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The Effect of Income on General Life Satisfaction and Dissatisfaction

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Abstract Increasing evidence from the empirical economic and psychological literature suggests that positive and negative well-being are more than opposite ends of the same phenomenon. Two separate measures of the dependent variable may therefore be needed when analyzing the determinants of subjective well-being. We investigate asymmetries in the effect of income on subjective well-being with a single-item measure of general life satisfaction. Using data from the German Socio-Economic Panel 1984–2004, and a flexible multiple-index ordered probit panel data model with varying thresholds, we find that income has only a minor effect on high satisfaction but significantly reduces dissatisfaction.

Keywords Generalized ordered probit model · Marginal probability effects · Random effects · Fixed effects · Life-satisfaction

1 Introduction

Pinning down the income elasticity of subjective well-being is one of the great challenges in the emerging field of the economics of happiness (Layard 2005; Frey and Stutzer 2002; Bruni and Porta 2006). If this line of research is to have a lasting impact on economic policy making, a reliable estimate, and understanding, of the effect of income on well-being (the extent to which "money can buy happiness") will be a litmus test. The recent survey by Clark et al. (2006) bears witness to the intensive empirical economic research undertaken in this area.

The emotional model theory of subjective well-being, developed in the early 1980s by psychologist Ed Diener, posits that individuals' appraisals of their own lives (i.e., a person's individual judgment about his current status in the world) capture the essence of well-being (Diener 1984; Diener et al. 1985, 1999). The literature has identified three core

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components of subjective well-being: positive affect, (the lack of) negative affect, and general life satisfaction (i.e., subjective appreciation of life's rewards), separable constructs that can be independently examined. Together these three capture a broad range of hedonic and eudemonic experiences.

An important early result, sometimes referred to as "well-being paradox", is that average satisfaction in a country does not increase as countries grow wealthier (Easterlin 1974, 1995). At the individual level, there is a weak positive cross-sectional association between income and satisfaction. If one follows an individual over the life-cycle however, as income first increases and then levels off, subjective well-being remains unchanged. Income expectations and aspirations matter, which means that the effect is subject to habituation and comparison (Diener and Biswas Diener 2002; Clark and Oswald 1996; Luttmer 2005). As expected, the estimated effects differ somewhat depending on whether long-term or short-term income fluctuations are considered, whether truly exogenous variation in income is available, how exactly subjective well-being is measured, and what other controls are included in the model.

The contribution of our paper is to explore, for general life satisfaction (GLS), whether the effect of income is different in different parts of the satisfaction distribution. Is it perhaps the case that the effect of income differs for persons who are relatively dissatisfied, relative to those who report a high life satisfaction, regardless of income? Such a finding would not only improve our understanding of the mechanism underlying the GLS responses, but also add another explanation to why the overall effect is rather small although income may have a substantial effect for parts of the population. Any evaluation of the well-being consequences of economic policies would need to account for such response asymmetries.

We should briefly elaborate on what we mean by "asymmetries". In the traditional interpretation of the single item GLS scale, satisfaction is just the absence of dissatisfaction. In this view, the effect of income on satisfaction is equal to minus the effect of income on dissatisfaction. We avoid such a cardinal interpretation and rather focus on the ordering. For simplicity, consider the case where the GLS scale has only three categories: "satisfied", "neutral" and "dissatisfied".[1] The model we consider does not impose a priori that factors increasing the probability of satisfaction must also reduce the probability of dissatisfaction, and vice versa. This is new, as far as we can tell, although there have been a number of related approaches.

Huppert and Whittington (2003) use the General Health Questionnaire (GHQ-30) to identify positive items. The score on these positive items is then labeled "positive well-being", whereas a standard symptom measure of psychological distress, also from the GHQ-30, is used for "negative well-being". Similarly, Headey and Wooden (2004) compare well-being from a GLS question (as used in our paper) with *ill-being* obtained from a 5-item scale on mental health (i.e., capturing anxiety, depression, and the like). These studies therefore do not investigate differences in the effects of a variable, such as income, at different poles of the same scale. Our approach also differs from the large literature on positive and negative affect, spurred by Bradburn (1969), since we focus on global life satisfaction, a person's conscious evaluative judgment of life, rather than affect.

With data from the German Socio-Economic Panel 1984–2004, we find that income significantly reduces the incidence of low satisfaction but it does not increase the incidence of high satisfaction in a subsample of men living in one-person households. This finding corroborates previous evidence of asymmetric effects from multi-item analyses of subjective well-being, this time with a single-item measure of general life satisfaction.

[1] The question we actually use is a response to "How satisfied are you with your life, all things considered?" on an 11-point numerical scale, where "0" is labeled "completely dissatisfied" and "10" is labeled "completely satisfied".

2 Happiness and Income in Economics

For economists, empirical evidence on the relationship between income and subjective well-being (SWB) is important for (at least) two reasons. First, the design and evaluation of economic policies often takes income as the target quantity of interest. The idea is, of course, that income is a good proxy for well-being, and that it is easy to measure. If the link between income and well-being is less strong than suspected, then economic policies based on income (or GDP) maximization alone may turn out to be inferior from an overall well-being perspective.

Second, the relationship between income and well-being may be used to put a monetary value—or shadow price—on non-traded goods, usually in the context of cost-benefit analyses. The basic idea is one of compensation: in case of a "bad", how much of an increase in income is required to offset the negative effect of the bad, while keeping the person at the same level of SWB as in the absence of the bad? Similarly, in case of a good, one can implicitly determine the shadow price by asking how much income a person would be willing to give up in order to obtain the good, keeping SWB fixed.

Examples for this line of research are Blanchflower and Oswald (2004), who estimate the pecuniary value of a lasting marriage (relative to widowhood) to be $ 100,000 per year. Other examples include Winkelmann and Winkelmann (1998) who estimate the money-equivalent value of the psychological cost of unemployment, a trade-off that we will come back to below, and Schwarze (2003) who uses the principle to determine an income equivalence scale, i.e., the income compensation required to keep the same level of an individual's well-being with one additional household member present. Frey et al. (2004) estimate the value of public safety, or the absence of terrorism. Van Praag and Baarsma (2005) measure the external cost of air traffic noise for people living near the Amsterdam Airport.

