Breaking the 'floor' of the SF-6D utility function. An application to Spanish data.

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ABSTRACT

This paper presents a new scoring algorithm for the SF-6D, one of the most popular preference-based health status measures. Previous algorithms suffer from a phenomenon called the 'floor' effect (*i.e.*, lack of sensitivity of the instrument for detecting health gains of individuals whose baseline health is poor). Our algorithm expands the range of utility scores in such a way that the 'floor' effect vanishes. We get such a wider range thanks to the use of a lottery equivalent method through which preferences from a representative sample of Spanish general population are elicited.

Keywords: SF-36, SF-6D, floor effect, standard gamble, lottery equivalent methods

RESUMEN

Este trabajo presenta un nuevo algoritmo de puntuación para el SF-6D, una de las medidas de salud basadas en preferencias más populares. Los algoritmos previamente estimados adolecen del fenómeno denominado efecto 'suelo' (esto es, la falta de sensibilidad del instrumento para detectar ganancias de salud en individuos cuyo estado de salud de partida es malo). Nuestro algoritmo amplía el rango de utilidades de tal modo que el efecto 'suelo' desaparece. Este rango más amplio se consigue gracias al uso de un método de 'lotería equivalente', con el que se obtienen las preferencias de una muestra representativa de la población española.

Palabras clave: SF-36, SF-6D, efecto suelo, lotería estándar, métodos de 'lotería equivalente'

Introduction

The Short Form 36 (SF-36) is one of the most widely used generic health-related quality of life measures. It is extensively applied in clinical trials and population health surveys in order to assess changes of health status. Unfortunately, the SF-36 cannot be directly used in economic evaluations (Brazier et al., 1999) because it does not produce a preference-based single index able to be combined with life duration in order to obtain quality adjusted life years (QALYs), the metric used in cost-utility analysis.

The bridging of the gap between the descriptive information provided by the SF-36 and the population's preferences is provided by algorithms which convert either item responses, or summary scores, from the SF-36 into utility scores. Pickard et al. (2005) compared ten of such algorithms, most of them based on subsets of items from the SF-36 (e.g., the SF-12), concluding that "Brazier's algorithms for the SF-12 and SF-36 appear to be most favourable because of their methodological and theoretical basis" (p. 8). To estimate such preference-based algorithms Brazier and colleagues used a subset of SF-36 items, which were grouped in a six-dimensional measure called the SF-6D (Brazier et al., 1998; Brazier et al., 2002; Brazier and Roberts, 2004).

Pickard et al. (2005) give three main reasons why the SF-6D is preferable to other algorithms. First, the SF-6D is based on direct preference measurement. Second, the statistical design of the study from which preferences were elicited allowed the researchers to obtain a proper representation of severe states. Finally, direct preference measurements were performed by using the standard gamble (SG), a method which has been usually regarded as the 'gold standard', since it is a choice-based procedure rooted in the axioms of expected utility theory (Torrance et al., 2001).

Despite all these apparent advantages, it is widely recognized that the SF-6D suffers from a problem known as the 'floor' effect, that is, the potential lack of sensitivity of the instrument for detecting health gains of individuals whose baseline health is poor (Baker at al., 1997). Such a potential insensitivity to change has been extensively analyzed in comparison to the EQ-5D, in such a way that most of the published studies show greater utility benefits according to the EQ-5D than the SF-6D (Barton et al., 2008). Thus, in general, it could be expected that cost-utility ratios tend to be likely more favourable to the adoption of new technology according to the EQ-5D rather than with the SF-6D (Pickard et al., 2005). Notice that we are not asserting that the EQ-5D is a better instrument than the SF-6D, but the 'floor' phenomenon, the same as the ‘ceiling’ effect in the EQ-5D (Brazier et al., 2004), is a factor that contributes to the disagreement between both preference-based algorithms, enlarging heterogeneity in cost-utility ratios (Stiggelbout, 2006).

In this paper we argue that, at least partly, the ‘floor’ effect is caused by the type of valuation method (the SG) which the SF-6D algorithm is based on. Hence, the last of the apparent advantages attributed by Pickard et al. (2005) to the SF-6D would be actually a shortcoming of the model. Our claim is based in that the SG usually gives utility scores which are too high, suggesting a degree of risk aversion (i.e., a preference for riskless outcomes) so strong that they cannot be properly described by expected utility. Evidence on the extreme risk aversion raised by the SG includes studies performed with both monetary outcomes (Hershey and Schoemaker, 1985; Johnson and Schkade, 1989; Delquié, 1993) and health outcomes (Wakker and Deneffe, 1995; Bleichrodt et al., 2001; Bleichrodt et al., 2007).

That the SG yields utilities that are too high for severe health states is fully consistent with the range of scores generated by the SF-6D algorithm (Brazier and Roberts., 2004), whose lowest value is well above zero (0.296), while the utility score for the worst EQ-5D health state, according to the TTO tariff for the UK, is -0.594 (Dolan, 1997). Such a large discrepancy at the lower end of the scale makes the SF-6D gives values higher than those for the EQ-5D for poorer states, leading in consequence to smaller utility gains for less healthy people, which is the prediction of the ‘floor’ effect. Tsuchiya et al. (2006) provide empirical support to the hypothesis of the relevance of the valuation method in order to explain the discrepancy between the SF-6D and the EQ-5D, concluding that such a discrepancy is caused, among other factors, because “the TTO used for EQ-5D (generates) lower scores than the SG used for more severe SF-6D and higher scores for mild states” (p. 345). Obviously, we are aware that there are other explanations to the ‘floor’ effect besides the valuation method, such as the apparent inability of the SF-36 items used in the SF-6D to describe accurately severe health states (Hollingworth et al., 2002). This topic is left aside in this paper. Instead, we directly focus on the issue concerning how the validity of the valuation method behind the SF-6D algorithm can be improved.

