

Income and Subjective Well-Being: How Important is the Methodology?*

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The study examines the association between subjective well-being and income, using data of 3 600 individuals from the TÁRKI Household Monitor for the year 2007. To explore this relationship, most of the relevant empirical papers use either ordinary least squares (OLS) regression or ordered probit model, but the authors follow different approaches. Comparing the results of OLS regression with quantile regression and the ordered probit model with a generalized ordered probit model, they show that more flexible techniques provide a more complete picture of the income-satisfaction relationship. According to OLS regression, income has a positive impact on satisfaction, but the quantile regression models show that this association is weaker at the upper end and stronger at the lower end of the conditional distribution of well-being. The standard ordered probit model predicts a significant positive effect for the highest satisfaction category, whereas the generalized model finds that income does not affect the probability of this highest response. In addition, the generalized ordered probit model shows a more negative effect on the lower response categories of satisfaction than the standard ordered probit model. The results suggest that higher income reduces unhappiness, but one can be satisfied without high income as well. The findings draw attention to the importance of method selection in satisfaction research.

KEYWORDS:

Subjective well-being.

Income.

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One of the most important topics of papers on subjective well-being is the relationship between satisfaction and income. Since in subjective well-being research people are often asked about their life satisfaction on a scale with limited answer categories, the most frequently used methods to assess the income-satisfaction relationship are either OLS regression or ordered logit/probit models, depending on whether the well-being measure is assumed to be cardinal or ordinal. The overall conclusion of the literature is that material welfare has a positive but moderate effect on subjective well-being. In this paper we compare the results of the various models and examine whether different methods lead to different conclusions on the association between life satisfaction and income. Specifically, we compare the results of OLS regression with that of quantile regression, and ordered probit model with generalized ordered probit model.

Our paper is structured as follows. Chapter 1 reviews briefly the relevant literature on the relationship of subjective well-being and income. In Chapters 2 and 3 OLS and quantile regressions as well as ordered probit and generalized ordered probit models are described. Chapter 4 provides details about our data; Chapter 5 presents and discusses the results. Chapter 6 concludes.

1. Income and subjective well-being

Since our empirical analysis uses cross-sectional data, the literature review focuses primarily on studies that are based on similar data. Papers on income and subjective well-being using cross-sectional data have found positive but mostly moderate correlation at individual level. Both pioneering (*Easterlin* [1974]) and recent studies have showed that individuals with higher income report higher level of happiness than those with lower income; in the US, for example, those with high family income (over 90 000 USD) were almost twice as likely to be “very happy” as those with low household income (below 20 000 USD) (*Kahneman et al.* [2006]).

Despite the positive association between income and well-being, moving up on the income ladder, the effect of income seems to weaken. In other words, the relationship between well-being and income is non-linear; the marginal utility of income is declining (*Layard–Mayraz–Nickell* [2008]). A survey from the US showed that between 1994 and 1996, within the bottom five income deciles, doubling income had twice as strong impact on happiness as within the top five deciles (*Frey–Stutzer* [2002]). However, recent papers using richer datasets from several countries

conclude that among the poor and the rich, income increases happiness to the same extent (*Stevenson–Wolfers* [2008], [2013]).

Previous papers did not establish a causal relationship between income and well-being. Estimation of the causal effect needs to perform controlled field or natural experiments or to use instrumental variable regression. *Frijters, Haisken-DeNew and Shields* [2004] using panel data and building on the exogen changes after the German reunification estimated the impact of income on life satisfaction. Their results showed that a significant part of the rising level of East-Germans' subjective well-being can be explained by increases in their income. Other papers on instrumental variables regression estimated somewhat higher income effect on well-being than papers on standard OLS or ordered probit model (*Knight–Song–Gunatilaka* [2009], *Powdthavee* [2010]).

There are only a few studies that use quantile regression or generalized ordered probit/logit models. *Binder and Coad* [2011] applied quantile regressions on data from the British Household Panel Survey (BHPS) for the year 2006 to show that income is positively associated with life satisfaction, however, the effect was stronger at the lower end of the satisfaction distribution, but was insignificant for the most satisfied. *Mentzakis and Moro* [2009] analysed data from eight waves of the BHPS using a generalised ordered probit model. They found that income buys off unhappiness, but paradoxically, high income decreases the probability of reporting the highest level of well-being. Using data from the German Socio-Economic Panel for the years 1984–2004 and applying standard ordered probit and generalized ordered probit model, *Boes and Winkelmann* [2010] investigated the relationship between income and life satisfaction. They found that, contrary to the standard ordered probit model, the generalized ordered probit model suggests that income has no effect on high satisfaction but significantly reduces dissatisfaction for men, whereas for women, the effect of income is even weaker.

