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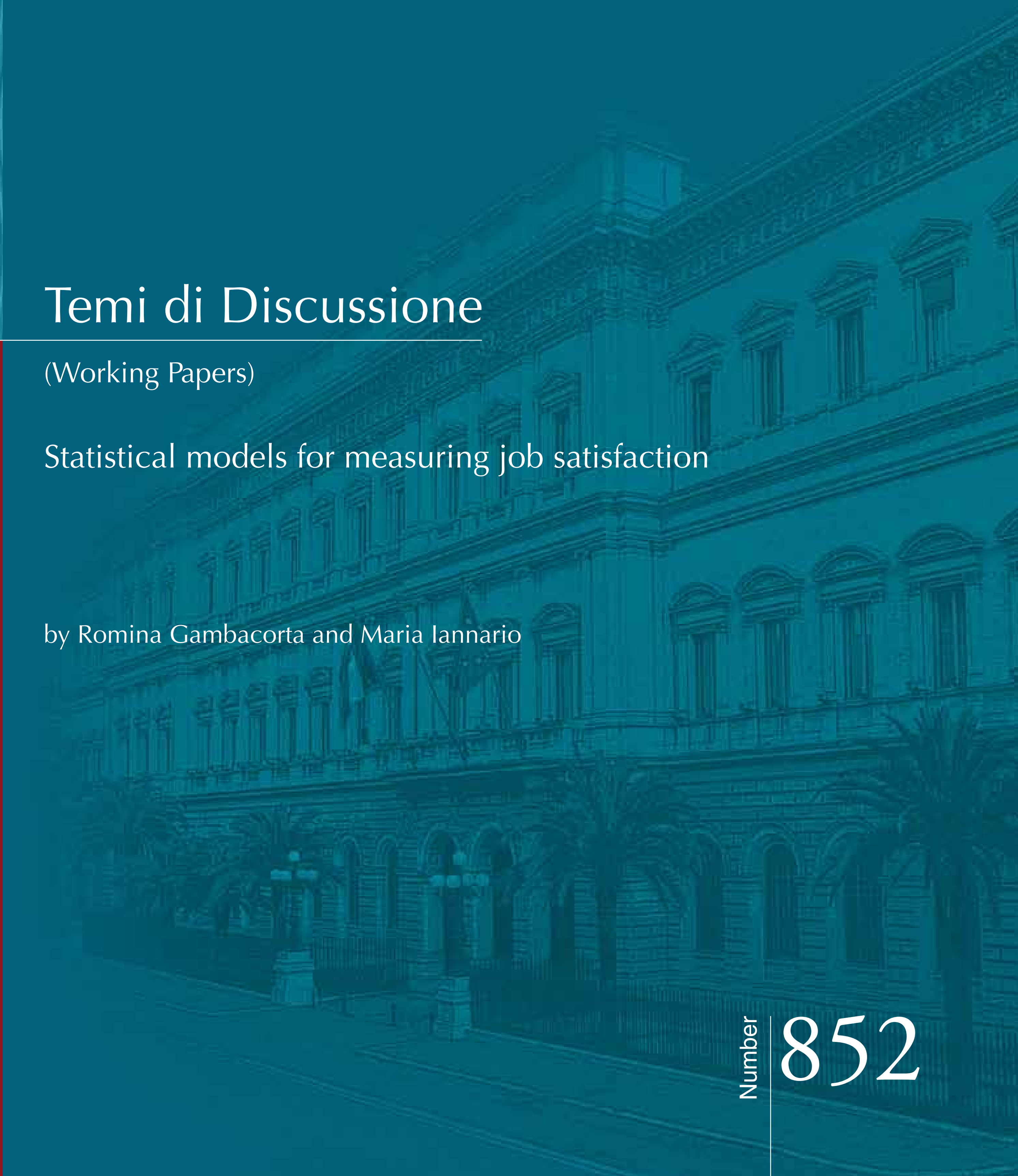

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STATISTICAL MODELS FOR MEASURING JOB SATISFACTION

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Abstract

In this paper we present two statistical approaches for discussing and modelling job satisfaction based on data collected in the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy. In particular, we compare two different classes of model for ordinal data: the Ordinal Probit model and the more recent CUB model. The aim is to establish common outcomes and differences in the estimated patterns of global job satisfaction, but also to stress the potential for curbing the effects of measurement errors on estimates by using CUB models, allowing us to control for the effect of uncertainty and shelter choices in the response process.

JEL Classification: J28, C25.
Keywords: job satisfaction, Ordinal data modelling, CUB models

Contents

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1 Introduction[1]

The study of job satisfaction in economics was initially motivated by its positive link with worker productivity. Recently the interest has moved towards the relevance that this component can have on individuals overall life well-being.[2] In this context, job satisfaction is part of a more general field of research called the "economics of happiness" that studies the factors affecting human well-being, in connection or apart from the usual economic variables like income and wealth.

In recent years, policy makers are becoming more and more aware that human well-being is a not negligible part of the economic development of a country and that it is necessary to include happiness in the measures of economic progress.[3] Understanding the determinants of job satisfaction can therefore help policy makers in developing strategies to improve household well-being or to study the impact of job market policies on worker satisfaction.

The main problem in analysing job satisfaction is associated with the collection of this information. In fact questions used to quantify individuals' satisfaction try to measure an underlying continuous variable through a rating scale. Standard regression methods used to study this kind of variables suppose that the discrete response outcome is obtained by grouping the latent variable into classes of values using cut-points (McCullagh 1980). Assuming that the error term has a standard normal distribution, we obtain Ordered Probit models (Aitchison and Silvey 1957).

Nevertheless, the answer to questions on individuals' attitudes is not only subject to the discretization process of the underlying latent continuous variable, but reflects a composite elicitation mechanism: the score assigned to a given item results from the liking/disliking feeling for it, and depends

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[2]Job satisfaction is indeed a particular domain of overall life satisfaction, a variable highly correlated with happiness (Blanchflower and Oswald 2004), together with, among others, individuals' perceptions of health, family and social conditions. All these features interact in determining the perceived subjective well-being. For recent results on the link between job satisfaction and life satisfaction see also Bakhshi *et al.* (2008) and Kapteyn *et al.* (2009).

[3]Stiglitz *et al.* (2009) underline the limits of GDP as an indicator of economic performance and social progress and in particular the need to account also for people's well-being and sustainable development.

also on the uncertainty of the ranking process itself.

Specifically, the uncertainty of the final choice may be due to 'satisficing behaviour' of the respondent that may choose to provide less accurate answers in the attempt to minimize his effort. Factors that can affect this source of uncertainty are the amount of time devoted to the answer, the use of limited set of information, partial understanding of the item, lack of self-confidence, laziness, apathy (Krosnick 1991). Furthermore, psychological factors may induce respondents to refrain to use certain values of the rating scale and to concentrate towards others (Poulton 1989). Neglecting these aspects implies adding an underlying noise in the model and lowering efficiency in the estimates.

These features are better accounted for a new class of statistical models (CUB models hereafter[4]) where the response is modelled as the combination of two latent components, one related to individual feeling towards the item and another to the uncertainty in the response process (Piccolo 2003; D'Elia and Piccolo 2005, Iannario and Piccolo 2011).

In this paper we implement and compare this approach with a more traditional one (Ordinal Probit) to study job satisfaction. In this way, we establish common outcomes and differences in the estimated patterns of global job satisfaction probability. We stress the possibility to reduce measurement error effects on estimates by using CUB models since they allow to model and control for the effect of uncertainty in the respondent process.

The paper is organized as follows. The next section delineates the problems associated with job satisfaction measurement. Section 3 describes and compares the methodologies used for the analysis of ordinal data, focusing on the CUB model's features. Section 4 describes the data employed in the empirical analysis, while in section 5 the results obtained by adopting Ordinal Probit and CUB models are presented, discussed and compared. The last section reports some conclusion.

2 Issues in measuring job satisfaction

Job satisfaction can be defined as the overall appraisal of all the different features associated with ones' occupation and includes individuals' feelings, behaviours and prospects. This variable is usually measured using a self-reported rating scale.

[4] The acronym stems from *C*ombination of discrete *U*niform and (shifted) *B*inomial distributions.

The question used to investigate job satisfaction in surveys can be referred to the overall job satisfaction, or use a range of specific questions regarding individual facets related to work, like pay, promotion, co-workers, education/job mismatches and job security, to study different aspects that can influence the global on-the-job satisfaction.

