The Journal of Socio-Economics 40 (2011) 700–708

Contents lists available at ScienceDirect

The Journal of Socio-Economics

journal homepage: www.elsevier.com/locate/soceco

Measuring inequality of subjective well-being: A Bayesian approach☆

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ARTICLE INFO

Article history:
Received 18 February 2010
Received in revised form 20 April 2011
Accepted 30 May 2011

JEL classification:
C11
C35
D63
I3

Keywords:
Bayesian ordered probit model
Markov chain Monte Carlo (MCMC)
Regretted subjective well-being

ABSTRACT

This article proposes a new measure for inequality of subjective well-being and shows the empirical results using a Bayesian ordered probit model. We introduce a new concept called "regret" as a measure for inequality of subjective well-being. Regret is the probability with which a respondent who chooses an option in a multiple-choice question pertaining to subjective well-being does not choose any other option indicative of better well-being. Regret is estimated in connection with demographic factors using the Markov chain Monte Carlo (MCMC) method and data of the World Values Survey. Furthermore, the relationships between regret and GDP per capita and the changes therein are shown to investigate those between inequality of subjective well-being and economic conditions.

1. Introduction

There has been considerable research on happiness (see, e.g. Frank, 1999; Frey and Stutzer, 2002; Layard, 2005). In particular, Frey and Stutzer (2002) conducted a detailed literature survey and carried out an empirical analysis on happiness. In the empirical analyses presented by Frey and Stutzer (2002, Chapter 3) and Blanchflower and Oswald (2004), happiness is regarded as life satisfaction. For example, the research by Blanchflower and Oswald (2004) deals with the degree of happiness in the United States, while their empirical analyses deal with life satisfaction in the United Kingdom.

The comments of Becker and Rayo (2008) and Krueger (2008) on Stevenson and Wolfers (2008a) are useful in understanding the difference between happiness and utility. Stevenson and Wolfers (2008a) show a positive relationship between GDP and subjective well-being across countries. However, Becker and Rayo (2008) note that the differences between utility and happiness are paid scant attention to in Stevenson and Wolfers (2008a) and that happiness is not a measure of utility but a commodity like other commodities usually used in the utility function.[1] Krueger (2008) also makes a similar comment on the relationship between subjective well-being and utility.[2]

This article primarily aims to propose a new measure for subjective well-being and to show the empirical analyses using a Bayesian ordered probit model. In a questionnaire survey concerning subjective outcomes such as subjective well-being, options are often ordinally arranged. An ordered probit model can be used to statistically analyze the data on such ordinal options. Kalmijn and Veenhoven (2005) state the possibility such that "an egalitarian policy aimed at reducing differences in happiness would differ from a utilitarian policy aimed at producing a higher average level of happiness."[3] That is, a society with the lowest level

[1] See Becker and Rayo (2008, pp. 88–89).

[2] "At best, subjective well-being captures a component of utility." See Krueger (2008, p. 100).

[3] "The main reason for looking at inequality of happiness in nations is in the possibility that this may reveal differences across nations other than those observed for the level of happiness. If so, this would mean that an egalitarian policy aimed at reducing differences in happiness would differ from a utilitarian policy aimed at producing a higher average level of happiness. To check this possibility we need measures for the general happiness level of a nation or nations and for inequality of the same, which are mutually independent, at least ideally." (Kalmijn and Veenhoven, 2005, p. 359).

☆ The authors appreciate the comments of anonymous referees, which improve the article greatly. The work of the first author was supported in part by a Grant-in-Aid for Scientific Research (No. 19530177) from the JSPS, while that of the first and second authors was supported in part by a Grant-in-Aid for Scientific Research (No. 21530203) from the JSPS.

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doi:10.1016/j.socec.2011.05.009

of happiness for all individuals is equal but unhappy, whereas a society in which a few people have the lowest level of happiness and most have the highest level of happiness is a happier one. Thus, it is necessary to consider an index that identifies an individual's situation at each level of happiness, or each ordinal option.

Subsequent to Albert and Chib's (1993) seminal work, which utilizes latent variable representation, the Bayesian analysis using the Markov chain Monte Carlo (MCMC) method has become popular for the estimation of the ordered probit model.[4] One merit of the Bayesian analysis is that we can obtain the values of latent variables directly from the posterior results.[5] In this article, using the probabilities associated with the values of the latent variables, we propose a new concept called "regret" to measure subjective well-being. Subjective well-being is often investigated using surveys that are responded to by choosing an option representing its degree. Regret is the probability with which a respondent who chooses an option in a multiple-choice question pertaining to subjective well-being does not choose any other option indicative of better well-being. Thus, it enables us to capture the degree of unhappiness of the respondents.

Further, how to measure inequality of happiness is a major research issue. Kalmijn and Veenhoven (2005) consider nine statistics of inequality of happiness and conclude that four measures, including the standard deviation and the mean absolute difference, are suitable statistics to measure inequality, but the other five measures, including the Gini coefficient and Theil's entropy measure, are not suitable for both theoretical and empirical reasons.[6] Stevenson and Wolfers (2008b) estimate the mean and variance of happiness with the ordered probit model using the data of the General Social Survey (GSS) and show that inequality of happiness has declined in the United States since the 1970s. They use the variance as a convenient measure of inequality of happiness and decompose it to "within-group" variance and "between-group" variance to analyze the influence of change in the average level of happiness.[7] In these previous studies, inequality of happiness is computed using numerical values to represent the rating of happiness, which are measured with ladder scale and verbal rating scale. They measure inequality of happiness using ordinal variables. Thus, differences of happiness between people are not measurable and ignored as pointed out in Kalmijn and Veenhoven (2005).[8]

Regret is computed using a Bayesian ordered probit model in this article. It is possible to compute the individual regret and the average regret of a country. It is also possible to analyze inequality of happiness using distributions of regret and some inequality measures of regret. Thus, regret can denote an index of subjective well-being of a country and be used for time-series and cross-national comparisons of subjective well-being. These are the advantages in regret.