How can the modest relationship between income and satisfaction be explained? Among explanations, we find adaptation, social comparison and aspiration theory (*Clark–Frijters–Shields* [2008]). Adaptation means that the positive impact of rising income on well-being is only temporal, individuals get used to the changing circumstances. If income grows, evaluation standards increase as well, in other words, the higher income becomes the reference point, hence individuals return to the baseline level of satisfaction. The process of adaptation is corroborated by several empirical findings (*Easterlin* [2005], *Di Tella–MacCulloch* [2010]).

The social comparison theory implies that life satisfaction depends on comparison of life circumstances to not an absolute but a relative standard. Individuals' satisfaction is determined by their absolute income and also their income compared to the (average) income of their reference group. *Ceteris paribus*, higher reference income reduces individual satisfaction, since higher earnings of the relevant others make one

feel relatively deprived (*Ferrer-i-Carbonell* [2005], *Luttmer* [2005]).¹ Flattened income-satisfaction relationship observed in cross-sectional data might be explained by this social comparison effect. The rich and the poor might have different reference groups, thus their satisfaction depends on different social and economic standards.

Aspiration level is the income level that individuals desire to attain (*Stutzer* [2004], *McBride* [2010]). It is constantly changing and determined e.g. by past income and one's income position relative to the relevant others. The higher the past income and the income of relevant others, the higher the required income (the aspiration level). Rising individual income might also imply that one changes his or her reference group, thus aspirations might grow in this way as well.

Another factor in the explanation of the moderate income-satisfaction relationship might be the higher workload and different time use of individuals with high income. People with above-average income spend more time on enjoyable activities (e.g. active leisure), but they also spend more time working and commuting that is associated with higher stress and tension (*Kahneman et al.* [2006]).

Other papers showed that money-related thoughts make people less helpful and decrease their needs for social relations (*Vohs-Mead-Goode* [2006], [2008]). Since social activities and social capital are positively associated with satisfaction (*Helliwell-Putnam* [2004]), ceteris paribus, money-minded people might be less happy because of their poorer social life. Indeed, *Kasser-Ryan* [1993] and *Kasser-Ahuvia* [2002] found that those who have strongly internalized materialistic values or have high level of financial success aspiration (and thus supposedly are in good financial situation) are less happy and have lower level of mental health. The formerly listed explanations together can account for the conclusion that income and wealth have limited impact on subjective well-being.

In accordance with the findings of the literature, there are two mechanisms that can explain the income-well-being relationship (*Diener et al.* [2010]). The basic needs theory states that the better financial situation increases subjective well-being since it allows to fulfil basic needs (e.g. shelter, food), but after fulfilment of these needs, the effect of income on well-being is diminishing. Nevertheless, it is possible that learned desires for material goods underlie the income and well-being association. Individuals with relatively low material aspiration might report high satisfaction even without much income, while those with high material aspiration need higher income and higher consumption to be happy. Papers showing impact of personality traits on marginal utility of income have similar conclusions (*Boyce-Wood* [2011], *Budria-Ferrer-i-Carbonell* [2012]).

¹ However, sometimes, relative income might be positively correlated with well-being. In an unpredictable, rapidly changing environment, rising income of the reference group might provide information about the future income prospect of the individual, hence it might increase individual satisfaction (*Senik* [2004]; *Hajdu-Hajdu* [2011a], [2011b]).

2. OLS versus quantile regression

In subjective well-being research, people are usually asked about their life satisfaction on a scale with limited answer categories.² Analysing the subjective well-being indicators, most of the empirical works use OLS regression where the categorical dependent variable is considered cardinal, which means that the difference in satisfaction between levels 9 and 10 is the same as the difference between levels 3 and 4.

