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How important is methodology for the estimates of the determinants of happiness?

Pagehead Title: **Happiness methodology.**

Abstract

Psychologists and sociologists usually interpret happiness scores as cardinal and comparable across respondents, and thus run OLS regressions on happiness and changes in happiness. Economists usually assume only ordinality and have mainly used ordered latent response models, thereby not taking satisfactory account of fixed individual traits. We address this problem by developing a conditional estimator for the fixed-effect ordered logit model. We find that assuming ordinality or cardinality of happiness scores makes little difference, whilst allowing for fixed-effects does change results substantially. We call for more research into the determinants of the personality traits making up these fixed-effects.

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The empirical economic literature on self-reported happiness, also termed life satisfaction, seems to be taking off. Whereas in the 1970s and 1980s there was only a trickle of articles on happiness, [1] the last couple of years witnessed a spate of empirical studies on this subject. [2,3]. Next to the economic literature, there are more than 3000 studies done in the last 30 years by psychologists and sociologists (see Veenhoven et al.,1994; Veenhoven, 1997). This means that there is now a large combined literature on what causes happiness.

In this paper, we investigate the robustness of all these findings. To this extent, we categorise the empirical studies on used methodologies that reflect the assumptions imposed on the meaning of satisfaction questions and on the influence of unobservables.

On the meaning of satisfaction questions, psychologists have by and large interpreted the answers as cardinal, i.e. that the difference in happiness between a 4 and a 5 for any individual is the same as between an 8 and a 9 for any other individual. In the economic profession, cardinality is still considered very suspect (see Ng, 1997). In studies of individual happiness therefore, we find that economic papers generally assume that satisfaction answers are only ordinally comparable, i.e. that it is unknown what the relative difference between satisfaction answers is but that all individuals do share the same interpretation of each possible answer.

On the influence of unobservables, we focus on the unobservables that are individual specific and constant across time. The great practical advantage of a cardinality assumption is that one can simply look at the changes in happiness and relate them to changes in observables. This means that any effect of time-invariant unobservables drops out in linear specifications. As a result, there are a lot of papers in the psychological literature that allow for time-invariant unobservables related to observables, i.e. econometric models with individual fixed effects. Most of the economic papers, on the other hand, employ latent variable models in which simple first-differencing leads to biased estimates, which has yielded a virtual absence of fixed-effects models in economic analyses of individual happiness.[4]

We compare the results of the various models to disentangle the influence of the assumptions on the results. To that end, we discuss the findings on a set of time-varying demographic and economic variables that are available in nearly every analysis. These variables are: age, income, living in partnership, number of children in the household, and health. Although these 5 variables have been used widely, each study in this literature focuses on its own particular point of interest and therefore includes a completely different set of controls. It will be clear that all the five variables are related to many aspects of life and that controlling for other aspects will change the results for these 5 variables. We therefore augment the empirical findings of others by adding for each different model our own estimates based on the German Socio-Economic Panel (GSOEP), which has been extensively used in satisfaction research and is summarily explained in the appendix A.

As a final exercise, we try to breach the methodological differences between economists and psychologists by setting up and estimating a latent-variable model with individual fixed-effects, i.e. a fixed effect ordered logit model. This model is mathematically very similar to the fixed-effect logit model developed by Chamberlain (1980), but we demonstrate that it is able to use much more information. Furthermore, it allows for an individual-specific interpretation of the happiness question, and hence relaxes the ordinality assumption. The results for the 5 chosen variables using the fixed-effect ordered logit model are surprisingly close to the results of a simple OLS on the changes in general satisfaction. Therefore, our main conclusion is that assuming cardinality or interpersonal ordinality of the satisfaction answers makes little difference to the results, while the time-invariant factors related to observables are very important in explaining happiness. This leads us to advocate a research shift towards the explanation of the distribution of these time-invariant factors.

For completeness, we then briefly discuss other methodological issues.

1. Satisfaction questions

Psychologists and sociologists have used subjective questions regarding individuals' happiness for over three decades. Cantril (1965) developed a question for life satisfaction. Similar question modules include the Likert (1932)-scale and the Visual Analog Scale (VAS). See also Bradburn (1969). The answer to these subjective questions has been indiscriminately termed 'happiness', 'general satisfaction', and 'subjective well-being'. In the GSOEP the satisfaction question is:

> Please answer by using the following scale in which 0 means totally unhappy, and 10 means totally happy.
>
> How happy are you at present with your life as a whole?

Here, we call the response to this question the General Satisfaction (GS) level of the respondent. In this case, there are 11 numerical categories, but the question has also been posed with 7 or 5 categories or with verbal labels, such as 'very happy/happy/so-so/somewhat unhappy/very unhappy'. The end result is invariably an ordered categorical evaluation of the quality of life of the individual. In the remainder, we shall abstract from the different formulations between these questions and simply use GS_{it} as the name of the endogenous variable of individual i at time t with happiness increasing together with the numerical values. This also allows for the possibility that, say, 'very happy' is denoted as a 1 and every other answer as a 0. The general research question is to determine, under various assumptions, the causal effect of observed characteristics $\mathbf{x}_{it}$ on GS_{it} when there are unobserved characteristics $\boldsymbol{\varepsilon}_{it}$.

2. Assumptions

2.1. General assumptions

There are three main assumptions that have been used on the interpretation of the answers of the satisfaction question. Increasing in restrictiveness, these are:

A 1 General satisfaction is a positive monotonic transformation of an underlying metaphysical concept called welfare and denoted by W(.): if $\mathrm{GS}_{it} > \mathrm{GS}_{is}$ then $\mathrm{W}_{it} > \mathrm{W}_{is}$.

A 2 General satisfaction is interpersonally ordinally comparable: if $\mathrm{GS}_i > \mathrm{GS}_j$ then $\mathrm{W}_i > \mathrm{W}_j$.

A 3 General satisfaction is interpersonally cardinally comparable: $(W_i - W_j) = \omega(GS_i, GS_j)$ with $\omega(.)$ a function that is known up to a multiplicative constant. Most normally $\omega(GS_i, GS_j)$ is taken to be $(GS_i\text{-}GS_j)$.

The first assumption implies a correspondence between what is measured, GS_{it}, and the metaphysical concept researchers are actually interested in, W_{it}. Obviously, welfare is not a physical phenomenon that can be easily and objectively measured. However, it is known (see Shizgal, 1999; Fernández-Dols and Ruiz-Belda, 1995; Sandvik et al., 1993) that there is a strong positive correlation between emotional expressions like smiling, frowning, brain activity, and the answers to the satisfaction questions. GS_{it} are also predictive in the sense that individuals will not choose to continue activities which yield low satisfaction levels (see Kahneman et al., 1993; Clark et al., 1998; Frijters, 2000; Shiv and Huber, 2000). If emotional expressions and choice behaviour are truly related to the underlying metaphysical concept of welfare, then GS can also be used as a proxy for welfare.

The second assumption, ordinal comparability, implies that individuals share a common opinion of what happiness is. This assumption relies on supporting evidence from two psychological findings. The first is that individuals are somewhat able to recognise and predict the satisfaction level of others. In interviews in which respondents are shown pictures or videos of other individuals, respondents were somewhat accurate in identifying whether the individual shown to them was happy, sad, jealous, etcetera (see Sandvik et al., 1993; or Diener and Lucas, 1999). This also held when individuals were asked to predict the evaluations of individuals from other cultural communities. Hence, it is arguable that there is a common human 'language' of satisfaction and that satisfaction is roughly observable and comparable among individuals. The second finding is that individuals in the same language community have a common understanding of how to translate internal feelings into a number scale, simply in order for individuals to be able to communicate with each other. Respondents have been found to translate verbal labels, such as 'very good' and 'very bad', into roughly the same numerical values (e.g. Van Praag, 1991). The empirical analysis of GS under the ordinal comparability assumption makes use of latent variable models, such as ordered probit and logit.

