Quality of Life Lost Due to Non-Fatal Road Crashes

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January 2010

Abstract

The objective of this paper is to evaluate the effect of a non-fatal road crash on the health-related quality of life of injured people. A new approach based on the cardinalization of categorical Self-Assessed Health valuations, is suggested. Health losses have been estimated by using different Time Trade-off and Visual Analogue Scale tariffs, in order to assess the robustness of the results. The methodology is based on the existing literature about treatment effects. Our main contribution focuses on evaluating the loss of health up to one year after the non-fatal accident, for those who are non-institutionalized, that would allow to properly estimate the aggregated health losses in quality-of-life terms.

JEL Classification: C25; I10

Keywords: Health-related quality of life; Health measurement; Road crashes; Scaling Methods.

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1 Introduction

We aim at estimating the loss of health following a non-fatal road crash. The methodology is based on the definition of comparison groups, by using the existing literature regarding treatment effects. The main contribution of this paper is the evaluation of health losses due to injuries in terms of quality of life. Moreover, this paper develops a different method for scaling categorical health measures, a powerful tool in health-related analysis.

The selection of the topic "road crashes" is not pointless. In 2001, injuries represented 12% of the global burden of disease (WHO, 2001). The category of injuries worldwide is dominated by those incurred in road crashes. In 2004, over 50% of deaths caused by road crashes were associated to young adults in the age range of 15–44 years, and traffic injuries were the second-leading cause of death worldwide among both children aged 5–14 years, and young people aged 15–29 years (WHO, 2004). In addition, road crashes are expected to be the main origin of the projected 40% increase in global deaths resulting from injury between 2002 and 2030 (WHO, 2007). Bishai et al. (2006) demonstrated that observed patterns in rich countries show only a decline in fatalities, but no decline of crashes or injuries. In this respect, focusing on the impact on health of injuries and sequelae is becoming more and more important. Nonetheless, few studies have dealt with this topic, in part due to the difficulties of properly addressing the problem.

The actual loss of health following *RTIs* equals the difference between the values associated to the post-injury health state and the potential health state (under the unreal scenario in which the accident does not happen). The so-called *potential* health status is always unidentified. and thus some assumptions must be made in order to approximate it. Regarding the *post-injury* health status, the ideal is to estimate the chronic sequelae that a traffic crash can have on the affected, and to evaluate the impact of these sequelae in their daily living. However, this is a challenging task, since it is hard to obtain a complete set of data that comprises all the required information. This setback is particularly relevant at evaluating the medium or long term health effects for those who have been seriously injured by a road crash, and who have been discharged from hospitals or analogous health care institutions. The impracticality of performing a follow-up for these affected individuals makes almost impossible to document any future health complications that could be indirectly caused by the *RTIs* suffered in the past. If such information is omitted, we run the risk of underestimating the actual toll of road crashes in society.

At reviewing the literature dealing with this topic, we found that few solutions have been proposed in order to correct this bias. Firstly, the post-injury health status is usually obtained from sources as police records, Hospital Discharge Registers, or databases from health care institutions. The nature of these databases is essentially linked to the estimation of the seriousness of the injuries, rather than focusing on the impact of the injury over the general health state of the individual. Particularly relevant is the methodology developed at estimating the potential health state. The earliest studies in this area directly assume the potential health state as that of being in "perfect health" (Sullivan et al., 2003; Redelmeier and Weinstein, 1999). More recently, a comparison group is taken as a proxy of the potential health state of the victim (Nyman et al, 2008). This methodology is mainly based on the use of population norms that provide some benchmark against which to compare post-injury outcomes. The common norms are stated in terms of changed health baselines for men/women and different age-groups.

The authors of this paper consider these methodologies unconvincing. Notice that the assumptions stated above treat road crashes either as fortuitous events or completely based on few observable factors. However, data show that people affected by *RTIs* can be neither considered as randomly selected, nor as a perfectly targeted population. We should think about the existence of unobservable factors, such as the degree of risk aversion, the driving ability, and so on, that could affect also the health state as well as the probability of having a road crash. Previous literature does not allow to control for the possible existence of a selection bias at the results. Moreover, they fail to express the result in preference-based metrics, so that it cannot be extended to a policy or social framework. Nyman et al. (2008) make a first attempt to outperform the previous studies. But these authors still use some scaling methods that lack from a theoretical framework, and they also consider road crashes as purely stochastic occurrences, without providing any rationalization. Therefore, we consider the existence of a gap in previous literature, concerning the impact of *RTIs* and sequelae in the daily living of the victims, in terms of quality of life lost.

In this work we estimate the loss of health (in quality of life terms) that is due to a road crash, for those who suffer from *RTIs*, up to one year after the crash. The analysis is performed for non-institutionalized individuals. The methodology is based on the definition of comparison groups, by using the existing literature concerning treatment effects. We analyze whether the introduction of variables that could capture risk aversion modifies substantially the results, with respect to the outcomes derived by treating road crashes as fortuitous events. If so, the results could suggest the existence of unobserved factors that had not been captured by the controls introduced in the model.

In Section 2 the methodology is described, starting with the cardinalization of categorical variables, and following with the estimation of the direct loss of health. Section 3 describes the data used for the analysis. In Section 4 we present the main results, and several robustness checks. Section 5 concludes.

2 Methodology

2.1 Measurement of health

A wide variety of metrics are used to quantify the burden of illnesses and injuries to population (an exhaustive description of these measures can be found in Seguí-Gomez and MacKenzie (2003), MacKenzie (2001) or Sturgis et al. (2001), among others). In general terms, we can talk about two different sort of measures, depending on the way of approaching the health status.

Measures in the first group focus on the impact of the injury over the general health state of the individual, developing a variety of indices or metrics that define "health". Measures as *Self-Assessed Health, Euroquol Time-Tradeoff tariff (EQ TTO tariff), Euro-*

quol Visual Analogue Scale tariff (EQ VAS tariff) or *Health Utility Index,* can be placed within such an approach. Metrics in the second group aim at estimating the seriousness of the injuries, either reflecting the degree of functional limitation of the injured individuals (*Functional Capacity Index*, *Disability weights*), or attending to the mortality risk or life threat (*Abbreviated Injury Scale*, *Injury Severity Score*, *ICD-9 Injury Severity Score*, *Anatomic Profile Score,* among others).

Scales belonging to the second group are the ones most commonly used to asses health losses due to injuries. However, several studies suggest that an individual's injury and acute psychological responses are strongly linked. Hence, both play important roles in determining quality of life and disability outcomes (e.g. O'Donnell et al., 2005). Although measures of severity in the second group provide some understanding of the relative seriousness of injuries in terms of threat to life and resource utilization, they still fall short in measuring the long-term impact of non-fatal injuries on the person, his or her family, and the society at large. These considerations have challenged the field to move beyond counting injuries by severity alone to measuring their direct impact on health-related quality of life.

In the present work we approach the problem from a quality-of-life perspective, that is: we analyze the impact of non-fatal injuries on the quality of life of the injured individuals, not only attending to the physical damage that the injury caused, but also contemplating the possible psychological consequences, as well as the potential impact on the well-being of those affected. To perform this exercise we use Spanish data. In order to check the robustness of the results, the analysis is performed by using different quality-related health state scores (*VAS tariff* and *TTO tariff),* that are obtained by applying the Spanish EQ-5D index tariffs (see Badia et al., 1995 and Badia et al., 2001). Our analysis is performed by using two different criteria for each measure:

1. The actual tariffs (that allow negative values, that is, health states worse than death), and
2. 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).

we denote the outcomes as *VASa*, *VASr*, *TTOa* and *TTOr*, depending on the tariff (*VAS tariff* or *TTO tariff*) and the adopted criterion (actual or re-scaled scores).

2.2 Cardinalization of *SAH*

The loss of health is derived from the respondent's assessment of her own health status. That piece of information about self-assessed health will be obtained from the categorical variable *SAH* : "In your opinion, how is your health in general?", where respondents must choose one of the following categories: "very good", "good", "fair", "bad" or "very bad". Since categorical measures of health are one of the most commonly used indicators in socioeconomic surveys, a wide variety of methods were developed with the aim of dealing with the cardinalization of ordinal health measures (e.g. Van Doorslaer and Wagstaff, 1994; Cutler and Richardson, 1997; Groot, 2000). In this study we focus on the interval regression model, stated by Van Doorslaer and Jones (2003). This model is shown to outperform other econometric approaches, in terms of validity and ability to mimic the distribution of scaling health measures.