OLS regression assumes a linear relationship between the dependent variable (y) and the regressors (x).³

$$y_i = \beta x_i + \varepsilon_i.$$

Minimizing the sum of squared residuals, we obtain the coefficient vector (β):

$$\min \sum_{i=1}^n (\hat{\varepsilon}_i)^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n (y_i - \hat{\beta} x_i)^2.$$

Thus, the estimated linear relationship fits the conditional mean of the dependent variable. In this way, we obtain the average effects of the independent variables.

However, this also means that we get an incomplete picture about the relationship between the dependent variable and the independent variables, since OLS focuses on the conditional mean of the dependent variable. At different parts of the conditional distribution, this relationship might be different, which can be estimated by quantile regression. Quantile regression provides a more complete picture: we can estimate the effects of the explanatory variables at different quantiles of the conditional distribution of the dependent variable. Comparing the estimated coefficients, we can answer the question whether the relationship estimated by OLS regression prevails at other parts of the conditional distribution of the dependent variable.

Just as OLS, quantile regression fits a linear model, but the estimated coefficient vector minimizes the asymmetric weighted sum of absolute deviations, instead of the sum of squared residuals. The weights are determined by the given quantile ($0 \leq \tau \leq 1$).

$$\begin{aligned} \min \sum_{i=1}^n \rho_{\tau} |\hat{\varepsilon}_i| &= \sum_{i=1}^n \rho_{\tau} |y_i - \hat{y}_i| = \sum_{i=1}^n \rho_{\tau} |y_i - \hat{\beta} x_i| = \\ &= \tau \cdot \sum_{y_i \geq \hat{\beta}_{\tau} x_i} |y_i - \hat{\beta}_{\tau} x_i| + (1 - \tau) \cdot \sum_{y_i < \hat{\beta}_{\tau} x_i} |y_i - \hat{\beta}_{\tau} x_i|. \end{aligned}$$

² E.g. in the European Social Survey, respondents evaluate their life satisfaction on an 11-point scale answering the following question: "All things considered, how satisfied are you with your life as a whole nowadays?"

³ Throughout the paper ε stands for the usual error term.

The function ρ_τ (called the “check function”) weights differently the observations above or below the line of the best fit. For example, at the 8th decile ($\tau = 0,8$), observations above the predicted values (observations where the residual is positive) get weight four times higher than observations below the predicted values. In this way, we get the slopes (β_τ) of the linear relationship between the dependent variable and the independent variables along the entire conditional distribution (Koenker–Hallock [2001], Angrist–Pischke [2009]).

3. Ordered probit versus generalized ordered probit

In happiness research, dependent variables are usually ordinal, thus it is suitable to use ordered models (e.g. ordered probit), where answer categories of the subjective well-being are considered only ordinally comparable. In other words, the distances between the categories are not assumed to be equal. Ordered probit assumes an underlying continuous dependent variable (y^*) which is related linearly to the independent variables:

$$y_i^* = \beta x_i + \varepsilon_i .$$

This latent dependent variable – in our case subjective well-being – cannot be observed, instead, well-being data are available in ordinal categories ($y = 1, 2, \dots, J$), since respondents answer the question about their satisfaction on a J -point scale. They choose the answer category that describes best their own subjective well-being (y^*). If their “true” satisfaction falls below cut-point γ_1 , then they choose the lowest category; if their “true” satisfaction falls between γ_1 and γ_2 , they will pick the second category. Assuming J answer categories, the observed satisfaction is the following:

$$y_i = j \quad \text{if} \quad \gamma_{j-1} \leq y_i^* < \gamma_j ,$$

where j runs from 1 to J , $\gamma_{j-1} < \gamma_j$, $\gamma_0 = -\infty$ and $\gamma_J = \infty$.

The probability of observing $y = j$ for given values of the independent variables is:

$$Pr(y_i = j | x_i) = Pr(\gamma_{j-1} \leq y_i^* < \gamma_j | x_i) = Pr(y_i^* < \gamma_j | x_i) - Pr(y_i^* < \gamma_{j-1} | x_i) .$$

Using the definition of the cumulative distribution function (cdf) and the linear relationship between the latent dependent variable and the independent variables, the predicted probabilities can be expressed as:

$$\Pr(y_i = j | x_i) = F(\gamma_j - \beta x_i) - F(\gamma_{j-1} - \beta x_i),$$

where F is standard normal cdf.⁴

The estimated β and γ parameters are obtained by the maximization of the following log-likelihood function:

$$\log L = \sum_{i=1}^n \sum_{j=1}^J I(y_i = j) \cdot \log \left[F(\gamma_j - \beta x_i) - F(\gamma_{j-1} - \beta x_i) \right],$$

where I is a binary indicator function that equals 1 if $y_i = j$, and 0 otherwise.