In general, questions on individual's attitudes and opinions try to measure an underlying continuous latent variable, but for practical reasons the answer is usually expressed through an ordered set of categories, presented as a rating scale. In particular, with respect to questions where the respondent is asked to provide his/her agreement to a statement the usual reference is the Likert scale (Likert 1932) that provides a verbal description of ordered response levels (for example: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree). The scale used to measure job satisfaction may be also coded as a numerical rating.

Different factors can influence the psychological process that leads the respondents to translate their judgment into an ordered answer.[5]

Some authors have argued that response may be affected by the number of scale points used (Dawes 2008). In general, if too few scale points are provided respondents will not be able to differentiate among their feelings towards the topic while too many categories may introduce rounding and difficulty to distinguish between adjacent response classes.[6] Furthermore, even when the same number of scale points is used, response may vary, if different ranges for the numeric scales are used. Schwarz *et al.* (1991) show that, when negative scale values are used, responses are biased towards the positive end of the scale. However, the effect of scale points' range can be reduced by the use of verbal labels clarifying the meaning of response categories (Schaeffer and Barker, 1995).

Another form of distortion, labelled as *response contraction bias* (Poulton 1989), may arise from the fact that respondents may refrain from using extreme values of the scale when more scale points are provided, while they are usually more concentrated on the central value when an odd-numbered scale is used (Kulas and Stachowski 2009). On the other hand, when questions concern self-reports of behaviours, feelings or personality traits, respondents may tend to provide answers that may be considered positively from the oth-

[5] For a complete review of this aspect see Tourangeau *et al.* (2000).

[6] There is no agreement on the optimal number of response categories that should be adopted: Krosnick and Fabrigar (1997) favor a seven point scale while Cummins and Gullone (2000) state that using an expanded scale is desirable for the subjective quality of life measurement and that the appropriate scale format may be a 10-point, end-defined scale.

ers *social desirability bias*. This is particularly true in the case of face to face or telephone interviews when the respondent wants to positively impress the interviewer. In the case of job satisfaction this may led to a concentration toward the extreme positive values as having a satisfactory job expresses personal fulfilment (Arnold *et al.* 1985). Indeed, Conti and Pudney (2011) show that the level of job satisfaction reported on oral interviews are on average higher than those registered in self-completion questionnaires. The authors also found differential results on response bias due to the presence of different members of the family to the interview.

Finally, errors in worker satisfaction measurement can be related to respondent's lack of attention or to other psychological mechanisms that can affect the response behaviour.[7] In general respondents will be prone to select the answer adopting a "satisficing" behaviour (Simon 1957), choosing an adequate answer that may not be the optimal one, in the attempt to minimize the burden of the question (Krosnick 1991). The degree of uncertainty used to answer a question may vary, ranging from a complete lack of satisficing behaviour, where the respondent provides a completely accurate answer, to strong satisficing, where the respondent randomly selects the answer. Krosnick (1991) suggests three main factors that affect respondent's likelihood of satisficing: the difficulty of the task, the ability of the respondent and his/her motivation.

With respect to job satisfaction we may think to the first factor as having low relevance. The ability of the respondent is influenced by his cognitive sophistication, his experience in thinking about the specific topic and the presence of pre-existing opinions about it. Some of the variables that have been studied as being relevant to explain respondents ability are education, that affects learning and training experience and can enhance respondent's cognitive sophistication (Krosnick *et al.* 1996), and age, negatively related to the ability to retrieve information from memory (Knäuper 1999). Motivation can reflect the degree of importance of the specific topic for the respondent, his/her attitude towards the survey and the level of fatigue (that can be related to the position of the question in the questionnaire). All these factors can be influenced from the ability of the interviewer to arouse the interest of respondents in the survey, to hold his attention and to promote accurate reporting, expecially in face to face interviews (Holbrook *et. al* 2003). Finally, respondent's *state of mind* can influence his tendency to engage in effortful

[7] These errors are far for being negligible. Biancotti *et al.* (2008) analysed discrepancies between recorded data and "true" values due to measurement errors affecting different kind of variables in income and wealth surveys. Their finding, based mainly on the comparison of time-invariant variables, is that inconsistencies arise also for easy items.

cognitive endeavours and thus to provide accurate answers (Davis 2009).

In summary, once the number of scale points and the wording of the question are settled, the methodology used to analyse response on job satisfaction should account for the process of discretization of a latent continuous variable. The latter can be affected by:

- the presence of attractiveness or repulsion towards specific response classes (response bias);
- the influence of a disturbance factor, which we will refer as 'uncertainty' in what follows, mainly due to the degree of satisficing behaviour adopted by the respondent.

3 Methodologies

One of the most interesting aim of economic research is to analyse subjective perceptions (like job satisfaction) by means of statistical methods able to measure latent traits, i.e., variables not directly observed.

As mentioned before, a very simple tool to assess subjective attitudes is the rating scale, also referred to as raw score. The most natural way to view this measurement system is to postulate the existence of an underlying latent (unobserved) variable associated with each response. Such variables are often assumed to be drawn from a continuous distribution that varies from individual to individual. Often this latent trait is modelled as a linear function of the respondent's covariate vector.

To interpret these probabilities, it is clearly necessary to identify models and techniques able to produce quantitative measures of rating assumption.

The two techniques analysed in this study share the same objective, since they suppose a latent trait underlying a rating scale with ordered responses. Both of them are stochastic models: observations come from a data generating process with known probability structures and unknown parameter values.

The main difference lays in the possibility with the CUB models to recognize that the response to the question has been substantially produced by two latent variables, one related to individual feelings and the other to uncertainty. This distinction becomes important in defining inferential statistics and individual deviance contributions.

In the rest of this paragraph we first briefly recall the property of standard Ordinal Probit Models (subsection 3.1) and then describe more in detail

CUB models, its specification and parameters' interpretation (subsection 3.2). In subsection 3.3 the two approaches are compared.

3.1 Ordinal Probit models

First considered by Aitchison and Silvey (1957), Ordinal Probit models result from modelling the probit of the cumulative probabilities as a linear function of the covariates. This kind of models are suitable for the analysis of job satisfaction as can appropriately account for latent variables measured through ordered responses and also allows to estimate the unknown threshold parameters. Widely implemented in econometric contexts (Greene 2008), these models can be obtained from the latent-variable formulation assuming that the error term has a standard normal distribution, and that is usually the way one would interpret the parameters.

Specifically, they have been obtained (Agresti 1996) by postulating the existence of an underlying latent (unobserved) variable $Y_i = \boldsymbol{x}_i'\beta + \boldsymbol{\epsilon}_i$ associated with each response, where $\boldsymbol{x}_i$ is the vector of covariates associated with the i-th individual and $\boldsymbol{\epsilon}_i$ is the noise random variable distributed according to the distribution function of Φ (link probit). Such variables are often assumed to be drawn from a continuous distribution centered on a mean value that varies from individual to individual.

Often, this mean value is modeled as a linear function of the respondent's covariate vector. Thus, the probability that individual i receives/expresses a grade/score of j, conditioned to regressor values is:

$$\begin{aligned} p_r(Y_i = j|x) &= \int_{\tau_{j-1}}^{\tau_j} \phi(Y - x_i'\beta)\, dy \\ &= p_r(\tau_{j-1} < Y_i < \tau_j) \\ &= \Phi(\tau_j - x_i'\beta) - \Phi(\tau_{j-1} - x_i'\beta). \end{aligned}$$

where τ_j are cut-points and the observations are classified in $j = 1, 2, \ldots, m$ categories. To preserve the ordering, the cut-points τ_i must satisfy $\tau_0 < \tau_1 < \tau_2 < \ldots < \tau_{m-1} < \tau_m$; it is convenient to set $\tau_0 = -\infty$ and $\tau_m = +\infty$. We observe that grade $y_i = j$ if the latent variable Y falls in the interval (τ_{j-1}, τ_j).

Suppose that the manifest response results from grouping an underlying continuous variable using cut-points, the probability that the response of the i-th individual will fall in the j-th category, given covariates, satisfies the equation in terms of the transformation of a link function of the cumulative probabilities, that -as mentioned- is the inverse of the standard normal cumulative distribution function (c.d.f.) of the error term with mean 0 and constant standard deviation. In this case, the introduction of a link probit among the probabilities of response and covariates allows a peculiar interpretation of parameters in terms of a latent variable[8] (Agresti 2010). This model presents the same logic interpretation of the pass/fail response (binary data) model with the extension to the original grade data of additional cut-points.[9]

The cut-point can be interpreted in terms of z-scores by evaluating the boundary between low and medium/medium and high satisfaction whereas the remaining coefficients can be interpreted as in a linear regression model.

