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Scaling methods for categorical self-assessed health measures*

Patricia Cubí-Mollá **

Abstract

The lack of a continuous health valuation is a major drawback in health analyses over broad populations. The use of categorical health variables to estimate a continuous health variable is an usual procedure in health studies. The most common approaches (ordered probit/logit model and interval regression model) do not admit any skewness in the distribution of health. In the present study a new procedure is suggested, that is attaching a log-normal distribution to health values. Different scaling procedures have been compared, with data obtained from the Catalan Health Survey (2006). The validity of the scaling approaches is assessed by measuring to what extent the health values derived from categorical health variables suit the actual health values. Two different health tariffs have been used for each procedure (VAS tariff and TTO tariff), so that the results are robust to the selection of a metric. In general, models under lognormality outperform the other approaches.

Keywords: Health-Related Quality of Life, Health Measurement, Interval Regression, Ill-Health.

JEL Classifcation: C01, I10.

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1 Introduction

The estimation of a quality weight related to a particular health state is the basis of an extensive area of health-related studies. Fundamentally, quality weights are required for the computation of health-related quality of life (HRQoL) measures, that represent an essential tool in cost-effectiveness and cost-utility analysis. The use of these weights is also desirable in other health issues, as measuring health levels for populations, estimating quality adjustments of life expectancy, or analyzing inequalities and inequities in health, among others.

Theoretically, quality of life associated to health states is considered as a continuum, with maximum and minimum values, that admits a complete order. Thus, health states can be represented in a 0 -1 scale, where 0 represents the worst health state and 1 the best health state. In practice, however, the information about the health state of individuals are often derived from general health surveys. More concretely, from the respondent's assessment of her own health status, typically measured on an ordinal scale. Thus, a wide variety of methods have been developed for deriving quality weights from categorical health measures. This paper compares alternative procedures designed to impose cardinality on the ordinal health responses, and suggests a new methodology.

Most studies in this area deal with the cardinalization of the so-called *self-assessed health* (SAH). This piece of information is usually obtained from a question such as: "In your opinion, how is your health in general?", where respondents must choose one between several categories, typically ranging from "excellent" to "very poor". SAH measures present numerous advantages. First, they are one of the most commonly used indicators in socioeconomic and epidemiological surveys. Second, they offer a summary of the general health state of the respondents. Third, they have shown a good performance at predicting future mortality and morbidity (Idler, 1997).

The usual procedures assume the existence of a latent, continuous but unobservable health variable (y^*) with a *normal distribution*. This framework can embrace well-known approaches as the estimation of ordered-probit regressions (Groot, 2000) or combining the distribution of observed SAH with external information (the interval regression approach, in Van Doorslaer and Jones, 2003). Ordered-probit regressions have the requirement of re-scaling to compute quality weights. The use of external information allows to identify the scale of y^* without having any scaling or identification problems, but it requires the use of additional assumptions. The interval regression approach is found superior to the ordered-probit approach (Van Doorslaer and Jones, 2003; Lauridsen et al., 2004), and is one of the most widespread methods of scaling (Lecluyse and Cleemput, 2006).

The major drawback of those approaches is that they rule out any *skewness* in the distribution of the latent health variable y^*. This fact is specially important for the analysis of health measures in developed countries, where a large proportion of the general population report good health. One possible strategy is to use the standard *lognormal distribution* rather than the standard normal distribution. The shape of the health distribution is captured better, but the estimation will require an ex-post re-scaling. Wagstaff and Van Doorslaer (1994), assigned to every category of SAH a value that equals the midpoints of the intervals corresponding to the standard lognormal distribution. However, this method fails to introduce the required continuity in health scales. Up to my knowledge, no other approach under log-normality has been suggested.

In this work we propose methods for scaling SAH measures, considering that the latent health variable is log-normally distributed. These new methods are compared to the existing procedures, which contemplate values of health as normally distributed. Data from the *Catalonia Health Survey 2006* (*CHS*) are used to provide the results. In this survey every respondent reports a categorical SAH evaluation. Also, utility values can be derived by means of the EQ-5D descriptive system provided by the survey. Thus, we can take advantage of having actual continuous health values in this study. The validity of the scaling approaches is assessed by measuring to what extent the health values derived from SAH suit the actual health values, available in the survey.

The paper is structured as follows: Section 2 summarizes the different scaling methodologies: ordered probit model and interval regressions, both under normal and log-normal distribution. In Section 3 the data are presented. Section 4 presents the results and compares the performance of different models. Section 5 summarizes the main conclusions and provides a discussion about the validity of the scaling approaches.

2 Methodology

This section describes the different scaling methods that are compared in this paper. All of them assume the existence of a continuous latent health variable y^* underlying the categorical SAH variable. We divide them into two groups, depending on the distribution properties that are assigned to y^* (normal or lognormal distribution). The objective of these procedures is to estimate the quality weight associated to every respondent i (w_i), conditioning on the self-assessed health value of individual i, SAH_i, and on a vector of socioeconomic variables for individual i, x_i.

We will compare the characteristics of these continuous health values as well as the regression-based measures obtained from these actual values, with the descriptive performance of the scaling methods.

2.1 A standard normal latent health variable

Suppose that SAH has J categories, with category 1 corresponding to the worst health and J corresponding to the best. The SAH stated by individual i, and her/his true health state are recorded as SAH_i and y_i^*, respectively. Then, y_i^* and SAH_i are related as follows:

$$SAH_i = j \text{ iff } \mu_{j-1} < y_i^* \leq \mu_j \ , \ j = 1, 2...J \tag{1}$$

where $y^* \in (\mu_0, \mu_J]$, and μ_j, $j = 1, 2, ..., J$ stand for the thresholds between categories of SAH, with $\mu_{j-1} \leq \mu_j$. Note that the thresholds are constant for individuals. Depending on each methodology, the support of y^* may vary. In general, we are interested in obtaining a continuous health index for every respondent $w_i \in [0, 1]$.

The usual scaling methods (the ordered probit model and the interval or grouped data regression model) are summarized below.