Knowing coefficients β is not enough to precisely describe the relationship between the dependent variable and the independent variables. Merely knowing the magnitude of β is not informative about the effect of the independent variables on the change of the probabilities of observing $y = j$. Assuming that β is positive, we only know that growth in variable x decreases the probability of being in the lowest category, while the probability of being in the highest category increases it (*Greene* [2002], *Greene–Hensher* [2010]). We need further calculation to get the predicted change of the probabilities being in a particular category. Marginal probability effects (MPE) are the partial effects of the independent variables on the outcome probability. Since marginal probability effects measure the change in the outcome probabilities, the sum of these effects will be zero. MPE for outcome j can be calculated as

$$MPE_j(x_i) = \frac{\partial \Pr(y_i = j | x_i)}{\partial x_i} = \left[f(\gamma_{j-1} - \beta x_i) - f(\gamma_j - \beta x_i) \right] \cdot \beta,$$

where f is normal probability density function.

MPE values depend on the specific covariates values (x_i) of the observation. The calculated partial effects of income can be different for each individual, thus it is not evident which individual's MPE describe best the association between income and subjective well-being. To rule out this problem, we can compute the marginal proba-

⁴ Since $\Pr(y_i^* < \gamma_1 | x_i) = \Pr(\varepsilon_i < \gamma_1 - \beta x_i | x_i)$.

bility effects for an average person by using the sample means of the explanatory variables (\bar{x}):

$$MPE_j(\bar{x}) = \frac{\partial Pr(y_i = j | \bar{x})}{\partial x} = [f(\gamma_{j-1} - \beta \bar{x}) - f(\gamma_j - \beta \bar{x})] \cdot \beta.$$

Another possibility to compute average marginal probability effects (AMPE) by calculating the marginal probability effects for each individual and taking the average of those:

$$AMPE_j(x) = \frac{1}{n} \sum_{i=1}^n MPE_j(x_i),$$

where n is the number of observations.

In the ordered probit model there is an implicit assumption called parallel regression assumption (*Winkelmann–Boes* [2006], *Greene–Hensher* [2010], *Long–Freese* [2010]). Using the probabilities of the particular outcomes, we can compute cumulative probabilities, i.e. the probabilities of $y \leq j$:

$$Pr(y_i \leq j | x_i) = Pr(y_i = 1 | x_i) + \dots + Pr(y_i = j | x_i) = F(\gamma_j - \beta x_i).$$

In this way we can define both $J - 1$ cumulative probabilities⁵ and $J - 1$ binary probit model. If we look at these probit models, we can see that the slope coefficients (β) are identical across each regression. This means that the ordered probit model is equivalent to $J - 1$ binary probit regressions where β coefficients are equal for each equation, and only the constants are different. So if we create $J - 1$ binary dependent variables and estimate probit models, we should get the results:

$$\beta_1 = \beta_2 = \dots = \beta_{J-1} = \beta,$$

where β_i 's are the slope coefficients of the binary probit regressions and β is the slope coefficient of the ordered probit estimate.⁶

The second interesting feature of the ordered probit model is that marginal probability effects change sign exactly once moving stepwise from the first to the last out-

⁵ Since $Pr(y_i \leq J | x_i) = 1$.

⁶ Using Brant test, we can test whether the coefficients are identical across the binary equations (*Greene–Hensher* [2010]).

come (single crossing property) (*Boes–Winkelmann* [2006], *Winkelmann–Boes* [2006]). If β is positive, then the marginal probability effects start negative and then become positive. If β is negative, we see an opposite change, MPE's are first positive and then negative.

Boes–Winkelmann [2006] and *Winkelmann–Boes* [2006] also note that for any two explanatory variables (x_i^a and x_i^b), the ratio of the marginal probability effects is constant, irrespectively of the outcome category (j):

$$\frac{MPE_j(x_i^a)}{MPE_j(x_i^b)} = \frac{[f(\gamma_{j-1} - \beta x_i) - f(\gamma_j - \beta x_i)] \cdot \beta^a}{[f(\gamma_{j-1} - \beta x_i) - f(\gamma_j - \beta x_i)] \cdot \beta^b} = \frac{\beta^a}{\beta^b},$$

where β is the coefficient vector of the covariates, whereas β^a and β^b are the coefficients of the variables x^a and x^b . It means if income is more important than health in the lower part of the outcome distribution, it must be also more important at the higher part of the distribution.

