The marginal utility of income*

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1 Introduction

The central idea in normative public economics is the comparison of social costs and benefits. To do this, we compute for each individual the change in welfare (measured in dollars) multiplied by the "marginal social value" of that person's dollar. This marginal social value equals the marginal utility of income to the individual (an empirical concept) times the marginal social value of an additional unit of utility accruing to that individual (an ethical concept). In this paper we focus on the first of these, the marginal utility of income, and how it varies with income.

Information on this point is also required for the related measurement of inequality. The Atkinson index of inequality uses the following social welfare function, where u is utility and y income:

$$W = \sum_i \frac{1}{\beta} u_i^\beta, \ \beta \leq 1 \tag{1}$$

It is further assumed that the *ceteris paribus* relationship between utility and income takes the form of a constant relative risk aversion utility function:

$$u_i = \begin{cases} \frac{y_i^{1-\rho}-1}{1-\rho} & \rho \neq 1 \\ \log y_i & \rho = 1 \end{cases} \tag{2}$$

The key issue for both cost-benefit analysis and the measurement of inequality is the value of the coefficient of risk aversion ρ, which determines the rate at which marginal utility declines with income. If we take two people A and B, with A richer than B, then the ratio of their marginal utilities is a function of ρ and of the ratio of their incomes:

$$\frac{\partial u^B/\partial y}{\partial u^A/\partial y} = (\frac{y^A}{y^B})^\rho > 1 \tag{3}$$

For example, in the case where $\rho = 1$ (and so $u = \log y$), the marginal utilities are inversely proportional to income, so that someone with an income \$10,000 has ten times the marginal utility of someone with income of \$100,000. If $\rho > 1$ the difference is even greater. Interestingly, Dalton, who pioneered these issues at the London School of Economics in the 1920s and later became a Chancellor of the Exchequer, assumed that $\rho = 1$[1].

The ratio of marginal utilities is also crucial to the issue of optimal income tax (Mirrlees, 1971). In essence, we should transfer a dollar from A to B at an efficiency cost c, only so long as

$$\frac{\partial u^B/\partial y}{\partial u^A/\partial y} > \frac{1}{1-c} \tag{4}$$

To compute the efficiency cost c we need a broader concept of utility which includes leisure l, as in $u(y,l)$. Mirrlees (Mirrlees, 1971) used a theoretical utility function of this type. Stern (Stern, 1976) took this further by taking empirical estimates of the elasticity of substitution between income and leisure from the labour supply literature. But, when it came to the behaviour of the marginal utility of income, no one was able to offer any defensible empirical estimates. Thus in spite of remarkable theoretical progress in the 60s and 70s, normative public economics made little progress thereafter - partly due to lack of empirical evidence on the utility function.

Now, however, we can begin to remedy this defect. In this paper we study the value of ρ, using six major surveys of individuals which collected data on both their utility and their income.

For normative public economics, we must of course be able to measure changes in utility in a cardinal way and in a way that is comparable across individuals. In Section 2 we therefore discuss the measurability of utility as it relates to the six surveys. In Section 3 we describe the survey data in more detail. In Sections 4 and 5 we give our results and conclude in Section 6. The results from all six surveys are remarkably similar, and are broadly consistent with Dalton's hypothesis, that the marginal utility of income is inversely proportional to the level of income.

For a survey of empirical studies of the impact of income on utility see the recent paper by Clark et al. (Clark *et al.*, 2006). None of the existing studies focuses on the issue of the functional form, which is the subject of the present paper.

[1]Dalton (Dalton, 1920) measured inequality by W_e/W, where W_e is the welfare that would be obtained if everybody got $\bar{y}$. This measure is only invariant with respect to equi-proportional changes in all income if $\rho = 1$. By contrast, Atkinson measured equality by $y_e/\bar{y}$ where y_e is the equal income which would yield W if everybody had it. This measure is invariant to equi-proportional changes, even if $\rho \neq 1$.

2 Measuring utility

As is well known, the limited case of choice behaviour under certainty can only provide information on ordinal properties of the utility function, and so no inferences on ρ are possible. However, the more typical case of choices that involve uncertainty or multiple time periods can only be explained using cardinal utility, in which intervals on the utility scale have real meaning. Consequently, such choices can be used in principle to make inferences on the curvature of the utility function.