2.1.1 Ordered Probit model (OP+N)

Now the latent health variable y^* can take any real value (that is, $\mu_0 = -\infty$ and $\mu_1 = +\infty$), and for each individual it is assumed to be a function of a vector of socioeconomic variables x_i:

$$y_i^* = x_i'\alpha + \varepsilon_i, \quad \text{with} \ \ \varepsilon_i \sim N(0, 1)$$

Predictions of the linear index, $E[y_i^*|x_i]$, can then be used as a measure of individual health and, after appropriate re-scaling, as 'quality weights' or utility proxies. We use one of the re-scaling methods proposed by van Doorslaer and Jones (2003), that do not require the availability of a continuous health variable. Let $y_i^0 = x_i'\widehat{\alpha}$ and let $y^{\max}$ and $y^{\min}$ the largest and smallest individual predictions, respectively. Then the re-scaled values (w_i), that represent quality weights, can be calculated as:

$$w_i = \frac{y_i^0 - y^{\min}}{y^{\max} - y^{\min}} \tag{2}$$

2.1.2 Interval Regression (IR+N)

This method provides an alternative to (OP+N) when the threshold values (μ_j) are directly observed. In many cases, the thresholds are not observed, but they can be obtained from external information. The methodology proposed by Doorslaer and Jones (2003) for establishing the μ's consists in combining the distribution of observed SAH with external information on the distribution of a generic measure of health utilities y, ranging from 0 to 1. The relationship between y^*(latent), SAH (available at the current data) and y (obtained from external information), is assumed to be as follows: the higher the value of y^*, the more likely the individual is to report a higher category in SAH, and a higher value in y. For such a connection to be correct, it is necessary to assume that the reported variables have rank properties: the *qth*-quantile of the distribution of y will correspond to the *qth*-quantile of the distribution of y^*, and this will also correspond to the *qth*-quantile of the distribution of SAH. The model results:

$$SAH_i = j \text{ iff } \mu_{j-1} < y_i \leq \mu_j, \quad j = 1, 2...J$$

with

$$y_i = x_i'\beta + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2)$$

where it is set that $\mu_0 = 0, \mu_J = 1$ and $\mu_j \leq \mu_{j+1}$.

Since μ's are known, the variance of the error term can be estimated. Also the predicted values from the interval regression are measured in the same units that the thresholds, avoiding an ex-post re-scaling.

The previous model establishes that $y_i \sim N(x_i'\beta, \sigma^2)$, and $y_i \in [0, 1]$. Under these assumptions, the variance in the distribution of y_i is forced to be small enough, in order to define values inside the $0-1$ interval. Although this is not an appealing assumption, it allows the estimated values to be expressed in the required units. Moreover, the variance is restricted, but not completely determined, as in ordered probit models.

Figure 1 illustrates the relationship between the different measures (for simplicity, we take $J = 5$).

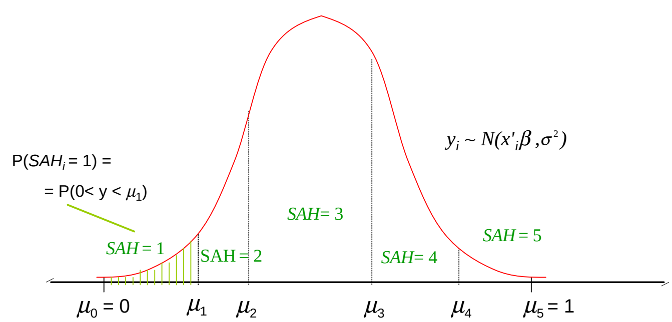

Figure 1. Relation of SAH and y^* under normality

A slight variation with respect to Doorslaer and Jones (2003) for determining the thresholds is introduced in this study.[1] Since the main objective of this method is injecting continuity into the distribution function of health, the threshold values result from interpolating the closest quantiles. More formally, let G_j represent the cumulative relative frequency of the j-th category of SAH, and $F(\cdot)$ be the empirical distribution function (EDF) of the continuous health variable y (variables SAH and y may be obtained from different samples). Let $F^{-1}(\cdot)$ be the inverse of $F(\cdot)$. We denote the set of actual values of $F(\cdot)$ as $\operatorname{Im} F$. Now define (for $j = 1, 2, ..., J-1$):

$G_j^l = \{g \in \operatorname{Im} F \text{ such that } g < G_j \text{ and } \nexists g' \in \operatorname{Im} F \text{ with } g < g' < G_j\}$,
$G_j^u = \{g \in \operatorname{Im} F \text{ such that } g > G_j \text{ and } \nexists g' \in \operatorname{Im} F \text{ with } g > g' > G_j\}$, and
$q_j^l = F^{-1}(G_j^l), q_j^u = F^{-1}(G_j^u)$

Therefore, the threshold μ_j is obtained with the expression:

$$\mu_j = q_j^l + \left(q_j^u - q_j^l\right) \cdot \frac{G_j - G_j^l}{G_j^u - G_j^l} \tag{3}$$

[1] The interpolating method is also used by Lecluyse and Cleemput (2006).

Since the thresholds are derived form self-assessed valuations, it is necessary to analyze if they change among different subgroups of population, e.g. male, younger, etc. (the so-called cut-point shift). If so, the estimated thresholds should be conditioned on each group.

Finally, the estimated quality weights are given by:

$$w_i = E[y_i|x_i]$$

2.2 A standard lognormal latent health variable

It is well-known that the health of a general population sample has a very skewed distribution, with the great majority of respondents reporting their health in higher levels. To ensure that the latent health variable is skewed in the appropriate direction, we redefine the true health of the individual in the range $(-\infty, 0]$, and assume that $h^* = -y^*$ has a standard lognormal distribution. The new variable h^* is decreasing in health, so that represents the latent "ill-health" of the individual. Then, respecting the notation in (1), h_i^* and SAH_i are related as follows:

$$SAH_i = j \text{ iff } -\mu_j < h_i^* \leq -\mu_{j-1} \quad , j = 1, 2, ..., J$$

where $y^* \in (\mu_0, \mu_J]$, $\mu_0 = -\infty, \mu_J = 0$.

The procedures described above (ordered probit and interval regression models) are now reinterpreted in terms of h^*.

2.2.1 Ordered Probit model (OP+LN)

The latent ill-health variable for individual i is assumed to be a function of a vector of socioeconomic variables x_i as follows:

$$\begin{aligned} \ln(h_i^*) &= x_i'\gamma + \varepsilon_i \text{ , with } \varepsilon_i \sim N(0,1), \quad \text{or} \\ h_i^* &= e^{x_i'\gamma} \cdot e^{\varepsilon_i} \text{ , with } \varepsilon_i \sim N(0,1) \end{aligned}$$

Thus the expression:

$$h_i^0 = E\left[y_i^*|x_i\right] = -E\left[h_i^*|x_i\right] = -e^{x_i'\widehat{\gamma}} E\left[e^{\varepsilon_i}|x_i\right] = -e^{x_i'\widehat{\gamma}} e^{1/2}$$

gives us the predictions of health values in a continuous scale $(-\infty, 0]$. For obtaining health indices or quality weights, we perform the same re-scaling method that we used under the assumption of normality, shown in equation (2):

$$w_i = \frac{h_i^0 - h^{\min}}{h^{\max} - h^{\min}} \tag{4}$$

2.2.2 Interval Regression (IR+LN)

Since the connection between y_i and SAH_i is due to represent the latent variable, an adaptation is needed.