This methodology combines the distribution of observed *SAH* with external information on the distribution of a generic measure of health y, in order to construct a continuous standardized latent health variable. The crucial idea that lies beneath the selected methodology (interval regression) is to consider the true health state of an individual i as a latent, continuous but unobservable variable (y_i^*), that can take on any real value. The relationship between the true health state of individual i (y_i^*) and the self-reported health variables (SAH_i and y_i) is assumed to be as follows: the higher the value of y_i^*, the more likely the individual is to report a higher category in SAH_i, and a higher value in y_i. For such a connection to be correct, it is necessary to assume that there is a stable mapping from y_i^* to y_i that determines SAH_i, and that this applies for all individuals in both samples. This statement implies that the reported variables have rank properties; that is, the *qth*-quantile of the distribution of y will correspond to the *qth*-quantile of the distribution of SAH.

The range of y and y^* is divided into five intervals, each one corresponding to a different value of SAH:

$$SAH_i = j \quad if \quad \mu_{j-1} < y_i^* < \mu_j, \quad j = 1, 2, 3, 4, 5 \tag{1}$$

$$SAH_i = j \quad if \quad \eta_{j-1} < y_i < \eta_j, \quad j = 1, 2, 3, 4, 5 \tag{2}$$

where it is set that $\mu_0 = -\infty, \mu_5 = +\infty, \eta_0 = 0, \eta_5 = 1, \mu_j \leq \mu_{j+1}, \eta_j \leq \eta_{j+1}$ and y_i^* is assumed to be a linear function of a vector of socioeconomic factors X_i

$$y_i^* = X_i\beta + u_i, \text{ with } u_i \sim N(0, \sigma^2) \tag{3}$$

Expressions (1) and (3) represent the well-known ordered logit model, and (2) will allow us to use a nonparametric approach to estimate the (re-scaled) thresholds of the model, by using the cumulative frequency of observations for each category of SAH to find the quantiles of the empirical distribution function for y. The setting of the thresholds allows us to identify the variance of the error term $\widehat{\sigma}^2$ and hence, the scale of y^* without having any scaling or identification problems (Van Doorslaer and Jones, 2003).

In this paper we apply a variation of the previous methodologies suggested by Cubí-Mollá (2010). 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 a range $(-\infty, 0]$, and assume that $h_i^* = -y_i^*$ has a standard lognormal distribution. The new variable h_i^* is decreasing in health, so that represents the latent "ill-health" of the individual. Since the connection between y and SAH is due to represent the latent variable, an adaptation is needed.

Let us denote $h = 1 - y$, and define SAH^{ih} as a new variable where the ordering of the self-assessed health categories has been reversed, 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 I** shows.

(Table I about here)

Let $\eta_0 = 0, \eta_1 = 1 - \lambda_4, \eta_2 = 1 - \lambda_3, \eta_3 = 1 - \lambda_2, \eta_4 = 1 - \lambda_1$ and $\eta_5 = 1$. The methodology assumes that the latent true ill-health h^*can be represented by h in a $0 - 1$ scale, and the thresholds of the intervals determining SAH^{ih} $(\eta_j, j = 1..4)$ are obtained from external information and thus, are observable.

Therefore, the model becomes:

$$SAH_i^{ih} = j \text{ iff } \eta_{j-1} < h_i < \eta_j, \; j = 1, 2, 3, 4, 5$$

$$\log(h_i) = X_i \beta + u_i, \text{ with } u_i \sim N(0, \sigma^2) \tag{4}$$

Our aim is to estimate the average health valuation in a continuous 0 -1 scale, for each individual by conditioning on X_i. Noticing that $\exp(u_i) \sim lognormal(0, \sigma^2)$, we obtain the expression:

$$H(i) = E[h_i | x_i] \approx \exp\left(X_i \widehat{\beta}\right) \cdot \exp\left(\widehat{\sigma}^2/2\right),$$

where $H(i)$ captures the estimated average value of ill-health, ranging from 0 to 1, associated to the observable characteristics of individual i.

In order to evaluate the robustness of this methodology, the thresholds are determined in terms of different generic health measures obtained from external data. we use $TTOa$, $TTOr$, $VASa$ and $VASr$ as the continuous self-assessed measures.

2.3 Evaluation of health losses

The analysis of health losses due to *RTIs* can be performed by using the *treatment effects* literature. In this context, the "treatment" is interpreted as the occurrence of a road crash that causes severe injuries to the affected individuals. Some notation is useful at this point. Let D_i indicate whether individual i had a road crash ($D_i = 1$) or not ($D_i = 0$). Let $H(i)$ represent the health status[1] for individual i. This health state is measured after the road crash takes place.

Following Rubin (1974) and Heckman (1990), causality is defined in terms of potential outcomes. $H_0(i)$ is the outcome that individual i would attain if he had not been affected by the treatment. Equivalently, $H_1(i)$ is the outcome that individual i would realize if he had received the treatment. In this paper we focus on the average loss of health as a result of a road crash, for those who had a non-fatal accident. This quantity is known as the average treatment effect on the treated ($ATET$) and is written as follows:

$$ATET = E\left[H_1(i) - H_0(i) \mid D_i = 1\right] = E\left[H_1(i) \mid D_i = 1\right] - E\left[H_0(i) \mid D_i = 1\right]$$

The $ATET$ cannot be identified using observational data since $H_0(i)$ is only observed for those targeted by $D_i = 0$. A suitable solution is to approximate the average health state that injured people would have had in the absence of the road crash (potential health status) by the average health state observed in a comparable group of people that have not had an accident. As we mentioned in the Introduction, data show that traffic crashes are not random, but they are more likely to happen to people with particular traits (for instance men aged 15-29). Therefore the average health of injured (*affected group*, hereafter) and non-injured (*comparison group*, hereafter) individuals cannot be unconditionally compared. Thus, the validity of this approximation is likely to be higher once differences in the distribution of observed individual characteristics are controlled

[1]The concept "health status" could be interpreted broadly. In this case, we consider $H(i)$ as a continuous measure of ill-health, ranging from 0 (absence of ill-health or perfect health) to 1 (full ill-health).

for.

Let $Z(i)$ be a vector including information relative to individual i that is a priori thought to influence his probability of suffering a road crash. Under this approximation the $ATET$ can be expressed as follows:[2]

$$ATET = E\left[H|Z, D=1\right] - E\left[H|\, Z,\, D=0\right] \,, \tag{5}$$

where $H = DH_1 + (1-D)H_0$ is the observed health status of the individuals.

The power of this estimator to identify the $ATET$ relies on the so-called "selection on observables" restriction, that can be formally written as:

ASSUMPTION 1: $E\left[H_0|Z, D=1\right] = E\left[H_0|\, Z,\, D=0\right]$

This condition states that the average potential health status, conditional on observable characteristics Z, is equal to the average health status of those who did not suffer an accident ($D=0$) conditional on observable characteristics Z. In other words: the effect of events other than the road crash do not contaminate the causal analysis. Furthermore, Assumption 1 implicates that unobserved individual characteristics do not affect the causal analysis, or its overall average impact is equal for both affected and comparison group.

Abadie (2005) develops a simple two-step procedure to estimate the $ATET$ using the difference-in-differences estimator. In Abadie (2005), the only element required to estimate the $ATET$ is the conditional probability of receiving the treatment, also called *propensity score*. This procedure is now adapted to the situation where only cross-section data for the post-treatment period are available. Since identification is attained after conditioning on covariates, it is required that for a given value of each covariate there is some fraction of the population in the pre-treatment period to be used as controls.[3]

[2] Hereafter the individual argument will dropped out to simplify notation.

[3] Assumption 2 is a well-known condition for identification of the average impact on the treated under selection on covariates (see, e.g. Heckman et al., 1997).

ASSUMPTION 2: $P(D=1)>0$ *and with probability one* $P(D=1|Z)<1$.