Moreover, let p_i denote the vector of probabilities associated with assignment of the i-th item into categories $(1, 2 \ldots, m)$; that is $p_i = (p_{i1}, p_{i2}, \ldots, p_{im})'$, where each element of p_{rij} denotes the probability that individual i is classified in category j. If we introduce a dummy variable related to the i-th respondent when he/she chooses the j-th category[10]:

$$d_{ij} = \begin{cases} 1, & \text{if } Y_i = j; \\ 0, & \text{otherwise.} \end{cases}$$

we can introduce $L(\boldsymbol{\theta})$ and $l(\boldsymbol{\theta}) = log(L(\boldsymbol{\theta}))$, which denote likelihood and log-likehood functions, respectively, as function of parameter vector $\boldsymbol{\theta}$. Then, given the sample data $y = (y_1, y_2, \ldots, y_n)'$, the log-likelihood function is:

$$\begin{aligned} l(\boldsymbol{\theta}; y) &= l(\boldsymbol{\theta}) = \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} \log(p_r(Y_i = j|x_i)) \\ &= \sum_{i=1}^{n} \sum_{j=1}^{m} I[y_i = j] \log \left[\Phi(\widetilde{\tau}_j - x_i \widetilde{\beta}) - \Phi(\widetilde{\tau}_{j-1} - x_i \widetilde{\beta}) \right] \end{aligned}$$

where $I(.)$ indicates the indicator function and $\tau = (\tau_1, \tau_2, \ldots, \tau_m)'$ denotes the vector of grade cut-points. These can be estimated by maximum likeli-

[8]The inverse standard normal c.d.f. as the link function corresponds to a standard deviation for the error term that equals 1. This is also the conditional standard deviation for the latent variable. Thus, for each coefficient β_k of the *included* covariate x_k, a unit increase in covariate corresponds to an increase in the expectation of the latent variable of parameter β_k conditional to its standard deviation, keeping the other predictor values fixed.

[9] Precisely, it has been obtained by creating an additional category or cut-points grade within the model by imposing an ordering constraint on the values of cut-points.

[10] If we do not include covariates in the model we obtain deterministic structure specified by observed frequencies (satured model).

hood method, simultaneously with the coefficients.[11] McKelvey and Zavoina (1975) gave expressions for the information matrix for the model.

3.2 CUB models

Starting from the consideration that both individual's feeling towards the item and uncertainty/inattention in the response affect the process of selection among discrete ordered alternatives, we propose the mixture probability structure known as the CUB model to describe the resulting selections.

The main consideration of CUB models is that they take the latent continuous variables into account exclusively in the cognitive process (before the expression of score) and they allow for the possibility to explicitly include subjects' covariates as possible causes of the final score. The rationale stems from the interpretation of the respondent's final choice, a discrete random variable R defined over the support $\{1, 2, \ldots, m\}$, as a weighted combination of a personal *feeling* (parameterized by a shifted Binomial random variable, which is the discrete version over the support $\{1, 2, \ldots, m\}$ of a latent unimodal continuous component) and some intrinsic *uncertainty* (modeled by a proportion of a Uniform random variable, which is the extreme solution for a totally indifferent choice).

Formally, given $m > 3$ prefixed ordinal categories, a CUB model (without covariates) is defined by:

$$p_r(\boldsymbol{\theta}) = \pi \, b_r(\xi) \, + \, (1-\pi) \, U_r(m), \qquad r = 1, 2, \ldots, m \, ,$$

where p_r is the probability of having an answer $R = r$ and the parameter vector $\boldsymbol{\theta} = (\pi, \xi)'$ is defined on the parametric space: $\Omega(\pi, \, \xi) = \{(\pi, \xi) : \, 0 < \pi \leq 1, \; 0 \leq \xi \leq 1\}$.

We denote by $b_r(\xi) = \binom{m-1}{r-1}(1-\xi)^{r-1}\xi^{m-r}$ the shifted Binomial distribution and by $U_r(m) = \dfrac{1}{m}$ the discrete Uniform random variable.

In terms of interpretation of the parameters, the quantity $(1 - \xi)$ can be interpreted as the agreement (*feeling*) towards the 'object'. This consideration may be formally assessed by considering that a positively (negatively) skewed distribution implies $\xi > 1/2$ ($\xi < 1/2$). We may deduce therefore that ξ is related to the predominance of 'disapproving' responses (lower than the midrange). Briefly, the feeling parameter ξ may be interpreted as mostly

[11] Residual analysis and goodness of fit could be analysed with indexes discuss in Hagle and Mitchell (1992), Veall and Zimmermann (1990), and Franses and Paap (2001), among others.

related to location measures and strongly determined by the skewness of expressed ratings: it increases when respondents choose low ratings, and vice versa.

Uncertainty parameter (π) adds dispersion to the shifted Binomial distribution. It is related to heterogeneity and depends on the specific components/values concerning people degree of satisficing behaviour (due, for example, to knowledge or ignorance of the item, personal interest, boredom, engagement, time spent to decide), expressed by the value of $1 - \pi$. In particular, the extreme values of the parameter are associated with:

- complete uncertainty ($\pi = 0$): the mixture resolves to a discrete Uniform random variable where any category has the same probability to be chosen;

- no uncertainty effect ($\pi = 1$): the choices are completely determined by feelings and no measurement error is generated by uncertainty.

Iannario (2010) proved that these models are identifiable for $m > 3$. This probability structure proved flexible for fitting real case studies as it accounts for different skewness, an intermediate mode, peaked and flat distributions (Piccolo 2003).

An interesting consequence of the approach is the ability to identify a collection of estimated CUB models as a set of points located in the parametric space. This representation allows effective comparisons and interpretations of data and models; it has also been exploited by Corduas (2008) for clustering ordinal data.

Inferential issues have been explored by the maximum likelihod method (Piccolo 2006; Iannario and Piccolo 2011) .

Diagnostics and fitting of CUB models have been investigated by Iannario (2009), Di Iorio and Iannario (2011). Among the goodness-of-fit measures proposed, we will refer to the Dissimilarity index (Leti, 1979; Simonoff, 2003) that measures the relative frequency of subjects that would be necessary to move among the cells of the frequency distribution to achieve a perfect fit. It is defined as follows:

$$Diss = \frac{1}{2}\sum_{r=1}^{m} |f_r - p_r(\hat{\pi}, \hat{\xi})|,$$

where f_r are the observed relative frequencies and $p_r(\hat{\pi}, \hat{\xi})$ are the estimated probabilities using the CUB model.

The class of CUB models may be generalized by assuming that, given n subjects, the parameters of satisficing (*uncertainty*) and perception/evaluation (*feeling)* are related to covariates by a logistic function, that is by means of two *systematic components*:

$$\pi_i = \frac{1}{1+e^{-\boldsymbol{x}_i\boldsymbol{\beta}}}\,; \qquad \xi_i = \frac{1}{1+e^{-\boldsymbol{w}_i\boldsymbol{\gamma}}}\,; \quad i=1,2,\dots,n;$$

where $\boldsymbol{x}_i$ and $\boldsymbol{w}_i$ are the observed subjects' covariates and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the associated coefficients. This extension gives the possibility to study separately factors affecting feeling and uncertainty. If p and q covariates are introduced for explaining uncertainty and feeling, respectively, we will denote such structure as a $CUB(p,q)$ models.

For the estimation purposes, if both the π and the ξ parameters are explained by covariates, the log-likelihood function is defined by:

$$\ell(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log\left\{\frac{1}{1+e^{-\boldsymbol{y}_i\boldsymbol{\beta}}}\left[\binom{m-1}{r_i-1}\frac{(e^{-\boldsymbol{w}_i\boldsymbol{\gamma}})^{r_i-1}}{(1+e^{-\boldsymbol{w}_i\boldsymbol{\gamma}})^{m-1}} - \frac{1}{m}\right] + \frac{1}{m}\right\},$$

where the parameter vector has been denoted as $\boldsymbol{\theta} = (\boldsymbol{\beta}',\, \boldsymbol{\gamma}')'$.

This class of models allows interesting results to be obtained with direct interpretation of parameters and possible constructions of respondent' profiles; specifically, in contrast to Ordinal Probit models, links are explicitly assumed among parameters and covariates throughout a monotone non-decreasing function which deserves the ability to relate most probable profiles to respondent's covariates (Iannario and Piccolo 2009b). Of course, the significance of covariates may be statistically assumed by means of ML framework and related asymptotic tests.