Let $h_i = 1 - y_i$ denote a new health variable now interpreted in terms of ill-health. If the values of the generic measure y yields in the range $[0, 1]$, the connection between the variables holds as **Table 1** shows:

	health	ill-health
SAH	y	h
J	$(\mu_{J-1}, 1]$	$[0, 1 - \mu_{J-1})$
$\vdots$	$\vdots$	$\vdots$
2	$(\mu_1, \mu_2]$	$[1 - \mu_2, 1 - \mu_1)$
1	$[0, \mu_1]$	$[1 - \mu_1, 1]$
	$[0, 1]$	$[0, 1]$

Table 1. Connection of different health variables

Let us call $\overline{\mu}_j = 1 - \mu_{J-j}$, for $j = 1, 2, ..., J - 1$, with $\overline{\mu}_0 = 0, \overline{\mu}_J = 1$.
The model turns out to be:

$$SAH_i = j \text{ iff } \overline{\mu}_{j-1} \leq h_i < \overline{\mu}_j, \quad j = 1, 2...J$$

where

$$\ln(h_i) = x_i'\delta + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2)$$

The values of $\overline{\mu}_j$, $j = 1, 2, ..., J - 1$ can be obtained in a similar way to (3), being h and SAH (with the categories reversed) the variables to be interpolated. However, due to the "ceiling effect" of health valuations (high proportion of observations with $y_i = 1$), the higher categories of SAH may possibly be linked to $h_i = 0$. In that case no interpolation is feasible, and those categories should be merged. In order to avoid this possible drawback, we obtained the thresholds directly from the μ's values computed in equation (3), by applying the definition of $\overline{\mu}_j = 1 - \mu_{J-j}$, $j = 1, 2, ..., J - 1$. With such thresholds the same continuity that was induced into the empirical distribution function of y is also considered into the EDF of h, what establishes consistency between (IR+N) and (IR+LN). Also, the is no need of reducing the number of categories of SAH, what would mean a loss of information.

Figure 2 illustrates the context of (IR+LN) for the typical case of $J = 5$:

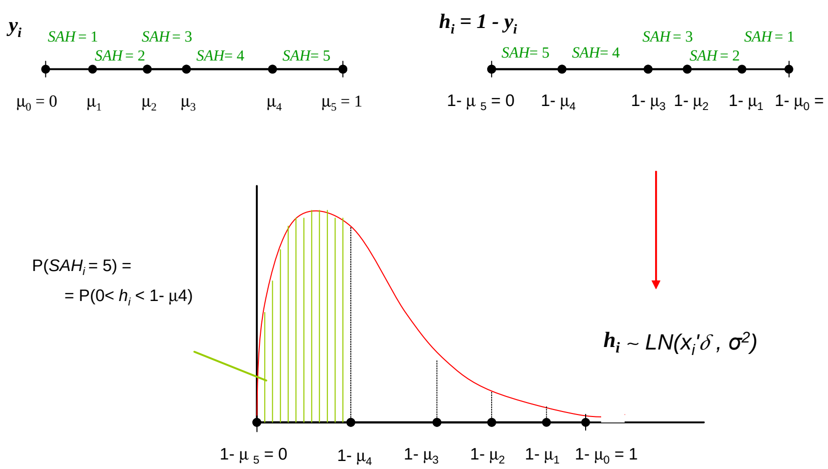

Figure 2. Relation of health and ill-health measures under lognormality

As we discussed in (IR+N), the possible existence of cut-point shift should be determined. The unconditional predictions are computed straightforward (here, there is no need of rescaling, since σ^2 can be identified):

$$w_i = E\left[h_i|x_i\right] = E\left[e^{x_i'\delta}e^{\varepsilon_i}|x_i\right] = e^{x_i'\delta}E\left[e^{\varepsilon_i}|x_i\right] = 1 - e^{x_i'\delta}e^{\sigma^2/2}$$

3 Data

My source of data is the *Catalonia Health Survey 2006* (*CHS,* hereafter). The data were collected throughout the year 2006, and comprise a total of 18,126 individuals (Generalitat de Catalunya, 2007). The survey includes questions on the state of health, the habits of life (including feeding, physical exercise and tobacco and alcohol consumption), and the utilization of the health services-managed by the regional government.

Several measures of the health state are provided by the *CHS*: first, a numerical self-evaluation of the health state (SAH question); second, the EQ-5D descriptive system; and third, the EuroQol visual analogue scale or EQ VAS (The EuroQol Group, 1990). The EQ-5D descriptive system comprises the following 5 dimensions: mobility, self-care, usual activities, pain/discomfort and anxiety/depression. Each dimension has 3 levels: no problems, some problems, severe problems. A total of 243 possible health states is defined in this way. In order to translate these variables to a particular score of health status, a 'preferences tariff' is needed.[2]

Two tariffs for these scores have been computed for Spain: the *VAS tariff* (based on the EQ VAS), by Badia et al. (1997), and the *TTO tariff* (based on the temporal equivalence method), by Badia et al. (2001). Both tariffs are used as health measures ($y =$*VAS tariff* , $y =$*TTO tariff*), in order to control for the robustness of the results. Notice that both scores allow for negative values, that is, health states worse than death. Our analysis is performed by using the re-scaled scores to the interval (0,1), based on the minimal and maximal values obtained in the tariff, related to health states 33333 and 11111, respectively (see Busschbach et al., 1999). This criteria will allow us to reduce the number of observations at the bottom of the distribution. The regression procedures explained in previous sections are used to approximate these tariffs by the response category of SAH, conditioning on several socioeconomic factors. If the approximation is good enough, in situations where health tariffs are not available, the scores obtained from these regression models (w) could be adopted as quality weights.

For practical reasons, the analysis is performed over the population aged 15 or higher. From the *CHS,* $2,342$ observations (corresponding to children aged under 16) have been dropped, as well as 76 missing values or inconsistent answers and 60 individuals whose answers in the relevant variables were not considered trustworthy by the interviewer. The final size for the sample is $15,648$ individuals. Sampling weights are not used in the analysis.

We consider a wide range of factors that can affect the self-valuation of the health state of an individual: age-gender groups, activity status (employed, unemployed, unable, retired, student, houseworker), educational level (no

[2] See Cutler and Richardson (1997) and Torrance (1986).

studies, primary, secondary, superior), marital status (single, married, widow, separated or divorced), household size, if born in a foreign country, existence of a chronic illness (epilepsy, cholesterol,...), existence of some deficiency (mental, visual,...), if sleeps 8 hours or more, if practices sports regularly, Body Mass Index (BMI: less than 18, between 18 and 25, and higher than 25), if heavy smoker (in the present or in the past), if a hard-drinking individual. The variable related to income has not been included as a regressor ($6,373$ missing values); an indicator of the social class of the respondent (high, medium, low) has been taken as a proxy.