In a similar way to Abadie, we establish the following lemma (the proof can be derived easily from Lemma 3.1 in Abadie, 2005):

LEMMA: *If Assumptions 1 and 2 hold, then* $E[H_1-H_0|Z,D=1] = E[\rho \cdot H|Z]$, where

$$\rho = \frac{D-P(D=1|Z)}{P(D=1|Z)\cdot(1-P(D=1|Z))}$$

Due to the previous Lemma, the $ATET$ can be expressed as follows:

$$E[H_1-H_0|D=1] = E\left[\frac{H}{P(D=1)}\cdot\frac{D-P(D=1|Z)}{1-P(D=1|Z)}\right] \tag{6}$$

Equation (6) suggests a simple two-step method to estimate the $ATET$ under Assumptions 1 and 2. First, the conditional probabilities are estimated using a logit model and the fitted values of $P(D=1|Z)$ are calculated for each individual in the sample. Second, the fitted values are plugged into the sample analog of Equation (6). Then, a simple weighted average of the outcome variable recovers the $ATET$. Finally, the asymptotic variance of the estimator is also calculated, following the procedure developed in Abadie (2005) for the conventional difference-in-differences estimator, now adapted for the selection on observables case.

For the results derived from such methodology to be correct, it is necessary to assume that 1) there are no unobservable factors affecting both the outcome and the probability of having a crash, or 2) if unobservable factors exist, these can be captured by the observable ones (e.g. risk-loving behavior is usually related to consumption of alcohol), or 3) if unobservable factors exist and are not reflected by the observables, its overall average impact is equal for both the affected and the comparison group.

People affected by *RTIs* can be neither considered as randomly selected, nor as a perfectly targeted population. The existence of some random component cannot be denied, mainly related to the occurrence or non-occurrence of a road crash, rather than the seriousness of the injures. For instance, being involved into a crash caused by a different individual, or an unexpected puncture on the road. However, many factors that influence the existence of *RTIs* (as can be wearing seat-belts, airbags, driving carefully, not being drunk, using the pedestrian crossing, etc.) are chosen by the individual. In fact, data show that the group of people that have a road crash includes higher proportion of male, aged 16-35, have unhealthy habits as smoking or consumption of alcoholic drinks, among other features. These characteristics, that may affect both health status and the probability of being injured by a road crash, are observable.

However, we could think about the existence of unobservable factors, such as the degree of risk aversion, the driving ability, and so on, that could affect also the health state as well as the probability of having a road crash. In order to ensure that the results provide an accurate estimation, the propensity score will be computed under different sets of controls. We will analyze whether the introduction of variables that could capture risk aversion modifies substantially the *ATET*, with respect to the results derived by treating road crashes as fortuitous events. If so, the results could suggest the existence of unobserved factors that had not been captured by the controls introduced in the model.

3 Data and variable definitions

The analysis is performed with data collected from diverse sources of information:

For estimating the impact of *RTIs* on population health, we use the survey about diseases, disabilities and health states (*Encuesta de Discapacidades, Deficiencias y Estados de Salud*), arranged by the Spanish National Institute of Statistics (*INE,* 1999). The survey includes 70,402 households (about 217,760 individuals), selected with a probability proportional to the size of each region. The survey is divided into two sections: Diseases and Disabilities Unit (*Módulo de Discapacidades y Deficiencias*), and Health Unit (*Módulo de Salud, MS* hereafter). We use data from the *MS* section. In that unit an individual in each household is randomly chosen - in total: 69,555 individuals; however, 840 observations from Ceuta and Melilla were dropped for practical reasons. The interviewed is confronted with a battery of questions related to health habits, as well as demographic and socioeconomic information.

A wide range of factors are considered that can affect the self-valuation of the health state of an individual (some observations are dropped because of missing values in some of the regressors):

(a) Socioeconomic *factors:* age, gender, marital status, education, labour (unemployed, unable, retired, housekeeper, student, other), income, household size, residence location, population size, and citizenship.

(b) *Health-related factors:* BMI (underweight, BMI < 18 / normal weight, $18 \leq$ BMI≤ 25 / overweight or obese, BMI> 25) existence of a chronic illness (bronchitis, allergy, epilepsy, diabetes, hypertension, heart injuries, cholesterol, cirrhosis, arthritis, ulcer, hernia, cardiovascular diseases, anaemias, nerves, migraines, menopause, other), existence of disorders (mental, visual, auditory, articulation, bones, nervous system, visceral, other), if the individual has had an accident during the last 12 months (serious road crash or other kinds of accident), if the individual is currently taking medicines.

(c) *Lifestyles:* if the person sleeps more than 8 hours, practices sports (working days / weekend), if the person is a usual smoker or a hard drinker.

Two questions in *MS* have been selected to target those seriously injured due to traffic accidents. These questions state as follows: "During the last 12 months, have you suffered from a traffic accident that has prevented you from performing any usual activity?" (Yes/No), and "How has this traffic accident influenced in your daily life" (Seriously/ Quite a lot /Slightly). From a total of 959 individuals who give an affirmative answer to the first question, we select those who answered "Seriously" (148) or "Quite a lot" (186) in the latter. Those who answer "Slightly", are dropped from the sample. For practical reasons, the analysis is performed over the population aged between 15 and 75. Observations with missing values are also dropped from the sample. The final sample size is $45,864$ individuals (297 affected by *RTIs*).

Average characteristics for key variables are given in **Table V** (columns for *affected individuals* and *comparison group* with *no adjustment*)**.** For a start, injured individuals self-report lower health levels than non-injured ones (2.59 versus 2.81), what is consistent with the hypothesis about the existence of chronic health losses following road crashes. A Mann-Whitney rank-sum test is used to compare the means of each variable[4] for injured and non-injured (the null hypothesis is equality of means). Men are more likely to result seriously injured by a road crash than woman. Also, the group of injured people includes a higher proportion of individuals aged 16-25 or 26-35, and present more unhealthy habits: smoking and consumption of alcoholic drinks. The highest level of education completed differs mainly by the higher proportion in secondary studies, in contrast to a lower proportion of superior studies and less than secondary. On average, income is not significantly different between both groups. Given these differences in the distribution of observed individual characteristics, it is necessary to control for them, with the aim of obtaining a valid estimate of the *ATET*.

The required external information is obtained from the Catalan health surveys *Enquesta de Salut de Catalunya* 2002 (*ESCA02* hereafter) and *Enquesta de Salut de Catalunya* 2006 (*ESCA06* hereafter), arranged by the Catalan government (*Generalitat de Catalunya*). A total of 8,400 individuals (in the former) and 18,126 individuals (in the latter) were selected for the surveys, which include different health measures as *VAS*, *EQ-5D* and *SAH*. From these variables, three cardinal health measures could be obtained: *VAS* (directly from the survey), *VAS tariff* and *TTO tariff* (estimated from *EQ-5D*). These measures are used to estimate the health effect. In the *ESCA02* we dropped 1,837 observations from the sample: 19 observations because either *VAS* or *SAH* were not reported, 1748 observations related to individuals aged under 15 or over 75, and 66 proxy-respondent interviews (due to impairments). A total of $4,133$ observations ($3,896$ corresponding to

[4] A t-test is used at evaluating the income.

individuals aged less than 15 or more than $75,192$ proxy-respondent interviews and 45 observations that were considered untruthful by the interviewer) were dropped from the *ESCA06.*

Finally, some observations (3) presenting inconsistencies were discarded. Those have been detected based on the values provided by the variables *VAS* and *SAH.* Thus, several individuals reported "excellent" health or *VAS* close to 1, but negative values for the tariffs. Similarly, some individuals reported "bad" health or *VAS* close to 0, but tariff values close to 1. The analysis uses pooled individual data from both surveys (*ESCA02/06* hereafter).[5] The final sample size is $20,557$ individuals.

It is important to notice that the *SAH* variable included in both surveys is not identical to the *SAH* variable incorporated into *MS.* The dissimilarity lies in the five possible answers given to the respondents: the category "very bad" is not available in *ESCA02/06*, but "excellent" is incorporated. In order to define a single health index, the construction of *SAH* containing 4 categories is performed (the new variable will be called $SAH4$), following the approach adopted by several authors (e.g. Lindley and Lorgelly, 2007; Hernández-Quevedo et al., 2005; García and López, 2004). The collapsed categorizations are summarized in **Table II**. We define $SAH4^{ih}$ as a new variable where the ordering of the self-assessed health categories has been reversed, now interpreted in terms of ill-health. Similarly, we denote $y^{ih} = 1 - y$, for $y \in \{TTOa, TTOr, VASa, VASr\}$.