This paper reports the results of the first study conducted in Spain to estimate a SF-6D algorithm for the SF-36. The main novelty of such an algorithm is that it is not based on the SG. We used instead a variant of the so-called lottery equivalent procedures introduced by McCord and de Neufville (1986). Such procedures are based on the comparison of two gambles, and were developed precisely to avoid the dislike for gambling exhibited by methods such as the SG. The psychological intuition for justifying the use of lottery equivalent methods instead of the SG is that people value outcomes more highly when they occur with certainty than when they appear in a risky prospect. This phenomenon, commonly referred to as the certainty effect (Kahneman and Tversky, 1979), makes people facing a SG question tend to overvalue the riskless outcome in comparison to the gamble, in such a way that the probability used to yield indifference must be additionally high to compensate for such an overvaluation of the certainty (Wakker and Stiggelbout, 1995). Such overweighting of the certainty is "drastically reduced" (Cohen and Jaffray, 1988) when assessments are made by lottery equivalent methods in which no sure outcome is involved (McCord and de Neufville, 1986; Wakker and Deneffe, 1996; Pinto and Abellan, 2005). This seems to be the main reason why violations of expected utility are less pronounced when both alternatives are risky (Camerer, 1992). An elaborate theory to justify the use of lottery equivalent methods is provided by Bleichrodt and Schmidt's (2002) context-dependent model. In this model expected utility is satisfied as long as the set of options contains only risky prospects. If the context of valuation changes, including some riskless outcome, then violations of expected utility are permitted. Bleichrodt et al. (2007) in a recent study with health outcomes, did not find significant differences between two lottery equivalent methods under expected utility, concluding that their data "seem to add to the evidence that violations of expected utility primarily occur when one of the prospects under evaluation is riskless" (p. 479). Nevertheless, Bleichrodt and Schmidt's model was not able to reconcile the utilities elicited by such lottery equivalent methods with the utilities elicited by other three riskless-risk methods (e.g., with the SG). Probably such a paradox suggests that reality is too complex as to be explained by one single theory, although, as we have shown, empirical available evidence points out that one should expect that the 'floor' effect was mitigated by using a lottery equivalent method. The results presented in this paper confirm such a prior expectation: there is not a perceptible 'floor' effect in the Spanish SF-6D algorithm.

The paper is organized as follows. Section 2 provides background on the SF-6D classification system and the existing SF-6D algorithms. Section 3 describes the computer assisted questionnaire we used to survey a sample of the Spanish general population, outlining the differences between our lottery equivalent method and the variant of the SG used by Brazier and colleagues. Results are described in section 4. Section 5 discusses our main findings.

2. Background

The SF-6D (Brazier et al., 2002) takes 11 items from the SF-36 to generate a health status classification system able to describe a total of 18,000 possible health states. The SF-6D system has six dimensions (physical functioning, role limitations, social functioning, pain, mental health, and vitality), each with between four to six levels. Each SF-6D health state is defined by selecting one level from each dimension. For example, health state 645655 denotes the worst possible health state that can be described by the SF-6D system because each dimension is fixed at its lowest level. For that reason, such a state is called the 'all worst' or 'pits' health state.

Because of the descriptive richness of the SF-6D system, it is impossible to value all possible permutations of each dimension. Hence, a subset of health states has to be identified in order to estimate additive or multiplicative algorithms. Brazier et al. (2002) elicited preferences for a selection of 249 health states from a sample (N=611) of the UK general population. Another recent paper (Lam et al., 2008) reports the results of a pilot survey (N=126) performed in Hong Kong using the same protocol as in the UK, though only 49 health states were valued in this case. Such a selection of 49 states, which were already included within the set valued previously by Brazier et al., result from an orthogonal design which allows the researchers to estimate an additive model. Brazier et al. included more health states in order to account for more complex specifications.

Bearing in mind that it is impossible that each respondent values the whole selection of health states, two strategies arise: either maximize the number of health states valued by each interviewee or, alternatively, maximize the number of respondents who value the same health state. Both Brazier et al. (2002) and Lam et al. (2008) opted for the first approach, in such a way that each participant in Brazier et al.'s study valued six SF-6D health states (five intermediate states plus the 'pits' state 645655), whereas respondents surveyed by Lam et al. valued one state more. This design meant that each health state was valued an average of 15 times.

The elicitation procedure applied in the two abovementioned studies was a chained SG method. Chained variants for the SG have been proposed (Torrance, 1986) as a way to avoid that people refuse to accept any risk of death as a typical (unchained) SG question requires. Such insensitivity at the upper end of the scale was found in Brazier et al.'s (1998) pilot study, the reason for which Brazier and colleagues decided to valued SF-6D health states through a two-stage process. In a first stage, Brazier et al.'s (2002) replaced the worst outcome in a normal SG question (*i.e.*, death) by the 'pits' state 645655. Five intermediate SF-6D health states were valued in such a way. Next, in a second stage, the 'pits' state was valued against death by means of another SG question. The final utility of each intermediate state was chained to death by means of the 'pits' state, allowing the calculation of utilities onto a scale 0-1 (death-full health). Raw negative utilities for the 'pits' state were rescaled in such a way (Patrick et al., 1994) that the utilities had a lower bound at -1. Indifferences in all the SG questions were reached by through a sequence of choices implemented in a 'ping pong' way.

The last step to obtain the SF-6D algorithm is the estimation of the model. Ordinary least squares (OLS) and random effects (RE) models were estimated by Brazier et al. (2002) to predict all 18,000 SF-6D health states. The model recommended by the authors for use in cost-utility analysis was an OLS model using mean health state values. Brazier et al. (2004) improved the previous model by removing non-significant estimates and aggregating those coefficients which were inconsistent between them. They referred to such a model as the "parsimonious consistent model". The econometric methods applied by Lam et al. (2008) to estimate their algorithm for the Chinese population living in Hong Kong were identical to Brazier et al.'s (2002).

