Policy assessment based on subjective data:

A new challenge to policy makers and researchers.

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Governments and policy-makers are increasingly aware that access to knowledge enables better policy-making practice. On the other hand, they are more and more concerned about the impact of their decisions on the well-being and quality of life of citizens.

Also, it is imperious to fully understand why apparently similar policies lead to different outcomes when implemented in different environments, different countries or even different regions within the same country. Therefore, policy-makers are becoming to face common challenges and accept to learn useful lessons from across national boundaries that shed light on their own specific national situation.

Specifically speaking about health and healthcare, the assessment of health policy's impacts used to be based on the so-called "objective" indicators, such as mortality, life expectancy and morbidity. The paradigm shift that created the need to consider health as a positive concept, similar to well-being and quality of life, and not merely the absence of disease, was then responsible for a lesser importance given to these indicators. Nowadays, they do not represent any longer the semantics of the health concept.

However, these new measurement approaches created new challenges in the assessment of health policies. Because measurements are now based on subjective assessments, one may question whether they may be dependent from the personal characteristics of the individuals. And, if so, what are the consequences of comparing results from populations with different characteristic distributions?

In other words, we may hypothesize that the population surveys' scores, obtained as an impact of health policies, are not only an image of the actual "true" outcome of the policies, but also they are dependent from the individual's filters based on their own personal characteristics. These filters affect the location of the various scale thresholds. As a consequence, the reported scores are not necessarily identical to the scores of the "true" and latent variable.

Therefore, the models used to assess the impact of health policies on the individuals should take into account this sort of speculations. Because the scales normally used are ordinal and of a Licket type, the models also have to be adjusted to the kind of the data generated by these scales.

Traditionally, the econometric models used are the ordered probit (or logit) models. However, these models do not take into consideration the previously mentioned fact that individuals with different personal characteristics may assess differently the same latent health level.

Consequently, a modified ordered probit model may be suitable to integrate these aspects. This is the case of the hierarchical ordered probit model, the so-called hopit model, with the following structural form:

For each individual, $H^* = X' \beta + \varepsilon$, with $\varepsilon \sim N(0,1)$ and where HS is the reported subjective score, H^* is the latent (unobserved) true outcome and X is a vector containing personal characteristics.

The relationship between H^S and H^* is assumed to be $H^S = m \Leftarrow c_{m-1} \leq H^* \leq c_m$, where $m=1,...,5$; $c_0 = -\infty$; $c_1 = 0$; $c_5 = +\infty$. IF c is independent from a set of regressors (e.g., personal characteristics), we have the ordered probit model. On the other hand, if c is dependent from these regressors, we turn into a hopit model.

The purpose of this presentation is to contribute to the evidence that the scales of reference used by individuals, when assessing their own health status and quality of life, are sensitive to individuals' characteristics such as age group, gender and education. That is, the scales thresholds shift their location according to the characteristics of the individuals.

Using data taken from the Portuguese National Health Survey we applied the above mentioned models and evidenced that the scales of reference used to assess health status and quality of life are sensitive to personal characteristics. The results of the application of these models are given and discussed.

JEL codes: C, I

Introduction

In order to have continuous improvement and to better respond to the legitimate expectations of the citizens, a health system has to constantly analyze, monitor and learn from the different outcomes of its different areas of production. However, this learning process has to be based on decision making processes sustained on proofed evidence. Otherwise, it is a mere inconsistent and incoherent set of actions without any governance, mission, vision or strategy. And — that is the most important issue — no one is able to learn from it.

Traditionally, the assessment of health policy's impacts used to be based on the so-called "objective" indicators, such as mortality, life expectancy and/or morbidity. The paradigm shift that created the need to consider health as a positive concept — meaning well-being and quality of life, and not merely the absence of disease — was then responsible for a lesser importance given to these indicators.

In fact, nowadays, they do not represent any longer the semantics of the health concept. Measurements are now based on subjective assessments and one may question whether they may be dependent from the personal characteristics of the individuals, including socio-demographic characteristics, economic and living experience related characteristics and health-related characteristics. And, if so, what are the consequences of comparing results from populations with different characteristic distributions?

Related to these concerns, two important issues have to be pointed out. The first one is the hypothetical relation between observed and self-reported scores; the second can be summarized as the response category cut-points shift.