(Table II about here)

4 Results

Before giving estimates for the continuous health measures, we explore whether interval boundaries widely differ across demographic groups. Pooled data from *ESCA02* and *ESCA06* are grouped by gender and age category; by the existence of (at least) one

[5] Similar analysis have been performed over *ESCA02* and *ESCA06* separately. The results are very similar to those obtained in this paper.

chronic illness; by the existence of disabilities; and whether the respondent has suffered or not a road crash during the last 12 months (*"RC"* hereafter). The thresholds are computed, conditioning on the different subgroups. **Table III** illustrates the results regarding the *VASr* tariff (the thresholds by groups derived from alternative tariffs show the same pattern). The thresholds are presented in terms of good health.

(Table III about here)

Table III show that subjective thresholds are quite similar by age, gender, disability status or existence of a chronic illness. This pattern is also observed in different samples, by Van Doorslaer and Jones (2003). However, individuals who report having been seriously injured by a road crash present dissimilar cut-points. For instance, the threshold between categories "Bad" and "Fair" is considerably higher than thresholds derived from different subgroups, maybe with the exception of women aged 15-29. On the contrary, the thresholds between "Fair", "Good" and "Very good or Excellent" are much lower than the rest. Different analysis have proved that this effect cannot be induced by the age-gender composition of the subsample. Thus, maybe these thresholds are capturing an effect of road crashes, and so the interval regression approach is likely to be sensitive to making the interval boundaries *RC*-specific. This response-category cut-point shift is taken into account at scaling the *SAH* answers in *MS.* The analysis is also performed by using homogeneous thresholds, that is, not conditioning on *RC* ("All").[6]

Table IV shows the characteristics of the thresholds obtained in the *ESCA02/06,* in terms of health, by health tariff and *RC*.

(Table IV about here)

Observe that when the actual health tariffs are used, the lower bound corresponds to the minimum value of the tariff. Also, in the absence of *RC*, the boundaries are mostly

[6]In order to assess the robustness of this assertion, the results have also been derived from all the established groups of thresholds shown in Table III. Since the ATET derived from these conditional thresholds do not difer substantially from the ATET derived from the homogeneous thresholds, the results have not been reported in the paper. The authors can provide the results upon request.

equal than the homogeneous thresholds. Thus, if the results obtained by using conditioned or unconditioned boundaries are rather different, this could highlight the importance of controlling for possible response-category cut-point shifts.

Observe that λ_3 is very close to 1 both for the *VAS* and *TTO tariffs*. This is a direct consequence of the "ceiling effect" of these scores: a value of health equal to 1 is assigned to a great percentage of the population (63.7%). The interpolation used for estimating the thresholds avoids that $\lambda_3 = 1$ for these metrics.

The values should be interpreted as follows: for instance, referring to $VASa$, and using the homogeneous thresholds (not conditioning on RC): an individual who reports the worst category of health is assumed to have a $VASa$ level that belongs to the interval $[-0.076, 0.416]$. Similarly, the values for the remaining $SAH4$ categories are $(0.416, 0.790]$ for the "fair" category, $(0.790, 0.926]$ for the "good" category and $(0.926, 1]$ for the "very good" and "excellent" categories.

The specification for intervals is implemented into parallel regression models. The characteristics of the regressors as well as the parameter estimates of the interval regression model are found in **Appendix.**[7] The health status of each individual is controlled for a wide range of socioeconomic variables, and most of the coefficients are significant (CI 95%). The McKelvey and Zavoina[8] pseudo-R^2 is computed for each model, and rounds 0.48, indicating that these predictors account for approximately 48% of the variability in the latent outcome variable. On average, 65% of the estimated health tariffs lay into the correct interval (settled by the reported answer to the SAH question). A Regression Error Specification Test (RESET test)[9] has been applied to each interval and logit regression model, and none of them shows evidence of misspecification.

[7]Since the thresholds derived from $VASr$ and the $TTOr$ tariffs are defined as an affine transformation of those derived from $VASa$ and $TTOa$, the coefficients and standard errors coincide, up to the intercept. The Appendix show the results reported by the actual health tariffs ($VASa$ and $TTOa$), as well as the changes in the intercept.

[8]The McKelvey and Zavoina pseudo-R^2 is an attempt to measure model fit as the proportion of variance accounted for: $\text{var}(h)/[\text{var}(h) + \text{var}(u)]$.

[9]RESET test is popular means of diagnostic for correctness of functional form. I test: $H_0 : \gamma = 0$ against the alternative $H_1 : \gamma \neq 0$, in $\log(h_i) = X_i\beta + y_i\gamma + error$, where y_i is generated by taking powers of the predicted values $\widehat{\log(h_i)}$ in (4). A failure to reject H_0 says the test has not been able to detect any misspecification.

It is important to remark that the value of health is highly linked to the self-perception of health status, rather than the actual health status per se. A positive coefficient means that an individual has a higher value of latent ill-health and is more likely to report a lower category of self-assessed health. The regressors have been built so that the reference individual is a Spanish woman aged 25-35, who lives in La Rioja, single, employed, completed higher education, who did not suffer an injury during the last 12 months, no chronic illness, non-smoker, sleeps more than 8 hours per day, does not make any physical exercise and has a proper BMI (does not show underweight or obesity).[10]

As it was expected, the ill-health decreases with income, level of education, absence of chronic illness, and absence of injuries or limitations. Besides, ill-health is decreasing with sleeping more than 8 hours per day, exercising, living in cities with higher population. Students are healthier than any other employment condition, married and widowers are more likely to report a lower category of SAH^{ih} (and thus higher value of true health) than single people. The results also provide evidence about the decline of quality of life as age increases.

The *propensity score* is meant to capture the factors that make an individual more likely to have a severe road crash. For evaluating the propensity score we perform different logit models, in order to identify the nature of the selection bias. In a first set of variables (*xvars1*) only age-gender controls are included. The second group of factors (*xvars2*) adds new characteristics concerning the resident location, educational level, household size, population size and logincome. The third group (xvars3) adds controls that try to capture the behavioral and physiological characteristics of the individuals, as proxies for the unobservable factors that could affect the probability of having a road crash (e.g. risk aversion). These controls are: if the individual has suffered another sort of accident (not a road crash); if the individual has restricted his/her nocturnal outing during the last 12 months by fear of being robbed; if he/she has been a usual smoker during the previous

[10]In order to allow for some variability in the effect of a road crash in health, several interactions (e.g. with gender, age, education, labor status) were introduced in the preliminar models; since any interaction was significant, and they did not modify the results, they were finally dropped.

year.

We must take special care for not including causal-effect reversals into the regression. The characteristics of the injured people are recorded up to one year after the accident, so that they could be reflecting the consequences of a road crash rather than the probability of suffering it. These sort of variables could introduce an additional problem, that is the endogeneity in the regression, what could reduce the estimated effect of the treatment. Taking this fact into consideration, the individual characteristics that are likely to be a consequence rather than a factor related to the propensity to have an accident, are dropped from the regression. For instance, the current labour status, number of hours of sleep, BMI, among others.

The estimations of the odds ratio and standard errors corresponding to the logit models are included in **Appendix**. The propensity score is larger (CI 95%) for men aged between 15 and 24, with secondary studies. Remark that the coefficients of the behavioral factors are significantly different from zero, of a larger propensity score.

It interesting to stress the main objective of the logit regression. From equation (6) we can write:

$$ATET = E_{comp}\left[w \cdot H\right] - E_{aff}\left[H\right]$$

where $E_{aff}\left[\cdot\right] = E\left[\cdot|D=1\right], E_{comp}\left[\cdot\right] = E\left[\cdot|D=0\right]$ and $w = \frac{P(D=1|Z)}{1-P(D=1|Z)} \cdot \frac{P(D=0)}{P(D=1)}$.

Thus, the logit model balances the samples of comparison and affected groups, by introducing a weight for each individual in the comparison group. **Table V** illustrates this idea.