The third assumption usually amounts to assuming that the difference between a satisfaction answer of, say, an 8 and a 9 is the same as the difference between a 4 and a 5 (see Ng, 1996; 1997). It precludes any tendency for extreme response behaviour such as driven by cultural norms where one is supposed to be either very sad or very glad in which case there is little welfare difference between the middle categories. Two arguments are in favour of it. Schwartz (1995) argues that respondents try to work out what the researcher is trying to ask as if they were in conversation with her. Hence, one may argue that respondents interpret a choice of numbers as a cardinal question, much in the same way as they interpret weights in the supermarket in a cardinal sense. The second, related argument, is that an even-spaced welfare difference between satisfaction answers, which is the most popular cardinalisation, corresponds to a situation where individuals try to maximise the information they give in the questionnaire (Van Praag, 1991; Parducci, 1995). When GS is assumed to be a cardinal measure of welfare, the empirical analysis is often realized by means of OLS or similar methods.

2.2. Statistical assumptions

The statistical assumptions made hinge on the existence and effects of unobserved factors in the data set at hand:

- S1 There are time-varying unobserved factors, ε_{it}, related to observables in an unknown way.
- S2 There are time-invariant unobserved factors, $\boldsymbol{\upsilon}_i$, related to initial levels of observed factors, and there are time-varying unobserved factors, ε_{it}, unrelated to observed factors: $cov(\varepsilon_{it}, x_{it}) = cov(\boldsymbol{\upsilon}_i, \Delta\mathbf{x}_{it}) = 0$ and $cov(\boldsymbol{\upsilon}_i, \mathbf{x}_{it}) \neq 0$.
- S3 Unobserved factors, $\boldsymbol{\varepsilon}_{it}$ or $\boldsymbol{\upsilon}_i$, are either unrelated to observed factors or their relationship is known: $cov(\boldsymbol{\varepsilon}_{it}, \mathbf{x}_{it}) = \mathbf{z}^1_{it}$, and $cov(\boldsymbol{\upsilon}_i, \mathbf{x}_{it}) = \mathbf{z}^2_{it}$, with z either 0 or a known function.

The first statistical assumption would seem to arise very often according to economic theory: because individuals continuously make decisions based on constraints and future expectations, anything unobserved that affects GS and also changes expectations or constraints will influence observed decisions. Under an S1 situation causal inferences cannot be made.

Under S2, all relevant time-varying factors are thought to be observed. For instance through randomised experiments or rich data sets, all the unobserved variables appearing under S1 are then known or exogenous. The remaining fixed unobserved factors are believed to influence the levels of other variables, though not their changes. A prime candidate for such a fixed unobserved factor in economic analyses are personality traits: Diener and Lucas (1999) and Argyle (1999) survey extensive psychological evidence that very persistent personality traits are the best predictors of satisfaction levels. Whereas demographic and socio-economic variables are at best found to be able to capture only 15% of the variance of GS_{it} (Diener, 1984), genes and persistent psychological traits have been found to have a correlation of up to 80% with GS_{it} (Lykken and Tellegen, 1996). Personality traits are furthermore related to many demographic variables and hence studies that do not include personality variables, which includes most of the economic studies mentioned in this paper, operate in an S2-world.

Under S3, there may be unobserved factors, but they are either orthogonal to what is observed and hence do not normally bias the results, or their relation to what is observed is (due to some assumed structure) known and hence can be controlled for. This would seem to reasonably apply only in cases where the data used is extremely rich and simultaneous account can be taken of all this information.

3. Models used and their results

3.1. Models with A3.

One popular model under A3 is to estimate

$$GS_{it} = \mathbf{x}_{it}\beta + \varepsilon_{it}. \tag{1}$$

Here, ε_{it} has expectation 0 and is orthogonal to x, leading to an OLS of the raw scores GS_{it} on $\mathbf{x}_{it}$. We include in this model set-up the very popular practice in psychology of having as the main results a table with correlations between the raw scores GS_{it} and some observed characteristics, because this can be seen as a particular representation of the results of an OLS with 1 variable. Note, however, that in that case, this single characteristic must be orthogonal to everything else for its correlation score to be interpreted as causal.

This model requires an A3-S3 world for the resulting parameters to be seen as causal. It is the workhorse model for cross-section data in psychology: for instance, of the more than 50 psychological studies cited in Argyle (1999) alone, all the psychological studies based on cross-sections used this model. The same goes for cross-section studies in the surveys by Diener et al. (1999) and Veenhoven (1997). Amongst economists, an early study by Morawetz (1977) looking at individual satisfaction in two Israeli settlements and one of Gardner and Oswald (2001) with time and region dummies, also employ an OLS. Apart from these two studies, the only other examples in economics we could find of this model as the *main* model of a paper are those that compare aggregates of satisfaction over countries and hence also implicitly rely on cardinality. These studies include Easterlin (1974; 1995), Oswald (1997), Micklewright and Stewart (1999), Kenny (1999), and Di Tella et al. (2001).

An advantage of assuming A3, is that it is particularly easy to relax S3 and to assume S2 by taking a first-difference estimator of (1):

$$GS_{it} - GS_{it-1} = \Delta\mathbf{x}_{it}\beta + \Delta\varepsilon_{it}, \tag{2}$$

for which it is obvious that if there was a fixed linear individual trait, $\boldsymbol{v}_i$, related to $\mathbf{x}_{it}$, it would drop out. This formulation is the standard model on causality in the psychological literature when using panel or time-series data sets (Diener and Suh, 1999; or Argyle, 1999). In economics, Gerlach and Stephan (1996) and Korpi (1997) seem to have been the only ones so far to use the same fixed-effects OLS framework on individual level data.

Clark and Oswald (1994), Oswald (1997), Ng (1996), and the studies surveyed by Easterlin (1995) also fall in this category because they use changes in aggregates of happiness indicators and correlate them with changes in other aggregates. This allows for fixed-effects at the level of countries, though not for individuals. A hybrid is the paper by Di Tella et al. (2001). They employ OLS-regressions on repeated cross-sections on individuals and, in a 2-step procedure, insert country specific fixed-effects. This means they do not allow for individual effects. If this leads to a bias in the coefficients of individual characteristics, then the changes in aggregate satisfaction in countries will be related to changes in the averages of individual characteristics. These time-varying changes cannot be picked up by time-invariant country fixed effects. The same problem applies for the other analyses of changes in aggregate satisfaction. Hence neither the paper by Di Tella et al. (2001) nor the other economic papers looking at aggregate GS correct for individual fixed-effects.

A3, in conjunction with S3 or S2, has lead to the following findings on the 'key' variables of interest in this paper, i.e. age, income, living in a partnership, children, and health:

Age, which is used as a proxy for cohort effects or unobserved social status and health deterioration, is found to have a small positive effect (*World Value Study group survey* 1994). Proposed explanations are that the old feel more in control of their environment (Ryff, 1995), have lower aspirations which are hence easier to meet (Cambell et al., 1976), or that it is the happy that live longer (Argyle, 1999). The effects, however, are small. Additionally, under specification (2), a linear effect of the change in age is indiscernible of the time-effects, meaning that only its non-linear effect can be identified but not its total effect. More will be said on this later.

On income, opinion is very divided. Studies based on equation (1) find strong positive effects (Diener et al.,1995), but those based on (2) range from positive (Veenhoven, 1997; Gerlach and Stephan, 1996; or Inglehart, 1990) to insignificant or even negative (Diener et al., 1993). The most convincing studies with (2) use quasi-experimental designs that follow individuals who unexpectedly acquired a lot of money via lotteries or bequests. These studies also find little long-term effect of increases in income (see Argyle, 1999) though they do find strong positive short-term effects (Gardner and Oswald, 2001). This is attributed to the finding that individuals adapt their aspiration level when they earn more.