As we have seen, another problem in analysing data on individuals' satisfaction is related to the possibility of distortions due to the attractiveness or unattractiveness of specific choices. An extended version of the CUB model, has been developed in order to account for categories more (or less) frequently selected from respondents, labelled as 'shelter choices' (Corduas *et al.*, 2009; Iannario 2011). Formally, the probability distribution of extended model with *shelter effect* is given by:

$$p_r(\boldsymbol{\theta}) = \pi_1\, b_r(\xi) + \pi_2\, U_r(m) + (1-\pi_1-\pi_2)\, D_r^{(c)}\,, \quad r=1,2,\dots,m,$$

where $\boldsymbol{\theta} = (\pi_1,\, \pi_2,\, \xi)'$ is the parameters vector characterizing the distribution of this mixture random variable and $D_r^{(c)}$ is a degenerate random variable located at $r=c$, for $c \in \{1,2,\dots,m\}$. We are assuming that c is a know integer defined on the support (a common situation with real data) but a sequential testing may be assumed if c is unknown. For a given order of components, such models are identifiable only for $m > 4$ and require $\pi_1 > 0$, $\pi_2 \geq 0$, $\pi_1 + \pi_2 \leq 1$, $0 \leq \xi \leq 1$.

Finally, CUB models have been implemented in the R statistical environment using an R code that can be freely downloaded with a detailed documentation (Iannario and Piccolo 2009a).[12]

3.3 Comparisons of the approaches

Although Ordinal Probit and CUB models both achieve similar objectives; however, there are some differences among them since they are generated by different paradigms.

- In Ordinal Probit model the omission of uncertainty adds underlying variability in the estimated models and may hide significant effects; thus, CUB models avoid this possible lack of efficiency in the statistical procedures and inconsistency in the estimates by explicitly modelling this source of measurement errors.

- CUB models specify and measure the role of uncertainty of respondents in a formal manner; thus, the researcher may study its relationship with relevant covariates, as suggested from the literature.

- Ordinal Probit model links mean values and covariates and assumes the same expected rate for different profiles of response. Instead, CUB models explicitly relate subjects' covariates to the unobservable components; thus, the interpretation of feeling and uncertainty seems more immediate.

- Ordinal Probit models imply estimation of threshold values for a latent variable which causes the observed responses; instead, in CUB models latent variables are just logical constructs for motivating the selected mixture and the estimation of cut-points is not required. As a consequence, CUB models are generally more parsimonious.

- In Ordinal Probit models a relationship between parameters and covariates is strictly necessary for fitting purposes, otherwise it is deterministically specified by frequencies; on the other hand, this restriction does not concern CUB models, in which we are not compelled either to include both or use different covariates to explain perception/feeling and/or uncertainty.

[12] The program and the related instructions can be downloaded from: http://www.dipstat.unina.it/cub/cubmodels1.htm.

- Ordinal Probit models imply a visualization by means of distribution functions (Johnson 1987, Becker and Kennedy 1992). They are not immediate for the contemporary visualizations of parameters, thresholds and related impact on responses. On the other hand, visualization of CUB models, performed in the parametric space, is an added value generated by CUB models since these plots improve interpretation of similarity, clusters, modification of patterns, asymmetries, and so on.

- Extended CUB models allow analysts to test and model the presence of *shelter* choices. Ordinal Probit does not account for this feature, usually catched and covered up by a sequence of thresholds; thus, it is not immediate to split the standard behaviour and an atypical category.

From a statistical point of view it is not easy to compare these models. They both assume a connection between a latent variable with some covariates, but using different assumptions with respect to the nature of this relationship. Nevetheless it is still possible to compare the fitting of these models to the data using methodologies developed for non-nested models. In particular, in the empirical analysis we will refer to the Vuong (1989) test.[13]

4 Data description

The Survey on Household Income and Wealth (SHIW, hereafter) has been conducted by the Bank of Italy since 1965 to collect information on the economic behaviour of Italian households and specifically to measure income and wealth components. The main objective is to estimate how these are distributed across Italian households. The basic statistical unit is the household, defined as a group of individuals linked by ties of blood, marriage or affection, sharing the same dwelling and pooling all or part of their incomes.[14] Data collection is entrusted to a specialized company and the interview stage is preceded by a series of meetings at which officials from the Bank of Italy and representatives of the company give instructions directly to the interviewers. The sample includes approximately 8,000 households and is drawn using a two-stage sample design. The questionnaire also collects information on demographics, consumption, savings, and several other topics.[15]

[13] For furhter details about non-nested model comparison, see Clarke and Signorino (2010), among others.

[14] Institutionalized population is not included.

[15] Further details on survey design and on the content of the questionnaire can be found in Faiella *et al.* (2008).

Specifically, with respect to job satisfaction, in 2006 the SHIW asked a sub-sample of workers - those whose household head was born in an odd year - to judge their overall satisfaction at work.

The question used was: *How satisfied are you with your present job? Use a scale from 1 to 10 where 1 stands for 'Very unsatisfied' and 10 for 'Very satisfied'.*

The survey also collected other information regarding their job, like the level of specialization, of work experience and of qualification required from the current activity. The questionnaire contains also a set of hypothetical questions concerning job mobility, like the probability of working for another employer in a short time period, the difficulty for the employer to find a replacement and for the respondent to find a similar job in terms of salary and overall quality. Due to the selection procedure described above, the number of available observations for the empirical analysis is 1290 individuals.

A complete description of the variables contained in the SHIW questionnaire and used in the present work is reported in Table 1. The variables have been arranged into three groups:

1. a first one related to the monetary compensation from the job and to the family economic condition;

2. a second one regards other job characteristics, like that contained in the section on job satisfaction described above, working time, variables related to job security (kind of contract, public job, size of the company), type of job and respondents' working history (past experience);

3. the latter group contains information on individual demographic characteristics (age, gender, marital status), education, geographical collocation (geographical area and town size), health status, risk attitudes and overall well-being.

5 Empirical analysis

In this section we first study the impact of the variables described in paragraph 4 on job satisfaction through the use of a Ordinal Probit and CUB models. We then compare the results obtained with the two models. We refer to Nicoletti (2006) for a recent review of the literature concerning job satisfaction.

5.1 Empirical evidence using Ordinal Probit models

Considering all the statistically significant determinants of global job satisfaction [16], we obtain the Ordinal Probit model reported in Table 2. In the case of Ordinal Probit the interpretation of the coefficients in terms of the effect on the underlying latent variable (global job satisfaction, *global*) is not straightforward for intermediate outcomes, so it is necessary to consider marginal effects of each explanatory variable on the probability of a specified outcome. For the model presented in this subsection, marginal effects are reported in Table 3.[17] The main variable that economists have been studying for its effect on job satisfaction is monetary compensation related to the occupation. The principal reason is linked to its effect on individual income and thus on his satisfaction function (Grund and Sliwka 2001).

In our model a higher level of individual income (*indincome*) increases the probability to reach greater outcomes in job satisfaction. Among monetary variables also individuals' perception of general family economic condition (*familycond*) moves in the same direction (although with a lower strength), showing that people whose total household's income is considered sufficient for family expenses (once accounted for their individual income) are more satisfied at work.[18]

With respect to job characteristics, job security is considered a relevant determinant of overall job satisfaction (Blanchflower *et al.* 1999). Jobs with permanent contracts (Kaiser 2002) or in the public sector (Ghinetti

[16] We present the result obtained by removing all the covariates not statistically different from zero at 5% level. The model is estimated using sampling weights and 334 Jackknife Repeated Replications for the estimate of parameters' standard errors. For further details about the SHIW Sampling Error Calculation Model see Faiella (2008)

[17] For dummy variables we also calculated the 'Average Treatment Effect' (ATE hereafter), which summarizes the mean effect of the presence of a certain characteristic on the level of job satisfaction when all the other covariates are evaluated at their mean. Following Ghinetti (2007), this value is obtained as the weighted sum of the differences in the predicted probabilities for respondents with and without the selected characteristic (i.e. for the ith dummy variable $D_i = 1$ or $D_i = 0$) using the following formula: $ATE_i = E(global|D_i = 1) - E(global|D_i = 0) = \sum_{j=0}^{J} j * [Pr(global = j|D_i = 1)] - [Pr(global = j|D_i = 0)]$.

[18] It should be noted that, although these two variables present an obvious correlation (equal to 0.5 in our data) they express two different concepts. *Familycond* is only partially determined from individuals' income (*indicome*), even in households with only one member, as it reflects also individual's expectations and the comparison with the external socio-economic context. To verify the presence of multicollinearity in the model, potentially introduced from the contemporaneous use of these variables, the Variance Inflaction Factor has been calculated. Values are not larger than 2 for all the included covariates in the model, ruling out the presence of multicollinearity.