(Table V about here)

The average health effect under "selection of observables" is estimated in terms of decrease in health. The standard errors and confidence intervals are computed by bootstrapping. The number of iterations is 1,500, and the bias-corrected estimate has been considered, assuming that standard errors are normally distributed. It can be observed that the effects differ depending on the metric in which the ratio is expressed. The results of the estimation and the confidence interval are illustrated in **Figure 1 and Figure 2**. For a better comprehension, the results are expressed in terms of decrease in health, instead of increase in bad health. On average terms, we can talk about a decrease in health from 0.039 (*TTO tariff*, after re-scaling, with the global thresholds and using *xvars3*) to 0.123 (*VAS tariff*, being the thresholds obtained by RC and the propensity score from *xvars1).* For every health measure, the confidence interval embraces values strictly negative, what gives evidence to the existence of a reduction in quality of life for those injured by a road traffic crash.

(Figure 1 about here)

(Figure 2 about here)

The differences between simple averages of health for affected and comparison group have been computed (**Tables VI-IX**). The results differ from the estimated $ATET$, what supports the validity of the hypothesis about the existence of selection on observables. In order to highlight the real impact of the total loss of health on individuals' health state, we compute the following rate:

$$\Delta H = \frac{E_{aff}\left[H\right] - E_{comp}\left[w \cdot H\right]}{E_{comp}\left[w \cdot H\right]} = \frac{ATET}{E_{aff}\left[H\right] - ATET}$$

ΔH indicates the proportion of health that on average individuals have lost due to a road crash, with respect to the health state that, on average, individuals would have had if the accident had not happened, estimated by using adjusted comparison groups. The confidence interval of ΔH is also re-scaled. The results are also shown in **Tables VI-IX.**

(Table VI about here)

(Table VII about here)

(Table VIII about here)

(Table IX about here)

RTIs involve a decline in health from 14.93% (*VAS tariff*, being the thresholds obtained by *RC*, and being the affected and comparison group averages adjusted by age and gender) to 4.27% (*TTO tariff*, after re-scaling, with the global thresholds and using *xvars3).*

For every health measure, the *ATET* derived from the balanced data is considerably higher (in absolute terms) than the effect estimated by considering that road crashes are completely random. Thus, to control for a selection bias is a relevant factor in the analysis. The results also suggest that the potential health state of the injured is, on average, better than the health status of those who have not had a road crash. Such differences in quality of life are barely reduced at introducing controls to capture observable and unobservable factors that could affect the probability of having a road crash (xvars2 and xvars3, respectively). In fact, the correlation between both results (random and non-random treatment) remains almost constant, even though the coefficient of the additional variables are significantly different from zero.

It is remarkable how the estimates change depending on the measurement of health indices. At a first step, the definition of the thresholds by *RC* does not imply a monotonous cut-point shift. However, the use of different thresholds for scaling self-assessed health for injured and non-injured individuals affects importantly the estimation of the *ATET*. By deriving homogeneous thresholds, we could be excluding some physiological component that may be linked to the health self-perception among the affected, which seems to lead to a lower *ATET*. The consideration of different thresholds by *RC* can be interpreted as a way to control for another source of selection bias.

5 Conclusions

The fact that road crashes represent an alarming threat to health has been reported by most of studies that deal with *RTIs*, causes of death or the evaluation of the burden of diseases. The application of different policies aimed at reducing the magnitude of the problem is essential. The effectiveness of these policies should be estimated carefully, allowing for making a distinction among the different outcomes they could yield: a reduction of the number of crashes, fatalities and severity of the non-fatal *RTIs*. In order to pursue this task, and for allowing a comparison among analysis of different interventions, we should express the total toll of deaths, injuries and sequelae derived from traffic accidents in a simple metric, that could estimate the total loss of health that could be avoided.

Up to our knowledge few studies evaluate health losses due to non-fatal *RTIs* in *QoL* terms. Redelmeier and Weinstein (1999) estimate that *RTIs* report a loss of health of 0.127 *QoL*. Sullivan et al. in 2003 estimated the morbidity caused by *RTIs* in 0.356. These authors consider the baseline quality of life for calculating the decrement due to injury as 1.00 (this is, non-injured are always in perfect health). Also, Sullivan et al. (2003) do not express the result in preference-based metrics, so that it cannot be extended to a policy or social framework. More recently, Nyman et al. (2008) computes the health lost following a non-fatal road crash as 0.061. These authors do not take "perfect health" as baseline; however, they consider road crashes as stochastic occurrences, contrary to our main hypothesis.

The main drawback at dealing with health consequences of *RTIs* is the data availability. There is still much to do before there is a complete set of data that comprises all valuable information (details of the accident, joint with description of the health state of the injured individuals, etc.). Meanwhile, the short-term objective consists of obtaining the best estimation of health losses under the limitation of the lack of available data.

In this paper, several measures have been developed in this direction. To start with, monitoring health-related quality of life have been enhanced by establishing equivalences between cardinal and categorical health variables, since the former are the preferred measures for cost-effectiveness analysis, but the latter is more frequently enclosed in surveys. Furthermore, typical assumptions have been overcome. Firstly, the potential health status has not been assumed to be as perfect health. Secondly, the methodology developed in this paper has contemplated the need of controlling for the possible existence of a selection bias. Different thresholds for scaling self-assessed health for injured and non-injured individuals have been defined with this aim. Also, the *ATET* has been estimated under three different assumptions regarding the occurrence of a road crash: treating them as fortuitous events, completely based on different sets of observable factors, or involving additional behavioral or phycological features which are, accordingly, unobservable. The *ATET* has been shown to increase significantly when allowing for non-random components, remain essentially stable when controlled for different sets of socioeconomic characteristics, and decrease slightly under controls for risk aversion. Hence, the results have been proved to be robust to the estimation of the propensity score in the first part of the procedure. The estimation also suggests that the potential health state of the injured is, on average, better than the health status of those who have not had a road crash.

Our research has limitations, mainly derived from the source of data. Due to the lack of available information, continuous measures of health have been partially obtained from external data. Despite the validity of the model, it may have introduced some bias, derived from different self-perceptions. Furthermore, both surveys are administered to non-institutionalized population, so that the analysis cannot be performed for those individuals, maybe the most seriously injured, that still remain in trauma centers. There is also missed information regarding possible *RTIs* occurred in the past (more than one year previous to the survey), that may be affecting the actual health state of the individual but is not observed. Finally, the *ATET* is likely to be affected by a slightly decrease if additional unobserved factors could be incorporated in the analysis. Our results bring to light the relevance of the impact of road crashes in health-related quality of life.

We are grateful to Ildefonso Méndez, Eduardo Sánchez and Juan Oliva for their stimulating comments on a draft of this paper. Usual disclaimers apply. We thank DGT and Generalitat de Catalunya for providing the data. Financial support from Fundación BBVA is acknowledged. We also benefit from support from the Spanish Ministerio de Educación y Ciencia under project SEJ2007-62656, and Generalitat Valenciana, under project GV06/275.

6 Appendix

Coefficients for logit regressions, by group of covariates.

(Table AI about here)

Interval regression models, by different thresholds (dependent variable: health indices VASa and TTOa)

(Table AII about here)

(Table AIII about here)

(Table AIV about here)

(Table AV about here)

(Table AVI about here)

(Table AVII about here)

Constant term and robust z statistics for interval regressions. By tariff and selected thresholds (*RC* / global)

(Table AVIII about here)

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health			ill-health		
SAH	y	y^*	SAH^{ih}	h	h^*
1	$[0, \lambda_1]$	$(-\infty, \alpha_1]$	5	$[1 - \lambda_1, 1]$	$[-\alpha_1, +\infty]$
2	$]\lambda_1, \lambda_2]$	$[\alpha_1, \alpha_2]$	4	$[1 - \lambda_2, 1 - \lambda_1]$	$[-\alpha_2, -\alpha_1]$
3	$]\lambda_2, \lambda_3]$	$[\alpha_2, \alpha_3]$	3	$[1 - \lambda_3, 1 - \lambda_2]$	$[-\alpha_3, -\alpha_2]$
4	$]\lambda_3, \lambda_4]$	$[\alpha_3, \alpha_4]$	2	$[1 - \lambda_4, 1 - \lambda_3]$	$[-\alpha_4, -\alpha_3]$
5	$]\lambda_4, 1]$	$[\alpha_4, 0]$	1	$[0, 1 - \lambda_4]$	$[0, -\alpha_4]$