These limitations of the standard ordered probit model (parallel regression assumption, single crossing property, constant relative marginal probability effects) can be relaxed using generalized ordered probit model (*Boes–Winkelmann* [2006], *Winkelmann–Boes* [2006], *Greene–Hensher* [2010]), which allows for different coefficients across outcomes. For some explanatory variables (z) we can estimate $J - 1$ parameters (α), while we can maintain the assumptions of the standard model for other explanatory variables (x). In this case, the probabilities of observing the outcomes $y = j$ are the following:

$$Pr(y = j | x, z) = F(\gamma_j - \alpha_j z - \beta x) - F(\gamma_{j-1} - \alpha_{j-1} z - \beta x).$$

Thus, marginal probability effects for variables z are given by

$$MPE_j(z) = f(\gamma_{j-1} - \alpha_{j-1} z - \beta x) \cdot \alpha_{j-1} - f(\gamma_j - \alpha_j z - \beta x) \cdot \alpha_j.$$

Since α_j varies across outcomes, the generalized model is much more flexible than the standard model, and relaxes the parallel regression assumption. Moreover, the relative marginal probability effects no longer need to be constant and the sign of the marginal probability effects can change more than once moving from the lowest outcome category to the highest.

4. Data

We use data from the TÁRKI Household Monitor for the year 2007.⁷ The database contains 3 653 individual questionnaires from 2 024 households and it is representative for the 16 year-old or older population with respect to socio-demographic characteristics such as age, sex, types of settlement, and education. We exclude respondents with missing subjective well-being variables (11 observations) or control variables (37 observations). The final sample size is 3 602.

Subjective well-being is measured with a single-item question on an 11-point scale (0 – not satisfied at all, 10 – fully satisfied): “All things together, how satisfied are you with your life?” Scores of 0–2 are combined in a single score due to the small number of observations, thus our satisfaction variable has nine categories (on a scale from 0 to 8).

Income is measured as equivalent income (using the original OECD equivalence scale), and included in the models in logarithmic form.⁸ We used the following control variables: gender, age, squared age, education (four categories), marital status (four categories), economic activity (seven categories), subjective health (four categories), and household size. Summary statistics of all variables are given in the Appendix.⁹

5. Results

In the next sections we present and compare the results of the models, in Section 5.1 those of quantile regression and OLS regression, while in Section 5.2 those of ordered probit and generalized ordered probit models.

5.1. OLS and quantile regression

First we analyse the association between income and life satisfaction, using OLS regression. Table 1 presents the results. Equivalent household income has positive

⁷ Data were provided by TÁRKI Data Archive. Full title of the data collection: TÁRKI Household Monitor 2007, The Financial and Labor Market Position of Hungarian Households. Primary investigators: *Péter Szivós* and *István György Tóth*.

⁸ The original OECD scale assigns a value of 1 to the head of the household, a value of 0.7 to other adults and a value of 0.5 to children.

⁹ We have run our models with other indicators of material welfare (equivalent expenditures, number of assets owned by the household) as well. The results are substantially similar to those of the models presented here.

and highly significant association with life satisfaction. Individuals with higher income tend to report higher satisfaction. A 10% increase in income would be associated with a 0.05-point increase in life satisfaction ($\ln(1.1) \cdot 0.53 = 0.051$). In comparison, married individuals have 0.61 point higher satisfaction than those who are single; individuals with bad health status have 1.66 points lower satisfaction than those with good health; losing job is associated with a 0.5-point decrease in life satisfaction. It means that the phrase “money doesn’t buy happiness” seems not to be true, however, the effect of income on well-being is much lower than the effects of other factors.