4 Results

Before giving estimates for the continuous health measures, we explore whether interval boundaries differ greatly across demographic groups. Data are grouped by gender and age category. SAH is mapped into *VAS tariff* and *TTO tariff*, as it is detailed in (IR+N). **Figures 3** and **4** illustrate the results:[3]

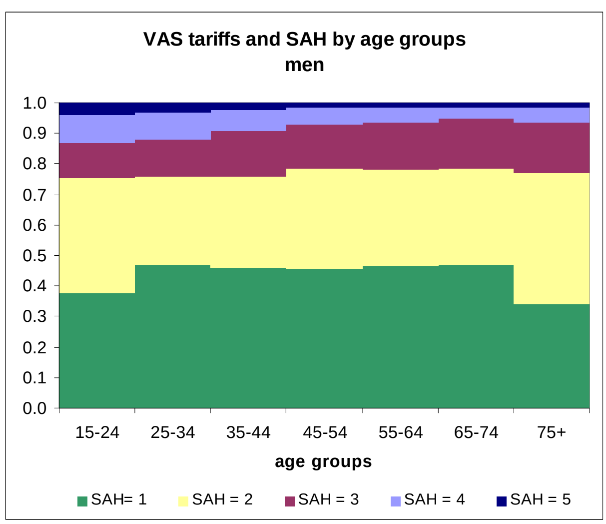

Figure 3. Thresholds by age category. Women.

[3]Figures regarding *TTO tariff* show similar results. For simplicity, only figures regarding *VAS tariff* are reported.

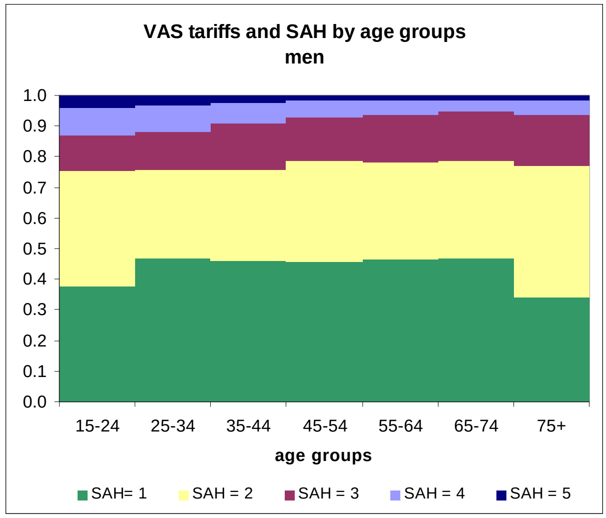

Figure 4. Thresholds by age category. Men

Figures 3 and **4** show that subjective thresholds do not differ significantly among the subpopulations. They tend in particular to be constant in populations aged 25-74. This pattern is also observed in different samples, by Van Doorslaer and Jones (2003). Thus the interval regression approach is unlikely to be sensitive to making the interval boundaries age–sex specific, so the response-category cut-point shift is ignored hereafter.

Table 2 and **Table 3** show summary statistics for *TTO tariff* and *VAS tariff* by *SAH* category, respectively. The last rows show the upper bounds of intervals corresponding to (IR+N) and (IR+LN)

		Emp. cum. freq. (%)				Upper bounds	
SAH	N	health	ill-health	mean	sd	(IR+N)	(IR+LN)
poor	863	0.0552	1.0000	0.5587	0.2427	0.5436	1.0000
fair	3,131	0.2552	0.9448	0.8178	0.1818	0.9006	0.4564
good	6,971	0.7007	0.7448	0.9546	0.0883	0.9713	0.0994
very good	3,522	0.9258	0.2993	0.9791	0.0630	0.9929	0.0287
excellent	1,161	1.0000	0.0742	0.9888	0.0467	1.0000	0.0071

Table 2. Summary statistics of *TTO tariff* by categories of *SAH* and upper bounds in IR

		Emp. cum. freq. (%)				Upper bounds	
SAH	N	health	ill-health	mean	sd	(IR+N)	(IR+LN)
poor	863	0.0552	1.0000	0.4255	0.2216	0.4131	1.0000
fair	3,131	0.2552	0.9448	0.7058	0.2139	0.7675	0.5869
good	6,971	0.7007	0.7448	0.9064	0.1403	0.9019	0.2325
very good	3,522	0.9258	0.2993	0.9545	0.1058	0.9757	0.0981
excellent	1,161	1.0000	0.0742	0.9746	0.0808	1.0000	0.0243

Table 3. Summary statistics of *VAS tariff* by categories of SAH and upper bounds in IR

The most chosen category of SAH is the one in the middle, "good health"; however, the continuous variables are very skewed to better health valuations. Standard deviations of *VAS tariff* and *TTO tariff* also show an increase in low categories of SAH.

The upper bounds of the thresholds are interpreted as follows: for instance, referring to the methodology of (IR+N) for the *VAS tariff* in **Table 3**, an individual who reports the worst category of health (SAH = "poor") will be assumed to have a *VAS tariff* that belongs to the interval [0, 0.4131]. Similarly, the values for the remaining SAH categories are (0.4131, 0.7657] for the "fair" category, (0.7657, 0.9019] for the "good" category, (0.9019, 0.9757] for the "very good" level and (0.9757, 1] for the "excellent" category. Similarly the continuous health valuations can be interpreted as a measure of "ill-health": the thresholds corresponding to the (IR+LN) approach show that an individual who reports the lowest amount of ill-health (SAH = "excellent") will be assumed to have a continuous ill-health valuation (derived from *VAS tariff*) belonging to the interval [0, 0243], etc. **Figure 5** illustrates the procedure for obtaining the thresholds and their interpretation.