Table I. Relationship among health and ill-health variables

	SAH	
SAH4	ESCA02/06	MS
1	Bad	Very bad Bad
2	Fair	Fair
3	Good	Good
4	Very good Excellent	Very good

Table II. Definition of SAH4

	N	Upper bound of interval			
		Bad	Fair	Good	VG or Exc
By age-group and gender					
men, 15-29	2,732	0.4531	0.7692	0.9102	1.0000
men, 30-44	3,123	0.4603	0.7757	0.9292	1.0000
men, 45-59	2,548	0.5032	0.7863	0.9519	1.0000
men, 60-75	1,921	0.5017	0.7892	0.9584	1.0000
women, 15-29	2,580	0.5028	0.7780	0.9148	1.0000
women, 30-44	2,967	0.4588	0.7609	0.9260	1.0000
women, 45-59	2,565	0.4549	0.7772	0.9454	1.0000
women, 60-75	2,121	0.4204	0.7745	0.9556	1.0000
By disability status					
Disabled	2380	0.4200	0.7555	0.9465	1.0000
Non-disabled	18177	0.4675	0.7814	0.9301	1.0000
By existence of a chronic illness					
Yes	15,007	0.4570	0.7797	0.9380	1.0000
No	5,550	0.4538	0.7789	0.9197	1.0000
If had a serious road crash (RC)					
Yes	99	0.5406	0.7574	0.8979	1.0000
No	20,458	0.4566	0.8050	0.9309	1.0000
All	20,557	0.4569	0.8050	0.9308	1.0000

Table III. Thresholds by subgroups of population. *VASr*

		Thresholds (health)				
		λ_0	λ_1	λ_2	λ_3	λ_4
$VASa$	RC	-0.076	0.506	0.730	0.890	1.000
	No RC	-0.076	0.416	0.790	0.926	1.000
	All	-0.076	0.416	0.790	0.926	1.000
$VASr$	RC	0.000	0.541	0.757	0.898	1.000
	No RC	0.000	0.457	0.805	0.931	1.000
	All	0.000	0.457	0.805	0.931	1.000
$TTOa$	RC	-0.653	0.481	0.827	0.951	1.000
	No RC	-0.653	0.311	0.877	0.955	1.000
	All	-0.653	0.313	0.877	0.955	1.000
$TTOr$	RC	0.000	0.686	0.895	0.970	1.000
	No RC	0.000	0.583	0.926	0.973	1.000
	All	0.000	0.585	0.926	0.973	1.000

Table IV: Interval boundaries, by health tariff and RC

	Affected	Comparison groups			
		no adjust.	xvars1	xvars2	xvars3
N	297	45567	45567	45567	45567
male	54.8	47.2***	54.9**	54.9***	54.9***
age	41 (20.7)	46 (20.1)***	41 (11.5)**	40.6 (19.6)	40.6 (25.6)*
16 - 25	24.2	14.1***	24.2***	24.2***	24.2***
26 - 35	23.9	17.9***	23.9	23.8**	23.9**
36 - 45	14.8	16.5	14.8	15.0	14.8
46 - 55	10.1	14.9**	10.1	10.2*	10.1*
56 - 65	9.4	16.1***	9.4**	9.4**	9.4**
66 - 75	17.5	20.6	17.5	17.5	17.5
income	103354	106221	107088.5	102759.4	102466.3
	(65407.64)	(65998.35)	(85017.51)	(88973.42)	(100546)
smoker	55.2	42.7***	43.0***	43.1***	55.2***
alcohol	44.8	40.7***	40.9**	40.9***	44.8**
other accidents	5.1	2.3***	2.2***	2.3***	5.1***
education					
less prim.or primary	45.8	51.5**	43.5***	45.3	45.8
secondary	43.4	32.7***	39.8**	43.7**	43.4***
more secondary	10.7	15.8**	16.7**	11.0*	10.8*

(Standard deviation in brackets)* Sign. at 10% ** Sign. at 5% *** Sign. at 1%

Table V. Average characteristics for affected groups, comparison groups and comparison groups.with adjustment

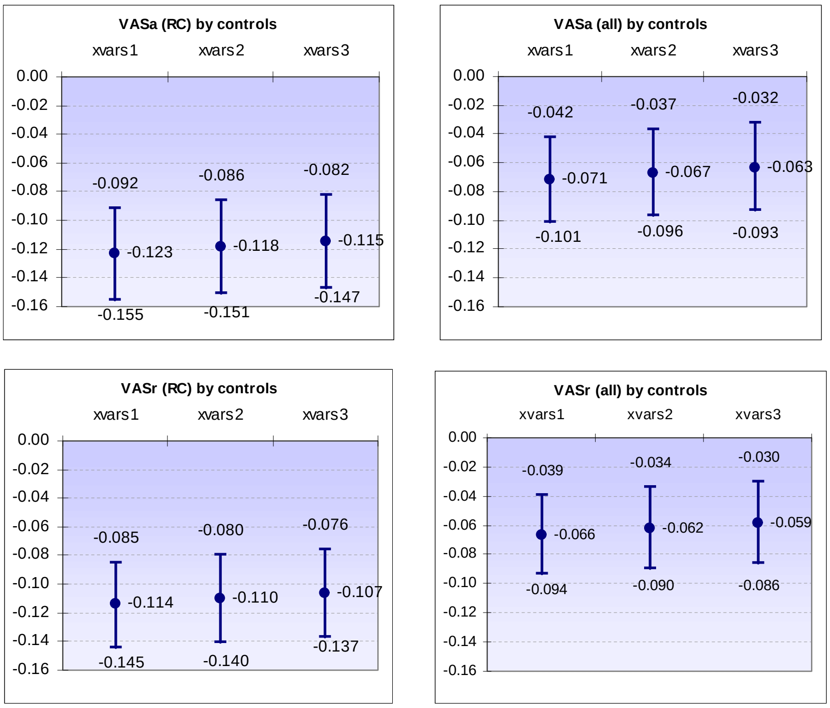

Figure 1. *ATET* for the VAS tariff (actual and re-scaled), by different thresholds and controls

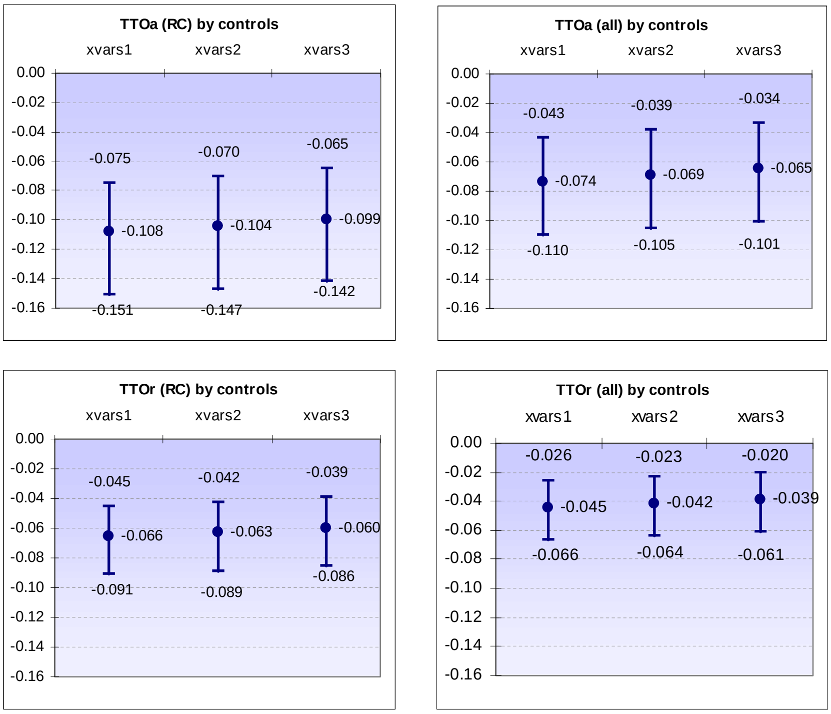

Figure 2. *ATET* for the TTO tariff (actual and re-scaled), by different thresholds and controls

		Random	Non-random	ΔH (%)	CI(95%)	
RC	xvars1	-0.102	-0.123	-14.93%	[-18.18%	-11.59%]
	xvars2	-0.102	-0.118	-14.48%	[-17.75%	-10.94%]
	xvars3	-0.102	-0.115	-14.08%	[-17.40%	-10.50%]
All	xvars1	-0.051	-0.071	-8.68%	[-11.83%	-5.35%]
	xvars2	-0.051	-0.067	-8.19%	[-11.38%	-4.68%]
	xvars3	-0.051	-0.063	-7.77%	[-10.98%	-4.13%]

Table VI. $ATET$ estimates for $VASa$.

