
CI (observed)	0,0884	
IC (95%)	0,0658	0,111

The impact of each step on the total index of inequality is computed as described in section 3.3. The comparison of these effects is presented in the following table:

	Δ 98
Morbidity	-0,0034
Age	-0,0044
Prat part	0,0381
Prat cond	-0,0351
Socio	0,0537
Coef socio	0,0481
Heterog	-0,0087

Table 5: Contribution of each step to total inequality - specialists, 15+

	Δ 98
Prat cond	-0,0436
Prat part	0,0219
Age	-0,0038
Morbidity	-0,0022
Socio	0,0633
Coef socio	0,0642
Heterog	-0,0115

Table 6: Contribution of each step to total inequality - specialists, 15+

After changing the order of introduction of the various effects, we get approximately the same order of magnitude.

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