Looking further and addressing the first issue, health is consistently reported if the self-reported health status is identical to the observed health status. In Figure 1, this concept is represented by the 45° line through the origin. Any deviation from this line means inconsistent reporting.

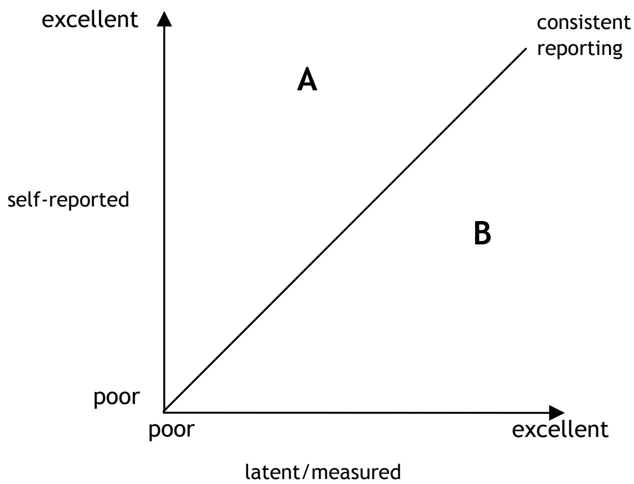
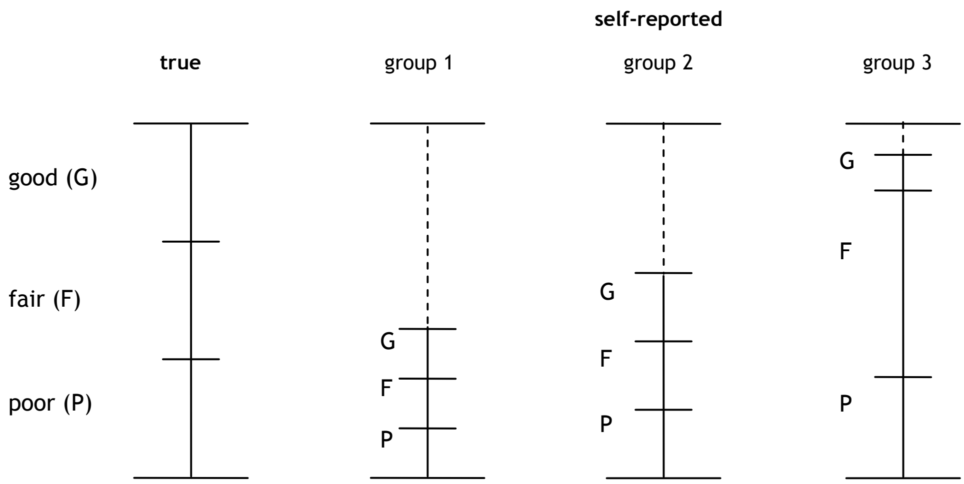


Figure 1
Hypothetical relation between observed and self-reported health

In general, this is exactly what happens when patients' characteristics are taken into account. In fact, considering the two areas A and B, we usually evidence that area A corresponds to the area where scores from sub-population groups (e.g. older, poor and male) are located. On the other hand, self-reported scores from young, rich and female are lower than the latent ones (area B).

On the other side, the comparability requires that the end-points and the cut-points of the scales are identical. However, the evidence shows that these end-points and cut-points differ for individuals with different characteristics.

For instance, if we look at the full range of self assessed health (SAH), groups 1, 2 and 3 of individuals show scales which are compressed (the end-points are closer) relatively to the true scale. In our fictional example, group 1 may represent people with fewer expectations about his/her health status. On the other hand, while groups 1 and 2 show scales with equal intervals, in group 3 the intervals differ.



Adapted from Sadana et al. (2000)

Figure 2 - Scaling properties of true and self-reported quality

Due to their fewer expectations, one of the impacts of these different scales and anchors is that individuals from group 1 may rate health status as good whereas the true latent health status may be fair or poor.

The purpose of this paper is to contribute to the evidence that the scores provided by patients, when SAH is measured, are sensitive to patients' characteristics such as age, gender, education and other personal variables. That is, if we denote the true health status by H* and its assessment by H, we may state that H = f (H*, individuals' characteristics); SAH depends on the true individual health status as well as on the personal characteristics.