2007) are usually perceived as less risky and thus associated with higher job satisfaction.

These results are confirmed by our estimated model since the variables related to job security are statistically significant and show the expected sign: workers with a permanent contract (*indet*) and working in the public sector (*public*) have a higher level of job satisfaction.[19] The size of the firm (*size-firm*) and the presence of occasional work (*occasional*) are not statistically different from zero once controlled by the former variables.

Another variable among job characteristics that is considered as having an effect on job satisfaction is the amount of hours worked. Infact, more time dedicated to a job can be associated with a higher salary or higher gratification. On the other hand, when the hours of work exceed what can be defined as a "subjective threshold" the marginal utility of leisure is greater than the marginal utility of work.[20] Nevertheless, none of the considered variables related to working time are statistically different from zero in our model, probably due to their correlation with income.

With respect to the other characteristics of the respondent's work, employment status (*bluecoll, offwork, manager, profess, selfemp*) shows no statistical significance, while among the branch of activity (*agricoulture, industry, pubadm, othersec*), only *industry* is statistically different from zero and has a negative impact on job satisfaction (on average, working in this sector reduces reported job satisfaction by 0.36 points).

More years of experience in the current activity (*expyear*) have a negative effect on job satisfaction, while having changed employer in the last two years (*changeempl*) increases job satisfaction (the ATE of the latter variable is 0.58). These variables show appreciation of workers with respect to heterogeneity in their occupation experiences. Higher satisfaction levels are reached by workers with a specialized job (*specialize*).

Among the variables related to the consistency between the skills possessed by the worker and those required by their occupation, working in a task below their level of experience (*lessexp*) makes people less gratified (on average reported satisfaction decreases by 0.62 points).[21] Finally, the difficulty of being replaced from the employee (*equival*) is not statistically

[19] The ATE for these variables is equal to 0.72 and 0.39 respectively, in line with what find in Ghinetti (2007).

[20] Bijwaard *et al.* (2008) show that the discrepancy between the actual and the desired number of hours worked can lead to dissatisfaction and job mobility.

[21] This result is in line with the findings of De Grip *et al.* (2009) who argue that workers performing jobs requiring a lower level of competence, with respect to the one they have, are less satisfied.

different from zero in this model.

A positive effect on job satisfaction can also be attributed to workers' health status (*health*).[22] People reporting better physical health are more probably satisfied on-the-job while health problems or disabilities can generate obstacles in the working environment or a worse occupational status and thus lead to lower levels on-the-job satisfaction (Fischer and Sousa-Poza 2008).

In this model, education (*educat*) has a negative effect on job satisfaction. This can be ascribed to the fact that higher education is usually associated with higher expectation with respect to working status and thus it can generate disappointment when there is a mismatch between worker aspirations and current job conditions (Clark and Oswald 1996).

Age can increase employees' job satisfaction as these traits are usually associated with higher organizational commitment and confidence in one's skills (Kumar and Giri 2009). Another finding in the literature is that also very young workers usually show a higher level of job satisfaction, possibly due to the presence of positive expectations in future working conditions. Therefore, we expect the age to show a non-linear U-shaped relationship with job satisfaction (Clark 1996). Nevertheless, in this model, *age* is not statistically different from zero as its effect on job satisfaction is probably already accounted for the years of experience.

With respect to gender and family composition, we haven't found any of the considered variables (*gender*, having children (*nchild*), being married (*married*), the presence of an elder person in the family (*elderly*), the number of components (*compon*) or of earners (*earners*)) to be statistically different from zero.

Following Cornelissen *et al.* (2008), risk inclined workers may reach a higher level of job satisfaction, for example by moving into more interesting, but riskier positions or by choosing performance pay jobs. However, we found no influence of individuals' risk attitude towards financial instruments (*riskatt*) on worker satisfaction.

Finally, with respect to geographical factors, the location of the region of residence (*north, centre, south*), the town size (*townsize*) and citizenship (*citizen*) were not statististically different from zero in the estimated model.

Figure 1 and 2 provide a graphical representation of some of the results obtained with the Ordinal Probit model. In particular, they contain a comparison of predicted probabilities for job satisfaction arranged in 3 classes

[22]The negative sign of health is due to the reverse scale adopted to measure this variable, see Table 1.

(1-4 low, 5-6 medium, 7-10 high) for different combinations of personal, income and job related characteristics.

In Figure 1 we consider a benchmark individual labelled as "benchmark job" which is endowed with the maximum level of individual income we observed in the sample and a permanent contract in the public sector. All the other variables are set to median values. We then observe the shift in predicted probabilities we obtain when we change one of those characteristics at time. For example, if we shift the level of income to the minimum we observe in the sample, predicted probabilities at high level of job satisfaction become lower, while those at low and medium levels rise. The same happens when we shift to fixed term contract or the private sector, but with different magnitudes. In particular, we observe that the higher probability to report low level of job satisfaction is obtained with the reduction of the salary, while the effect of working in the private sector generates the minimum change to predicted probabilities distribution.

In Figure 2 we consider the effect of personal characteristics and of the economic condition of the family. The benchmark individual (benchmark personal) has excellent health conditions, no educational qualification and reports the best family economic conditions. Also in this case, all the other variables are set to median values. Keeping the same characteristics, but shifting to very poor health status (*bad health*), makes it less probable to achieve the high levels of job satisfaction, while it substantially raises the probability that it reaches lower levels. Keeping constant the other characteristics, individuals with higher level of education (in this case we consider those having at least a five-year university degree) are less likely to be very satisfied at work. Finally, a similar effect is obtained when we shift to those declaring to have problems to make ends meet (*bad family condition*).

5.2 Empirical evidence using CUB models

Data collected in the section relative to job satisfaction have also been inspected through the use of CUB models. As we have seen in paragraph 2, the measurement of the true latent variable can be biased due to the presence of psychological mechanisms that can affect the response behaviour. Using CUB models we can represent all these features by separating the measurement error component (it modifies the heterogeneity of the distribution and reflects the degree of satisficing in answering the ordinal question) from the feeling, which contains the true opinion with respect to the item.

Before going through the model (similar to that reported in the previous subsection) and using the peculiarities of this class of models, we present several considerations on the structure of variables and their performances obtained implementing this class of models. Figure 3 shows a graphical representation of the results in terms of feeling and uncertainty for five variables concerning ordinal rating related to the *job session* reported in SHIW sample.[23]

With respect to uncertainty, it is possible to observe that respondents answer the questions with a low uncertainty regarding their level of job satisfaction[24] (*global*), the perceived probability to change job (*changeprob*) and the level of specialization of their job (*specialize*). On the other hand, uncertainty increases when hypothetical questions are addressed, like the ones relative to the difficulty in finding a similar job to the one the person is occupied at the moment (*otherjob*) or for the employer to find a replacement (*equival*). With respect to feeling, results are consistent among the different questions. Once corrected for uncertainty, on average, respondents show a high level of job satisfaction, and report a low probability to change their job. They think their work is quite specialized and that it would be difficult for their employer to find a replacement for their position. Respondents also think that it would be difficult to find a similar job in terms of salary and overall quality.

From the inspection of the information provided by the interviewer[25], we observe that all the opinions about the quality of the interview show quite high level of feeling and they are answered with a low level of uncertainty (Figure 4). This can be the result of a psychological motivation that induces the interviewer to judge better the interviews as these opinions can somehow be an indicator of his behaviour or of the quality of his job. We can therefore observe only slight differences among the items. The rate on the reliability of the information on income and wealth provided by the interviewee (*trueincome*) seems to be the item with higher uncertainty and lower feeling.

If we focus on job satisfaction, the graphical inspection of the distribution of answers with respect to the one predicted by the CUB model without covariates shows a good fit (Figure 5, left panel).

[23] All the results are obtained using sampling weights. The construction of design-based variance estimators for CUB models is currently under study (Gambacorta, Iannario, and Valliant 2012).

[24] This is the ordinal variable we have chosen to summarize the global level of job satisfaction. The low uncertainty in this answer is a proxy of personal interest, certitude, awareness in the answer.

[25] With respect to this item five variables are available, see last part of Table 1 for a complete description.

It should be noted that in this case the *shelter* effect (right panel) *gains* the high level of respondents' score in one particular answer.[26] Specifically, this effect allows the reasons (of psychological nature) which could draw people to assign the maximum amount of a scale to their feeling. This result is consistent with the presence of a *social desirability bias* as discussed in paragraph 2.