However, the resulting estimates vary wildly[2] (Lanot *et al.*, 2006), partly due to the importance of reference-dependent utility for decision making[3] (Kahneman & Tversky, 1979; Rabin, 2000). Moreover choice behaviour may involve forecasting errors, and we are interested in ex-post "experienced utility" rather than ex-ante "decision utility"(Kahneman, 1999).

Given these problems, the natural way to study the long run relationship between utility and income (which is needed for public economics) is to collect data on those variables and explore their relationship. That is our approach.

2.1 The nature of the survey evidence

In the surveys that we analyse a typical question is "Taking all things into account, how happy are you these days?". The respondent then chooses one of a number of values, for example:

	0	1	2	3	4	5	6	7	8	9	10	
extremely unhappy												extremely happy

In most surveys, each individual is surveyed only once, but in the German Socio-Economic Panel (GSOEP) and the British Household Panel Study (BHPS) she is surveyed in a number of years. The datasets we use are described in detail in Section 3. The subjective well-being questions are listed in Appendix A.

[2]It is nonetheless interesting to note that our estimate of $\hat{\rho} = 1.2$ fits well within the range that economic models typically assume. Mehra and Prescott (Mehra & Prescott, 1985) suggested that a value of between 0 and 10 be used for representative agent models. In practice, however, macroeconomists typically use values between 0.5 and 3. Finance economists often use higher values, but that is because implausibly high values are required to explain the equity premium puzzle using expected utility theory.

[3]People often accept the normative validity of expected utility, but exhibit reference-dependent utility in their decision making. Reference dependent utility is also important for experienced utility in the short-run. However, because of adaptation, it is not so important for the long-run relationship between utility and income.

2.2 True utility and reported happiness

We seek to estimate the relationship between utility and income, but what we can actually observe are survey reports. The nature of the mapping between true utility, u, and reported happiness, h, can thus determine our ability to interpret our findings.

We think of true utility as a real number on a cardinal scale[4]. As there are no natural units we can normalise u using any two reference points, such as 0 for "extremely unhappy" and 10 for "extremely happy". Denoting the function linking true utility with reported happiness by f, we can in general write:

$$h = f(u) \tag{5}$$

We take it for granted that f is increasing, and consider the following three possibilities:

A Each individual uses his or her own idiosyncratic interpretation of the scale provided, so the replies are not comparable:

$$h_i = f_i(u_i) \tag{6}$$

If this is the case we can in principle expect cross-section analysis to provide little or no explanation of the answers given. But in survey after survey, similar patterns of explanation arise, with very similar effects of the different right hand variables, such as income, employment status and marital status[5]. Furthermore, these effects are measured with some precision. Finally, when person dummies are introduced into panel data, thereby concentrating on time series variation for each individual, the coefficients change little from the cross-section results[6]. All of this implies some common understanding across individuals about the meaning of the intervals on the scale. We are not ruling out *some* dispersion in the coefficients across people, but the observed precision of the estimates rules out excessive variation. In the terms of Equation 5 the implication is that the slopes of the transformation functions f_i cannot vary very much.

As regards the level of the scale, our surveys can throw less light on the degree of common understanding, as different origins may disappear into the error term. However we have independent cross-section evidence that respondents report their level of happiness in a way that is consistent with other meaningful measures of their happiness. For example we can ask a

[4]Cardinal utility is invariant to arbitrary positive affine transformations, which can include sign preserving scaling and positive or negative shifts.

[5]See also (Di Tella *et al.*, 2003) which gives regressions country by country

[6]See results in Section 4.2.

person's friend to rate the subject's happiness, or even ask an independent observer who has never met the person before. The reports of these "third parties" turn out to be well correlated across people with the subject's own report (Diener & Suh, 1999). In addition, neuropsychologists can now measure the level of activity in the areas of the brain where positive and negative affect are experienced. These levels of activity too are well correlated across people with the subject's self-report (Davidson, 1992; Davidson, 2000; Davidson *et al.*, 2000).

For these reasons we do not consider this possibility further in this paper.

B Individuals use the scale in the same way, but it represents some potentially non-linear transformation of their true utility:

$$h_i = f(u_i) \tag{7}$$

In this is the case, equal intervals on the reported happiness scale need not reflect equal intervals of true utility. However, it would have to be the case that all individuals report their happiness using a similar transformation, since we can explain their reports with some precision.