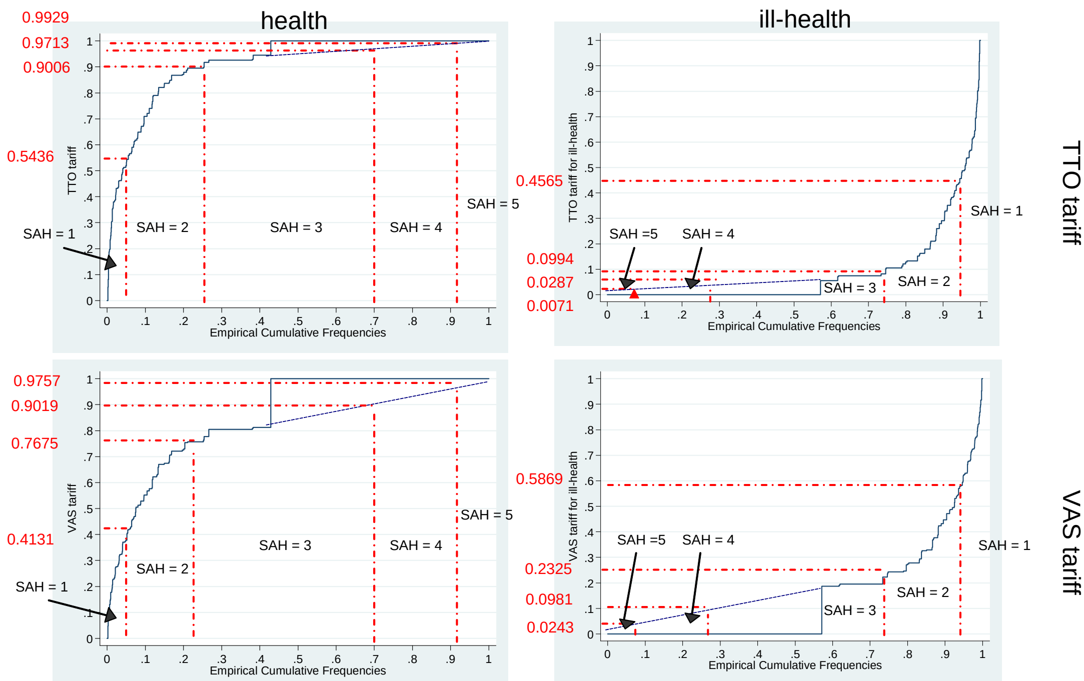

Figure 5. Estimated health and ill-health intervals for TTO tariff and VAS tariff.

Notice that the values corresponding to the *TTO tariff* are higher than those corresponding to the *VAS tariff*.

We display a comparison of the descriptive performance of scaling methods with the regressions based on actual health valuations (*TTO tariff* and *VAS tariff*, respectively). The purpose is to examine to what extent the TTO and VAS tariffs can be approximated by the predicted values of the scaling approaches. The following measures are contrasted:

(i) Actual *VAS tariff* / *TTO tariff*
(ii) OLS regression of actual VAS/*TTO tariff* on x_i
(iii) (IR+N)
(iv) (OP+N) re-scaled by (2)
(v) (IR+LN)
(vi) (OP+LN) re-scaled by (4)

Although the tariffs in (i) are considered as continuous variables, the actual quantities that appear in the survey constitute a reduced selection of values. For instance, the formation of these tariffs allow for 243 different values, but only 149 of them are assigned to individuals in the survey. These tariffs also present the negative aspect of the existence of a "ceiling effect" (a value of health equal to one is assigned to the majority of the individuals, 57.1% in CHS for both tariffs), what makes difficult the comparison of health outcomes along different sub-groups of population. An OLS regression on actual tariff values can be seen as a proper interpretation of continuity for those tariffs. Yet the extended use of the assumption of normality in the distribution of health (e.g. Van Doorslaer and Jones, 2003; Lauridsen et al., 2004) may be a too restrictive assumption. The predictions in (v) and (vi) allow for considering a skewed distribution of health valuations.

Variable	mean	sd	min	p(25)	p(50)	p(75)	max
Actual TTO	0.9135	0.1591	0.0000	0.8951	1.0000	1.0000	1.0000
OLS actual TTO	0.9135	0.1003	0.4957	0.8914	0.9554	0.9741	1.0321
OLS re-scaled	0.7789	0.1870	0.0000	0.7378	0.8570	0.8919	1.0000
(OP+N)	0.5759	0.1863	0.0000	0.4629	0.5978	0.7086	1.0000
(IR+N)	0.8979	0.0786	0.5836	0.8704	0.9255	0.9507	1.0119
(OP+LN)	0.8908	0.1213	0.0000	0.8721	0.9342	0.9643	1.0000
(IR+LN)	0.8905	0.1007	0.1862	0.8723	0.9260	0.9532	0.9865

Table 4. Descriptive statistics of actual and predicted TTO tariffs.

Tables 4 and **5** show some descriptive statistics of actual and predicted TTO tariffs and VAS tariffs, respectively. The regression results are presented in **Tables 6** and **7** (TTO index) and **Tables 8** and **9** (VAS index), in the Appendix.

Concerning to the *TTO tariff*, **Table 4** shows that the non-rescaled OLS predictions on actual values approximates properly the observed scores. The negative aspect of this methodology is the fact of reporting predictions higher than 1. It also fails to represent the lower tariffs, since this model assigns a minimum value of 0.4957. However, re-scaling these predictions does not yield to a better estimation of the actual tariff. Upon the assumption of normality, predictions from the interval regression (IR+N) outperform those obtained by the ordered probit model (OP+N). This result accords well with the statements reported by other authors (Van Doorslaer and Jones, 2003;

Lauridsen et al., 2004). But the methods that are based on the log-normality of the latent health variable approximate better the actual *TTO tariff*, specially for lowest values. The slight differences for higher values of the variables is understandable, because of the cumulative estimation errors. These methods also retain the standard deviation of the actual values.

Variable	mean	sd	min	p(25)	p(50)	p(75)	max
Actual VAS	0.8557	0.2067	0.0000	0.7574	1.0000	1.0000	1.0000
OLS actual VAS	0.8557	0.1368	0.3365	0.8103	0.9034	0.9387	1.0468
OLS re-scaled	0.7309	0.1925	0.0000	0.6670	0.7981	0.8478	1.0000
(OP+N)	0.5759	0.1863	0.0000	0.4629	0.5978	0.7086	1.0000
(IR+N)	0.8060	0.1009	0.4356	0.7597	0.8335	0.8762	0.9802
(OP+LN)	0.8908	0.1213	0.0000	0.8721	0.9342	0.9643	1.0000
(IR+LN)	0.7926	0.1266	0.1085	0.7468	0.8288	0.8808	0.9567

Table 5. Descriptive statistics of actual and predicted VAS tariffs.

Similar conclusions can be obtained in relation to the *VAS tariff* predictions (**Table 5**). In this case, predictions from (OP+LN) seems to approach the actual values even better than the OLS.