Unfortunately, the implied compensation may be sensitive to the chosen model, and too restrictive assumptions may lead to spurious estimates. An obvious concern is that the same income change has a different meaning for poor than for rich people. This concern resonates throughout the literature. Typically, it is found that the correlation between income and subjective well-being is much stronger among the poor. While the absence of poverty does not guarantee happiness, the presence often prevents it (Diener and Biswas Diener 2002). Such non-linearities can be addressed, for instance, by studying the correlation between GLS and logarithmic income. In this case, a proportionate effect is assumed: To achieve the same increase in satisfaction, larger and larger absolute changes in income are necessary. Semi-parametric estimators have provided some support for a log-linear functional form.

The topic of our paper is different. Not all poor people are dissatisfied with their lives, nor are all wealthy people satisfied. The general life satisfaction scale integrates the subjects' reflected valuation of various domains of their lives, weighting them in whatever way they choose (Van Praag et al. 2003). In the broadest sense, one can distinguish two domains, a pecuniary domain and a non-pecuniary domain (that includes, perhaps most importantly, health and social relationships). Our working hypothesis is that the non-pecuniary domain moderates the effect of the pecuniary domain on GLS. Specifically, if the valuation of the non-pecuniary domain contributes to a low GLS, then the effect of the pecuniary domain becomes stronger, i.e., an income increase will have a more favorable effect on GLS, compared to the case where the non-pecuniary domain leads to a high GLS score. Such a framework will lead to the aforementioned response asymmetries: income will lower dissatisfaction more than it will increase satisfaction.

To test this hypothesis, we cannot use conventional regression or ordered response models, because in these models the effect of income at various satisfaction levels cannot be estimated freely but rather is dictated by functional form, essentially a single parameter. A naive approach would be to split the scale, for example by defining the outcomes "dissatisfied" for scores below an arbitrary cut-off, and "satisfied" for values above an arbitrary cut-off, and analyzing their response patterns separately. Slightly more sophisticated approaches can be based either on a latent class framework, or on generalized ordered probit models as proposed here.

In latent class models, one can define any number of latent groups and estimate the effect of income conditional on group membership. A recent example for such an approach is the study by Clark et al. (2005) who used GLS data from the European Community Household Panel. They found that the effect of income changes were larger in the "latent satisfied" than in the "latent dissatisfied" classes. Here we address the issue from a different angle: Rather than inferring response asymmetries from unobservable class membership, we model them directly using an alternative approach with outcome-specific parameters, a generalized ordered probit model for panel data. The technical details of the model are discussed in the next section.

3 Econometric Modeling

Most empirical work on the determinants of subjective well-being uses either linear regression or single-index ordered probit and logit models. While the latter account for the discreteness and ordering of the dependent variable, they impose an implicit cardinalization such that, for example, the trade-off ratios between income and other determinants of well-being must be constant across the distribution of outcomes (Boes and Winkelmann 2006). Since we want to estimate unrestricted income effects for low and high levels of well-being, we need to use more flexible models, and the multinomial logit with its multi-index structure is certainly one option. However, this model does not make any use of the ordering information and therefore cannot be efficient. We propose instead a generalization of Maddala's (1983) and Terza's (1985) model to panel data, a model that is as flexible as the multinomial logit model and in addition accounts for the ordinality.

3.1 Model and Assumptions

Let $Y_{it} \in \{1,\ldots, J\}$ denote the survey response to the GLS question of individual $i = 1,\ldots, n$ at time $t = 1,\ldots, T_i$, and let X_{it} denote the vector of covariates (including logarithmic income). The relationship between Y_{it} and X_{it} is specified in terms of cumulative conditional probabilities:

$$P(Y_{it} \leq y | X_{it}; \theta_y) = \Phi(-X'_{it}\theta_y) \qquad y = 1, \ldots, J-1 \tag{1}$$

where $\Phi(\cdot)$ denotes the cumulative density of the standard normal distribution, and θ_y denotes a vector of category-specific parameters, including a constant.[2] The function $\Phi(\cdot)$ maps the linear index onto the unit interval, and we require $\theta = (\theta_1 \; \ldots \; \theta_{J\text{-}1})$ to fulfill the strict inequalities $X'_{it}\theta_1 > \cdots > X'_{it}\theta_{J-1}$ such that the cumulative probabilities increase with each increment in y. Due to adding up $P(Y_{it} \leq J|X_{it}) = 1$, so that we can only identify

[2] For the ease of exposition, we set up the model in terms of cumulative conditional probabilities. Like the standard ordered probit, the generalized model may also be motivated in terms of a latent variable and a threshold crossing mechanism generating the ordinal response variable. We refer to Winkelmann and Boes (2006, Chap. 6) for a detailed outline of the underlying assumptions and identification issues in this framework.

$J-1$ category-specific parameter vectors. The model reduces to the standard ordered probit model if only the constant term in θ_y is category-specific.

In order to exploit the advantages of panel data more fully, the model can be augmented by individual specific time invariant effects. Conditioning on such effects avoids bias if, for example, unobserved personality traits affect well-being as well as observable characteristics (Ferrer-i-Carbonell and Frijters 2004). Let η_i denote such individual effects, and rewrite the cumulative probabilities (1) conditional on η_i as

$$P(Y_{it} \leq y|X_{it}, \eta_i; \theta_y) = \Phi(-X_{it}'\theta_y - \eta_i) \qquad y = 1, \ldots, J-1 \tag{2}$$

We assume that X_{it} is strictly exogenous conditional on η_i and that outcomes are independent conditional on (X_i, η_i), where X_i contains X_{it} for all t. The first assumption rules out lagged dependent variables in X_{it}, the second assumption allows for dependencies in Y_{it} across t if conditioned only on X_i. Note that the independence assumption restricts the covariance matrix of individual effects to be diagonal, i.e., $Cov(\eta_i, \eta_{i'}) = 0 \forall i \neq i'$.