Table 1

The association of income and life satisfaction in OLS regression model

Explanatory variable	Coefficient
ln(Equivalent household income)	0.529*** (0.085)
Control variables	yes
Adjusted R^2	0.244
N	3 602

Note. Dependent variable: life satisfaction. Control variables: gender, age, age squared, education, marital status, economic activity, subjective health, and household size. Robust standard error adjusted for clustering by household is in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As we mentioned earlier, OLS provides an incomplete picture on the relationship between the dependent variable and independent variables, since it focuses on the conditional mean of the former. To assess the relationship at different part of the conditional distribution, we need to look at the results of quantile regressions. Table 2 presents the income coefficients for every decile of the distribution of life satisfaction estimated by quantile regressions. The first column provides the association between income and satisfaction for the least satisfied 10%, whereas the second column shows the same association for the next 10%, and so on.

We can observe declining coefficients moving from the first decile to the last decile, i.e. income is associated more strongly with life satisfaction among the less satisfied individuals. What does it mean? On the one hand, the least satisfied individuals among the rich report significantly higher satisfaction than the least satisfied individuals among the poor. On the other hand, the most satisfied people among the rich have only slightly higher satisfaction level than the most satisfied individuals among the poor. In other words, people can be satisfied without high material welfare, but dissatisfaction is less frequent among the rich than among the poor.

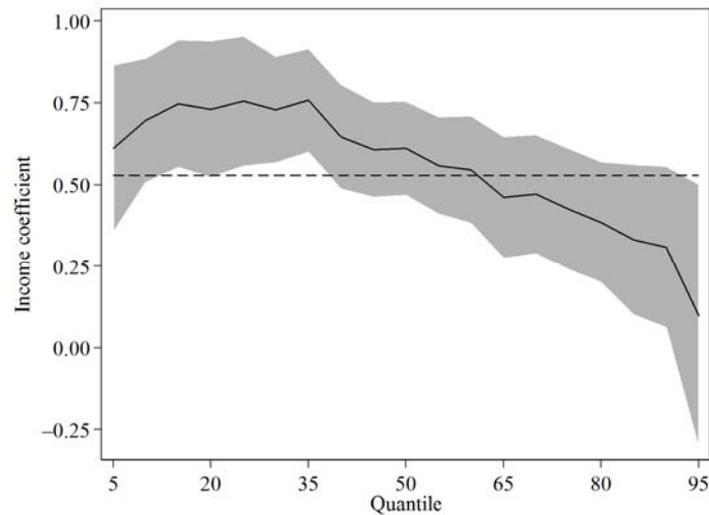
The estimated coefficients are the most similar to the OLS result around the median, which means that focusing on the average effect leads to under- or overestimation of the effect of income at the ends of the conditional satisfaction distribution. A 10% increase in income would be associated with a 0.07-0.08-point increase in life satisfaction at the lower part of the conditional distribution, whereas this effect would be 0.03-0.04 point at the upper part of the conditional distribution.

Table 2

The association of income and life satisfaction in quantile regression model

Explanatory variable	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9
ln(Equivalent household income)	0.697*** (0.097)	0.731*** (0.107)	0.730*** (0.083)	0.647*** (0.082)	0.611*** (0.074)	0.546*** (0.084)	0.471*** (0.093)	0.385*** (0.095)	0.309*** (0.127)
Control variables	yes								
Adjusted R^2	0.193	0.144	0.152	0.166	0.175	0.135	0.140	0.084	0.060

Note. Dependent variable: life satisfaction. Control variables: gender, age, age squared, education, marital status, economic activity, subjective health, and household size. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. The estimated income coefficients

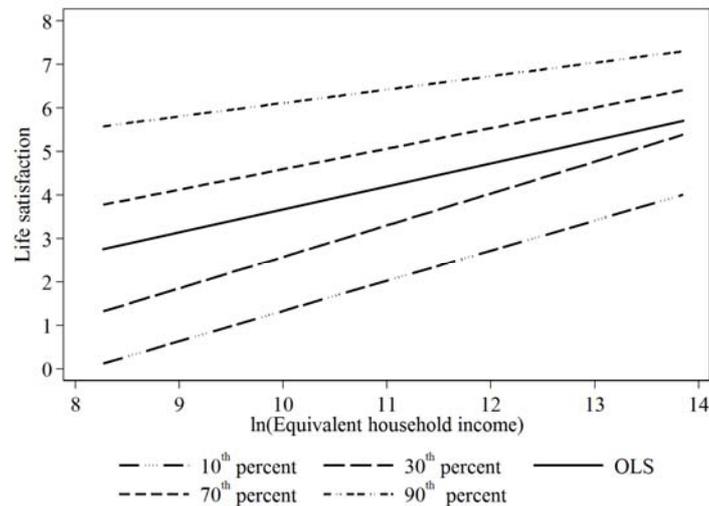
Note. The solid line depicts the quantile regression coefficients of income. The grey-shaded area illustrates the 95% confidence intervals of the quantile coefficients. The dashed line shows the OLS estimate.