		Random	Non-random	ΔH (%)	CI(95%)	
RC	xvars1	-0.095	-0.114	-13.68%	[-16.70%	-10.58%]
	xvars2	-0.095	-0.110	-13.25%	[-16.30%	-9.98%]
	xvars3	-0.095	-0.107	-12.89%	[-15.97%	-9.57%]
All	xvars1	-0.047	-0.066	-7.95%	[-10.86%	-4.88%]
	xvars2	-0.047	-0.062	-7.50%	[-10.45%	-4.27%]
	xvars3	-0.047	-0.059	-7.11%	[-10.08%	-3.77%]

Table VII. $ATET$ estimates for $VASr$.

		Random	Non-random	ΔH (%)	CI(95%)	
RC	xvars1	-0.089	-0.108	-12.49%	[-16.55%	-8.96%]
	xvars2	-0.089	-0.104	-12.04%	[-16.20%	-8.44%]
	xvars3	-0.089	-0.099	-11.57%	[-15.72%	-7.85%]
All	xvars1	-0.054	-0.074	-8.48%	[-12.14%	-5.19%]
	xvars2	-0.054	-0.069	-8.01%	[-11.73%	-4.64%]
	xvars3	-0.054	-0.065	-7.52%	[-11.31%	-4.07%]

Table VIII. $ATET$ estimates for $TTOa$.

		Random	Non-random	ΔH (%)	CI(95%)	
RC	xvars1	-0.054	-0.066	-7.12%	[-9.63%	-5.02%]
	xvars2	-0.054	-0.063	-6.85%	[-9.41%	-4.72%]
	xvars3	-0.054	-0.060	-6.57%	[-9.11%	-4.38%]
All	xvars1	-0.033	-0.045	-4.84%	[-7.04%	-2.91%]
	xvars2	-0.033	-0.042	-4.56%	[-6.79%	-2.60%]
	xvars3	-0.033	-0.039	-4.27%	[-6.54%	-2.28%]

Table IX. $ATET$ estimates for $TTOr$.

Table AI: Coefficients for logit regressions, by group of covariates

	xvars1	xvars2	xvars3
Age-gender groups (ref: male 15-24)			
Male 25-34	0.788	0.841	0.705
	(0.172)	(0.194)	(0.165)
Male 35-44	0.525	0.567	0.446
	(0.131)***	(0.147)**	(0.119)***
Male 45-54	0.396	0.415	0.326
	(0.114)***	(0.124)***	(0.100)***
Male 55-64	0.327	0.338	0.27
	(0.101)***	(0.114)***	(0.093)***
Male 65-75	0.404	0.407	0.327
	(0.108)***	(0.128)***	(0.105)***
Female 15-24	0.691	0.699	0.706
	(0.167)	(0.169)	(0.17)
Female 25-34	0.534	0.596	0.525
	(0.129)***	(0.149)**	(0.134)**
Female 35-44	0.363	0.392	0.339
	(0.102)***	(0.114)***	(0.099)***
Female 45-54	0.28	0.287	0.285
	(0.089)***	(0.097)***	(0.095)***
Female 55-64	0.259	0.256	0.286
	(0.080)***	(0.089)***	(0.099)***
Female 65-75	0.433	0.427	0.491
	(0.103)***	(0.126)***	(0.147)**
Resident location (ref: La Rioja)			
Canary Islands		5.91	6.142
		(6.035)*	(6.279)*
Other regional dummies		Not sig.	Not sig.
Education (ref: more than secondary)			
Less than primary or primary		1.642	1.562
		(0.377)**	(0.353)**
Secondary		1.687	1.605
		(0.345)**	(0.327)**
Observations	45864	45864	45864

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AII: Coefficients for logit regressions, by group of covariates (cont.)

	xvars1	xvars2	xvars3
Additional SE factors			
Household size		0.982	0.995
		(0.059)	(0.058)
Population size		1.053	1.036
		(0.129)	(0.128)
Logincome		0.963	0.96
		(0.108)	(0.108)
Behavioral			
Accidents (not RC)			2.253
			(0.617)***
Fear			1.902
			(0.601)**
Usual smoker			1.816
			(0.256)***
Observations	45864	45864	45864

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AIII: Interval regression models, by different thresholds (dependent variable: health indices $VASa$ and $TTOa$)

	Thresholds by RC		All	
	VAS	TTO	VAS	TTO
male 15-24	-0.074	-0.074	-0.068	-0.068
	(4.87)***	(4.90)***	(4.07)***	(4.07)***
male 25-34	0.011	0.011	0.02	0.02
	(0.85)	(0.83)	(1.4)	(1.42)
male 35-44	0.068	0.068	0.07	0.07
	(5.11)***	(5.12)***	(4.71)***	(4.71)***
male 45-54	0.121	0.121	0.118	0.117
	(8.47)***	(8.46)***	(7.17)***	(7.17)***
male 55-64	0.141	0.142	0.133	0.133
	(9.19)***	(9.20)***	(7.24)***	(7.26)***
male 65-75	0.076	0.076	0.043	0.043
	(4.17)***	(4.20)***	(1.85)*	(1.87)*
female 15-24	-0.064	-0.064	-0.063	-0.063
	(4.15)***	(4.16)***	(3.74)***	(3.73)***
female 35-44	0.055	0.055	0.046	0.046
	(4.40)***	(4.41)***	(3.32)***	(3.33)***
female 45-54	0.13	0.13	0.134	0.134
	(9.22)***	(9.23)***	(8.08)***	(8.09)***
female 55-64	0.15	0.15	0.162	0.162
	(9.92)***	(9.92)***	(8.81)***	(8.81)***
female 65-75	0.112	0.112	0.108	0.108
	(6.94)***	(6.94)***	(5.34)***	(5.35)***
Andalucia	-0.092	-0.092	-0.113	-0.113
	(3.24)***	(3.24)***	(3.28)***	(3.27)***
Aragon	-0.031	-0.031	-0.046	-0.045
	(1.03)	(1.02)	(1.25)	(1.23)
Asturias	0.036	0.036	0.038	0.038
	(1.14)	(1.15)	(0.99)	(1.00)
Canarias	0.026	0.026	0.03	0.031
	(0.84)	(0.86)	(0.81)	(0.81)
Cantabria	-0.02	-0.02	-0.034	-0.034
	(0.61)	(0.61)	(0.88)	(0.87)
CLM	-0.042	-0.042	-0.06	-0.06
	(1.42)	(1.43)	(1.69)*	(1.68)*
CYL	-0.009	-0.009	-0.02	-0.02
	(0.33)	(0.33)	(0.59)	(0.59)

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AIV: Interval regression models, by different thresholds (dependent variable: health indices $VASa$ and $TTOa$). (Cont.)