Without specifying the relationship between X_{it} and η_i, i.e., treating η_i as fixed parameters to be estimated along with θ, a model based on (2) will suffer from the incidental parameters problem. For fixed time and large cross-sectional dimension, the number of parameters η_i is unbounded, with available information on η_i being fixed, which in general yields inconsistent estimators of η_i and θ. We solve this problem by treating η_i as random variable drawn along with (X_i, Y_i). Following the idea of Chamberlain (1980) and Mundlak (1978) we allow for possible correlation between η_i and X_i:

$$\eta_i = \bar{X}_i'\gamma + \alpha_i \tag{3}$$

where $\bar{X}_i$ is the vector of averages of X_{it} over time, γ is a conformable parameter vector, and α_i is an orthogonal error with $\alpha_i|X_i \sim Normal(0,\, \sigma_\alpha^2)$.[3] The distributional assumption and the independence ensure that the correlation matrix of the random effects is the identity matrix. If we replace η_i in (2) by (3), then we obtain

$$P(Y_{it} \leq y|X_{it}, \bar{X}_i, \alpha_i; \theta_y, \gamma) = \Phi(-X_{it}'\theta_y - \bar{X}_i'\gamma - \alpha_i) \qquad y = 1, \ldots, J-1 \tag{4}$$

or in terms of a conditional probability model for all y = 1,..., J

$$P(Y_{it} = y|X_{it}, \bar{X}_i, \alpha_i; \theta, \gamma) = \Phi(-X_{it}'\theta_y - \bar{X}_i'\gamma - \alpha_i) - \Phi(-X_{it}'\theta_{y-1} - \bar{X}_i'\gamma - \alpha_i) \tag{5}$$

where α_i is the individual specific time invariant random effect, and it is understood that $\Phi(-X_{it}'\theta_0 - \bar{X}_i'\gamma - \alpha_i) = 0$ and $\Phi(-X_{it}'\theta_J - \bar{X}_i'\gamma - \alpha_i) = 1$. The joint distribution of Y_i = (Y_{i1},..., Y_{iT_i}) conditional on observables but unconditional on α_i is obtained by integrating the joint distribution of Y_i and α_i over α_i, formally

$$f(y_i|x_i, \bar{x}_i; \theta, \gamma, \sigma_\alpha) = \int_{-\infty}^{\infty} \prod_{t=1}^{T_i} \prod_{y=1}^{J} P(y_{it} = y|x_{it}, \bar{x}_i, \alpha_i; \theta, \gamma)^{\mathbf{1}(y_{it}=y)} \frac{1}{\sigma_\alpha} \phi\left(\frac{\alpha_i}{\sigma_\alpha}\right) d\alpha_i \tag{6}$$

where $\mathbf{1}(\cdot)$ is the indicator function. The inner product over all J categories selects the appropriate likelihood contribution for each observation (individual i at time t) according to the observed category, and the independence of Y_{it} conditional on X_i and α_i ensures that the joint probability of (Y_{i1},..., Y_{iJ})|(X_i,α_i) can be written as the product of single

[3] A straightforward generalization of (3) would be to let γ vary by the satisfaction levels, i.e., replace γ by γ_y. Computationally somewhat more involved would be to let α_i vary by the satisfaction level. Note that only time-varying covariates are included in $\bar{X}_i$ because otherwise θ_y and γ would not be separately identified.

probabilities over all periods T_i. The integral in (6) does not have a closed form solution, but it can be rewritten in a form amenable to Gauss-Hermite quadrature for numerical approximation.

Estimation of parameters by maximum likelihood is straightforward once the integral has been evaluated, and the resulting estimator is consistent, efficient, and approximately normally distributed. The generalized ordered probit model with random effects specification has been implemented in a new Stata module calledregoprob available via thessc commands in Stata.[4]

3.2 Interpretation of the Model

There are a number of ways to interpret the estimated parameters, but we focus here on two quantities that offer a very intuitive interpretation when dealing with conditional probability models. First, we may ask the question "How does a small *ceteris paribus* change in income affect the distribution of GLS responses?" which is answered by marginal probability effects (MPE's). Such effects are of particular interest for the asymmetry hypothesis since we are able to identify whether income effects on GLS differ for low and high GLS. Second, we may look at asymmetric effects from a different (probability) angle insofar as we do not investigate the change in the GLS distribution at different poles, but instead we keep the GLS distribution fixed and analyze income changes required to compensate for a change in another covariate, thereby distinguishing between trade-offs for low and high GLS.

MPE's are defined as first derivatives of (5) with respect to the variable(s) of interest. Since α_i is an unobserved random variable, we cannot directly calculate the MPE's without further assumptions. One possibility would be to take advantage of the probit form and the normality of α_i and rewrite the conditional probabilities marginal on α_i as

$$\begin{aligned} P(Y_{it} = y|X_{it}, \bar{X}_i; \theta, \gamma, \sigma_\alpha) =& \Phi\left(\frac{-X'_{it}\theta_y - \bar{X}'_i\gamma}{\sqrt{1+\sigma_\alpha^2}}\right) - \Phi\left(\frac{-X'_{it}\theta_{y-1} - \bar{X}'_i\gamma}{\sqrt{1+\sigma_\alpha^2}}\right) \\ =& \Phi\left(-X'_{it}\vartheta_y - \bar{X}'_i\psi\right) - \Phi\left(-X'_{it}\vartheta_{y-1} - \bar{X}'_i\psi\right) \end{aligned} \tag{7}$$

where $\vartheta_y = \theta_y(1+\sigma_\alpha^2)^{-1/2}$ and $\psi = \gamma(1+\sigma_\alpha^2)^{-1/2}$ denote the population-averaged coefficient vectors. The coefficients are called population-averaged since they are obtained as the expectation of (5) over α_i. Taking derivatives of (7) yields