Living with a partner, usually proxied by a marriage dummy, is generally found to have a strong positive effect on happiness (Argyle, 1999; Veenhoven et al., 1994, Gerlach and Stephan, 1996), whether found via equation (1) or (2).

>From Cantril's (1965) initial study of 35000 respondents in 11 countries onwards, the effect of having children on happiness does not appear to be very strong, though a meta-analysis on cross-sectional evidence for the United States suggests their overall effect to be negative (Glenn and Weaver, 1979). This is thought to result from the fact that children increase stress levels (Argyle, 1999).

The effect of health on happiness has been found to be strongly positive under both (1) and (2) (*World Value Study group survey,* 1994; Diener et al., 1999, Gerlach and Stephan, 1996).

Below, in Table 1, we show our own regressions on the GSOEP for both equation (1) and (2). We only present the estimates of our 5 chosen variables. The sample was restricted to the West-German workers in order to avoid the issue of the negative effect of unemployment on satisfaction and the related problem of the strong interrelation between age, health, and employment (Clark and Oswald, 1996; Korpi, 1997; Blanchflower and Oswald, 2000a). Available time-invariant controls are added for (1), but not for (2). In both specifications time-dummies are incorporated for the different waves.

[Table 1 about here]

Several typical findings come out of Table 1. The results with model (1) are standard: satisfaction increases with age, income, living with a partner, and health; and the effect of the number of children is negative. Adding several controls does not increase R^2 much, and only significantly increases the marriage dummy. The R2 for model (2) is lower because the estimation only uses information on the variation within the group. The results with model (2), reported in columns 5 and 6 of Table 1 are also conform to previous findings with this model: the number of children is insignificant, whereas having a partner and health are positively significant. One-year changes in income have a reduced positive effect, in line with most studies based on (2).

3.2. Models with A2

The main model under A2, i.e. assuming ordinal comparability, is of a latent variable form:

$$\begin{aligned} GS_{it}^{*} &= \mathbf{x}_{it}\beta + \varepsilon_{it}, \\ GS_{it} &= k \Leftrightarrow \lambda_k \leq GS_{it}^{*} < \lambda_{k+1}, \end{aligned} \tag{3}$$

where $\varepsilon_{it} \perp \mathbf{x}_{it}$; GS_{it}^{*} is the latent variable, and GS_{it} is observed general satisfaction. Depending on the assumed distribution of the error-term ε_{it}, this leads to an ordered probit or an ordered logit model, which can be solved by maximum likelihood methods or logistic regression. In order for the ensuing estimator to be causally interpreted, S3 has to hold. This is the model used mostly by economists. The ordered probit model was used by Blanchflower and Oswald (2000a), Clark and Oswald (1994), Plug (1997), Ferrer-i-Carbonell (2002), Frey and Stutzer (1999; 2000), Hartog and Oosterbeek (1998), McBride (2001), Pradhan and Ravaillon (2000), van Praag et al. (2003) and Wottiez and Theeuwes (1998). Ordered logit was the main model in, among others, Alesina et al. (2001), Blanchflower and Oswald (2000b), Theodossiou (1998), Winkelmann and Winkelmann (1998). The ordered latent-response model also seems to be the one most used in economic analyses of job satisfaction (e.g., Clark, 1997; Levy-Garboua and Montmarquette, 1997; Sousa-Poza and Sousa-Poza, 2000; see also Hamermesh, 2001) and health satisfaction (e.g., Cutler and Richardson, 1997; Kerkhofs and Lindeboom, 1995).

Unlike (1), this model does not lend itself easily to an inclusion of unobserved individual heterogeneity. In an ordered probit setting, it is known since Maddala (1983) that allowing for fixed individual effects yields inconsistent estimates. Fixed effects also bias the estimates of statistics like whether GS_{it} increases or not, and hence there is no simple first-difference estimator for the fixed-effect latent response model. This has severely hampered implementing an S2 assumption for this model in a panel data context. There is a conditional maximum likelihood estimator for the fixed effects logit model that can be employed when one reduces the number of discerned categories to two, which has been used once for general satisfaction by Winkelmann and Winkelmann (1998), and which is more fully discussed in Section 2.5.

An alternative within this A2 world is to assume a concrete structure on the relationship between time-invariant unobservables and observables. One option is that advocated by Mundlak (1978), which is to specify the correlation between the time-invariant unobservables and the time-varying observables as a linear function of those observables (see, van Praag et al., 2003).[5] Additionally, one can implement an ordered probit or ordered logit model with random individual effects that are fixed over time.[6] The effect of both options will be empirically examined below.

In the literature under specification (3), the resulting estimate of the effect of age is slightly different in comparison with the literature under (1), not least because age-squared is often included as a regressor in (3), whereas it is not in the psychological studies mentioned previously. Some studies under (3) find that happiness increases with age till some point (around 40) where it starts to decrease (Alesina et al., 2001), whereas others find that satisfaction is first decreasing and then increasing (Blanchflower and Oswald, 2000a; Frey and Stutzer, 1999; 2000; van Praag et al., 2003; Wottiez and Theeuwes, 1998). This high degree of ambiguity in the age effect is also noted by Theodossiou (1998). A possible explanation is that because age itself is only a proxy for unobservables, its coefficient is highly dependent on the set of regressors included in the regression. For instance, the two studies based on the British Household Panel Survey (Blanchflower and Oswald, 2000a; Theodossiou, 1998) do not include the number of children but do have extensive information on work-related issues.

In all these studies, the effect of income is strongly positive. In this sense, the results under

(3) are similar to the ones under (1): cross-sectional general satisfaction, be it ordinal or cardinal, is higher with higher income.

The effect of marriage or other indicators of having a steady partner is always strongly positive. This result is consistent with empirical studies under (1) and (2).

The effect of the number of children is mixed. Alesina et al. (2001) find for 13 countries a small negative effect of children. Negative effects are also reported by Frey and Stutzer (1999; 2000) and Wottiez and Theeuwes (1998). However, Plug (1997), using a much larger set of variables as controls, finds that the effect is on average slightly positive, but that it varies with income and turns negative for very low incomes.

The effect of health, whenever included as a regressor, is positive (see Hartog and Oosterbeek, 1998; Wottiez and Theeuwes, 1998; or McBride, 2001).

>From the above evidence, we conclude that the results of the economic literature under (3) and the psychological literature under (1), although differing strongly in their willingness to make a cardinality assumption, find surprisingly similar results with respect to these 5 key variables.

Below, in Table 2, the analyses of Table 1 are done for the ordered logit (column 1 and 2) and ordered probit model (column 3 and 4). In column 5 and 6, the results for the ordered probit model with individual random effects are shown. Finally, in column 7 and 8, we present the ordered probit with individual random effects models in which we include the averages over time of some variables $\mathbf{x}_{it}$ under a Mundlak-assumption of the error-term.

[Table 2 about here]

>From the results in Table 2, there seems to be little difference between running a simple OLS on the raw scores, specification (1), or taking an ordered logit or probit model. That is, the sign of the coefficients are the same; whether a coefficient is significant is the same; and the trade-offs between variables are roughly the same, which means that indifference curves are similar. This is in line with Dunn's (1993) simulation findings that the difference between an OLS with measurement error and an ordered logit without measurement error is very small. Nevertheless,

one has to keep in mind that different scaling of the variance of the error terms hampers the comparison of the three models, i.e. OLS, Logit and Probit. The variance of the disturbance term is 1 for Probit and $\pi^2/6$ for Logit.