In contrast to previous algorithms, which relied on parametric models, Kharroubi et al. (2007) -using the same data set as Brazier and colleagues- estimated a set of non-parametric (Bayesian) utility scores for the SF-6D. Notice that, as the next section will show, the assumptions behind our estimations are parametric, so our estimates cannot be directly compared to those inferred by Kharroubi et al. Nevertheless, as far as Kahrroubi et al.'s (2007) algorithm is affected by the 'floor' effect, the implications derived from using a different valuation method are also applicable to their model.

3. The valuation study

General design

We designed two valuation surveys. The main survey (survey 1) was addressed to estimate the SF-6D algorithm. This survey included the questions with the lottery equivalent method. Through the other survey (survey 2) we elicited preferences from an independent sample in order to test whether the typical (unchained) SG indeed yielded higher utility scores than our (also unchained) lottery equivalent method. In this way, we tried to corroborate that the SG produces utilities which are too high, even though there is no chaining involved. There is extensive evidence showing that the chained SG method tends to generate higher valuations than the unchained one (Llewellyn-Thomas et al., 1982; Rutten-van Molken et al., 1995; Bleichrodt, 2001; Oliver 2003). Although evidence is much scarcer for other methods, it appears that chaining leads to higher values as well (Pinto and Abellan, 2005), even affecting (though more weakly) a variant of lottery equivalent methods (Oliver, 2005). In addition to that, chaining is prone to propagation of error (Wakker and Deneffe, 1996).

The sample

We used two independent samples in order to avoid anchor biases and response error derived from fatigue and cognitive overload. Both samples were representative of the Spanish adult general population with respect to age and sex. As the two samples were randomly drawn, we expected that preferences in both groups would be similar to each other as long as a common elicitation procedure was applied. Such an ex-ante homogeneity condition was tested by including a visual analogue scale (VAS) in the questionnaires administered to both samples.

The main sample (survey 1) consisted of 1020 subjects. This sample was divided into 17 subsamples (N=60 each) retaining representativeness with respect to age and sex. The size of the other sample (survey 2) was identical (N=60) to any of the subsamples used in survey 1. Both surveys took place in the region of Murcia over a period of two months. All the interviews were face-to-face and run on laptops. The average time per interview was around 20 minutes.

The health states

To select the subset of health states to be directly valued by the respondents we opted for an intermediate approach between the two extremes represented by Brazier et al. (2002) and Lam et al. (2008). A total of 78 health states (see Table 1) were chosen. 49 out of them were obtained by running the orthoplan module of SPPS version 17. The remaining states till 78 were selected through a stratified sampling method, and including the ‘pits’ state. Limiting the number of health states directly valued to 78 allowed us to obtain a number of valuations by state substantially higher (60 valuations per health state on average) than those obtained previously (15 per health state on average), thus resulting in more liable and robust mean values. This is of particular relevance since the predictive validity of the estimation methods we applied relies largely on the liability of the sample means. Each of the 17 groups of respondents included in survey 1 valued a different subset of five health states, although seven out of the 78 states were included in two subsets and then valued by two different groups.[1] The only group involved in survey 2 valued five of the health states assessed by the main sample (survey 1). Specifically, such health states were 222332, 141314, 311112, 132612, and 412422.

[Insert Table 1 about here]

The questionnaire

The questionnaire was organized as follows. Each interview began with an introduction in which the SF-6D classification system was explained to the respondents through a 'tutorial' displayed on the computer screen. Once the respondents confirmed that they had understood the meaning of the dimensions and levels of the instrument, they were asked to rate five SF-6D health states (anonymously labelled as *V*, *W*, *X*, *Y*, *Z*) by means of a VAS similar to the 'thermometer' used by the EuroQol group. The purpose of this task was twofold: on the one hand, to familiarize the respondents with the health states that would be valued next by using a lottery equivalent method (or a SG in case of survey 2); and, on the other hand, to check if the two independent samples were actually comparable in terms of preferences. In the final part of the questionnaire respondents were asked to answer some sociodemographic questions (sex, age, studies, income level, etc.), to describe their health status by means of the EQ-5D system, and to complete the items included in the SF-36 (v.2) health survey.

Elicitation procedures

a) The probability lottery equivalent method

The type of lottery equivalent procedure we administered in survey 1 could be called a probability lottery equivalent (PLE) method since the equivalence between the two gambles is reached by varying the probability of one of them. Notwithstanding, the framing of such a PLE method is different to those previously used with health

[1] These health states were the so-called 'corner' states (*i.e.*, health states in which one of the dimensions is set at its lowest level whereas the rest of the dimensions remain fixed at the highest level) and the 'pits' state. We needed a higher sample size for those health states in order to address a different investigation on the SF-6D, which will be reported elsewhere.

outcomes (Oliver, 2005; Bleichrodt et al., 2007) in one important respect. Our method asks for the probability p that makes the respondents indifferent between the gamble denoted by (full health, p; death), yielding full health with probability p and death with probability 1-p, and the 50/50 gamble denoted by (full health, 0.5; h), yielding full health and the health state h with the same probability.

This framing allowed us to elicit preferences for both better-than-death and worse-than-death states, something that, to the best of our knowledge, has never been done before by using a risky elicitation method. If the respondent preferred the second gamble to the first one for $p = 0.5$, it meant that h was regarded as better than death. In consequence, the final probability of indifference p^* was elicited between 0.5 and 1. On the contrary, if the first gamble was preferred to the second one for $p = 0.5$, then h was considered as worse than death, and p^* was elicited between 0 and 0.5. Lastly, if the respondent was indifferent between (full health, 0.5; death) and (full health, 0.5; h), then h was regarded as equal to death. Under expected utility, assuming the convention that the utility of full health is 1 and the utility of death is 0, the utility of the health state h is calculated according to the expression $U(h) = 2p^* -1$.