	Thresholds by *RC*		All	
	VAS	TTO	VAS	TTO
Catalunya	-0.034	-0.034	-0.046	-0.045
	(1.19)	(1.18)	(1.31)	(1.30)
CV	-0.083	-0.082	-0.105	-0.104
	(2.82)***	(2.81)***	(2.95)***	(2.93)***
Extremadura	-0.031	-0.031	-0.035	-0.035
	(0.99)	(0.99)	(0.91)	(0.91)
Baleares	-0.051	-0.051	-0.066	-0.066
	(1.54)	(1.55)	(1.66)*	(1.66)*
Galicia	0.085	0.086	0.095	0.095
	(2.92)***	(2.93)***	(2.68)***	(2.69)***
Madrid	-0.01	-0.01	-0.015	-0.015
	(0.33)	(0.33)	(0.42)	(0.42)
Murcia	-0.046	-0.045	-0.053	-0.052
	(1.41)	(1.38)	(1.35)	(1.33)
Navarra	0.004	0.004	0.001	0.001
	(0.11)	(0.14)	(0.02)	(0.03)
PVasco	0.032	0.032	0.028	0.029
	(1.02)	(1.03)	(0.76)	(0.77)
bronchitis	0.256	0.256	0.36	0.36
	(20.92)***	(20.91)***	(20.63)***	(20.62)***
allergy	0.029	0.029	0.033	0.032
	(3.51)***	(3.46)***	(3.11)***	(3.07)***
epilepsy	0.22	0.221	0.309	0.31
	(5.64)***	(5.68)***	(5.42)***	(5.45)***
diabetes	0.179	0.179	0.259	0.259
	(13.51)***	(13.55)***	(13.24)***	(13.27)***
blood pr.	0.039	0.038	0.058	0.058
	(4.22)***	(4.20)***	(4.61)***	(4.60)***
heart fails	0.23	0.23	0.347	0.347
	(17.36)***	(17.34)***	(17.36)***	(17.36)***
cholesterol	0.063	0.063	0.088	0.088
	(6.60)***	(6.63)***	(6.69)***	(6.71)***
cirrhosis	0.252	0.251	0.382	0.381
	(5.69)***	(5.67)***	(5.64)***	(5.62)***
arthritis	0.281	0.281	0.36	0.36
	(33.94)***	(33.91)***	(32.11)***	(32.08)***

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AV: Interval regression models, by different thresholds (dependent variable: health indices *VASa* and *TTOa*). (Cont.)

	Thresholds by *RC*		All	
	VAS	TTO	VAS	TTO
ulcer	0.125	0.125	0.168	0.168
	(10.32)***	(10.35)***	(10.08)***	(10.09)***
hernia	0.127	0.127	0.171	0.17
	(10.14)***	(10.13)***	(9.70)***	(9.69)***
cardiovasc.	0.112	0.112	0.163	0.163
	(12.17)***	(12.18)***	(12.56)***	(12.55)***
anaemias	0.146	0.145	0.205	0.204
	(6.90)***	(6.87)***	(6.83)***	(6.80)***
nerves	0.221	0.222	0.313	0.313
	(22.48)***	(22.54)***	(22.09)***	(22.11)***
migraine	0.073	0.074	0.098	0.098
	(7.47)***	(7.52)***	(7.42)***	(7.43)***
menopause	-0.025	-0.025	-0.028	-0.028
	(1.26)	(1.28)	(0.99)	(1.01)
other	0.251	0.252	0.327	0.328
	(20.96)***	(21.00)***	(19.72)***	(19.74)***
mental handicap	0.217	0.216	0.322	0.32
	(7.33)***	(7.28)***	(7.26)***	(7.23)***
visual handicap	0.061	0.061	0.097	0.097
	(3.04)***	(3.03)***	(3.33)***	(3.34)***
auditory handicap	0.039	0.038	0.052	0.052
	(2.09)**	(2.06)**	(1.94)*	(1.92)*
articul. handicap	0.175	0.174	0.214	0.213
	(2.15)**	(2.14)**	(1.75)*	(1.74)*
bones handicap	0.264	0.266	0.442	0.444
	(17.65)***	(17.71)***	(18.90)***	(18.93)***
nervous handicap	0.377	0.378	0.602	0.603
	(10.90)***	(10.91)***	(11.33)***	(11.33)***
visceral handicap	0.269	0.268	0.466	0.463
	(9.07)***	(9.01)***	(10.09)***	(10.04)***
other handicap	0.148	0.148	0.264	0.264
	(4.41)***	(4.40)***	(5.00)***	(5.00)***
road crash	0.358	0.169	0.359	0.202
	(11.98)***	(4.53)***	(8.09)***	(4.23)***
other injuries	0.11	0.109	0.157	0.156
	(5.72)***	(5.69)***	(6.09)***	(6.07)***

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AVI: Interval regression models, by different thresholds (dependent variable: health indices $VASa$ and $TTOa$). (Cont.)

	By chronic illness		All	
	VAS	TTO	VAS	TTO
sleep +8h	-0.032	-0.032	-0.041	-0.041
	(5.81)***	(5.82)***	(6.15)***	(6.14)***
exercise free time	-0.103	-0.103	-0.114	-0.113
	(14.46)***	(14.46)***	(13.95)***	(13.95)***
exercise wk. days	-0.028	-0.028	-0.038	-0.038
	(3.69)***	(3.72)***	(4.18)***	(4.19)***
BMI infra	0.06	0.06	0.069	0.068
	(2.82)***	(2.81)***	(2.75)***	(2.72)***
BMI supra	0.016	0.016	0.014	0.014
	(2.66)***	(2.66)***	(1.95)*	(1.95)*
medicines	0.223	0.223	0.237	0.237
	(34.28)***	(34.23)***	(30.85)***	(30.80)***
smoker	0.006	0.006	0.003	0.003
	(0.90)	(0.89)	(0.40)	(0.40)
alcohol	-0.019	-0.019	-0.023	-0.023
	(3.12)***	(3.10)***	(3.17)***	(3.19)***
married	-0.006	-0.006	-0.001	-0.001
	(0.76)	(0.75)	(0.13)	(0.15)
widow	-0.095	-0.095	-0.129	-0.129
	(7.03)***	(7.02)***	(7.35)***	(7.36)***
sep/div	0.042	0.042	0.059	0.058
	(2.44)**	(2.44)**	(2.79)***	(2.76)***
nostuds	0.259	0.259	0.309	0.309
	(21.38)***	(21.37)***	(20.65)***	(20.68)***
primstuds	0.156	0.156	0.163	0.163
	(16.43)***	(16.38)***	(15.02)***	(14.99)***
secndstuds	0.074	0.074	0.074	0.074
	(8.71)***	(8.70)***	(7.85)***	(7.84)***

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table AVII: Interval regression models, by different thresholds (dependent variable: health indices $VASa$ and $TTOa$). (Cont.)

	Thresholds by RC		All	
	VAS	TTO	VAS	TTO
unemployed	0.032	0.031	0.032	0.031
	(2.95)***	(2.90)***	(2.55)**	(2.50)**
unable	0.214	0.214	0.305	0.306
	(6.52)***	(6.53)***	(6.13)***	(6.15)***
retired	0.077	0.077	0.096	0.096
	(6.18)***	(6.17)***	(5.80)***	(5.79)***
housekeeper	0.049	0.049	0.051	0.05
	(4.90)***	(4.86)***	(4.11)***	(4.08)***
student	-0.059	-0.059	-0.057	-0.057
	(4.46)***	(4.43)***	(3.94)***	(3.96)***
other	0.058	0.058	0.068	0.069
	(2.90)***	(2.90)***	(2.59)***	(2.60)***
logincome	-0.08	-0.08	-0.092	-0.092
	(14.24)***	(14.27)***	(13.61)***	(13.62)***
househ. size	0.006	0.006	0.007	0.007
	(2.60)***	(2.59)***	(2.57)**	(2.58)***
municip. size	-0.018	-0.018	-0.022	-0.022
	(3.23)***	(3.18)***	(3.18)***	(3.14)***
nation	0.065	0.066	0.069	0.069
	(2.35)**	(2.37)**	(2.19)**	(2.21)**
Constant	-1.516	-1.514	-1.912	-1.912
	(19.49)***	(19.44)***	(20.48)***	(20.49)***
Obs	45864	45864	45864	45864
Variance	0.234	0.234	0.355	0.355
% fit	66%	64%	66%	64%
pseudo-R2	0.481	0.481	0.504	0.503

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

McKelvey-Zavoina pseudo-R2 =[Var(predicted-h*)/Var(h*)]

Table AVIII: Constant term and robust z statistics for interval regressions. By tariff and selected thresholds (RC / global)

	$VASa$	$VASr$	$TTOa$	$TTOr$
Thresholds by RC				
constant	-1.516	-1.589	-1.912	-2.415
std. error	(19.49)***	(20.43)***	(20.48)***	(25.87)***
Global thresholds (All)				
constant	-1.514	-1.587	-1.912	-2.414
std. error	(19.44)***	(20.38)***	(20.49)***	(25.88)***