The declining coefficients are more apparent in Figure 1, where we plot the income coefficients and their confidence intervals for every 5th percentile from 5 to 95. We can see that at the 95% quantile the income coefficient does not differ significantly from zero. In the upper part of the conditional life satisfaction distribution the quantile regression coefficients tend to be lower than the OLS coefficient, whereas in the lower quantiles the quantile coefficients tend to be higher.

As *Angrist and Pischke* [2009] emphasize, the quantile regression results tell us about the effects on distribution, not on individuals. Figure 2 illustrates how life satisfaction changes as income increases from the lowest to the highest level. It shows the estimated association of income and life satisfaction at the 10th, 30th, 70th, 90th quantiles, and at the mean (OLS).¹⁰ We can see that the slopes at the lower quantiles are steeper than at the higher quantiles, which results in a less wide satisfaction distribution at the higher income levels, and the average satisfaction increases with higher income.

Summing up, OLS regression predicts a positive association between income and life satisfaction, however, quantile regressions show that this relationship is more complex, not uniform along the entire conditional satisfaction distribution. Higher income reduces unhappiness, but one can be fairly satisfied without high income as well.¹¹

Figure 2. The association of income and life satisfaction at different parts of the conditional life satisfaction distribution



¹⁰ The slopes are equivalent with the corresponding coefficients in Table 2.

¹¹ The conclusion remains the same even if we exclude the poorest and richest 2% from the analysis.

5.2. Ordered probit and generalized ordered probit

Table 3 displays the estimated coefficient of income in the standard ordered probit model. We find a positive and strongly significant parameter as in the OLS regression. The positive coefficient means that an increase in income decreases the probability of being in the lowest satisfaction category, while the probability of being in the highest satisfaction category increases it. We need further calculation to get the exact change of the probabilities being in a particular category (the MPE's), but first let see the estimated coefficients of the generalized model.

In the generalized ordered probit model we allow for different income coefficients for outcomes, but we maintain the assumptions of the standard model for other explanatory variables.¹² These results are shown in Table 4. Since life satisfaction has nine categories, we get eight separate income parameters. Looking at the estimation results, we can see that the estimated coefficients differ considerably in the satisfaction categories, which means that we can reject the hypothesis of equal income coefficients. The income coefficients are higher for the lowest satisfaction categories than the estimate in the standard model, while they are lower for the highest categories. Moving toward the highest satisfaction categories, the estimated coefficient decreases and finally turns negative; for the two highest categories, they become statistically insignificant.

Table 3

The association of income and life satisfaction in ordered probit model

Explanatory variable	Coefficient
ln(Equivalent household income)	0.319*** (0.053)
Control variables	yes
Pseudo R^2	0.068
N	3 602

Note. Dependent variable: life satisfaction. Control variables: gender, age, age squared, education, marital status, economic activity, subjective health, and household size. Robust standard error adjusted for clustering by household is in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

¹² The results remain the same even if every parameter vector is allowed to vary across outcomes.

Table 4

*The association of income and life satisfaction
in generalised ordered probit model*

Satisfaction category	Coefficient ln(Equivalent household income)	Satisfaction category	Coefficient ln(Equivalent household income)
0	0.656*** (0.123)	5	0.222*** (0.064)
1	0.617*** (0.103)	6	0.106 (0.070)
2	0.578*** (0.093)	7	-0.117 (0.087)
3	0.473*** (0.064)	Control variables	yes
4	0.443*** (0.062)	Pseudo R^2	0.074
		N	3 602

Note. Dependent variable: life satisfaction. Control variables: gender, age, age squared, education, marital status, economic activity, subjective health, and household size. Robust standard errors adjusted for clustering by household are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