The performance of the CUB model with respect to both feeling and uncertainty is reported in Table 4. Uncertainty in job satisfaction response is mainly driven from the perception of overall life well-being: people that declare higher level of happiness tend to answer with less uncertainty. It supports the idea that individual state of mind influences respondent commitment in providing accurate answers.[27] With respect to feeling towards job satisfaction, better perceived economic family condition (*familycond*), working in the public sector (*public*) or in a job with permanent contract (*indet*) increase respondents' feeling through job satisfaction, probably due to its positive effect on job security. This direction is confirmed for workers that show a higher consideration for their working skills, because they think it would be easy for them to find a similar job (*otherjob*), consider their job as specialized (*specialize*) or that have changed employee in the last two years (*changeempl*).

Moreover, respondents with a job requiring less work experience (*lessexp*) have a negative effect on job satisfaction probably due to the presence of a non-stimulating job.

In Figure 6 we show the effect of two statistically significant covariates respectively on uncertainty and feelings components of respondents about job satisfaction. In the top side of Figure 6 we notice the level of uncertainty related to interviewees response about overall life well-being (*happiness*), performed as covariate on π parameter. Specifically, it is possible to observe a reduction of uncertainty in the expressed ratings with increasing overall life satisfaction. In the bottom of Figure 6 we observe that satisfaction about the family economic condition (*familycond*) results in higher level of feeling towards job satisfaction. From the Figure it can also be noted that, other variables being equal, open ended workers (blue with indet=0, public=0) are

[26] As mentioned we define as a *shelter choice* the modality that receives an upward bias of preference with respect to the expected response of the maintained model. In this case, the maximum value of the scale shows higher levels with respect to the responses predicted from the model.

[27] Once this variable is considered, the other predictors that may be related to respondents' likelihood of satisfacing, like the level of education or age, are not statistically significant in the model.

less satisfied with respect to their job.

Finally, to draw a more comprehensive summary of the estimated model, we present in the parametric space (Figure 7) two plots concerning all estimated covariates of the comprehensive CUB(1,7) model reported in Table 4.[28] We present the cluster results for respondents who did not change employer or type of work (left panel) and people who change them (right panel) with a fixed level of uncertainty. In this coupled graphic it is possible to observe the higher level of satisfaction for the second cluster by stressing the level of distance between different grades of satisfaction with blue for earned income and green for open-ended jobs.

5.3 Comparing Ordinal Probit and CUB models

If we compare the results obtained with Ordinal Probit and CUB models, we found that most of the variables resulting in exerting a significant impact on job satisfaction are similar. The exceptions are individual income, health, education, years of experience and industry which were not statistically different from zero in estimated CUB models and the easyness to find another job which was, on the other hand, only significant in CUB models. This latter result assumes therefore a lower number of covariates than Ordinal Probit Model for catching the most relevant results of global satisfaction. In addition, in CUB models it is not necessary to estimate cut-points as in Ordinal Probit, therefore achieving an adequate fitting of the data but with a more parsimonious model. The main difference among the two models pertains to the introduction of uncertainty in CUB models that allows to filter the data from this source of measurement error and to explicitly model it. Furthermore, the extended CUB model used shows the presence of a shelter effect due to the tendency of respondents to score (more than expected) extreme positive values. Therefore we may think that models that do not account for this psychological process in the production of response may be biased (Iannario 2011).

Finally, we have to considered the problem of choosing between statistical models that are non-nested in terms of their functional forms. In order to evaluate the fitting ability, a formal assessment about the selection of the

[28] In this Figure, the *familycond* covariate is expressed in three different levels -low, medium and high- obtained with weighted average of frequencies. For ordinal covariates we use the mode as reference value; the dummies, instead, are treated through two different profiles: with flexible/open-ended job (indet=0, public=0) represented with green colour; with earned income/safe job (indet=1, public=1) represented with blue colour; the four profiles concerning the differences between respondents who changed employer or type of work during last two years. They express the extreme limits.

best model may be formally pursued by the Vuong (1989) test . In this case, we get an observed statistic of $t_n = 3.730$. Choosing a critical value from the standard normal distribution, we reject null hypothesis that models are the same in favor of CUB models with a p-value less than 0.0001. In addition, if we follow Vuong's suggestions and modify such test by a sort of BIC criterion (to take different numbers of parameters into account) we get an adjusted test of statistic of $t'_n = 4.229$ with an approximate p-value less than 0.0001 which confirms a preference for CUB models. Given the sample size ($n = 1290$), a distribution-free test (Clarke, 2003; 2007) would reach similar conclusion.

6 Conclusions

This paper provides an empirical analysis of the determinants of job satisfaction in Italy using data from the SHIW collected from the Bank of Italy. Specifically, we compared Ordinal Probit and CUB models applied to a rating scale for measuring job satisfaction.

Since models derive from different assumptions regarding the selected variables, comparison of results should be done with caution. We observe that both model gather similar results with respect with a subgroup of covariates, but CUB models are generally more parsimonious. Furthermore, from a statistical point of view the comparison of the two models provides results supporting CUB models as those showing the best fit. We can therefore infer that statistical significance of variables which present an effect on job satisfaction only in the Ordinal Probit may be the result of the presence of measurement errors due to respondent uncertainty that cannot be accounted for in this class of model.

The study of the psychological factors affecting the elicitation process is particularly interesting for questions regarding personal attitudes, like in the case of job satisfaction, and CUB models have shown to be particularly useful with this respect. Indeed the estimated CUB models show the presence of uncertainty in the answer process regarding job satisfaction, mainly driven from respondents' state of mind, and are able to capture a response bias by means of a *shelter* effect.

In this context we implemented two alternative models which cast light on generating process of answers. Our conclusion is therefore that the choice between CUB models and standard Ordinal Probit should be pursued from the researcher in function of the exposure of the studied variables to measurement errors due to psychological causes and of its potential effect on inherent inference. If, like in the case of job satisfaction, these factors can have a relevant impact on the data, CUB model offers a more appropriate way to study the phenomena.

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Figures and Tables

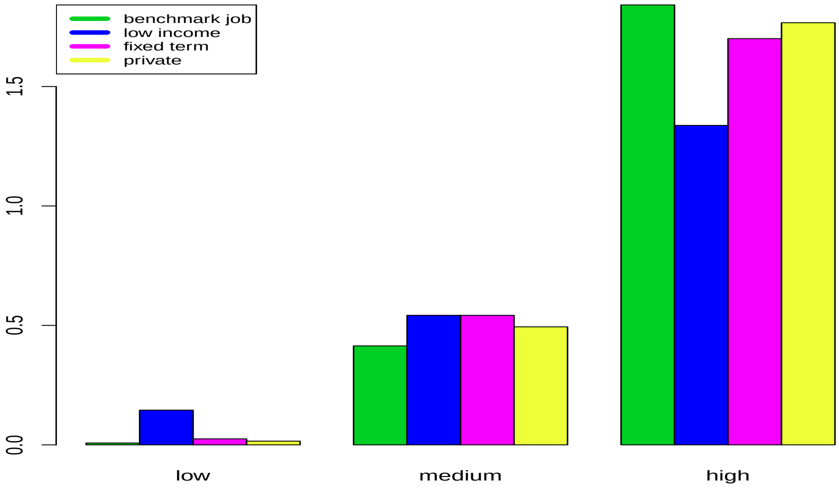

Figure 1. Job satisfaction predicted probabilities for different monetary and job related characteristics

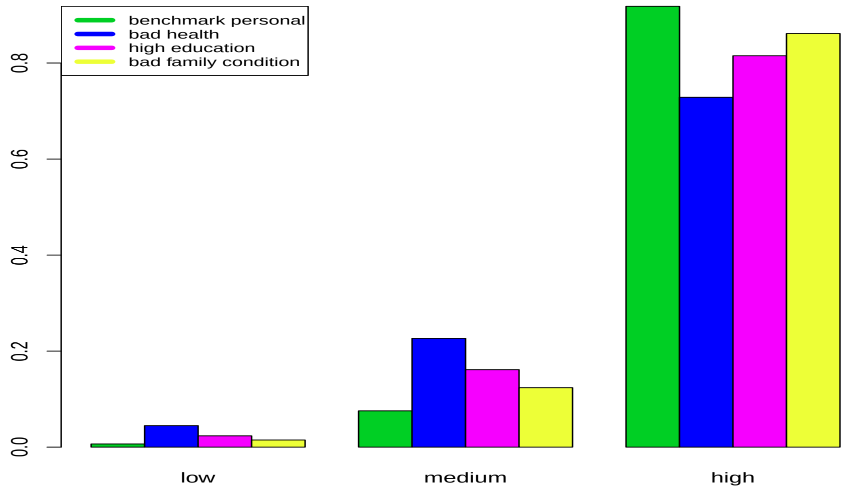

Figure 2. Job satisfaction predicted probabilities for different personal characteristics and family economic conditions