$$\begin{aligned} MPE_y^{(l)} =& \frac{\partial P(Y_{it} = y|X_{it}, \bar{X}_i; \vartheta, \psi)}{\partial X_{it}^{(l)}} \\ =& \phi(-X'_{it}\vartheta_{y-1} - \bar{X}_{i'}\psi)\vartheta_{y-1}^{(l)} - \phi(-X'_{it}\vartheta_y - \bar{X}'_i\psi)\vartheta_y^{(l)} \end{aligned} \tag{8}$$

where $\phi(\cdot)$ denotes the density function of the standard normal distribution, and $X_{it}^{(l)}$ denotes the l-th element in X_{it} (here assumed to be logarithmic income) and $\vartheta_y^{(l)}$ the corresponding scaled (income) coefficient. The difference between the standard ordered probit model and the generalized model becomes apparent in Eq. 8: while the generalized model allows for different parameter vectors ϑ_y for all $y = 1,..., J-1$, the standard model restricts those parameters to be the same. Thus, the generalized model allows for additional

[4] Stata is a registered trademark of StataCorp, College Station TX, USA. Typenet search regoprob or ssc install regoprob in the command line of Stata to find out more about regoprob. See also the documentation of regoprob for details on the command syntax and the output generated by Stata.

flexibility in estimating marginal probability effects. For example, the implied effect of a change in one element of X on the probability of border outcomes, $P(Y = 1|X)$ and $P(Y = J|X)$, can have equal sign in the generalized model but not in the standard one (see Boes and Winkelmann 2006, for further discussion). Note that the MPE's are functions of the covariates and therefore depend on the values of X_{it} and $\bar{X}_i$. We estimate the MPE's replacing the unknown coefficients by the maximum likelihood estimates and evaluating at the sample averages of the regressors.

The second quantity of interest, the trade-off ratio, assesses the importance of income *relative* to other determinants. It follows from totally differentiating (7) that

$$dP(Y_{it} = y|X_{it}, \bar{X}_i; \vartheta, \psi) = MPE_y^{(l)} dX_{it}^{(l)} + MPE_y^{(m)} dX_{it}^{(m)} \tag{9}$$

where $X_{it}^{(l)}$ denotes logarithmic income, $X_{it}^{(m)}$ denotes any other covariate in X_{it}, and the MPE's are given by (8). The approximation in (9) directly leads to the concept of compensating variation: How much of a variation in one regressor (here income) is needed to offset the given change in another regressor such that $dP(Y_{it} = y|X_{it}, \bar{X}_i; \vartheta, \psi) = 0 \forall y$, i.e., all probabilities remain unchanged. Rearranging terms yields

$$\frac{dX_{it}^{(l)}}{dX_{it}^{(m)}} = -\frac{MPE_y^{(m)}}{MPE_y^{(l)}} \tag{10}$$

In the standard model, this trade-off ratio reduces to the ratio of coefficients, i.e., we obtain $dX_{it}^{(l)}/dX_{it}^{(m)} = \vartheta^{(m)}/\vartheta^{(l)}$, which does not vary across outcomes, whereas in the generalized model such an restriction is not imposed. Rather, we can let the data speak and determine empirically how these trade-off ratios look like.

4 Data

The German Socio-Economic Panel (GSOEP) is a large annual panel survey of randomly selected households in Germany (see Burkhauser et al. 2001 for more details). Personal information is available for all household members aged 16 and above. Our data are drawn from the West German (A) subsample 1984–2004, yielding a maximum of 21 observations per individual (on average about five observations per individual). We apply a number of standard selection criteria: included individuals are between 25 and 65 years old at the time of the survey, and we require non-missing information on all the included variables.[5]

In addition, we employ a novel restriction by considering single person households only. The rationale for this selection is that the match between reported household income and individual material well-being is much better in single-person households than we could possibly hope for in a multi-person household. General household surveys such as the GSOEP typically include two types of income measures, one being total household income (from all sources), the other being personal labor earnings. Clearly, personal labor earnings are not a very good indicator of material well-being, in particular, but not only, for persons who do not work, as it does not include any government transfers (e.g., child benefit, government grants, or rent subsidies). Household income (net of taxes and social security contributions) is in general a more appropriate measure. However, in multi-person

[5] The variables we include in the model generally have very high response rates with missing information for only a few respondents, in particular for the GLS variable, so that we do not expect significant bias in the results from dropping these observations.

households, there remain two types of ambiguities. First, there is an ongoing debate on the right equivalence scale in order to reflect economies of scale in household production and consumption. Secondly, we do not know whether resources are shared evenly within the household, but such an (arbitrary) assumption is required when assigning one income to several household members.

For these reasons, we find it instructive to study the relationship between income and SWB in the (reference) population of single person households. We do not claim that such a sample is representative for the whole population, and of course, this raises the question of external validity: To what extent can results for single person households be extrapolated to the population of all households? While single person households are non-representative with respect to a number of factors (such as age, and possibly also income), we controlled for this in our analysis, and it is a priori unclear why the well-being function (after including these factors) should be different for such persons. In fact, Mentzakis and Moro (2009) provide evidence in favor of the asymmetry hypothesis adopting similar methods as the ones proposed here in a sample of multi-person households.

All in all, this approach leaves us with 5,008 person-year observations for men, and with 4,727 person-year observations for women. The dependent variable is, as mentioned before, the response to the survey question "How satisfied are you with your life, all things considered?". There are relatively few responses in the 0–2 range. For this reason, and to preserve some degrees of freedom (a full set of regression parameters is added for each additional category), we use a modified scale where the original 0–2 responses have been grouped into the lowest "dissatisfied" category.

Figure 1 depicts the frequency distribution of GLS responses in our sample, separately for men and women. Most people are satisfied with their life: about two thirds report a GLS level of seven or higher, and women have a slightly higher average GLS level than men. The distribution in Fig. 1 is characteristic of most SWB distributions in the sense that the majority of people reports a relatively high level of GLS, although the highest response category is chosen relatively infrequently.