Our procedure may be intended to be as the analogue under risk to the 'life profile' approach developed by Robinson and Spencer (2006) for decisions under certainty for two main reasons. Firstly, the way according to which preferences are elicited is symmetrical for both better and worse than death health states. That is, irrespective the health state is regarded either worse or better than death, the larger the probability p is the milder the health state is. Secondly, resulting utilities are automatically bounded between -1 and +1 as a consequence that the probability used as stimulus in the assessment of the health state is fixed at 0.5. As it is not obvious why there should be no health states valued below -1 (Devlin et al., 2008), such possible valuations should not be precluded ex ante, but they should not be transformed ex post to be bounded by -1 either, which is, unfortunately, the usual practice. This is the case both the SF-6D (Brazier et al., 2002) and the EQ-5D (Dolan, 1997), whose rescaled negative utilities are meaningfulness, being no longer possible that they are interpreted as true utilities (Patrick et al., 1994). Bearing in mind this, we do not report any individual utility reaching -1 in this study[2], so no value lower than that bound seems to have been

[2] The utilities closest to -1 were five values of -0.96 obtained for the pit state.

excluded. We will return to the point of the ability of the PLE to elicit bounded negative valuations in the Discussion.

In all the questions, the probability of indifference was elicited through a non-transparent sequence of choices implemented according to the parameter estimation by sequential testing (PEST) procedure suggested by Luce (2000). Such a procedure appears to be less prone to inconsistencies than other search procedures (*e.g.*, ping-pong), in which respondents are aware that the aim of the whole sequence of choices is to produce indifference (Fischer et al., 1999).

Therefore, the specific lottery equivalent method we applied has, in our opinion, four potential advantages over the variant of the SG procedure used by Brazier et al. (2002), namely, that our probability lottery equivalent technique avoids: (i) the certainty effect caused by the inclusion of a riskless outcome; (ii) the problem of biases and propagation of error caused by chaining; (iii) the usual methodological drawbacks caused by the valuation of worse than death health states; and (iv) the potential inconsistencies provoked by using a transparent sequence of choices to reach indifference.

b) The standard gamble method

The SG method we used in survey 2 asks the respondents for the probability r that makes them indifferent between intermediate health state h for sure and a gamble, denoted by (full health, r; death), yielding full health with probability r and death with probability 1-r. Under expected utility, assuming the convention that the utility of full health is 1 and the utility of death is 0, the utility U of the health state h equals r*.

There was no need to apply the variant of the SG able to elicit negative utilities because none of the respondents regarded any of the five health states as worse than death, so we omit its description.

The modelling

Our initial specification is the main effect model which explains the utility score h that respondent i assigns to health state j using a set of binary dummy variables (x_{dl}) that describe each level l and dimension d of the health state. For example, x_{42}, denotes dimension d=4 (pain), level l=2 (there is pain but it does not interfere with normal work). The model is formally written as follows:

$$h_i = \sum_d \sum_l \beta_{dl} x_{dl} + e_i \quad , \tag{1}$$

where e_i is a zero-mean error term, and the constant has been forced to unity in order to ensure that the health state describing full health has the value of one.

We also estimate more extended versions of Equation (1) which include variables denoting the presence in the state of the highest (worst) level in, at least, one of the dimensions, as well as interactions between variables in the main effect model (*e.g.*, as the so-called MOST term used by Brazier et al., 2002). The optimal specification is chosen according to the usual criteria of consistency (*i.e.*, that utility declines with severity), goodness of fit (*i.e.*, that predictions of the model are accurate), and parsimony (*i.e.*, the simpler the better).

When we use individual data, both Equation (1) and its extensions are estimated by the random effect (RE) estimators, that is, assuming that the error term is normally distributed. In particular, we used the RE estimator because it takes into account that the same individual values several health states, increasing the efficiency of the estimates relative to an OLS estimator. Thus, the error term e in Equation 1 is decomposed into an individual-specific error term (η_i)[3] and a traditional error term unique to each health state and individual (ε_{ij}). The coefficients of the model are then identified by estimating Equation 1 by maximum likelihood. The same applies for equations including interaction terms.

Since the model recommended by Brazier et al. (2002) for use in cost-utility analysis was a model estimated at the mean level, we also estimate mean models. In those cases, Equation 1 and its extensions including interaction terms are estimated by OLS regressions.

4. Results

The data set

A number of 15 individuals were left out of the analysis because of inconsistencies in their valuations of health states by means of the VAS and the PLE (survey 1). These inconsistencies occurred when a logically better health state received a lower value than a logically worse state. That is the case when a health state that has equal or lower levels than another state in each of the six dimensions (*i.e.*, it is a milder state) is valued below a health state with equal or higher levels in each of the six dimensions (*i.e.*, a more

[3] Alternatively, the fixed-effects estimator could be used to correct for individual valuation effects. However, there are efficiency reasons to prefer the RE estimator because the explanatory variables describe a hypothetical health state and, thus, they are uncorrelated to the respondent's valuation. The results of the Hausman test confirm this reasoning. These results are available upon request to the authors.

severe state). Another 7 respondents were excluded from the definitive sample because of their reluctance to assume any risk of death when they answered PLE questions. These 7 individuals were not willing to assume any risk of death in, at least, three out of the five states that they had to assess. No exclusion was performed in the sample belonging to survey 2.

After exclusions, the final sample used as an input to estimate the SF-6D algorithm consisted of 998 individuals. Table 2 shows sociodemographic characteristics of the sample. Compared to those of the general population, the study sample was a little younger (nearly two years and a half) because it was age-stratified (additionally, no subject older than 80 years was selected). Because of the relatively greater youth of our sample, some differences in educational and income levels arise (our sample has higher levels in both cases). If the comparison is made with the Spanish population aged between 18 to 75 years, then the mean age is the same (43.6 years), and differences in terms of education and income largely vanish. Finally, the sample distribution by sex (male/female) was fairly similar to the adult general one (50%/50% *vs.* 49.6%/50.4%).

The information at the end of the table confirms the 'ceiling effect' affecting the EQ-5D system, and the greater sensitivity of the SF-6D to discriminate among mild health states. Overall, the sensitivity of the SF-6D outperformed that of the EQ-5D, since 80% of the respondents clustered in only three EQ-5D states, while nearly 200 SF-6D states are required to describe such a percentage of the sample.