Figure 6 illustrates the approximation of the scaling methods to the actual values, by representing jointly the empirical cumulative frequency of each method, for both tariffs. The predicted values for OLS (say, $\widehat{y_i}$) have been taken as a baseline. In order to assess the goodness of the approximations, we define the area $[\widehat{y_i} - 2\widehat{\sigma}, \widehat{y_i} + 2\widehat{\sigma}]$, where $\widehat{\sigma}$ stands for the standard error of the predictions in (ii). Each scaling method is represented together with the distribution of the predicted values for OLS as well as that confidence interval of 95%. The illustration clearly supports the results commented above.

Health

TTO

VAS

Ill-health

TTO

VAS

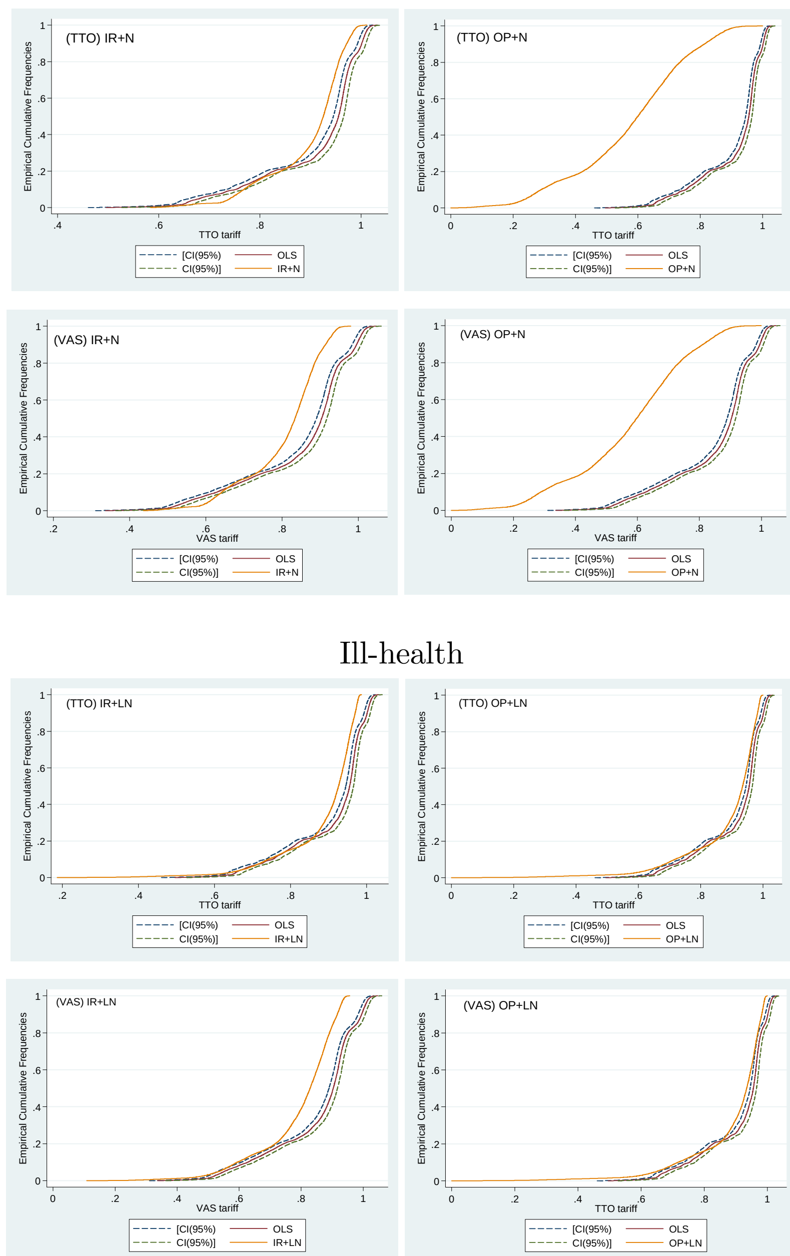

Figure 6. Empirical cumulative frequency for different scaling methods

Finally, it is worth to say that using the IR model applies only if there is no continuous health weight in a database, and thus the thresholds are obtained from external information. If so, it is neccessary to assume that the population from both samples are highly comparable. On the contrary, we could be bringing some bias on the health measures. If it is not possible to find that external information from a proper survey, the OP model shall be the optimal scalig method.

5 Conclusions

The lack of continuous health measures is a major drawback in health analyses over broad populations. On the contrary, general surveys usually include self-assessed health questions, where the respondents must choose among different health levels or categories. The use of these categorical responses to approximate a continuous health variable is an usual procedure in health studies. The most common approaches (ordered probit/logit model and interval regression model) assume that health is an unobservable latent variable that is normally distributed. However, this is a rough assumption, since many studies have reported skewness in the distribution of self-assessed health (that is, a great majority of the population reporting good health), what is consistent with the idea of a skewed distribution of latent health. In the present study we suggest a new procedure: to assume that health values are lognormally distributed.

The scaling methodologies discussed above have been compared. Data has been obtained from the Catalan Health Survey, taking advantage of having actual continuous health values as well as SAH questions. The validity of the scaling approaches is assessed by measuring to what extent the health values derived from SAH suit the actual health values. In order to ensure robustness to the selection of a metric, we use two different health tariffs for each procedure (*VAS tariff* and *TTO tariff*).

In general, models under lognormality outperform the other approaches. In particular, the (OP+N) model is clearly surpassed by the others. The Interval Regression model under normality (suggested by Van Doorslaer and Jones, 2003, and probably the most used in recent years), approximates the actual health tariffs in a similar way to the same model under lognormality; however, the latter seems to match better the lower values. Surprisingly, the (OP+LN) procedure is the one that better models the distribution of health, specially if the *VAS tariff* is used. It is also the closest to the OLS predictions.

As a drawback, it is important to notice that (IR+N) and (IR+LN) are developed under the most ideal scenario: the thresholds between categories have been directly derived from actual data, whereas they are assumed to be obtained from external information. Therefore, using (OP+LN), we are omitting the possible bias associated to combining different sources of data, if the two sources do not arise from the same population.

Introducing cardinality in health valuations is nowadays a challenging task. Cardinalization is an intrinsic problem even at the definition of HRQoL valuations. As Busschbach et al. (1999) stated, whatever method is used for the evaluation of health states (VAS, TTO, Standard Gamble), the responses must be assumed to have interval properties rather than ratio properties; otherwise, the empirical order cannot be extended to additional health states. For instance, VAS is introduced to the respondent as a thermometer, what somehow entails the idea of continuity; however, many surveys report that a high percentage of respondents choose scores ending in 0 (about 81% or respondents in CHS). This suggests that individuals tend to use the thermometer as a combination of a numerical and a rating scale.