Adding individual random effects also makes little difference. Nevertheless, including the averages of some variables to control for the correlation between the time-invariant unobservables and the regressors $\mathbf{x}_{it}$ does make a difference. This difference also holds when we compare it with specification (2), indicating that the results are sensitive with respect to the assumptions one makes about time-invariant unobservables.

4. Ordinal response models with fixed effects

In order to complete our empirical analysis, we here look at models that do not require S3, but only S2, whilst avoiding the cardinality assumption often used in the psychological literature. Such A2-S2 models combine the reluctance of economists to assume cardinality with the ability of the 'cardinalists' to use individual fixed-effects estimators. In the literature, there are two papers within this approach, i.e., Winkelmann and Winkelmann (1998) and Hamermesh (2001). Their model is

$$\begin{aligned} GS_{it}^* &= \mathbf{x}_{it}\beta + f_i + \varepsilon_{it}, \\ GS_{it} &= I(GS_{it}^* > 0). \end{aligned} \tag{4}$$

Which is hence a dichotomous model with fixed effects. This means they can only discern two categories and both have to reduce their data in order to fit this model. Winkelmann and Winkelmann reduce general satisfaction on a (0,10) scale to whether general satisfaction is higher than 7 or not. Similarly, Hamermesh reduces his job-satisfaction measure on a 5 category scale to a (0,1) scale. Both then look at the statistic that Chamberlain (1980) suggested:

$$P[\mathbf{GS}_{i1}, .., \mathbf{GS}_{iT} | \sum_t \mathbf{GS}_{it}, \beta, f_i, \mathbf{x}_{it}] = \frac{e^{\sum_t (\mathbf{GS}_{it}\mathbf{x}_{it})\beta}}{\sum_{GS \in S(\sum_t \mathbf{GS}_{it})} e^{\sum_{t=1}^{T} I(GS_{it} > k_i)\mathbf{x}_{it}\beta}},$$

which in words is the probability of observing $\mathbf{GS}_{i1}$, .., and $\mathbf{GS}_{iT}$, conditional on their sum.[7] Here, $S(\sum_t \mathbf{GS}_{it})$ denotes the set of all the possible combinations of $GS_{i1},..,GS_{iT}$ that sum up to $\sum_t \mathbf{GS}_{it}$. For T=2, this means the likelihood becomes $\frac{e^{(\mathbf{GS}_{i1}\mathbf{x}_{i1}+\mathbf{GS}_{i2}\mathbf{x}_{i2})\beta}}{e^{\mathbf{x}_{i1}\beta}+e^{\mathbf{x}_{i2}\beta}}$ and only uses individuals for which $\mathbf{GS}_{i1}+\mathbf{GS}_{i2}=1$.

Because this model can only use individuals who move across the cut-off point, there is a large loss of data. Winkelmann and Winkelmann (1998), who start out with around 10000 individuals are left with only 2523 individuals who actually fit this condition. Hamermesh, working with the same GSOEP data set as us, is left with only 712 individuals who fit his condition. A danger of such heavy loss of data is that measurement errors may well become a large source of residual variation.

Another limitation both papers face is that they do not include time-dummies which means time-specific factors are not controlled for. To see what this implies, consider that for log-income we can write $\ln(p_t y_{it}) = \ln(p_t) + \ln(y_{it})$ where p_t is the general price level. When including time-dummies, any effect of $\ln(p_t)$ is absorbed in a time-specific intercept and the coefficient of $\ln(p_t y_{it})$ only reflects the pure effect of the real incomes $\ln(y_{it})$. Similarly for age, we can write $age_{it}\beta_{age} = age_{i1}\beta_{age} + (t-1)\beta_{age}$. Now, $age_{i1}\beta_{age}$ is time-invariant and will hence be picked up by the individual effects. The term $(t-1)\beta_{age}$ is common to all individuals. Therefore, as noted before, the linear effect of age will be absorbed in a time-specific intercept. Vice versa, this means that age will pick up any time-specific effects if time-dummies are not used.

Hamermesh (2001) uses only a set of income variables as regressors, which means that terms denoting current incomes can be affected by inflation and other average differences over time. Winkelmann and Winkelmann (1998) also do not have time-specific intercepts, which allows them to include age as a regressor. They find that age almost everywhere has a negative effect which is the reverse for what is found elsewhere in the literature. We show some sensitivity analyses in the appendix B suggesting that the inclusion of time dummies indeed has a large effect on estimated coefficients.

Here, we try to address these limitations of the fixed-effect logit case by extending the idea of Chamberlain (1980) to a fixed-effect ordered logit-setting. Our model is

$$\begin{aligned} GS_{it}^* &= \mathbf{x}_{it}\beta + f_i + \varepsilon_{it}, \\ GS_{it} &= k \Leftrightarrow \lambda_k^i \leq GS_{it}^* < \lambda_{k+1}^i, \end{aligned} \tag{5}$$

$t = 1, ..T$; $k = 0, ..K$; $G(\varepsilon_{it}) = \frac{e^{\varepsilon_{it}}}{1+e^{\varepsilon_{it}}}$ is the c.d.f of ε_{it}. This is an ordered logit model with fixed individual effects and *individual* specific thresholds, λ_k^i. All we assume about the intercepts are that they are increasing, i.e. that $\lambda_k^i < \lambda_{k+1}^i$. Ordinal comparability is not assumed. This means it is an A1-S2 model.

The statistic we look at is

$$\begin{aligned} P[I(\mathbf{GS}_{i1} &> k_i), .., I(\mathbf{GS}_{iT} > k_i) | \sum_t I(GS_{it} > k_i) = c] \\ &= \frac{\frac{\prod_{t=1}^T \{1+I(\mathbf{GS}_{it}>k_i)(e^{-\lambda_{k_i}^i + (\mathbf{x}_{it}\beta + f_i)} - 1)\}}{\prod_{t=1}^T (1+e^{-\lambda_{k_i}^i + (\mathbf{x}_{it}\beta + f_i)})}}{\sum_{GS \in S(k_i,c)} \frac{\prod_{t=1}^T \{1+I(GS_{it}>k_i)(e^{-\lambda_{k_i}^i + (\mathbf{x}_{it}\beta + f_i)} - 1)\}}{\prod_{t=1}^T (1+e^{-\lambda_{k_i}^i + (\mathbf{x}_{it}\beta + f_i)})}} \\ &= \frac{e^{\sum_{t=1}^T I(\mathbf{GS}_{it}>k_i)\mathbf{x}_{it}\beta}}{\sum_{GS \in S(k_i,c)} e^{\sum_{t=1}^T I(GS_{it}>k_i)\mathbf{x}_{it}\beta}}, \end{aligned}$$

with 0<c<T and where $S(k_i, c_i)$ denotes the set of all the possible combinations of $GS_{i1}, .., GS_{iT}$ for which $\sum_t I(GS_{it} > k_i) = c_i$, where c_i denotes the number of times that general satisfaction is above the barrier k_i. We can again see that all the nuisance parameters drop out.

This is the same estimator as in the simple fixed-effect logit case in the sense that the data is still collapsed to binary variables, but then applied to an individual-specific recoding of the data via the free parameter k_i. It means we can include observations of all individuals whose satisfaction score changes and hence much more fully encompasses the information gained by having K categories instead of just 2.[8] This includes practically all respondents with multiple observations because any individual whose $\mathbf{GS}_{it}$ changes can then be used. In the appendix D, we describe the estimator more fully and work out how to choose k_i efficiently.