[Insert Table 2 about here]

Direct health state valuations

a) PLE utilities

Some descriptive statistics for a selection of the 78 health states directly valued are shown in Table 3. Each of the states was valued by 64 individuals on average, ranging from a minimum of 56 subjects to a maximum of 119.[4] Mean values range from –0.515 to 0.988, two of the health states showing a negative value. This is in contrast with the results reached by Brazier et al. (2002), whose mean values were above zero in all cases. Median values were above mean values for nearly 53% of the health states (41 out of 78), whereas Brazier et al. reports that their median health state values usually exceeded mean values, reflecting the positive skewness of their distribution.

[4] Such a maximum number of respondents was due to the fact that seven health states were valued by two different sub-samples, such as explained in footnote 1.

[Insert Table 3 about here]

At the individual level, our data reveals a certain degree of negative skewness. Although the proportion of utilities below zero is relatively low (4.8%) –even lower than 7% obtained by Brazier et al. (2002)–, our negative values are, in broad terms, of a larger absolute magnitude than those of Brazier et al. Moreover, one-third of health states (26/78) were considered worse than death by, at least, one of the respondents. This may help to explain that our distribution is slightly shifted to the left when compared to that of Brazier et al. (2002). Mean and median values are lower in our study (0.499 and 0.50 vs. 0.5417 and 0.65, respectively), and the degree of negative skewness is clearly higher in our data (–1.23 vs. –0.78). Another fact that may help to understand the differences between both studies is that 63% of the respondents in Brazier et al.'s study assigned positive valuations to the 'pits state', whereas a higher percentage (77.5%) of individuals in our study assigned utilities under –0.30 to the 'all worst' health state.

To check to what extent the mean health state values were logically consistent, we examined all the ordinal pairwise comparisons that were possible from the 78 health states. There are 558 comparisons in which one of the sates should be valued logically higher than the other one, since the former has equal or lower levels than the latter for each of the six dimensions.[5] When mean values for these comparable states are confronted, logical inconsistencies only emerge for 2.51% (14/558). The fact that such a low inconsistency rate was found despite only five health sates being valued by each of the respondents, suggests that it is possible to assess a broad set of health states without overloading the interviewees, avoiding in this way the rise of random error due to tiredness and boredom.

b) Comparison between PLE and SG utilities

VAS scores for the five health states valued both in survey 1 and survey 2 were very similar to each other (p>0.05), in such a way that the result of the comparison between

[5] There are two exceptions to this consistency rule in the SF-6D. Firstly, levels 5/6 of the "physical functioning" dimension ("your health limits you a little/a lot in bathing and dressing") does not necessarily imply a poorer condition than that of levels 3/4 ("your health limits you a little/a lot in moderate activities"). In a similar way, level 3 of the "role limitations" dimension ("you accomplish less than you would like as a result of emotional problems") does not reveal a worse health condition than that described in level 2 ("you are limited in the kind of work or other activities as a result of emotional problems").

PLE and SG utilities for the same states could be considered as meaningful even though they came from two independent samples. Such a result is shown in Table 4. It is apparent that both mean and median utilities measured by means of the SG were significantly higher than those assessed through the PLE, corroborating our prior expectation of the discrepancy between the two methods.

[Insert Table 4 about here]

SF-6D algorithms

Estimated coefficients are shown in Table 5 for the three models which led to the best results in terms of goodness of fit and parsimony. Two of them are RE models at individual level data, whereas the third one is an OLS model using mean values. The RE model labelled as the ‘raw model’ is the starting model at individual level data, without removing non-significant variables. The RE model labelled as the ‘efficient model’ was constructed by eliminating non-significant regressors from the ‘raw model’ and by grouping the variables of whichever two consecutive levels when their coefficients are not significantly different from each other. This procedure maximizes the degrees of freedom available for the model estimation, as well as preventing from certain inconsistencies in predicting the tariff. These slight inconsistencies may result from differences in the estimation of the coefficients which correspond to consecutive levels that are not significantly different from each other.[6] The mean OLS model is the algorithm more comparable to the “preferred” one by Brazier et al. (2002), since both are mean level models. Finally, unlike Brazier and colleagues we did not find any significant interaction term (*e.g.*, the term they called MOST), so all our algorithms only reflect main effects.

[Insert Table 5 about here]

The inspection of Table 5 reveals that all the coefficients have the expected sign and are highly significant, with only the exemption of the coefficient corresponding to level 2 of the ‘role limitation’ dimension in the ‘raw’ RE model. There is an apparent inconsistency in both RE models between coefficients PF4 and PF5 in such a way that

[6] Brazier et al. (2002) group together the coefficients of whichever two consecutive levels when the estimated coefficient for the lower level is of a higher absolute value, that is to say, when the tariffs yielded by the estimated model are inconsistent. Our model is consistent, so our concern is its efficiency.

the coefficient associated to level 5 is lower in absolute value than the coefficient associated to level 4. However, as it was noted before (footnote 4) such an apparent inconsistency is not real, since those levels are not logically comparable. Thus, all our models are actually consistent. Moreover, the mean absolute error (MAE) attached to any of our models is only slightly higher than that reported by Brazier et al. (2002), who used a substantially higher number of health states, which shows the quality of fit we obtained.

The values of the coefficients for the two RE models suggest that the greater utility loss associated to the maximum level of severity in a dimension occurs for 'Pain', 'Physical functioning' and 'Social functioning' attributes, in this order. The conclusion, however, differs slightly for the OLS model at mean level, since it is 'Physical functioning' the dimension that produces the larger disutility, followed by 'Pain' and 'Social functioning'.

The OLS Mean model in column 3 is somewhat superior to RE models in terms of predictive ability. Although its MAE is only marginally lower, the distribution of prediction errors is slightly better than in RE 'raw' and efficient models. In consequence, the estimation at mean level is chosen as the preferred one. Since Brazier et al. (2002) and Brazier and Roberts (2004) also chose their mean OLS models among all other estimations, then the comparison of our results with those of Brazier and colleagues can be done in homogeneous terms.