We investigate this issue of non linearity in various ways in Section 5. We cannot reject the notion (coming from psychophysics) that the use of bounded scales leads to some compression of the utility scale at higher levels of utility. But we also show that this has only a small effect on our conclusions. For most of the paper we shall therefore assume the third possibility:

C Individuals use the scale in the same way and their replies provide cardinal measurements of their true utility:

$$h_i = u_i \tag{8}$$

3 Data and strategy

The six surveys we use are described in Table 1. The surveys are highly varied, including 4 cross-sectional surveys and 2 panel surveys, and cover a wide range of countries and years. There is also potentially significant variety in the well-being and income questions. For this reason we should only trust results that generalise across different surveys. As it happens, our results are remarkably consistent across all the surveys we studied.

[Table 1 about here.]

3.1 The well-being variable

The questions for the well-being variable are described in Appendix A, which also includes histograms and quantitative descriptive statistics. In most of the surveys the well-being scales are numerical, but there is also some use of qualitative scales. To facilitate comparison across different surveys all the well-being data are normalised to the 0 to 10 scale using the appropriate affine transformation[7]. When both happiness and satisfaction with life as a whole were recorded, the responses were averaged to produce a single dependent variable[8]. The reason is that the averaged well-being variable was found to be as or more closely related to external circumstances than either happiness or life satisfaction on their own. This result suggests that, although there are some systematic differences between happiness and life satisfaction responses (see Appendix B for details), the averaged variable is more closely related to both underlying happiness with life and underlying life satisfaction than either variable on its own. This is consistent with the possibility that each of these variables includes a random measurement error.

3.2 The income variable

The survey item used is total household income, rather than the respondent's own income. Household income was generally normalised to units of constant purchasing power[9]. Income was not, however, normalised to standard of living units using based on the number of adults and children in the household. This choice was made for two reasons. First, we see children as a choice variable, and therefore income equivilisation is misleading for our purposes[10]. Second, regression analysis suggests that household income, rather than equivalised household income, is the right variable to use. For details refer to Appendix C.

Exact income figures are available for the panel surveys (German Socio-Economic Panel and British Household Panel Survey). In the cross-section surveys only income bands are available, and these we converted into numerical values using the mid point of each band. For respondents in the lowest income band (which is only bounded from above) we assumed an income of two thirds of the upper limit of the band, and for respondents in the highest income band (which is only

[7]For example, 1-7 was shifted and stretched to run from 0 to 10. Qualitative scales (e.g. not very happy, fairly happy, very happy) were first turned into numerical scales: $0, 1, 2, \ldots$ and then stretched.

[8]Weighted average in the case of the World Values Survey, in which happiness and life satisfaction were not measured with the same accuracy.

[9]The exception to this was the world values survey, where the information on income bands was also less reliable. Lack of normalisation does not matter provided we use log income as the regressor, since the presence of country and time dummies takes the place of the missing normalisation. However, the results of the world values survey are clearly not as reliable when we consider the curvature of utility of income relationship.

[10]Equivalised income is, of course, the right concept to use when thinking of the welfare of the child.

bounded from below) we assumed an income of 4/3 of the lower income limit of the band[11].

3.3 Other data issues

In order to have a relatively homogenous population we confined ourselves to people aged 30-55, for whom annual income is highly correlated with permanent income. For the same reason we excluded from regressions individuals with unusual or suspect income reports. Specifically, we excluded the 5% at either extreme of the distribution of fitted residuals from a linear regression of $\log y$ on a set of standard regressors. Our belief was that many of these observations are the result of measurement error, or else reflect transitory deviations from usual income. Taking such observations at face value could otherwise lead to misleading conclusions on the relationship between utility on the income. Consistent with this the plots of Section 4.1 show that no consistent functional relationship can account for these extreme income observations, while an excellent fit exists for all the other observations.