If defining HRQoL measures with cardinal properties from (presumably) continuous variables is a challenging task, then, obtaining them from ordinal variables is even more complicated. Assigning a numerical valuation for a category only masks the ordinal relationship between categories (an exhaustive discussion about this topic can be found in Kind, 2003). If the main goal of an analysis is obtaining quality weights from health states, regression methods are, therefore, a powerful tool as scaling procedures. The results obtained in this paper can provide a new benchmark for the proper cardinalization of health measures.

6 Appendix

	OLS	OP+N	IR+N	OP+LN	IR+LN
male 15-25	-0.010	0.079	-0.003	-0.079	-0.089
	(2.87)**	(1.60)	(1.24)	(1.60)	(1.76)
male 35-45	-0.002	-0.179	-0.005	0.179	0.182
	(0.71)	(4.57)**	(1.98)*	(4.57)**	(4.61)**
male 45-55	-0.004	-0.374	-0.012	0.374	0.368
	(1.28)	(8.78)**	(4.17)**	(8.78)**	(8.73)**
male 55-65	-0.006	-0.450	-0.017	0.450	0.439
	(1.23)	(9.14)**	(4.15)**	(9.14)**	(9.10)**
male 65-75	-0.004	-0.428	-0.014	0.428	0.410
	(0.45)	(6.43)**	(1.81)	(6.43)**	(6.41)**
male 75+	-0.029	-0.510	-0.024	0.510	0.496
	(2.83)**	(7.30)**	(2.68)**	(7.30)**	(7.40)**
female 15-25	-0.010	-0.000	-0.004	0.000	-0.007
	(2.64)**	(0.01)	(1.26)	(0.01)	(0.14)
female 25-35	-0.012	-0.126	-0.007	0.126	0.124
	(4.18)**	(3.17)**	(2.98)**	(3.17)**	(3.10)**
female 35-45	-0.022	-0.292	-0.015	0.292	0.285
	(6.21)**	(6.74)**	(5.09)**	(6.74)**	(6.60)**
female 45-55	-0.033	-0.518	-0.028	0.518	0.502
	(7.72)**	(11.27)**	(7.73)**	(11.27)**	(11.12)**
female 55-65	-0.052	-0.679	-0.047	0.679	0.653
	(9.02)**	(12.82)**	(8.81)**	(12.82)**	(12.70)**
female 65-75	-0.057	-0.718	-0.052	0.718	0.691
	(7.05)**	(11.21)**	(6.68)**	(11.21)**	(11.22)**
female 75+	-0.106	-0.701	-0.056	0.701	0.676
	(10.89)**	(10.33)**	(6.34)**	(10.33)**	(10.44)**
high social class	0.009	0.119	0.008	-0.119	-0.117
	(3.42)**	(4.69)**	(4.24)**	(4.69)**	(4.67)**
medium social class	-0.000	0.022	0.000	-0.022	-0.023
	(0.12)	(1.02)	(0.23)	(1.02)	(1.12)
household size	-0.001	-0.000	0.001	0.000	0.000
	(0.67)	(0.01)	(1.20)	(0.01)	(0.04)
alcohol	-0.003	0.030	0.004	-0.030	-0.032
	(0.84)	(0.70)	(1.42)	(0.70)	(0.75)
heavy smoker	-0.002	-0.111	-0.006	0.111	0.110
	(1.21)	(5.25)**	(3.88)**	(5.25)**	(5.31)**
sleeps +8h	0.003	0.071	0.006	-0.071	-0.069
	(2.50)*	(9.12)**	(6.69)**	(9.12)**	(9.16)**
sports	-0.000	0.135	0.006	-0.135	-0.142
	(0.08)	(5.14)**	(3.64)**	(5.14)**	(5.37)**
Observations	15648	15648	15648	15648	15648
R-squared	0.40				

Robust t statistics in parentheses. * significant at 5%; ** significant at 1

Table 6. Regression coefficients in procedures for converting SAH to *TTO tariff*

	OLS	OP+N	IR+N	OP+LN	IR+LN
BMI < 18	-0.026	-0.205	-0.027	0.205	0.189
	(2.83)**	(2.70)**	(3.72)**	(2.70)**	(2.55)*
BMI > 25	-0.006	-0.123	-0.007	0.123	0.120
	(2.71)**	(6.42)**	(4.06)**	(6.42)**	(6.46)**
chronic illness	-0.035	-0.590	-0.028	0.590	0.588
	(26.16)**	(26.58)**	(24.06)**	(26.58)**	(26.01)**
deficiences	0.146	0.752	0.106	-0.752	-0.720
	(32.56)**	(25.09)**	(23.44)**	(25.09)**	(25.49)**
unemployed	-0.021	-0.194	-0.021	0.194	0.179
	(4.33)**	(4.05)**	(4.74)**	(4.05)**	(3.82)**
unable	-0.154	-0.941	-0.150	0.941	0.867
	(14.30)**	(15.05)**	(13.57)**	(15.05)**	(15.72)**
retired	-0.003	-0.207	-0.016	0.207	0.197
	(0.49)	(4.59)**	(2.63)**	(4.59)**	(4.62)**
student	0.003	0.117	0.000	-0.117	-0.123
	(1.11)	(2.49)*	(0.07)	(2.49)*	(2.52)*
houseworker	-0.002	-0.115	-0.011	0.115	0.110
	(0.55)	(3.04)**	(2.68)**	(3.04)**	(3.04)**
other	-0.083	-0.454	-0.037	0.454	0.426
	(1.71)	(2.49)*	(1.19)	(2.49)*	(2.60)**
no studies	-0.030	-0.111	-0.020	0.111	0.105
	(5.98)**	(3.44)**	(4.47)**	(3.44)**	(3.42)**
secondary studies	0.006	0.129	0.010	-0.129	-0.122
	(2.25)*	(5.17)**	(4.38)**	(5.17)**	(4.99)**
superior studies	0.009	0.269	0.016	-0.269	-0.259
	(3.16)**	(8.99)**	(6.44)**	(8.99)**	(8.80)**
married	-0.003	0.016	-0.004	-0.016	-0.021
	(1.00)	(0.61)	(2.12)*	(0.61)	(0.81)
widow	-0.027	0.061	0.001	-0.061	-0.064
	(3.77)**	(1.33)	(0.17)	(1.33)	(1.45)
separed or divorced	-0.018	0.029	-0.008	-0.029	-0.033
	(3.21)**	(0.58)	(1.71)	(0.58)	(0.67)
foreigner	-0.003	-0.016	-0.002	0.016	0.013
	(0.93)	(0.45)	(0.85)	(0.45)	(0.37)
Constant	0.695		0.709		-2.004
	(53.16)**		(58.72)**		(22.07)**
Observations	15648	15648	15648	15648	15648
R-squared	0.40				