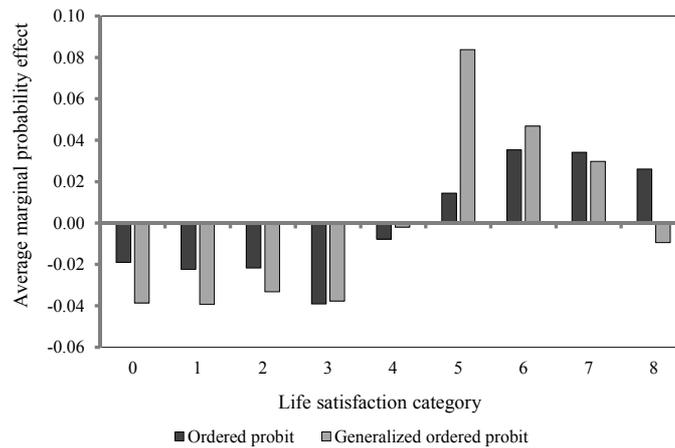
Since the estimated coefficients in themselves provide limited information about the income-satisfaction relationship, we need to look at the average marginal probability effects. Figure 3 introduces the estimated AMPE values of the standard ordered probit and the generalized ordered probit models. Each column shows the effect of a 1% increase in income on the probability of reporting a given satisfaction category.

We can see that the result of the generalized model differs considerably from that of the standard model. Comparing the AMPE's, we obtain a clear pattern. For the lowest satisfaction categories, the generalized model predicts a more negative income effect than the standard model, and for the upper middle response categories (5 and 6), the generalized model indicates a stronger positive effect. At the same time, for the highest satisfaction category, the generalized model predicts a negative (but insignificant) income effect, whereas the standard model forecasts a significant positive effect.

Summing up, the standard ordered probit model predicts a moderate positive income effect: higher income decreases the probability of dissatisfaction and increases the probability of satisfaction. Contrary to this result, the generalized ordered probit model shows a more negative effect on the lower satisfaction categories, but finds that income does not affect the probability of the highest satisfaction.¹³

¹³ The conclusion remains the same even if we exclude the poorest and the richest 2% from the analysis.

Figure 3. The effect of a 1% increase in income on the outcome probabilities (percentage point)



6. Conclusion

In this paper we have analysed the association between subjective well-being and income using cross-sectional data of 3 600 individuals. We have examined whether quantile regression and generalized ordered probit models yield different results and conclusions as compared to standard OLS regression and ordered probit models. Our findings have demonstrated that these more flexible techniques provide a more complete picture of the income-satisfaction relationship than standard models. In OLS regression income has had a positive impact on satisfaction, but in quantile regressions this association has been less strong at the upper end of the conditional distribution of life satisfaction and stronger at the lower end. This means that the least satisfied individuals among the rich are more satisfied than the least satisfied individuals among the poor, while the satisfaction level of the most satisfied individuals among the rich and among the poor is fairly similar. In other words, higher income reduces dissatisfaction, but one can be satisfied without high income.

Comparing the standard ordered probit model with the generalized ordered probit model, we have found that the standard model predicts a significant positive income effect for the highest satisfaction category, whereas the generalized model explores that income does not affect the probability of being extremely satisfied. Moreover, the generalized ordered probit model shows a more negative effect on the lower response categories of satisfaction than the standard ordered probit model. Overall, our results draw attention to the importance of method selection in happiness research.

Appendix

Summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Life satisfaction	4.35	1.91	0	8
Equivalent income (HUF)	90 454	60 793	3 900	1 036 667
Female	0.53	0.50	0	1
Age (year)	46.10	18.46	16	96
Household size (head)	3.10	1.41	1	9
Subjective health status				
Bad	0.10	0.31	0	1
Changing, not satisfactory	0.20	0.40	0	1
Changing, but rather good than bad	0.34	0.48	0	1
Good	0.35	0.48	0	1
Education				
Primary school or less	0.30	0.46	0	1
Vocational training school	0.30	0.46	0	1
Secondary school	0.28	0.45	0	1
College or university degree	0.13	0.33	0	1
Marital status				
Single	0.22	0.42	0	1
Married, cohabiting partner	0.59	0.49	0	1
Divorced	0.08	0.27	0	1
Widowed	0.11	0.32	0	1
Economic activity				
Employed	0.41	0.49	0	1
Self-employed	0.04	0.19	0	1
Temporarily not working	0.04	0.20	0	1
Unemployed	0.06	0.24	0	1
Pensioner	0.32	0.47	0	1
Student	0.09	0.29	0	1
Other inactive	0.03	0.17	0	1

Note. $N = 3\ 602$.

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