The empirical analyses on subjective well-being across countries are conducted using the data of the World Values Survey (WVS). Regret is estimated in connection with the demographic factors. The relationships between regret and GDP per capita are shown to investigate those between subjective well-being and economic conditions. For some countries, regret and GDP per capita were found to change in the same direction, which means that their subjective well-being decreases despite economic growth, and vice versa.[9]

The article proceeds as follows. In Section 2, we describe the Bayesian ordered probit model and its estimation procedure by using the algorithm in Nandram and Chen (1996) and Chen and Dey (2000). One merit of Bayesian analysis is that we can obtain the values of latent variables directly from the posterior results. In Section 3, using the values of latent variables, we propose a new inequality measure of subjective well-being. In Section 4, we present the posterior results for this measure using WVS data. Section 5 provides the concluding remarks.

2. Bayesian ordered probit model

Let y_i denote the ordinal discrete response of individual i for $i = 1, \ldots, n$; that is, $y_i = c$ for $c = 1, \ldots, C$. Further, let z_i denote the latent variable of individual i such that

$$y_i = c \quad \text{if} \quad z_i \in (\gamma_{c-1}, \gamma_c], \quad i = 1, \ldots, n, \quad c = 1, \ldots, C, \tag{1}$$

where γ_c is a cutoff point of ordinal response. We specify that

$$-\infty = \gamma_0 < \gamma_1 = 0 < \gamma_2 < \cdots < \gamma_{C-1} < \gamma_C = \infty,$$

where the condition $\gamma_1 = 0$ is required to establish the identifiability of the cutoff parameters.[10] The latent variable z_i is assumed to be determined by the following linear model:

$$z_i = \boldsymbol{x}_i'\boldsymbol{\beta} + u_i, \quad i = 1, \ldots, n,$$

where $\boldsymbol{x}_i = (x_{i1}, \ldots, x_{ik})'$ and $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_k)'$. Defining

$$\boldsymbol{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}, \quad \boldsymbol{z} = \begin{pmatrix} z_1 \\ \vdots \\ z_n \end{pmatrix}, \quad \boldsymbol{X} = \begin{pmatrix} \boldsymbol{x}_1' \\ \vdots \\ \boldsymbol{x}_n' \end{pmatrix}, \quad \boldsymbol{u} = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix},$$

the linear model for the latent variables is rewritten as

$$\boldsymbol{z} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u}.$$

Now, we assume that $\boldsymbol{u} \sim \mathrm{N}(\boldsymbol{0}, \sigma^2\boldsymbol{I}_n)$, that is,

$$\boldsymbol{z}|\boldsymbol{\beta}, \sigma^2, \boldsymbol{X} \sim \mathrm{N}(\boldsymbol{X}\boldsymbol{\beta}, \sigma^2\boldsymbol{I}_n). \tag{2}$$

Furthermore, following Nandram and Chen (1996) and Chen and Dey (2000), we assume that $\gamma_{C-1} = 1$; this is in addition to $\gamma_1 = 0$.[11] Since γ s are restricted as $0 < \gamma_2 < \cdots < \gamma_{C-2} < 1$, Chen and Dey (2000) propose the following transformation of cutoff points:

$$\delta_c = \log\left(\frac{\gamma_c - \gamma_{c-1}}{1 - \gamma_c}\right), \quad c = 2, \ldots, C-2, \tag{3}$$

where $\boldsymbol{\delta} = (\delta_2, \ldots, \delta_{C-2})'$ is unrestricted. The prior distributions are specified as follows:

$$p(\boldsymbol{\beta}, \sigma^2, \boldsymbol{\delta}) = p(\boldsymbol{\beta})p(\sigma^2)p(\boldsymbol{\delta}),$$

where

$$\boldsymbol{\beta} \sim \mathrm{N}(\boldsymbol{\beta}_0, \boldsymbol{B}_0), \quad \sigma^{-2} \sim \mathrm{Gam}(a_0, b_0), \quad \boldsymbol{\delta} \sim \mathrm{N}(\boldsymbol{\delta}_0, \boldsymbol{D}_0).$$

[4] From the frequentist viewpoint, an ordered probit model can be estimated by using the maximum likelihood method. See, for example, Greene (2008, Chapter 23).

[5] Although the latent variables are unknown, their full conditional distributions (FCD) follow a truncated normal distribution. This makes the estimation of the ordered probit model very tractable in Bayesian analysis. See Albert and Chib (1993).

[6] See Kalmijn and Veenhoven (2005, pp. 389–390).

[7] See Stevenson and Wolfers (2008b, S43, S70–S71).

[8] See Kalmijn and Veenhoven (2005, p. 361).

[9] It seems that cases similar to the well-known Easterlin paradox are observed. See Easterlin (1974).

[10] See, for example, Albert and Chib (1993, p. 673) and Johnson and Albert (1999, p. 131).

[11] Although the unit variance of disturbance, that is, $\mathrm{var}(u_{it}) = 1$, is the standard identification restriction, there are other ways of identifying the ordered probit model. Nandram and Chen (1996) and Chen and Dey (2000) provide an identification restriction based on the reparameterization of the cutoff points, that is, $\gamma_{C-1} = 1$. See also Jeliazkov et al. (2009, Section 2.2).