The econometric model

Based on what has been described in the Introduction, the dependent variable used in this study was SAH, a measure for the perception people have regarding their own health status. In health literature, the most common way to assess SAH is to ask the single question "How is your health in general". Usually the response scale associated to this question range from "excellent" to "poor". This ordinal variable is known to be a very good predictor of other outcomes, utilization of health care or even mortality (Lindeboom and van Doorslaer, 2003).

To explain this ordinal discrete choice variable we used the parametric ordered probit model briefly described below.

Let H_i be a categorical ordered random variable representing the health status perceived by the individual i, ranging from 1 to 5 on a 5-point Likert scale. Let us also assume that H_i^* is an unobserved latent variable, loosely representing the true health status and that $\boldsymbol{x}_i$ is a column vector containing the set of covariates (with the first element of each vector equal to one) which explain H_i^*. We assume that this latent variable H_i^* is generated by a linear regression structure like

$$H_i^* = x_i^t \beta + \varepsilon_i$$

where $\varepsilon_i \sim N(0,1)$ is a random error and β is a column vector of the coefficients of the model. In order to identify the model we have to assume that the random error follows a standard normal distribution (Bolduc and Poole, 1990).

However, the regression model described by the structural model above cannot be estimated because the dependent variable H_i^* is a latent and, by definition, an unobserved variable. So, in order to estimate the parameters β in this equation, we have to define a rule to relate both variables and to assess the impact of each regressor on the latent variable H_i^*.

The usual way to relate both unobserved H_i^* and observed H_i variables is to conceptualize that the observed responses are the result of a mapping between H_i^* and H_i, as follows:

$$H_i = m \Leftarrow c_{m-1} \leq H_i^* < c_m$$

where m = 1, ..., 5, $c_0 = -\infty$, $c_1 = 0$ and $c_5 = +\infty$. c_m are called cut-points or threshold levels on the latent variable that characterize the transition from an observed categorical score to the next (Tandon et al., 2000). For a more detailed description of these models, please see (Ferreira and Lourenço, in press)

If c are constants and, consequently, independent from personal characteristics the model is called ordered probit model. On the other hand if c is dependent from the personal characteristics, the model is called generalized ordered probit model. After estimating the generalized ordered probit model, we have the following set of estimates:

- β, measuring the impact of the variables in the vector x_i in the true health status. Recall that we've hypothesized the regression linear model (1); and
- $\beta_k (k = 2,3,4)$, measuring the impact of the variables on the different cut-points. We recall that, as an identifying restriction, we assumed that the first threshold is set to zero, thus equal for all individuals.

Data and Variables

To test this hypothesis we use data taken from the Portuguese National Health Survey. Between October' 98 and September'99, this survey collected information from 48,606 Portuguese inhabitants in households from Portugal mainland. To avoid biases due to seasonal variations, the sample was stratified by region and was collected during all the fifty-two weeks of the year.

The dependent variable studied in this research was the self-assessed health, being the results based on a sample of 30,597 individuals who gave valid responses to the question "How is your health in general"; the remaining records have been deleted due to the presence of missing values in the variables included in the analysis. The found distribution was as follows:

Response categories	Freq.	Perc.
Very bad	1293	4.2%
Bad	5004	16.4%
Fair	11446	37.4%
Good	11533	37.7%
Very good	1321	4.3%

Table 1 – Distribution of the variable SAH

Table 2 presents the variables used in this study.

Category	Variable	Description	Mean
Age	age	Years of age	41.78
Education	educ	Education, number of years	5
Gender	male	=1 if the individual is male; 0 otherwise	0.48
	female	omitted category	
Income	income	Income, in 100€	3.22
Work status	work	=1 if the individual as a professional occupation in the past two weeks; 0 otherwise	0.57
Region	north	=1 if the individual leaves in the North region; 0 otherwise	0.30
	centre	=1 if the individual leaves in the Centre region; 0 otherwise	0.20
	lvt	=1 if the individual leaves in the Lisbon and Tagus Valley region; 0 otherwise	0.26
	alentejo	omitted category	
	algarve	=1 if the individual leaves in the Algarve region; 0 otherwise	0.12
Loneliness	live_alone	=1 if the individual lived alone at home in he past two weeks; 0 otherwise	0.06
Healthy habits	phys_ex	=1 if the individual does physical exercise; 0 otherwise	0.08
	smoke	=1 if the individual daily smokes; 0 otherwise	0.15
Body mass index	bmi	weight/squared meter	25.45
Impairment and chronic diseases	impair	=1 if the individual is impaired; 0 otherwise	0.02
	phys_impair	=1 if the individual has a physical limitation their impairs him/her to perform daily activities; ; 0 otherwise	0.03
	chronic	Number of chronic diseases	0.85