There is another method that addresses the same limitations of the classic Chamberlain method, namely Das and Van Soest (1996; 1999). They developed an estimator based on a weighted average of the Chamberlain estimator for each particular k. Hence in their method, they get an estimate β_k based on those individuals for which T$>\sum_{t=1}^{t=T} I(\mathbf{GS}_{it} > k) > 0$ for each 0<k<K. Its intuitive appeal is that it involves for each individual all the possible k's and hence uses more information. Its main disadvantage is that there is not enough data in each category k to actually estimate every β_k. This means their method in our case cannot use the information for all categories and hence also implies dropping a number of individuals. This would probably be the case for most studies based on subjective satisfaction questions given that, at least in Western countries, there are very few individuals who feel very dissatisfied and answer one of the lowest categories (see *World Database of Happiness*). Furthermore, the Das and van Soest estimator needs stronger regularity assumptions because the weights of β_k depend on the joint probability of an individual being in the data sets for more than one k. This links it to the joint distribution of $\mathbf{GS}_{i1}, ..\mathbf{GS}_{iT}$ and hence to the nuisance parameters. The relative strengths and weaknesses of the Das and Van Soest estimator as compared to our estimator are dicussed more fully in the appendix C and D.

In Table 3 below, we report the results of our fixed effects ordered logit estimator and the Das and Van Soest estimator. For comparison, we include the results on ΔGS from Table 1 under assumptions A3-S2. We have also added the relevant parameters of the ordered logit results, A2-S3, of Table 2.

[Table 3 about here]

We can see that, at least for the significant coefficients, the similarity between the coefficients of the OLS on ΔGS and those of our fixed-effect ordered logit is very high in the sense of size and trade-off ratios.[9] Only the coefficients on $age * age$ are dissimilar. We also see that the number of individuals that we lose with the fixed-effect ordered logit compared to the OLS is only about 13%, which is hence the fraction of individuals whose GS_{it} does not change in the period. Most of these individuals in turn were only observed for 2 periods. The coefficients obtained by the Das and Van Soest estimator are similar to those of our own estimator, though their standard deviations are generally lower and the coefficients are somewhat larger. Their estimator is based on less individuals though as it misses out on extreme responses.

The results of the fixed-effect ordered logit models are, however, quite different from the ordered logit results. For one, the coefficient of income without individual fixed effects is much larger. The age effect for the simple ordered logit is negative over the relevant area. This means that although we do not know the full effect of age because of the ambiguity of the time-intercepts, we do know that the effect itself is decreasing over time. The effect of the number of children with individual fixed effects is also contrary to the results of the simple logit in that the effect is not negative and non-significant. For marriage and health the coefficients and significance are much larger for the simple logit model than when including individual fixed effects.

We have performed several checks on the sensitivity of these results. Apart from varying the set of variables included in the analyses, we have looked at the possible endogeneity problem of self-reported health and general satisfaction. To this end, we have instrumented subjective health with the reported number of days sicks during the year as the identifying instrument. Like Diener et al. (1999), we also find that instrumenting health reduces the significance of health, but the health coefficient still remains strongly positive. The reported analyses in the appendix B show that instrumenting health does not qualitatively change the other results.

The main conclusion here is that while the assumption of cardinality or ordinality does not qualitatively change the results, the treatment of the unobserved time-invariant effects does.

5. Other methodological issues in short

Some have used a structural equations framework (e.g. Van Praag et al., 2003), but this effectively only adds interpretation to a reduced form single equation as above.

Most writers throw away data with missing values. Some then reweight the data (e.g. Plug, 1997; Frey and Stutzer, 1999; 2000; Hartog and Oosterbeek, 1998), though none reports that reweighting makes a difference.

Bradlow and Zaslavsky (1999) take a different approach and, all be it for consumer satisfaction, developed an estimator that interprets 'no answer' to a satisfaction question as a separate category revealing that the individual does not have particularly strong feelings about the issue at hand. In the case of happiness, this seems rather unlikely. Indeed, response rates are generally very high for general satisfaction questions (in our data set above 90%).

Terza (1987) discusses how to deal with exogenous variables that are themselves only categorically observed.

Terza (1985) proposes an ordered probit in which the value of the thresholds is person-specific by allowing λ_k to be a linear function of $\mathbf{x}_{it}$. Kerkhof and Lindeboom (1995) apply this method to health satisfaction. The main extra assumption one needs to make in order to separate the differences in thresholds across individuals from the differences in actual latent satisfaction is a reference group for whom thresholds are not affected by individual circumstances.

Ravallion and Lokshin (2001; 2002) estimate an ordered probit model for a latent variable y_{it}^* whose observed values y_{it} are the *change* in reported satisfaction between t and t-1. If reported satisfaction is bounded by 0 and K, then y_{it} is bounded by -K and +K. Their model can, but in their application does not, allow for dependence between the thresholds λ_k and the satisfaction score in the previous period. The model relies on two unusual assumptions. First and foremost, the latent variable y_{it+1}^* is assumed to be 0 at t. This means that precisely after the interview at t the happiness of the person resets itself at the middle of the category in which she happens to be then and is not reset at any other time. Category boundaries are also reset only then. If happiness were reset at other times, then the model of Ravallion and Lokshin (2001; 2002) no longer holds.[10] As a consequence, their notion of happiness is unique to their interviews and does not exist at any other time. Second, the happiness change is unbounded only when happiness changes from 0 to K or from K to 0 because only then does the variable y_{it} attain its extrema of -K or K. Put more intuitively: true bliss is only possible after total despair and total despair is only possible after true bliss. We are not aware of anyone in the economic or the psychological literature ever explicitly making or testing these two assumptions.

6. Conclusions and discussion

In this paper, we found that assuming cardinality or ordinality of the answers to general satisfaction questions is relatively unimportant to results. What matters to the estimates is how one takes account of time-invariant unobserved factors. The positive influence of income on GS was reduced by about 2/3 when allowing for fixed unobserved factors. Also, the effect of having children was found to be insignificantly positive with fixed-effects, but significantly negative without fixed-effects. We can only surmise that the effect of many other variables used in the economic literature so far, be they on the individual or on the national level, will turn out to be very different when account would be taken of fixed individual traits.

As to future research, it would seem of great importance to take individual fixed-effects into account or else to include as regressors the time-invariant personality traits that have such large influence on general satisfaction. Additionally, given the importance of personality traits for individual GS, it would seem important for disentangling the cross-country differences in happiness to understand what determines the distribution of personality traits in the population.

Finally, a note on the unimportance of income for happiness. The coefficient of 0.11 of log-income in the OLS individual fixed-effect model, implies that an individual would need an income increase of over 800000 % to achieve an increase of one for general satisfaction on a (0,10) scale. This in itself raises the question of why individuals expend so much effort on obtaining more income to the extent that most economists since Jevons (1871) have taken this as the main human motivation. The psychologists Brickman and Cambell (1971) long ago answered this question by proposing that humans can be on an 'hedonic treadmill' in which they are constantly chasing objectives that cease to be satisfying once reached. This often repeated argument would fit the finding that average satisfaction hardly increases in countries where incomes increase (Diener and Suh, 1999; Kenny, 1999), but it would seem to need a high degree of imperfect forecasting and self-delusion on the side of individuals to be true. Is there perhaps more to individual choice than happiness?

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Appendix A: The GSOEP sample.

The German Socio-Economic Panel (GSOEP) is a representative panel of the German population that started in the Federal Republic of Germany in 1984. It currently tracks about 20000 individuals and 12000 households in both West Germany and the Former German Democratic Republic (see Wagner et al., 1993; Landua, 1992; or Plug, 1997 for a detailed description). We use the sample of 7806 West-German workers, which forms around 75% of the West-German total sample. Because the transition to unemployment or work was low in this period (see Hunt, 1999), this is a quite stable sample.