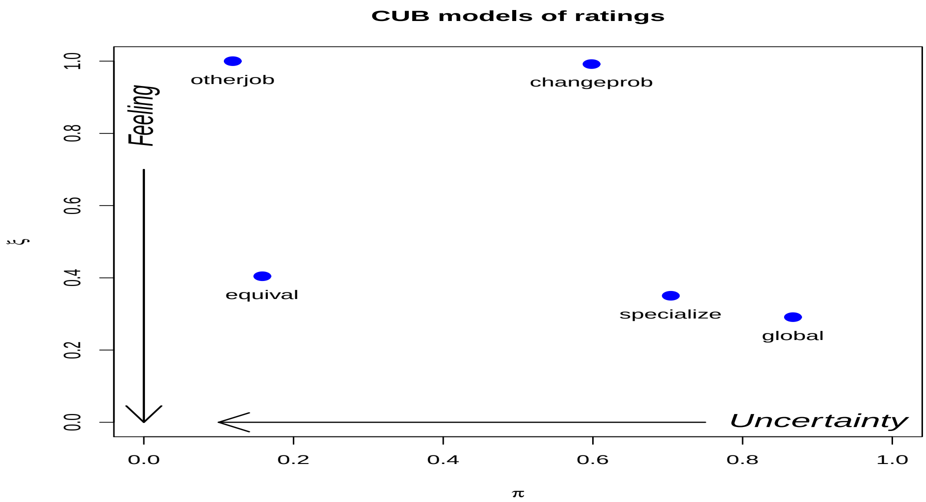

Figure 3. CUB models of ratings

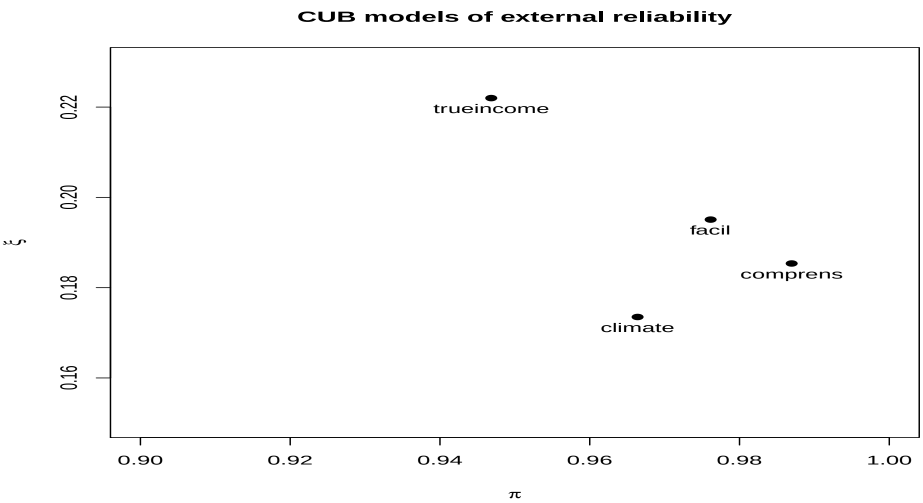

Figure 4. CUB models of external reliability.

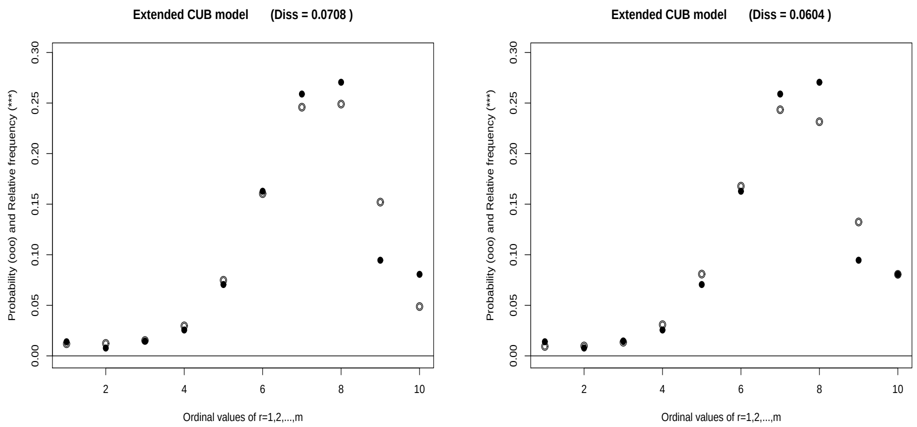

Figure 5. Estimated CUB (0,0) models of global satisfaction (left panel) with *shelter* effect in $c = 10$ (right panel).

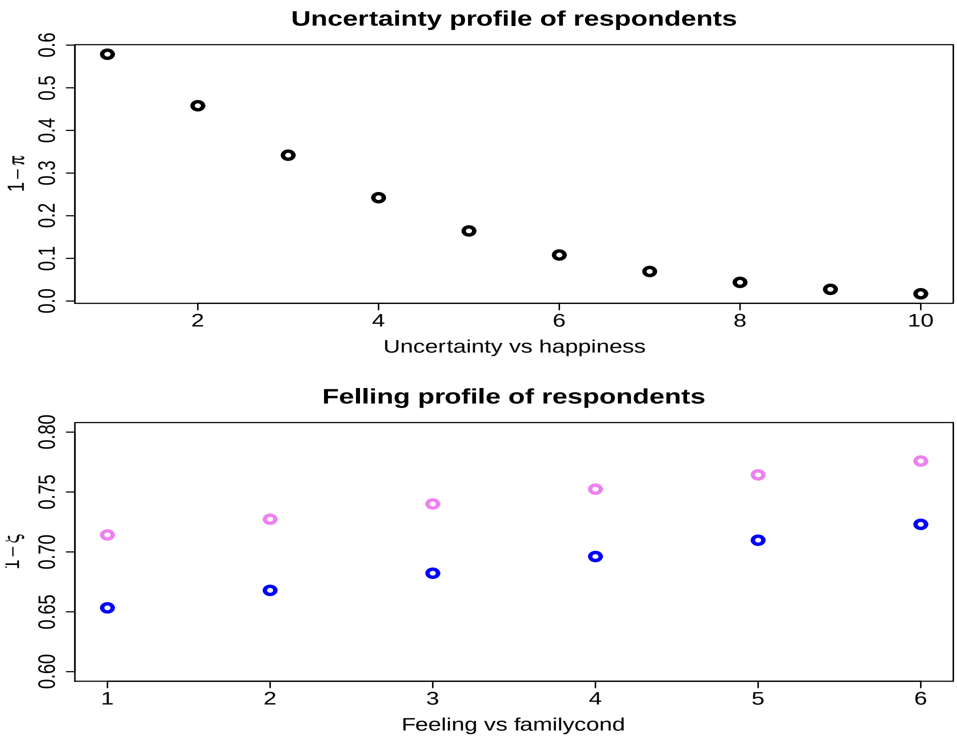

Figure 6. Profiles for comprehensive CUB models by varying happiness for uncertainty and economic family conditions for feeling parameters.

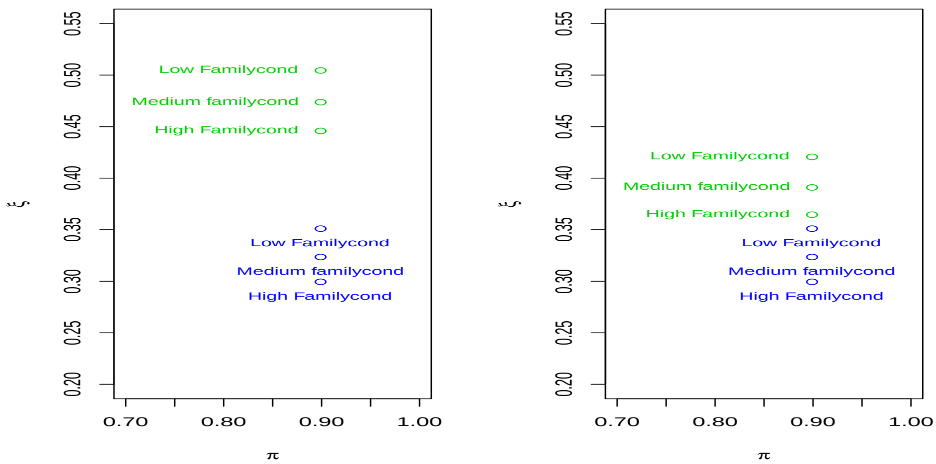

Figure 7. Profiles for comprehensive CUB models by varying Changed employer or type of work (change, right panel - not change, left panel), work security (blue, earned income/safe job - green, flexible/open-ended job) and economic family condition for feeling parameter.