Table 2 - Mean values of the variables

Results

Even if the analyzes of the results generated by the ordered probit model not be the main goal of this research we find interesting to look at some of the results presented in Table 3.

Variable	Beta	z	P>|z|
age	-0.024	-2.13	0.033
sqage	-0.000	-0.79	0.430
cubage	0.000	2.04	0.041
educ	0.044	15.72	0.000
male	0.031	16.79	0.000
income	0.052	14.31	0.000
chronic	-0.394	-42.49	0.000
work	0.364	17.1	0.000
live_alone	0.026	0.9	0.370
alentejo	0.189	5.53	0.000
lvt	0.072	2.43	0.015
centro	-0.040	-1.3	0.195
norte	-0.016	-0.55	0.582
phys_ex	0.227	6.8	0.000
smoke	-0.009	-0.37	0.712
bmi	-0.002	-1.08	0.281
impair	-0.617	-7.63	0.000
phys_impair	-0.794	-13.67	0.000
_cons	3.108	17.68	0.000
c1	1.219	61.94	0.000
c2	2.862	121.01	0.000
c3	4.762	145.51	0.000

Table 3 - Ordered probit model results for the dependent variable SAH

Looking at this table we may evidence that, in general, almost all variables have a statistical significant impact on the dependent variable. However, in this model, we assume that the impact of each variable on the SAH variable is not dependent from personal characteristics.

So, applying the generalized ordered probit model we will be able to overcome this weakness. The results of such model as presented in Table 4.

Variable	Beta	z	P>|z|
age	-0.029	-2.5	0.012
sqage	0.000	0.17	0.868
cubage	0.000	1.17	0.240
educ	0.029	3.6	0.000
male	0.225	5.41	0.000
income	0.044	4.88	0.000
chronic	-0.392	-42.09	0.000
work	0.360	16.86	0.000
live_alone	0.030	1.04	0.300
alentejo	0.192	5.59	0.000
lvt	0.072	2.44	0.015
centro	-0.038	-1.24	0.216
norte	-0.016	-0.53	0.593
phys_ex	0.243	7.18	0.000
smoke	-0.017	-0.7	0.486
bmi	-0.002	-1.12	0.261
impair	-0.390	-3.77	0.000
phys_impair	-0.822	-13.92	0.000
_cons	2.9854	14.21	0.000

Table 4- Impact of the personal characteristics on the latent variable H*

The impact only on H* is not too different from the impact shown on the previous model. However, this generalized model also gives us the actual impact of the personal characteristics variables on each threshold c_2, c_3 and c_4 (we assume that $c_1 = 0$ and $c_5 = +\infty$). Tables 5 to 7 show us these types of effect.

The threshold c_2, which divides the response category SAH bad to fair, is sensitive to all variables we have included in our model (see table 5).

Variable	Beta	z	P>|z|
male	-0.092	-2.25	0.024
age	0.009	5.97	0.000
income	-0.026	-3.14	0.002
education	-0.019	-2.41	0.016
impair	0.648	4.61	0.000
Const	0.854	8.76	0.000

Table 5- Impact of the personal characteristics on the threshold c_2

The threshold c_3 from SAH fair to good is only sensitive to gender and age (see table 6).

Variable	Beta	z	P>|z|
male	-0.124	-2.74	0.006
age	0.009	5.28	0.000
income	-0.003	-0.33	0.740
education	-0.016	-1.9	0.057
impair	0.081	0.36	0.718
Const	2.439	22.2	0.000

Table 6- Impact of the personal characteristics on the threshold c_3

The threshold c_4 from SAH good to very good (see tyable 7) is only sensitive to age variable.