[Insert Figure 1 about here]

Figure 1 shows the distribution of predicted utilities by both our mean OLS model and Brazier and Roberts (2004) mean consistent model. It is apparent that our model 'breaks' the minimum threshold of Brazier and Roberts's algorithm, expanding the left tail of the distribution near and even below zero. The minimum score predicted by our mean model is -0.357, a value very far from 0.296, the minimum threshold predicted by the UK tariff. We can conclude then that the Spanish SF-6D algorithm presented in this paper does not seem to suffer from the 'floor' effect.

Since the percentage of negative valuations in our study was even lower than those found by Brazier and colleagues (4.8% vs. 7%), one possible objection to our estimates could be that they are not consistent once a minimum fraction of observations are removed from the data set. To explore this possibility we repeated the OLS estimation by excluding from the data successively 5%, 10%, and 20% of the individuals with the lowest valuations, and afterwards we redid the analyses. The predicted utilities derived from the most demanding case (20% of exclusions) are shown in Figure 2. As can be observed, our SF-6D algorithm seems largely robust to the elimination of extreme values, which suggests that our model is very solid.[7] The minimum value of the Spanish tariff displayed in the figure is -0.231.

[Insert Figure 2 about here]

5. Discussion

The main conclusion of this paper is that it is possible to expand the range of SF-6D utility scores by using a different valuation method. In other words, it is possible to avoid the 'floor' effect without changing the SF-6D health status classification system. As we noted in the introduction we are aware that the SF-6D has problems when describing severe health states, but even so the sensitivity of the SF-6D algorithm for less healthy people can be largely improved if it is based on preferences elicited by means of a lottery equivalent method instead of the standard gamble.

Brazier et al. (2002) recommended their mean model (10) for use in cost-utility analysis. Brazier and Roberts (2004) modified such a model in order to get a consistent algorithm (*i.e.*, an algorithm without coefficients that decrease in absolute size with a worse level) which became the new preferred specification. If our mean model is compared with Brazier and Roberts's consistent model a great discrepancy arises between them. Basically, the 'tariff' that predicts our algorithm is shifted to the left with regards to that predicted by the consistent model. We have a significant part of the distribution (around one-fourth) below 0.3, which is the minimum threshold of Brazier and Roberts's algorithm. In fact, the value predicted by our algorithm for the worst SF-6D health state is far below zero, -0.357. We checked the robustness of our algorithm by dropping those individuals who gave the lowest utilities, verifying that the main message of our study remains true: the 'floor' effect is broken. After removing 20% of the respondents, the minimum value of our mean model is -0.231, a score clearly below zero.

[7] The conclusion is analogue for RE estimations.

Our mean model has a predictive ability slightly lower than Brazier and Roberts's (2004) (0.081 *vs* 0.074), but it exhibits a much greater internal consistency, since no inconsistency between coefficients on the SF-6D levels appear. We have not had to aggregate inconsistent estimates in order to achieve a consistent scale, such as Brazier and Roberts had to do, because all our coefficients were directly consistent. Moreover, all the coefficients in our mean model were significant, in such a way we did not have to remove any coefficient.

The econometric models we used are the same as Brazier and his colleagues applied in previous studies, so our findings cannot be justified on such a basis. It is true that none of our models included the interaction term MOST, but if we compare the range of the SF-6D values predicted by our mean model with that predicted by Brazier et al.'s (2002) main effect model (6), our range continues to be larger. The same occurs if the comparison is performed with respect to Lam et al.'s (2008) main effect model. Hence, it appears that it is necessary to look for other explanations to our findings.

One logical source of differences may come from the fact that our tariff is based on the Spanish population's preferences instead of British people's preferences as was the case of previous tariffs. It is evident that such a factor may explain a part of the discrepancy between British and Spanish SF-6D tariffs. We have some indirect evidence to support this from the comparison between the Spanish EQ-5D tariff and the UK one. Apparently, there exists genuine differences in preferences between the two countries, in such a way that the Spanish respondents tend to attach a higher weight to the functional dimensions of mobility, self-care and usual activities, whereas the UK respondents seem to assign greater weight to the more symptoms-based dimensions of pain/discomfort and anxiety/depression (Badía et al., 2001). However, even acknowledging such a variation in preferences between the two countries, it does not cause a change in the shape of the distribution of EQ-5D scores as drastic as in our case with the algorithm for the SF-6D. Therefore, it seems that country-specific differences though likely to affect results, cannot explain our findings by themselves.

Another difference with regards to Brazier et al.'s (2002) study is the design of the survey. Our respondents only had to value five health states, whereas respondents involved in Brazier et al.'s study valued one state more. Apart from that difference, the interview protocol used in our study is not the same as that applied by Brazier et al. (2002). Nevertheless, the design followed by Lam et al. (2008) to estimate the SF-6D algorithm in Hong Kong was not the same either, and despite this, their results were broadly similar to those obtained for the UK algorithm. On the other hand, the EQ-5D tariff has been estimated by using very different designs (*e.g.*, Dolan, 1997 *vs* Lamers et al., 2006) but the resulting score ranges have not been so different to each other as occurs in our case.

Therefore, it seems that our findings cannot be successfully explained unless we focus on the different valuation method used. There are both empirical evidence (Bleichrodt et al., 2007) and theoretical arguments (Bleichrodt and Schmidt, 2002) to expect that a lottery equivalent method such as we applied leads to lower scores than those yielded by the standard gamble. The valuations obtained for 78 SF-6D health sates were congruent with such a prior expectation, in such a way that mean, median and minimum values were lower in our study than in other studies previously performed. In addition to that, the comparison between our probability lottery equivalent method and the standard gamble for five different SF-6D health states confirmed the hypothesis that the standard gamble yields values which are too high.