>From this sample, we look at the six waves of the period 1992-1997. The number of waves an individual is observed differs for various reasons. First, there are individuals who leave the panel for reasons such as death, immigration and (temporary or permanent) attrition. Second, there are new individuals included in the sample for reasons that include moving into a surveyed household, reaching the age of 16, or splitting-off from a surveyed household. Third, those who moved from working to non-working, East to West, or *vice versa*, also have fewer than 6 observations. All this means that we have 7995 individuals and 30569 observations in total, which can all be included in the cross-sectional models (models (1) and (3)). Of this total, 1331 individuals only have one recorded wave in the period and hence they drop out in the fixed-effects OLS model (2), leaving 6664 individuals and 21104 observations. Of these remaining individuals, 863 have the same general satisfaction in all waves, meaning they cannot be used for the conditional estimator of the fixed-effect logit model presented in Section 2.5, leaving 5801 individuals. Of these individuals, all the observations are used in estimation however, meaning that these 5801 individual correspond to 25442 observations for that model.

Regarding the variable definitions: age is calculated from the date of birth; income is net monthly household income in German Marks; the number of children is the number of dependent children younger than 16 who live in the household; whether the respondent lives in partnership is self-reported and does not only include marriage; health is the cardinal score on the answer ‘how satisfied are you with your health situation' on a (0,10) scale.

Appendix B: Sensitivity analyses of the fixed-effect ordered logit model.

Our main worry is the endogeneity of GS and health since they are both subjectively evaluated. Therefore, we estimate the linear relation $\Delta Health_{it} = \Delta \mathbf{z}_{it}\gamma + \mathbf{u}_{it}$ and use $\Delta \mathbf{z}_{it}\hat{\gamma}$ as an instrument for $\Delta Health_{it}$. The identifying variable in $\mathbf{z}_{it}$ is the number of days off from work because of illness.

[Table 4 about here]

Replacing health by predicted health greatly reduces the significance of the health coefficient and the overall likelihood but only qualitatively affects the age coefficient. Because age is, amongst others, a proxy for health, this was to be expected. Hence, although the endogeneity of subjective health may indeed be responsible for the relatively high levels of R^2 found in Table 1, this endogeneity does not seriously affect most results.

Table 4 also presents the sensitivity analysis for the inclusion of time-dummies. These intercepts are, as expected, important to age and income results because their omission changes their coefficients. Nevertheless, because the time-period we look at here is shorter and more recent than those for Hamermesh (2001) and Winkelmann and Winkelmann (1998), this does not imply that the same change necessarily occurs in their papers.

Appendix C: The Das and van Soest method.

The Das and van Soest (1996; 1999) method first recodes each individual vector $\{\mathbf{GS}_{i1}, .., \mathbf{GS}_{iT}\}'$ into a set of K vectors $\{(\mathbf{GS}_{i1} > k), .., (\mathbf{GS}_{iT} > k)\}'$ for k=0 to K-1, where (K+1) is the number of categories of the dependent variable and the lowest category equals 0. For each k, the parameter vector is estimated using the Chamberlain method. Because this yields a consistent estimator we have

$$\sqrt{n_k}(\beta_k - \beta) \rightarrow N(0, \mathbf{\Sigma}_{kk}^{-1}), \qquad k = 0, .., K-1, \tag{6}$$

whereby the data set for a particular k consists of all those individuals for whom $T > \sum_{t=1}^{t=T}(\mathbf{GS}_{it} > k) > 0$. Asymptotically $\mathbf{\Sigma}_{kk} \rightarrow E[\mathbf{l}_k \mathbf{l}_k']$ where $\mathbf{l}_k$ is the score vector $\frac{\partial \ln L}{\partial \beta_k}$. To obtain the final estimator $\hat{\beta}$, Das and Van Soest use a minimum distance step:

$$\hat{\beta} = \arg\min_{\beta} \frac{1}{2}[\begin{pmatrix} \beta_0 \\ .. \\ \beta_K \end{pmatrix} - \begin{pmatrix} \beta \\ .. \\ \beta \end{pmatrix}]' \quad ^{-1}[\begin{pmatrix} \beta_0 \\ .. \\ \beta_K \end{pmatrix} - \begin{pmatrix} \beta \\ .. \\ \beta \end{pmatrix}], \tag{7}$$

where the weighing matrix $\quad = [w_{a,b}]$ has entries $w_{a,b} = \mathbf{\Sigma}_{aa}^{-1}\mathbf{\Sigma}_{ab}^{-1}\mathbf{\Sigma}_{bb}^{-1}$ with $a, b = 0, ..K-1$. This estimator is made operational by replacing the unknown variance matrices with their sample analog. This for instance means

$$\hat{\Sigma}_{ab}^{-1} = \begin{pmatrix} \frac{1}{N_{ab}} \sum_i \begin{matrix} \frac{\partial \ln L_i}{\partial \beta_{a1}} \frac{\partial \ln L_i}{\partial \beta_{bM}} & .. & \frac{\partial \ln L_i}{\partial \beta_{a1}} \frac{\partial \ln L_i}{\partial \beta_{bM}} \\ .. & .. & .. \\ \frac{\partial \ln L_i}{\partial \beta_{aM}} \frac{\partial \ln L_i}{\partial \beta_{b1}} & .. & \frac{\partial \ln L_i}{\partial \beta_{aM}} \frac{\partial \ln L_i}{\partial \beta_{bM}} \end{matrix} \end{pmatrix}^{-1}, \tag{8}$$

where M is the number of parameters and N_{ab} is equal to the number of individuals that are both in the data set for k=a and for k=b. Applying their method, we improve slightly on the Das and Van Soest estimator by using the sample hessian for $\mathbf{\Sigma}_{aa}^{-1}$ in stead of $\frac{1}{n_a}\sum_i [\mathbf{l}_{ik}\mathbf{l}_{ik}']$ because the sample hessian has better finite sample properties (see e.g, Hayashi, 2000, p. 476).

When the sample sizes are very high and there is a lot of variation in the exogeneous variables, the Das and Van Soest estimator seems to make better use of all the available information than our estimator. In applying it to our data though, there were a number of limitations. For one, the estimation of β_k requires that there are sufficient individuals who have both some observations of $\mathbf{GS}_{it}$ higher than k and an observation equal or less than k. This in our case only held for sufficiently large k: the number of individuals reporting a 0 was for instance only 15. Even the number of individuals reporting anything lower than a 5 was less than 300. Also, for some variables, such as the number of children, there is not very much time-variation. This increases the number of individuals one needs per k to get sufficient variation for the estimator to have good properties. Additionally, the estimation of $\mathbf{\Sigma}_{ab}^{-1}$ requires individuals both in the data set for k=a and for k=b. This involves fewer individuals than that are in either the data set for k=a or k=b. For these reasons, we could only apply the Das and Van Soest method to four groups: k=5, k=6, k=7, and k=8. This implies a loss of data to the extent that the Das and Van Soest estimates in the text are based on 5222 individuals which is about 11% less than the number of individuals for our own estimator.

Apart from these practical limitations appearing in our data, there is also a theoretical disadvantage to the estimator of Das and Van Soest: $\mathbf{\Sigma}_{ab}^{-1} = E[\mathbf{l}_a\mathbf{l}_b']$ depends on the joint distribution of the sets k=a and k=b and hence on the distributions of λ_k^i and f_i. This creates regularity problems. For instance, if $\lambda_a^i = \lambda_{a+1}^i$ for some $a \neq \{0, K\}$ then category a is empty. This does not affect the validity of any of the estimators β_k or their asymptotic properties. Neither will this affect our new estimator. However, in this case $\mathbf{\Sigma}_{ab}^{-1} = \mathbf{\Sigma}_{a-1,b}^{-1}$ and $\mathbf{\Sigma}_{b,a}^{-1} = \mathbf{\Sigma}_{b,a-1}^{-1}$ for all b, which means is singular and the method breaks down. Another example: if $\lambda_a^i = -\infty$ for some individuals and $\lambda_b^i = +\infty$ for all other individual with $1 < a < b < K+1$, then no category is empty. One still has consistent estimates for any β_k and for our new estimator, but there are no observations to estimate $\mathbf{\Sigma}_{a-1,b}^{-1}$.