Robust t statistics in parentheses * significant at 5%; ** significant at 1

Table 7. Regression coefficients in procedures for converting SAH to *TTO tariff*

	OLS	OP+N	IR+N	OP+LN	IR+LN
male 15-25	-0.008	0.079	0.000	-0.079	-0.088
	(1.68)	(1.60)	(0.10)	(1.60)	(2.04)*
male 35-45	-0.005	-0.179	-0.012	0.179	0.155
	(1.07)	(4.57)**	(3.44)**	(4.57)**	(4.76)**
male 45-55	-0.008	-0.374	-0.028	0.374	0.302
	(1.69)	(8.78)**	(6.59)**	(8.78)**	(8.87)**
male 55-65	-0.017	-0.450	-0.035	0.450	0.352
	(2.69)**	(9.14)**	(6.55)**	(9.14)**	(9.29)**
male 65-75	-0.011	-0.428	-0.032	0.428	0.329
	(1.05)	(6.43)**	(3.51)**	(6.43)**	(6.92)**
male 75+	-0.052	-0.510	-0.045	0.510	0.388
	(4.40)**	(7.30)**	(4.32)**	(7.30)**	(7.93)**
female 15-25	-0.015	-0.000	-0.003	0.000	-0.014
	(2.68)**	(0.01)	(0.71)	(0.01)	(0.32)
female 25-35	-0.019	-0.126	-0.012	0.126	0.099
	(4.26)**	(3.17)**	(3.29)**	(3.17)**	(2.97)**
female 35-45	-0.037	-0.292	-0.026	0.292	0.227
	(7.34)**	(6.74)**	(6.21)**	(6.74)**	(6.46)**
female 45-55	-0.054	-0.518	-0.048	0.518	0.392
	(9.28)**	(11.27)**	(9.77)**	(11.27)**	(10.97)**
female 55-65	-0.085	-0.679	-0.071	0.679	0.496
	(11.41)**	(12.82)**	(10.81)**	(12.82)**	(12.60)**
female 65-75	-0.088	-0.718	-0.077	0.718	0.521
	(9.01)**	(11.21)**	(8.58)**	(11.21)**	(11.42)**
female 75+	-0.140	-0.701	-0.079	0.701	0.508
	(12.77)**	(10.33)**	(7.92)**	(10.33)**	(10.71)**
high social class	0.014	0.119	0.012	-0.119	-0.090
	(4.23)**	(4.69)**	(4.64)**	(4.69)**	(4.50)**
medium social class	-0.000	0.022	0.001	-0.022	-0.020
	(0.12)	(1.02)	(0.49)	(1.02)	(1.23)
household size	-0.000	-0.000	0.001	0.000	0.002
	(0.19)	(0.01)	(0.73)	(0.01)	(0.27)
alcohol	-0.008	0.030	0.004	-0.030	-0.023
	(1.59)	(0.70)	(1.06)	(0.70)	(0.67)
heavy smoker	-0.007	-0.111	-0.010	0.111	0.088
	(2.51)*	(5.25)**	(4.63)**	(5.25)**	(5.37)**
sleeps +8h	0.006	0.071	0.009	-0.071	-0.051
	(4.93)**	(9.12)**	(7.77)**	(9.12)**	(9.31)**
sports	-0.000	0.135	0.011	-0.135	-0.120
	(0.13)	(5.14)**	(4.46)**	(5.14)**	(5.55)**
Observations	15648	15648	15648	15648	15648
R-squared	0.44				

Robust t statistics in parentheses * significant at 5%; ** significant at 1%

Table 8. Regression coefficients in procedures for converting SAH to *VAS tariff*

	OLS	OP+N	IR+N	OP+LN	IR+LN
BMI < 18	-0.027	-0.205	-0.032	0.205	0.127
	(2.64)**	(2.70)**	(3.58)**	(2.70)**	(2.19)*
BMI > 25	-0.010	-0.123	-0.012	0.123	0.093
	(3.47)**	(6.42)**	(5.22)**	(6.42)**	(6.53)**
chronic illness	-0.070	-0.590	-0.049	0.590	0.479
	(33.68)**	(26.58)**	(27.08)**	(26.58)**	(24.91)**
deficiences	0.188	0.752	0.123	-0.752	-0.482
	(35.44)**	(25.09)**	(24.98)**	(25.09)**	(24.67)**
unemployed	-0.034	-0.194	-0.027	0.194	0.120
	(5.45)**	(4.05)**	(4.80)**	(4.05)**	(3.32)**
unable	-0.188	-0.941	-0.165	0.941	0.572
	(16.90)**	(15.05)**	(14.30)**	(15.05)**	(15.45)**
retired	-0.016	-0.207	-0.024	0.207	0.140
	(2.08)*	(4.59)**	(3.41)**	(4.59)**	(4.66)**
student	0.005	0.117	0.005	-0.117	-0.113
	(1.00)	(2.49)*	(1.46)	(2.49)*	(2.71)**
houseworker	-0.011	-0.115	-0.014	0.115	0.075
	(1.99)*	(3.04)**	(2.91)**	(3.04)**	(2.82)**
other	-0.081	-0.454	-0.052	0.454	0.316
	(1.55)	(2.49)*	(1.54)	(2.49)*	(2.95)**
no studies	-0.033	-0.111	-0.022	0.111	0.067
	(5.79)**	(3.44)**	(4.26)**	(3.44)**	(3.10)**
secondary studies	0.009	0.129	0.015	-0.129	-0.087
	(2.67)**	(5.17)**	(4.98)**	(5.17)**	(4.69)**
superior studies	0.015	0.269	0.026	-0.269	-0.197
	(3.81)**	(8.99)**	(7.98)**	(8.99)**	(8.56)**
married	-0.002	0.016	-0.003	-0.016	-0.025
	(0.45)	(0.61)	(1.05)	(0.61)	(1.22)
widow	-0.029	0.061	0.004	-0.061	-0.056
	(3.59)**	(1.33)	(0.50)	(1.33)	(1.77)
separed or divorced	-0.021	0.029	-0.005	-0.029	-0.040
	(2.88)**	(0.58)	(0.81)	(0.58)	(1.06)
foreigner	-0.008	-0.016	-0.002	0.016	0.007
	(1.97)*	(0.45)	(0.62)	(0.45)	(0.25)
Constant	0.581		0.597		-1.408
	(37.88)**		(43.49)**		(21.06)**
Observations	15648	15648	15648	15648	15648
R-squared	0.44				

Robust t statistics in parentheses * significant at 5%; ** significant at 1%

Table 9. Regression coefficients in procedures for converting SAH to *VAS tariff*

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