We think that the weaknesses of the standard gamble are well established in the literature. The SG does not only suffer from failures of internal consistency (Bleichrodt, 2001; Oliver, 2003), but also seems to have a poor external validity, which casts doubts about how suitable the use of SG-based algorithms is (Abellan-Perpiñan et al., 2009). The potential drawbacks affecting lottery equivalent methods are much less known, however we are aware that such procedures may be also affected by biases. For example, the same as probability weighting may cause an upward bias in SG measurements (Bleichrodt, 2002), it might also make that utility values elicited by lottery equivalent methods even were too low (Wakker and Stiggelbout, 1995). Moreover, the specific probability equivalent method used in this study may not be exempted of potential limitations. As noted previously this procedure is able to make that utilities are bounded between -1 and +1. This is not a property of the generic family of lottery equivalent techniques, but a direct consequence of fixing at 0.5 the probability attached to full health in the lottery serving as stimulus in the elicitation. There is not lower bound at -1 for any other probability value different from 0.5. This feature of the PLE prompts questions about if the range of utilities actually measured by such a method might vary depending on which the ‘baseline’ probability was. This issue deserves to be explored in future investigations.

Notwithstanding, even taken into account all these possible limitations, given the substantial body of evidence suggesting that expected utility violations primarily arise for riskless-risk comparisons, we think that at present the balance is favourable to lottery equivalent methods, including the specific PLE applied in this study. Thus, we are inclined to see the floor effect as, in part, the result of applying an elicitation method –the SG- prone to bias utilities upward because of the overvaluation of the certain alternative which is confronted with the gamble. The PLE is the device we have used to obtain less biased inputs to estimate the SF-6D algorithm. The practical consequence of this ‘debiasing’ process is that the resulting range of SF-6D utilities is now more similar to that generated by the EQ-5D.

Further research is needed to explore in depth the validity of our new algorithm. For example, future investigations might address the task of comparing for the same subjects probability lottery equivalent measurements with standard gamble assessments adjusted according to prospect theory. In this way, we could test if, as Bleichrodt et al. (2007) found, prospect theory does not affect probability lottery equivalent values, whereas the standard gamble ones are largely reduced. Another interesting issue would be the development of new algorithms, using the same data set as this paper, by relaxing the parametric assumptions that are behind both random effects and OLS models. Finally, comparisons with EQ-5D tariffs should also be made, in order to obtain direct evidence as to what extent the two instruments, the SF-6D and the EQ-5D, are more comparable, after the ‘floor’ effect has vanished.

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Table 1. Health states directly valued

111131	112451	532113	242541	342623	623443
111411	121622	612321	331551	543152	245354
311112	133322	121525	514224	543233	444245
411111	141314	224152	632115	243543	524345
111115	222332	231424	641232	333633	532454
113131	235121	122255	223534	335244	644342
115111	333221	135242	333433	434631	325554
211213	641111	325412	343333	445125	434545
222222	132144	512522	423433	531435	444544
422211	132612	525311	423514	634512	445354
124123	144411	115533	431353	643233	615654
411142	322134	213615	521641	224635	545654
621121	412422	234243	314345	344425	645655

Table 2. Sociodemographic characteristics of subjects

	Sample (n=998)
Male/Female (%)	50/50
Mean (SD) age in years	43.6 (16.64)
Marital status	
Single	33.7
Married/Cohabiting	59.8
Separated/Divorced/Widow	6.5
Education level	
Illiterate /Primary studies	34.5
Secondary studies	34.4
University studies	31.1
Income level	
Up to €1,500	22.9
€1,501 – 2,000	28.4
€ 2,001 – 3,000	29.8
More than €3,000	18.9
Smoker (%)	27.0
Self-assessed health state (EQ-5D)	
11111	60.8
11121	15.8
11112	4.3
Other	19.1
Self-assessed health state (SF-6D/SF-36))	
111122	6.0
111112	4.3
111222	3.1
111111	2.9
Other	83.7

Table 3. Statistics for 30 SF-6D health state valuations

State	n	Min	Max	Mean	Median	SD
111411	119	0.540	1.000	0.803	0.780	0.105
112451	60	0.200	0.800	0.515	0.500	0.137
113131	58	0.800	1.000	0.988	1.000	0.036
115111	118	0.300	0.800	0.649	0.660	0.122
121525	60	0.160	0.900	0.569	0.600	0.145
121622	60	0.180	0.700	0.451	0.460	0.103
122255	59	0.200	0.900	0.469	0.460	0.167
132612	59	0.300	1.000	0.710	0.700	0.174
133322	59	0.360	1.000	0.671	0.660	0.136
141314	56	0.240	1.000	0.755	0.800	0.176
222222	60	0.520	1.000	0.891	0.930	0.130
222332	58	0.400	1.000	0.826	0.820	0.136
223534	56	0.060	0.820	0.474	0.420	0.190
224152	60	0.100	0.940	0.411	0.400	0.158
235121	59	0.400	1.000	0.610	0.600	0.134
314345	59	0.200	0.800	0.395	0.400	0.122
325412	58	0.000	0.900	0.552	0.510	0.182
344425	60	0.060	0.580	0.160	0.160	0.085
412422	60	0.300	1.000	0.599	0.600	0.178
434545	59	0.060	0.520	0.241	0.220	0.102
445125	60	0.100	0.800	0.369	0.330	0.140
512522	59	0.200	0.800	0.476	0.500	0.130
524345	59	-0.400	0.700	0.285	0.300	0.142
532454	58	-0.980	0.860	0.161	0.200	0.436
615654	60	-0.960	0.620	-0.263	-0.310	0.346
621121	60	0.240	0.980	0.657	0.700	0.176
634512	56	-0.200	0.600	0.158	0.100	0.172
643233	60	0.060	0.700	0.315	0.300	0.178
644342	57	-0.980	0.660	0.004	0.060	0.366
645655	116	-0.980	0.500	-0.515	-0.600	0.426

Table 4. Probability lottery equivalent (PLE) vs. Standard Gamble (SG) valuations