Summarising, the Das and Van Soest method requires stricter regularity assumptions on the distributions of λ_k^i and f_i. For samples that are very big, with a lot of variation in $\mathbf{x}_{it}$, combining the estimators β_k in a fashion suggested by Das and Van Soest would seem to work well though. In case of limited variation in some $\mathbf{x}_{it}$ and where little can be presumed about the distributions of λ_k^i and f_i, our method is more robust.

Appendix D: The properties of the estimator.

Our discussion of the estimator and our strategy for efficiency takes the notionally convenient case that β is of dimension 1 and T is equal for all individuals, but carries over to the case that T is variable and β is multi-dimensional.

We first transform our data in a way that only preserves the information we can use. We introduce the notation C_i for the set of possible different conditioning events for individual i. For a vector $\{\mathbf{GS}_{i1} = 5, \mathbf{GS}_{i2} = 7, \mathbf{GS}_{i3} = 4\}\prime$ this for instance means $\mathbf{C}_i = \{\begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}\}$ where the first element belongs to the conditioning event that $\mathbf{GS}_{i1} > 4$ and the second element belongs to the conditioning event that $\mathbf{GS}_{i1} > 5$. The vectors in $\mathbf{C}_i$ are denoted as $\mathbf{C}_{ij}$, where j runs from 1 to n_i^C. Each vector $\mathbf{C}_{ij}$ is implicitly related to a k, termed k_{ij}. The time observations in each vector $\mathbf{C}_{ij}$ are denoted by $\mathbf{C}_{ijt}$. The general problem is to find weights for the maximisation problem

$$\hat{\beta} = \arg\max_{\beta}[M = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{n_i^C} w_{ij} \ln L(\mathbf{C}_{ij} | \sum_{t=1}^{T} \mathbf{C}_{ijt}, \beta, \mathbf{x}_i)] \tag{9}$$

$$s.t. \quad \sum_{i=1}^{N}\sum_{j=1}^{n_i^C}(w_{ij})^2 = N, \tag{10}$$

where M is the function to be maximised. Now, $\mathbf{C}_{ij}$ is independently distributed over individuals, but not identically distributed. We have:

$$\begin{aligned}
\ln L_{ij} &= \ln L(\mathbf{C}_{ij}|\sum_{t=1}^{T}\mathbf{C}_{ijt},\beta,\mathbf{x}_i) = \ln \frac{e^{\sum_{t=1}^{T}\mathbf{C}_{ijt}\mathbf{x}_{it}\beta}}{\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta}}, \\
\frac{\partial \ln L_{ij}}{\partial \beta} &= \frac{1}{L_{ij}} * [\frac{\sum_{t=1}^{T}\mathbf{C}_{ijt}\mathbf{x}_{it}e^{\sum_{t=1}^{T}\mathbf{C}_{ijt}\mathbf{x}_{it}\beta}}{\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta}} - \\
&\quad \frac{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)}(\sum_t C_{ijt}\mathbf{x}_{it})e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})e^{\sum_{t=1}^{T}\mathbf{C}_{ijt}\mathbf{x}_{it}\beta}}{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})^2}], \\
E\frac{\partial \ln L_{ij}}{\partial \beta} &= \sum_{C^*_{ijt}\in S(\sum_{t=1}^{T}\mathbf{C}ijt)} L(C^*_{ijt}) * \frac{1}{L_{ij}(C^*_{ijt})} * [\frac{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}e^{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}\beta}}{\sum_{S(k_i,\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta}} - \\
&\quad \frac{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)}(\sum_t C_{ijt}\mathbf{x}_{it})e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})e^{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}\beta}}{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})^2}] = 0, \\
E\frac{\partial^2 \ln L}{\partial^2 \beta} &= E(\frac{\partial \ln L_{ij}}{\partial \beta})^2 = \sum_{C^*_{ijt}\in S(\sum_{t=1}^{T}\mathbf{C}ijt)} \frac{1}{L_{ij}(C^*_{ijt})}[\frac{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}e^{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}\beta}}{\sum_{S(k_i,\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta}} - \\
&\quad \frac{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)}(\sum_t C_{ijt}\mathbf{x}_{it})e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})e^{\sum_{t=1}^{T}C^*_{ijt}\mathbf{x}_{it}\beta}}{(\sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)} e^{\sum_{t=1}^{T}C_{ijt}\mathbf{x}_{it}\beta})^2}]^2,
\end{aligned}$$

where $C_.$ denotes the random variable and $\mathbf{C}_.$ the realisation. Because C_i is independently distributed and $E[L(\mathbf{C}_{ij}|\sum_{t=1}^{T}\mathbf{C}_{ijt},\beta,x_i)]$ is shown above to be maximised at the true β for any conditioning set, this establishes that the estimator $\hat{\beta}$ follows the regularity conditions required for extremum estimators to be consistent and normally distributed under mild conditions on w_{ij} (see Hayashi, 2000, c. 7). Most importantly, it implies that $E\frac{\partial \ln L_{ij}}{\partial \beta} = 0$ for any k_{ij}. Our approach is to impose the restriction that $w_{ij} = 0$,1 and that $\sum_{j=1}^{n_i^C} w_{ij} = 1$. One advantage of this is that we can interpret the ensuing estimator as a Maximum Likelihood estimator. Starting out with a consistent estimator of β which can be obtained by applying the standard Chamberlain method, we in a second step set $w_{ij} = 1$ for the j that minimises the analytically calculated $E\frac{\partial^2 \ln L_{ij}}{\partial^2 \hat{\beta}}$ for each particular individual i. This weighting strategy is analogue to weighted least-squares analyses where the variance is a known function of the conditioning information and the parameters β.

What our method circumvents is estimating $P[w_{ij} = 1]$ because this would require estimating the joint probability of $\mathbf{C}_{i1},..\mathbf{C}_{in_i^c}$ which involves the unknown nuisance parameters. For the same reason, we cannot construct a maximum likelihood estimator in which $w_{ij} > 0$ for more than 1 j per individual because the joint probability of any pair $\mathbf{C}_{ij}$ and $\mathbf{C}_{il}$ involves the unknown nuisance parameters. Hence our method produces the maximum likelihood estimator with minimal variance.

The Das and Van Soest method also circumvents the problem of estimating the joint probability of $\mathbf{C}_{i1},..\mathbf{C}_{in_i^c}$ by weighing M-1 separate consistent estimators (where each estimate for β_k is, by the way, not based on i.i.d. data because $\sum_{t=1}^{T}\mathbf{C}_{ijt}$ and even T varies per individual within the same set for k). This uses more information but involves the disadvantages for finite samples discussed in the previous appendix and the implicit reliance on stronger regularity conditions for the nuisance parameters.