Variable	Beta	z	P>|z|
male	0.025	0.43	0.670
age	-0.008	-3.54	0.000
income	0.005	0.48	0.629
education	-0.013	-1.37	0.169
impair	3.187	0.02	0.986
Const	4.863	36.16	0.000

Table 7- Impact of the personal characteristics on the threshold c_4

Conclusion

Looking at an aggregate level to all the thresholds' shifts we may conclude that male individuals tend to shift downwards the middle thresholds (c_2 and c_3). On the other hand, age is the only variable that has impact on all thresholds, shifting upwards the first two (c_2 and c_3) and having a slight negative effect on c_4.

Also, comparing to the poor, wealthier individuals tend to have the second threshold (c_2) in a lower position, being the other statistically non significant. Education only has a negative effect on threshold c_2.

Figure 3 shows a simulation of the joint behavior of the thresholds according to variation on the personal characteristics.

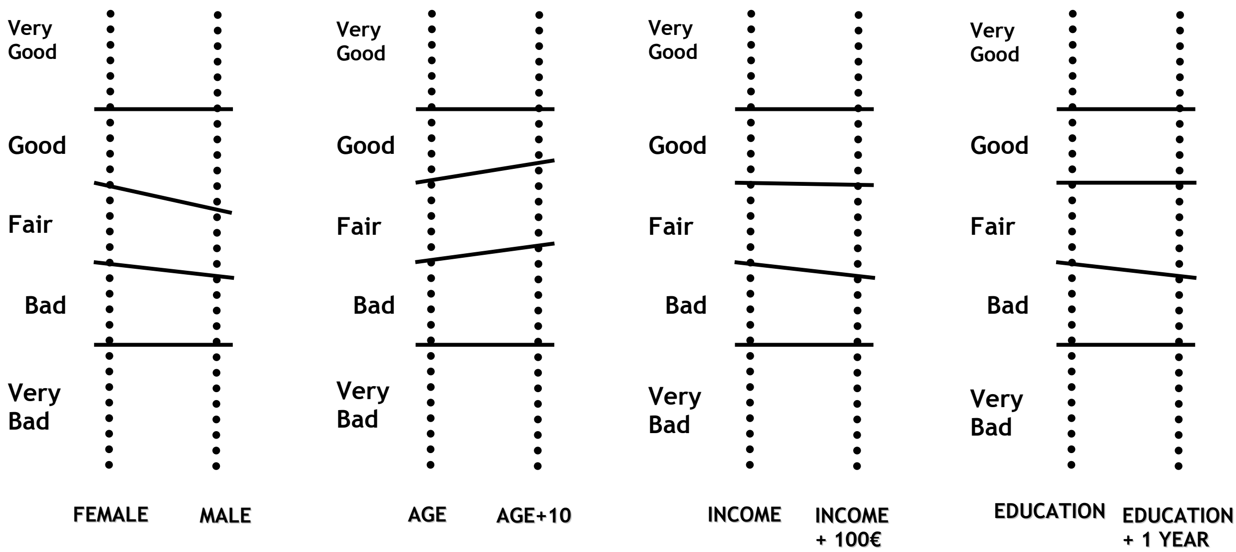


Figure 3 - Threshold's behavior based on individual characteristics

In summary, we may say that, even with having accounted for the impact of the personal characteristics on the measurement scales used by individuals when they assess their own health status, we don't obtain too significant differences on the impact of these variables on the latent health status.

However, these same models can be useful to understand why different groups of individuals give different scores regarding the perception they have about their own health status.

References

- Bolduc D, Poole E. Ordinal Probit Model With Random Bounds. Economics Letters 1990; 33: 239-244

- Ferreira PL, Lourenço OD. Avaliações subjectivas sobre qualidade em saúde: Um contributo para o estudo da equidade. Revista Portuguesa de Saúde Pública. In press.

- Lindeboom M, van Doorslaer E. Cut-point Shift and Index Shift in Self-reported Health. Tinbergen Institute Discussion Papers 03-042/3 / Tinbergen Institute, 2003.

- Tandon A, Murray CJL, Salomon JA, King G. Statistical models for enhancing cross-population comparability. The Global Burden of Disease 2000. In Aging Populations Research Paper 2000; 14.

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