Health States	Mean valuations			Median valuations		
	PLE	SG	t-test (p-value)	PLE	SG	Wilcoxon (p-value)
222332	0.711	0.815	0.000	0.700	0.800	0.000
141314	0.754	0.846	0.000	0.780	0.850	0.002
311112	0.832	0.905	0.025	0.820	0.900	0.025
132612	0.880	0.955	0.000	0.940	0.950	0.001
412422	0.599	0.780	0.000	0.600	0.800	0.000

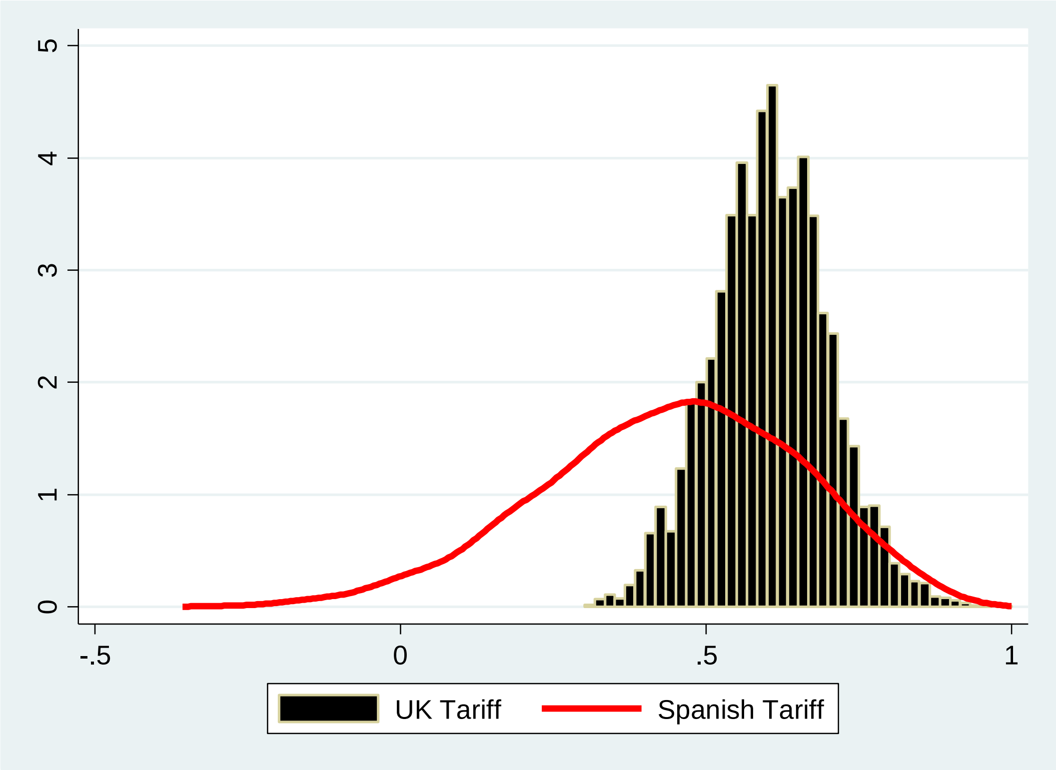
Table 5. SF-6D(SF-36) Health State Models

	Random Effects models				OLS Mean model
	'Raw' (1)		**Efficient (2)**		**Mean (3)**
Cons	1	Cons	1	Cons	1
PF2	-0,025	PF2	-0,022	PF2	-0,015
PF3	-0,056	PF3	-0,062	PF3	-0,034
PF4	-0,120	PF4	-0,122	PF4	-0,090
PF5	-0,107	PF5	-0,109	PF5	-0,111
PF6	-0,335	PF6	-0,340	PF6	-0,338
RL2	0,007			RL2	-0,014
RL3	-0,045	RL23	-0,018	RL3	-0,038
RL4	-0,089	RL4	-0,085	RL4	-0,070
SF2	-0,071	SF2	-0,069	SF2	-0,037
SF3	-0,078	SF3	-0,079	SF3	-0,060
SF4	-0,194	SF4	-0,194	SF4	-0,203
SF5	-0,239	SF5	-0,234	SF5	-0,208
PAIN2	-0,044			PAIN2	-0,018
PAIN3	-0,047	PAIN23	-0,044	PAIN3	-0,034
PAIN4	-0,172	PAIN4	-0,178	PAIN4	-0,198
PAIN5	-0,230	PAIN5	-0,225	PAIN5	-0,202
PAIN6	-0,343	PAIN6	-0,345	PAIN6	-0,318
MH2	-0,026	MH2	-0,029	MH2	-0,066
MH3	-0,050	MH3	-0,053	MH3	-0,078
MH4	-0,072	MH4	-0,075	MH4	-0,096
MH5	-0,196	MH5	-0,199	MH5	-0,224
VIT2	-0,043	VIT2	-0,042	VIT2	-0,058
VIT3	-0,093	VIT3	-0,091	VIT3	-0,121
VIT4	-0,158	VIT4	-0,156	VIT4	-0,157
VIT5	-0,181	VIT5	-0,179	VIT5	-0,199
n	4.990	n	4.990	n	78
Predictive ability					
MAE	0.0871		0.0872		0.0812
| pred. Error | < k					
k = 0,01	8.13		4.72		11.72
k = 0,05	36.41		35.25		36.49
k = 0,10	63.50		62.24		70.50

All coefficients are significant at a 99% confidence level except for PF2 in models (1) and (2), and RL(3) in model (2), which are significant at the 95% level; and RL2 in model (1) which is statistically non-significant.

Note: The estimation of the mean model incorporates corrective weights to account for the fact that mean health state values are not always calculated using the same number of observations.

Figure. 1. A comparison of the Spanish and UK tariffs' predicted values.



The Spanish Tariff corresponds to our OLS mean model in Table 5. The UK Tariff is the SF-6D (SF-36) 'consistent' model at mean level (column 2 of Table 4 in Brazier and Roberts, 2004).

Figure 2. Consistency-analysis. Spanish tariff after excluding 20% of the subjects from the sample vs. UK tariff