In the regression analysis, control variables include—apart from logarithmic income—a second order polynomial in age and dummy variables for unemployment and health status. We use a relatively simple specification with only a few variables. This has two main advantages. First, since eight regression parameters are estimated for each variable, fewer regressors keep the model manageable. Second, many of the additional variables used in

Fig. 1 Marginal distribution of satisfaction responses

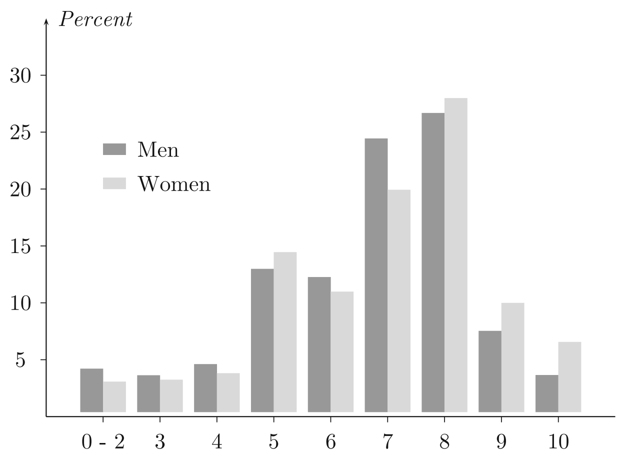

Table 1 Descriptive statistics by gender

Variable	Men		Women	
	Mean	SE	Mean	SE
Monthly income in EUR	1403.5	12.0	1140.9	10.3
Age in years	40.24	0.16	45.80	0.20
Unemployment (0/1)	0.083	0.004	0.058	0.003
Good health (0/1)	0.656	0.007	0.582	0.007
Number of obs.	5,008		4,727	

the previous literature are arguably endogenous choice variables, obstructing the interpretation of the results. Finally, all analyses are performed separately by gender.

Table 1 summarizes the sample means of the explanatory variables. Among one-person households, men have a significantly higher monthly income than women (about 260 Euros) and are on average more than 5 years younger. The unemployment rate is about 2.5% points higher for men than for women, and 58.2% of the women are relatively satisfied with their health status (compared to 65.6% of the men). These variations can largely be explained by the different age distributions of single male and single female households. Men are mostly living alone when they are young and at the beginning of their career path. Women are more likely to live alone when they are older, contributing factors being a higher incidence of widowhood due to greater life-expectancy.

Table 2 cross-tabulates the sample means of the dependent variable conditional on the GLS response, again separately for men and women. The income variable shows a lot of variation along the GLS dimension. For men (panel A), the lowest average monthly income (1,124 Euro) is observed for individuals with very low GLS, the highest income (1519 Euro) for those with response "8". When moving from the utmost left part of the GLS distribution to the right, average income is first increasing then decreasing. A similar pattern can be observed for women (panel B), although on a lower level. Concerning unemployment and health, we find that among less satisfied people the unemployment rate is relatively high and that reported health status and GLS are positively correlated.

5 Estimation Results

In this section, we report on the estimation results of the relationship between income and subjective well-being, the latter measured by general life satisfaction. We first present the estimated income parameters under several model assumptions, then turn our attention to the implications with respect to the asymmetry hypothesis, and finally discuss the robustness of our results.

We estimated two different models: A random effects ordered probit model (OProbit) including group means as additional regressors, and a generalized random effects ordered probit model (GOProbit), also including group means, where all parameters are outcome-specific. In both cases, the pooled models were clearly rejected against the panel models, which is reflected in Table 3 where we report the estimated variances (and standard errors) of the random effects, $\hat{\sigma}^2_\alpha$, separately for men and women. Furthermore, a joint significance test of the group means as additional regressors rejected the null hypothesis of zero correlation, and thus a simple random effects specification without $\bar{X}_i$ is rejected by the

Table 2 Sample means by gender and satisfaction level

Variable	GLS level								
	0–2	3	4	5	6	7	8	9	10
A. Men									
Relative freq.	4.21%	3.63%	4.61%	12.98%	12.26%	24.44%	26.68%	7.53%	3.65%
Income	1123.9	1152.0	1414.3	1255.8	1324.0	1477.9	1519.3	1473.6	1267.8
Age	43.86	41.83	41.07	43.55	40.32	38.99	38.91	38.19	43.79
Unemployment	0.336	0.176	0.182	0.126	0.103	0.056	0.030	0.029	0.022
Good health	0.336	0.319	0.338	0.340	0.549	0.732	0.841	0.897	0.896
B. Women									
Relative freq.	3.07%	3.24%	3.81%	14.45%	10.98%	19.93%	27.99%	9.99%	6.56%
Income	930.5	935.4	1047.4	978.1	1055.7	1196.7	1238.6	1290.7	1082.1
Age	47.50	45.75	45.59	49.28	46.25	43.37	44.62	45.34	49.84
Unemployment	0.234	0.124	0.172	0.089	0.052	0.036	0.039	0.013	0.035
Good health	0.159	0.196	0.267	0.274	0.420	0.601	0.767	0.847	0.845

Table 3 Estimated variances of the random effects by gender and model

	OProbit	GOProbit
Men	0.785 (0.184)	0.833 (0.212)
Women	0.666 (0.150)	0.708 (0.164)

Notes: The models are the ordered probit (OProbit) and the generalized ordered probit (GOProbit). Estimated standard errors in parentheses

data as well. These tests suggest that individual heterogeneity should be accounted for in the SWB equation.