Table 1. List of variables

Name of the variable	Description
global	ordinal overall job satisfaction indicator from 1 (very unsatisfied) to 10 (very satisfied)
Monetary compensation and family economic condition	
indincome*	total individual income
familycond	household's income sufficient to see the family through to the end of the month: from 1 (with great difficulty) to 5 (very easily)
Other job characteristics	
indet	dummy for permanent contracts (only payroll employees)
occasional	dummy for occasional work
sizefirm	company size
public	dummy for employment in the public sector
expyear	years of experience in the current activity
newjob	dummy for having searched for a new job during the year
changeempl	dummy for changed employer or type of work in the last two years
changeprob	probability to be working for another employer in six months' time 1 (low prob) 10 (high prob)
equival	difficulty/easiness for your employer to find a replacement from 1 (very difficult) to 10 (very easy)
otherjob	difficulty/easiness for the respondent to find a similar job in terms of salary and overall quality from 1 (very difficult) to 10 (very easy)
specialize	how specialised is your work from 1 (not at all specialized) to 10 (highly specialized)
lessexp	dummy for job requiring less working experience
bluecoll	dummy for blue-collar worker
offwork	dummy for office worker or school teacher
manager	dummy for cadre or manager
profess	dummy for sole proprietor/member of the arts or professions
selfemp	dummy for other self-employed
agricoulture	branch of activity: dummy for agricoulture
industry	branch of activity: dummy for industry
pubadm	branch of activity: dummy for public administration
othersec	branch of activity: dummy for other sector

*Box-Cox Transformation adopted

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Name of the variable	Description
Personal characteristics	
gender	dummy for females
citizen	dummy for Italian citizen
age	age of the individual in years
married	dummy for married
north	dummy for living in the northern regions of Italy
centre	dummy for living in the central regions of Italy
south	dummy for living in the southern regions or in the main islands of Italy
townsize	town size class (0-20.000 inhabitants, 20.000-40.000, 40.000-500.000, more than 500.000 inhabitants)
educat	education degree
compon	no. of household members
nchild	no. of children in the household
elderly	dummy for at least one person over 65 in the household
earners	no. of household income earners
health	health status from 1 (excellent) to 5 (very poor)
riskatt	risk attitude indicator (in financial investments) from 1 (high) to 4 (low)
happiness	overall life well-being indicator from 1 (Very unhappy) to 10 (very happy)
Information provided by the interviewer	
comprens	interviewee level of understanding of the questions from 1 (low) to 10 (high)
trueincome	reliability of the information on income and wealth provided by the interviewee from 1 (low) to 10 (high)
climate	general atmosphere is which the interview took place from 1 (low) to 10 (high)
facil	easiness for the interviewee to answer the questions from 1 (low) to 10 (high)

Table 2. Job satisfaction: *Ordinal Probit* model estimates

Variable	Value	Std. Error	Wald test
	Value	Std. Error	Wald test
indincome	0.2940	0.1156	6.4651
familycond	0.0762	0.0386	3.8918
indet	0.4752	0.1609	8.7215
public	0.2717	0.1406	3.7347
industry	-0.2466	0.0969	6.4750
expyear	-0.0123	0.0053	5.4926
changeempl	0.4151	0.2018	4.2297
specialize	0.1662	0.0243	46.6164
lessexp	-0.4149	0.1653	6.3012
health	-0.1958	0.0487	16.1859
educat	-0.1236	0.0618	3.9969
intercepts			
cut-point 2	0.2846	0.4158	0.4684
cut-point 3	0.1022	0.406	0.0633
cut-point 4	-0.1571	0.4273	0.1352
cut-point 5	-0.4797	0.4181	1.3166
cut-point 6	-0.9241	0.4199	4.8429
cut-point 7	-1.5682	0.4422	12.5753
cut-point 8	-2.3436	0.4338	29.1821
cut-point 9	-3.2245	0.4289	56.5294
cut-point 10	-3.7372	0.4218	78.4862

Table 3. *Ordinal Probit* marginal effects and average treatment effects

Variable	$Pr(global = j)$										
$j =$	1	2	3	4	5	6	7	8	9	10	ATE**
indincome	-0.005	-0.003	-0.006	-0.012	-0.025	-0.044	-0.021	0.046	0.034	0.036	
	(0.002)	(0.002)	(0.003)	(0.005)	(0.010)	(0.019)	(0.009)	(0.017)	(0.014)	(0.016)	
familycond	-0.001	-0.001	-0.002	-0.003	-0.007	-0.011	-0.005	0.012	0.009	0.009	
	(0.001)	(0.000)	(0.001)	(0.002)	(0.003)	(0.006)	(0.003)	(0.006)	(0.005)	(0.005)	
indet*	-0.014	-0.007	-0.014	-0.024	-0.045	-0.066	-0.009	0.086	0.048	0.044	0.72
	(0.008)	(0.004)	(0.007)	(0.013)	(0.018)	(0.020)	(0.009)	(0.031)	(0.014)	(0.014)	
public*	-0.004	-0.002	-0.005	-0.010	-0.022	-0.041	-0.024	0.038	0.032	0.038	0.39
	(0.002)	(0.002)	(0.003)	(0.005)	(0.011)	(0.022)	(0.013)	(0.018)	(0.017)	(0.023)	
industry*	0.005	0.003	0.006	0.011	0.022	0.037	0.015	-0.040	-0.028	-0.029	-0.36
	(0.003)	(0.001)	(0.003)	(0.004)	(0.009)	(0.014)	(0.007)	(0.017)	(0.011)	(0.011)	
expyear	0.000	0.000	0.000	0.001	0.001	0.002	0.001	-0.002	-0.001	-0.002	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	
changeempl*	-0.005	-0.003	-0.007	-0.013	-0.030	-0.061	-0.045	0.049	0.049	0.066	0.58
	(0.002)	(0.002)	(0.003)	(0.007)	(0.012)	(0.028)	(0.030)	(0.015)	(0.024)	(0.041)	
specialize	-0.003	-0.002	-0.003	-0.007	-0.014	-0.025	-0.012	0.026	0.019	0.021	
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	
lessexp*	0.012	0.006	0.012	0.021	0.040	0.058	0.009	-0.075	-0.042	-0.039	-0.62
	(0.008)	(0.004)	(0.007)	(0.011)	(0.018)	(0.022)	(0.008)	(0.033)	(0.015)	(0.011)	
health	0.003	0.002	0.004	0.008	0.017	0.029	0.014	-0.031	-0.022	-0.024	
	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.008)	(0.004)	(0.008)	(0.006)	(0.007)	
educat	0.002	0.001	0.003	0.005	0.011	0.019	0.009	-0.019	-0.014	-0.015	
	(0.001)	(0.001)	(0.001)	(0.003)	(0.006)	(0.010)	(0.004)	(0.009)	(0.007)	(0.008)	

Note: All marginal effects are computed at means of the explanatory variables, standard errors reported in brackets; * For dummy variables marginal effects are computed as the differences in predicted probabilities induced by the shift from 0 to 1 of that variable.
** The Average Treatment Effect (ATE_i) for the ith dummy variable D_i is calculated as (see Ghinetti, 2007, note 14):
$ATE_i = \sum_{j=0}^{J} j * [Pr(global = j|D_i = 1)] - [Pr(global = j|D_i = 0)]$.

Table 4. Job satisfaction: CUB *model* estimates

Variable	Value	Std. Error	Wald test
	CUB *Model*		
π_i			
constant	-0.8029	0.9438	-0.8508
happiness	0.4858	0.1432	3.3921
ξ_i			
constant	0.6553	0.1346	4.8702
familycond	-0.0652	0.0205	-3.1785
indet	-0.3914	0.0753	-5.1980
public	-0.2411	0.0569	-4.2367
changeempl	-0.3380	0.0775	-4.3629
otherjob	-0.0268	0.0090	-2.9822
specialize	-0.1227	0.0128	-9.6152
lessexp	0.3503	0.0804	4.3550

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