An open question is whether we can do better than maximum likelihood. The essential problem we have in finding variance minimising $\frac{w_{ij}}{\sum_j w_{ij}}$ is that this theoretically involves for each individual estimating $E\frac{\partial \ln L_{ij}}{\partial \beta}\frac{\partial \ln L_{il}}{\partial \beta}$. This expression can not be estimated empirically because we only have one observation of $\frac{\partial \ln L_{ij}}{\partial \hat{\beta}}\frac{\partial \ln L_{il}}{\partial \hat{\beta}}$ per individual. It also cannot be analytically calculated with some initial estimate of β because $E\frac{\partial \ln L_{ij}}{\partial \beta}\frac{\partial \ln L_{il}}{\partial \beta} = \sum_{S(\sum_{t=1}^{T}\mathbf{C}ijt)}\sum_{S(\sum_{t=1}^{T}\mathbf{C}ilt)}\frac{L(C_{ij}^{*},C_{il})}{L(C_{ij}^{*})*L(C_{il})}\frac{\partial L_{ij}}{\partial \beta}\frac{\partial L_{il}}{\partial \beta}$ which involves $L(C_{ij},C_{il})$ which does not factor out because this joint probability depends on the nuisance parameters. Hence, there seems no analytical way to optimally choose $\frac{w_{ij}}{\sum_j w_{ij}}$. A second-best option is to order the data in such a way that we have groups of observations with the same T and the same $\sum_{t=1}^{T}\mathbf{C}_{ijt}$ because these are i.i.d.. If each of these groups is large enough, then the optimal weighting of these different groups can use sample estimates of the cross-variance, circumventing the issue raised above. There is a large number of groups in our actual data however because both T and $\sum_{t=1}^{T}\mathbf{C}_{ijt}$ vary in our data. Therefore, this is not an appealing way forward in our case, but may be an option when data sets are very large and less heterogeneous.

Finally, we note that the implicit sampling out of $\mathbf{C}_i$ via the free parameter k_i does not affect the estimators. For one, $L(\mathbf{C}_i|\beta,x_i,f_i,\lambda_i)$ is also maximised at the true β. Hence, even though we do not know the true f_i and λ_i, the conditional likelihood of each individual $\mathbf{C}_{ij}$ with an implicit k_{ij} will also maximise the unknown unconditional likelihood. Because we can consistently estimate $E\frac{\partial^2 \ln L_{ij}}{\partial^2\beta}$ for each of the n_i^C conditioning events $\sum_{t=1}^T \mathbf{C}_{ijt}$ and base our weighing on it, means we consistently estimate the variance of our final conditional estimator by $\frac{1}{N}\sum_i \sum_j w_{ij} \frac{\partial^2 \ln L_{ij}}{\partial^2 \hat{\beta}}$. It is the case that likelihoods with other conditioning information, such as $L(\mathbf{C}_i|\beta,x_i,f_i,\lambda_i)$ and $L(\mathbf{GS}_i|\beta,x_i,f_i,\lambda_i)$, depend on the nuisance parameters: the asymptotic variance of $L(\mathbf{C}_i|\beta,x_i,f_i,\lambda_i)$ for instance is related to the nuisance parameters f_i and λ_i^k because $\mathrm{P}[w_{ij}=1]$ depends on them. The variance of the unconditional likelihoods is therefore unknown.

Footnotes

1 We found Easterlin (1974), Scitovsky (1975), Kapteyn and Van Praag (1976), Morawetz (1977), Ng (1978), Wansbeek and Kapteyn (1983), Martin and Lichter (1983), Sirgy et al. (1985), and Heady and Krause (1988).

2 E.g. Alesina et al. (2001), Blanchflower and Oswald (1998; 2000a), Clark and Oswald (1994), Frijters (2000), Di Tella et al. (2000), Frey and Stutzer (1999; 2000), Hartog and Oosterbeek (1998), Kenny (1999), Kahneman et al. (1997), Konow and Earley (1999), Oswald (1997), Winkelmann and Winkelmann (1998), Woitiez and Theeuwes (1998).

3 There is also an increased interest in the analysis of the satisfaction with particular domains of life, such as financial, job, health, consumption, and house satisfaction. See, for example, Cutler and Richardson (1997), Ferrer-i-Carbonell and Van Praag (2002), Hamermesh (2001), Kerkhofs and Lindeboom (1995), Pradhan and Ravallion (2000), Rain et al. (1991), Van Praag and Frijters (1999), and Varady and Carozza (2000). The arguments in this present paper apply also to the literature on domain satisfactions.

4 The articles by Hamermesh (2001) and Winkelmann and Winkelmann (1998) form an exception and they will hence be extensively discussed later on.

5 This implies $\varepsilon_{it} = \alpha x_i + v_i + \eta_{it}$ where αx_i is meant to pick up the correlation between fixed unobservables and observables. Obviously, other interpretations of αx_i are also possible, hampering the interpretation of results.

6 This means $\varepsilon_{it} = v_i + \eta_{it}$ with v_i and η_{it} both normally distributed, orthogonal to each other and both orthogonal to observed characteristics x_{it}.

7 It is also conditional on x_{it}, f_i and β. This also holds for the models before and after but we will from here on drop this in our notation.

8. This estimator, like the traditional fixed effects logit model, cannot predict probabilities and marginal effects without making an extra assumption. For example, that the individual fixed-effect is zero.

9 These two sets of coefficients are also in line with the ones obtained by Ordered Probit with random individual effects when including the averages of some variables to control for the correlation between the $\boldsymbol{v}_i$ and x_{it}. (See Table 2).

10 The 'resetting' assumption is crucial because only then is there no influence of fixed individual traits on satisfaction changes in their model. Without resetting, the level of happiness last period matters for the probability to change to another level and hence fixed traits re-appear. To see why it matters that resetting does not occur outside of the interview, consider the extreme alternative that resetting occurs very frequently. Then, only discrete jumps in variables or the error term could shift a person from one happiness level to another, whilst spread-out changes in variables could not. Hence, the assumed frequency of resetting affects parameter estimates.

Tables:

Table 1 The Determinants of Cardinal General Satisfaction for West German Workers in the GSOEP

	Model (1)				Model (2)	
	OLS on GS		OLS on GS		Fixed-eff. OLS	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
Age	−0.03	5.8	−0.05	10.0		
Age × age	0.0005	7.5	0.0007	11.3	−0.0006	6.5
ln(household income)	0.34	18.7	0.38	18.6	0.11	4.3
Number of children	−0.07	5.5	−0.05	5.2	0.01	0.9
Steady partner (1 = yes)	0.13	4.8	0.23	12.3	0.07	2.4
Subjective health	0.54	93.8	0.39	97.3	0.32	44.1
Controls	No		Yes		No	
Number of individuals	7,806		7,806		6,664	
R^2	0.25		0.26		0.09	
Number of cases	30,569		30,569		21,104	
Time-dummies were present in all estimates but are not shown. The number of individuals is lower for the fixed-effects because they require at least 2 observations per individual.						
The controls for the OLS on GS contains the following variables: education, working hours, gender, and the number of adults in the household.						

Table 2:

Table 2 The Determinants of Ordinal General Satisfaction for West German Workers in the GSOEP

	Model (3)							
	Ord. logit		Ord. probit		Ord. probit		Ord. probit	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
Age	−0.07	10.3	−0.04	11.4	−0.05	8.3	−0.03	5.9
Age × Age	0.001	12	0.001	12.6	0.001	8.9	0.001	7.7
ln(household income)	0.47	17.8	0.26	11.8	0.26	13.1	0.13	5.3
Number of children	−0.06	5.6	−0.03	5.1	−0.03	3.2	−0.01	0.8
Steady partner (1 = yes)	0.28	11.8	0.16	11.8	0.17	8.7	0.16	8.2
Subjective health	0.54	88.2	0.29	108.9	0.29	87.3	0.21	53.4
Controls	Yes		Yes		Yes		Yes	
Random effects	No		No		Yes		Yes	
Averages	No		No		No		Yes	
Number of individuals	7,806		7,806		7,806		7,806	
−log(Likelihood)	51004		50726		47853		47422	
R^2								
Number of cases	30,569		30,569		30,569		30,569	
Time-dummies were present in all estimates but are not shown.								
Included averages are on the variables income, number of children,working hours,umber of adults, and health.								