Table 4 displays the estimated coefficients on logarithmic income and unemployment separately for men (panel A) and women (panel B). Although the raw parameters are not very interesting *per se*, the comparison is useful for understanding our later results. For men, we find a positive and significant income parameter in the standard model (0.362 with z-value 6.67). In the generalized model, eight different parameters vectors $\theta_1,\ldots, \theta_8$ are estimated (where each vector contains coefficients for all the explanatory variables). The income coefficients are slightly higher for the parameter vectors θ_1 to θ_6 than the overall estimate in the standard model. The point estimate decreases but is still significant for θ_7, and finally turns negative and insignificant for θ_8. The estimated coefficients in the sample of women are smaller (in absolute value) and less significant than those for men indicating a weaker relative impact. For example, in the standard model we obtain an income point estimate of 0.131, which is only about a third of that for men, and the z-value decreases to 1.97. In the generalized model the income coefficients are significant on the 5%-level only for θ_4 and θ_5, while all other income coefficients are insignificant. For the unemployment coefficient in the subsample of men we obtain point estimates for low/high satisfaction that are smaller/higher (in absolute terms) than the overall estimate in the standard model, for women we observe the opposite pattern.

If we formally test the generalized ordered probit model against the standard model, we can reject the null hypothesis of equal slope parameters for men ($LR_{203} = 548.9$) and for

Table 4 Estimated income and unemployment coefficients by gender and model

	OProbit	GOProbit							
	Overall	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
A. Men									
Logarithmic income	0.362 (0.054)	0.417 (0.141)	0.470 (0.109)	0.423 (0.093)	0.372 (0.082)	0.429 (0.079)	0.456 (0.082)	0.314 (0.115)	−0.066 (0.152)
Unemployment	−0.696 (0.077)	−0.396 (0.173)	−0.351 (0.147)	−0.681 (0.125)	−0.587 (0.111)	−0.597 (0.111)	−0.661 (0.124)	−0.724 (0.189)	−1.189 (0.297)
B. Women									
Logarithmic income	0.131 (0.067)	0.256 (0.225)	0.060 (0.144)	0.144 (0.131)	0.234 (0.108)	0.329 (0.100)	0.175 (0.098)	−0.070 (0.117)	−0.045 (0.146)
Unemployment	−0.347 (0.096)	−0.893 (0.218)	−0.635 (0.185)	−0.720 (0.167)	−0.463 (0.147)	−0.300 (0.139)	0.027 (0.140)	−0.256 (0.198)	0.458 (0.244)

Notes: The models are the ordered probit (OProbit) and the generalized ordered probit (GOProbit). Each model controls for a quadratic form in age, good health (0/1), and time fixed effects. Individual effects are assumed to be decomposable into a linear function of individual group means and orthogonal error, and the likelihood for each individual is approximated using Gauss-Hermite quadrature. Estimated standard errors in parentheses women ($LR_{203} = 430.1$). The null hypothesis of equal income coefficients is also rejected for both, men and women, equal unemployment coefficients is only rejected for women. This result suggests that parameters are heterogeneous with respect to the outcome distribution.

In order to interpret the estimated parameters and evaluate the effects of income on low and high GLS we now turn to the quantities introduced in Sect. 3 and the marginal probabilities first. Table 5, Figs. 2 and 3 summarize the MPE's of income and unemployment by gender. Consider, for example, the results for men and take the *ceteris paribus* effect of an increase in logarithmic household income by a small amount on the probability of responding a GLS level of "8" (equal interpretation applies to the effects at all other GLS levels). Table 5 shows a value of 0.059 for the standard model. This means that the probability of a response of "8" increases by 0.059% points if we increase logarithmic income by 0.01, which corresponds approximately to a 1% increase in level income. A doubling of income, i.e., a change in logarithmic income by 0.693, increases the probability of response "8" by about $0.059 \times 0.693 \times 100$, or about 4.09% points, *ceteris paribus*.

Comparing the MPE's among the standard and the generalized models and over all possible outcomes, we obtain the following pattern. For men all models suggest that more income significantly reduces the probability of low GLS (0–5), and significantly increases the probability of response "8". For high GLS responses (9–10), the standard model predicts a significant positive effect, whereas the generalized model does not predict an effect significantly different from zero. Thus, based on the generalized ordered probit model, there is no evidence for income to have an effect on high satisfaction. Moreover, the effect of income is asymmetric: higher income decreases the probability of dissatisfaction, but it does not affect the probability of high satisfaction. Figure 2 illustrates the asymmetric effects and shows the differences between the MPE's in the standard ordered probit model and the generalized ordered probit model.

For women the relationship between income and GLS is relatively weak. While the standard model finds small but significant effects for low and high GLS, the generalized model predicts a significant negative effect only for responses "5" and "6". Concerning unemployment, we find evidence for men that an increased unemployment probability reduces the probability of response "8", or higher, and increases the probability of low responses, but the relationship for women is less clear. For example, an increase in the probability of being unemployed by 1% point reduces the probability of response "8" by about 0.096% points for men, and raises the probability of the same outcome by about 0.051% points for women. The gender difference might be explained by social norms that assign the role of primary income earner to men and therefore make income a relatively more important determinant of male well-being (e.g., Lalive and Stutzer 2004). Such a gender difference can also be observed when considering unemployment.

The relationship between GLS, income, and unemployment, for men and women, at various parts of the GLS distribution can alternatively be illustrated by the trade-off ratios. Table 6, Figs. 4 and 5 show the required changes in logarithmic income if the unemployment probability increases by one percentage point, given the GLS distribution is fixed. If we want to interpret the reported numbers, we need to be careful with respect to the significance of MPE's. The trade-off ratio does only make sense for significant income effects. In this case, the required change in income is either zero if the MPE of unemployment is statistically not different from zero, or the change is positive (or negative) for significant unemployment effects. We marked the four cases (non-sensible/zero/positive/negative) with $\times / \circ / + / -$.

Table 5 Marginal probability effects of income and unemployment by gender and satisfaction level

		Satisfaction level								
		0–2	3	4	5	6	7	8	9	10
A. Men										
Logarithmic income	OProbit	−0.016 (0.003)	−0.014 (0.001)	−0.016 (0.001)	−0.037 (0.003)	−0.020 (0.009)	0.003 (0.003)	0.059 (0.009)	0.027 (0.005)	0.014 (0.005)
	GOProbit	−0.020 (0.007)	−0.022 (0.006)	−0.014 (0.005)	−0.027 (0.006)	−0.037 (0.007)	−0.005 (0.007)	0.088 (0.033)	0.039 (0.109)	−0.002 (0.089)
Unemployment	OProbit	0.031 (0.005)	0.026 (0.002)	0.031 (0.001)	0.070 (0.005)	0.039 (0.012)	−0.005 (0.005)	−0.114 (0.014)	−0.051 (0.008)	−0.028 (0.009)
	GOProbit	0.019 (0.009)	0.012 (0.007)	0.058 (0.009)	0.040 (0.010)	0.037 (0.007)	0.014 (0.006)	−0.096 (0.027)	−0.044 (0.023)	−0.041 (0.013)
B. Women										
Logarithmic income	OProbit	−0.004 (0.002)	−0.005 (0.001)	−0.005 (0.001)	−0.016 (0.005)	−0.008 (0.012)	−0.003 (0.003)	0.020 (0.011)	0.012 (0.004)	0.008 (0.006)
	GOProbit	−0.009 (0.008)	0.005 (0.010)	−0.011 (0.008)	−0.036 (0.021)	−0.040 (0.022)	0.038 (0.029)	0.064 (0.030)	−0.008 (0.016)	−0.003 (0.011)
Unemployment	OProbit	0.011 (0.003)	0.012 (0.001)	0.014 (0.001)	0.042 (0.008)	0.020 (0.017)	0.007 (0.004)	−0.052 (0.017)	−0.032 (0.006)	−0.022 (0.009)
	GOProbit	0.030 (0.008)	0.013 (0.010)	0.031 (0.014)	0.026 (0.029)	−0.018 (0.031)	−0.091 (0.035)	0.051 (0.046)	−0.077 (0.026)	0.034 (0.018)

Notes: See notes Table 4. The marginal probability effects have been calculated for logarithmic income and unemployment, evaluated at the sample means of the explanatory variables and marginal on the individual effect. An increase in income by 1% corresponds to an increase in logarithmic income by 0.01, i.e., reported numbers can be interpreted directly as percentage point changes. Similarly, if changes in the unemployment probability by 0.01 are considered, then the reported numbers directly give percentage point changes. Approximate standard errors (delta method) in parentheses

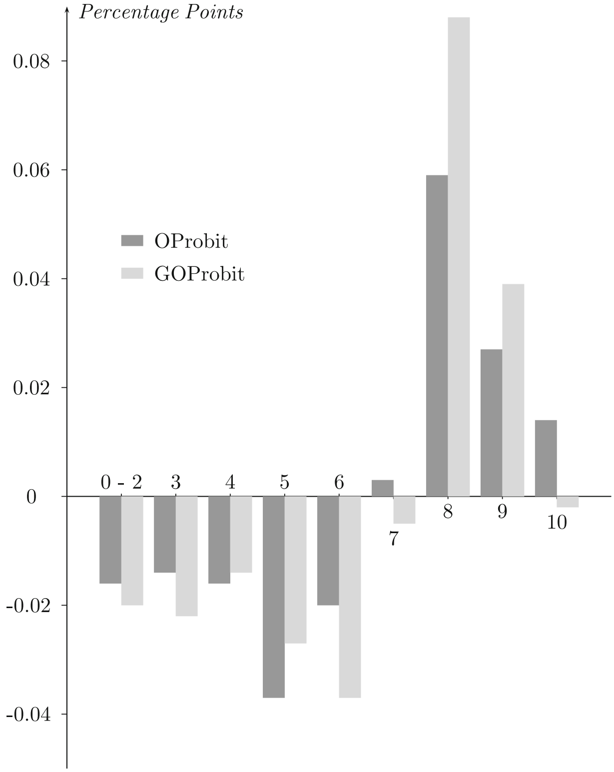

Fig. 2 Marginal probability effects of income—Men

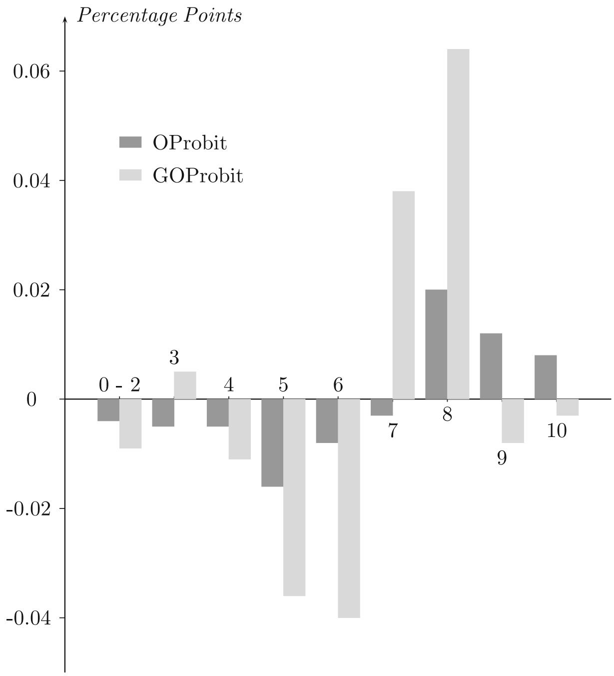

Fig. 3 Marginal probability effects of income—Women

Table 6 Trade-off ratios between income and unemployment

	Satisfaction level								
	0–2	3	4	5	6	7	8	9	10
A. Men									
OProbit	0.019^{+} (0.004)	0.019^{+} (0.001)	0.019^{+} (0.001)	0.019^{+} (0.002)	0.019^{+} (0.011)	$0.019^{\times}$ (0.036)	0.019^{+} (0.004)	0.019^{+} (0.005)	0.019^{+} (0.007)
GOProbit	0.009^{+} (0.006)	0.006^{+} (0.004)	0.042^{+} (0.014)	0.015^{+} (0.005)	0.010^{+} (0.009)	$0.028^{\times}$ (0.041)	0.011^{+} (0.006)	$0.011^{\times}$ (0.032)	$-0.179^{\times}$ (6.976)
B. Women									
OProbit	0.026^{+} (0.017)	0.026^{+} (0.001)	0.026^{+} (0.002)	0.026^{+} (0.011)	$0.026^{\times}$ (0.052)	$0.026^{\times}$ (0.033)	0.026^{+} (0.019)	0.026^{+} (0.011)	$0.026^{\times}$ (0.024)
GOProbit	$0.035^{\times}$ (0.034)	$-0.029^{\times}$ (0.102)	$0.029^{\times}$ (0.052)	0.007° (0.004)	-0.004° (0.004)	$0.024^{\times}$ (0.112)	-0.008° (0.073)	$-0.094^{\times}$ (1.420)	$0.102^{\times}$ (0.778)

Notes: See notes Table 4. The trade-off ratios show the required change in logarithmic income to compensate for an increase in the unemployment probability by one percentage point, fixing the probability of a GLS response. The ratio of significant (at the 10% level) marginal income and unemployment effects is marked + /− (if positive/negative). If the marginal income effect is insignificant, the ratio is marked ×. If the income effect is significant but the unemployment effect is not, the ratio is marked °. Approximate standard errors (delta method) in parentheses

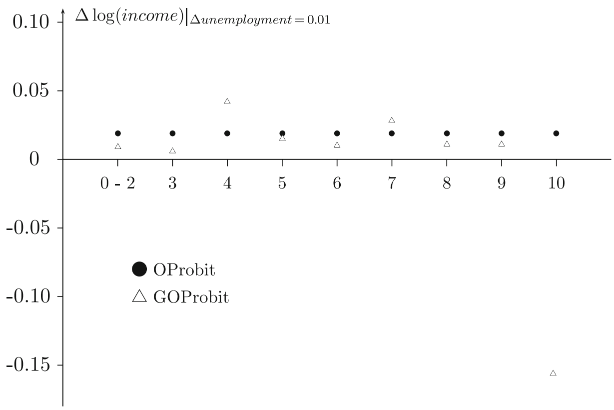

Fig. 4 Compensating variation in income—Men

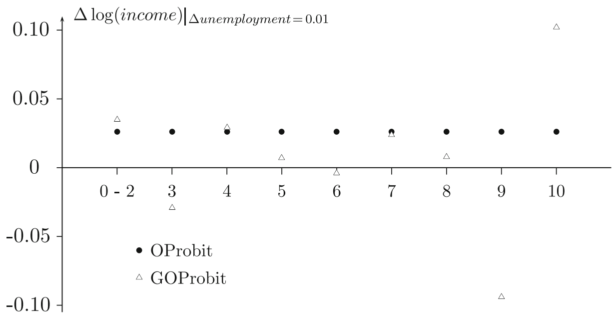

Fig. 5 Compensating variation in income—Women

The numbers in Table 6 (multiplied by 100) approximate the percentage change in income, e.g., for men in the standard model a 0.019 means that income must increase by 1.9% to offset the increase in the unemployment probability by 1% point. By construction, the trade-off ratios in the ordered probit model are constant for all levels of GLS, and interpretation therefore is not particularly interesting. In the generalized model, required income changes vary between 0.6 and 4.2%. An important observation is that income compensations are entirely ineffective for men with high GLS, and effective for medium to low satisfied men, though in an unsystematic way. For women, a compensation for unemployment in terms of income is rather unpromising, and other factors determining GLS need to be identified when looking for effective compensation schemes. Figures 4 and 5 provide a graphical illustration of the results.

While these results are obtained for a specific sample and a specific parametric model with its set of assumptions, we found a remarkable robustness of the main conclusions with respect to alternative specifications and samples. Possible alternatives include the use of different link functions (rather than the probit ones), including the logit, the log-logistic, and the complementary log–log; we estimated a series of binary models, where the dependent variables result from dichotomization of GLS responses, i.e., $Y_{it} > 2$ against $Y_{it} \leq 2$, $Y_{it} > 3$ against $Y_{it} \leq 3$, and so on; and conditioning on fixed effects using Chamberlain's (1982) conditional logit model. Alternative link functions did not provide a better fit, nor did the response asymmetry for men disappear under the alternative model assumptions.

6 Conclusion

The distinction between positive and negative well-being has been made for some time now. Huppert and Whittington (2003) point out that the determinants of positive and negative well-being are not necessarily the same. For example, in their study of participants in the British Health and Lifestyle Survey, paid employment was found to be an important determinant of positive well-being but to have less influence on psychological symptoms. Headey and Wooden (2004) use also two separate measures of well-being and ill-being. In their case, the pecuniary situation, captured through income and wealth, was found to affect both aspects equally.

Our paper takes a different approach. We also study the determinants of well-being, in particular the effect of income. However, we use a single item scale of general life satisfaction, where low scores are interpreted as a state of "dissatisfaction" and high scores signify "satisfaction". There are a number of advantages of such a single measure. It is widely available, and it allows for a straightforward computation of compensating income variations, an important application of this type of modeling in economics. We therefore propose a new and very flexible panel data model in which we can analyze whether income effects depend on the level of satisfaction. The model allows for individual specific effects and outcome-specific parameters, i.e., the effect of income on GLS may be non-monotonic.

In a sample of single-person households drawn from the German Socio-Economic Panel waves 1984 to 2004, we find support for the existence of asymmetric income effects for men. Based on our results, income has a large effect among men with low GLS responses, but no effect on men with high GLS responses. For women in single-person households income plays a minor role in the formation of GLS, and support of the asymmetry hypothesis is rather weak.

Clearly, more research is needed in this area. We think that our methodological focus on flexible estimation of marginal probability effects and trade-off ratios with a single measure of well-being, namely general life satisfaction, should prove useful in further investigations. If one wants to estimate marginal probability effects and compensating variations in a meaningful way, then one should use the generalized ordered probit model rather than the simpler models prevailing in earlier research.

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