We include the following as standard controls in all the regressions:

- Sex
- Age (including a quadratic in age)
- Education (dummies for degrees of achievement, or years of education and years of education squared)
- Marital status (dummies)
- Employment status (dummies)

In addition to these standard controls we always include country and/or time dummies, including interaction terms when there is variation along both dimension. The inclusion of these dummy variables enables us to control for common fixed effects to do with country or year. Most importantly, it allows us to control for systematic additive reporting biases. For example, in the European Social Survey a given level of income in Denmark is associated with higher well-being report than a similar level of income in Poland. There are good reasons to think this may have to do with the higher quality of life in Denmark, but it may also be the case that people in Denmark will report any given level of reported happiness more positively than would people in Poland. Using country and time dummies we avoid this issue altogether, and obtain *ceteris paribus* results that are valid across different countries and time periods[12].

[11] This method was also used in a derived variable provided with the European Social Survey.

[12] The flip side, of course, is that our evidence can shed no light on the source of this inter-country variability, or the remarkable lack of change in well-being reports across time (The Easterlin Paradox).

Since our interest is in policy we did not include choice variables, as these should not be considered as given. In particular, we did not include the number of children as regressors[13].

3.4 Strategy of analysis

We use the following assumptions:

1 Reported happiness, h, is linked to true utility, u, via a fixed transformation f, as in Equation 7.

2 The utility of person i can be written as follows:

$$u_i = a_i + \alpha g(y_i) + \sum_j \beta_j x_{ij} + \epsilon_i \tag{9}$$

where a_i is a person fixed effect, α is the partial derivative of u with respect to $g(y)$, and the $x's$ are other controls, such as sex, age, education, marital status, work status, and country and time dummies.

3 The function g of Equation 9 takes the form of a constant relative risk aversion function, where ρ is the coefficient of risk aversion:

$$g(y) = \begin{cases} \frac{y^{1-\rho}-1}{1-\rho} & \rho \neq 1 \\ \log y & \rho = 1 \end{cases} \tag{10}$$

In this formulation $\rho = 0$ corresponds to a linear relationship, with higher values of ρ denoting increasing concavity.

Our goal is to obtain an estimate of the coefficient of risk aversion ρ in Equation 10. Our strategy includes the following four steps. In the first three we assume that $h_i = u_i$:

1 Cross-sectional analysis: We plot reported happiness against log income, *ceteris paribus*, and find a remarkably linear relationship. We then regress reported happiness on log relative income and its square, and find the quadratic term has a relatively small effect.

2 Panel fixed-effects analysis: We repeat the analysis, with consistent results.

3 Analysis of curvature: We compute the log likelihood ratio for different values of the coefficient of risk aversion ρ. We find general support for ρ being somewhat greater than unity. This implies slightly more concavity than in the log formulation.

[13] In any case, when children are included in reported happiness regressions their effect is small. See Appendix C.

4 Non-linearity in $f(u)$. We find evidence for a compression of the scale at the top end, so that the function relating reported happiness to true utility is concave. The implication is that the estimate of ρ derived before may be biased upwards. We therefore use two different methods for correcting our estimates, and conclude that the required correction is small.

4 Main results

4.1 Cross-section analysis

We first plot the partial relationship between reported happiness and log income after removing from both variables the effect of controls[14]. The results in Figure 1 show this plot for all the surveys, including the panel surveys which were analysed as pooled cross-sections to facilitate comparison. In each graph we divide the individuals surveyed into 20 groups according to income, and then plot the average utility and average log income for each group. A line is then fitted to the central 90% of the data excluding the two extreme income groups (see discussion in Section 3.3). In all the surveys we find that the linear fit is good — a remarkable fact considering that the surveys are so different.

The slopes in the different surveys are listed in Table 2, which also shows the impact of a unit change in log income on utility measured in standard deviations. We find that the slopes do not differ very much across very different surveys. Table 2 also shows the significance of a quadratic component in log income relative to the relevant country and/or year[15]. As the table shows, the quadratic term is relatively unimportant.

The linear fit does not hold for the respondents with incomes that lie at the extremes of the income distribution We are not sure why that is the case. However, we conjecture that the outliers with very low incomes may well represent an atypical period of abnormal income, which has only minor effects on well-being. Other explanations include measurement error or false reporting.

[Figure 1 about here.]

[Table 2 about here.]

[14]By regressing each of the variables on the controls and taking the OLS residual.

[15]A quadratic in log relative income is used instead of a quadratic in log income because whereas $\log(y/\bar{y})$ and $(\log(y/\bar{y}))^2$ are roughly uncorrelated, $\log y$ and $(\log y)^2$ are highly correlated. Consequently it is easier to interpret the results using relative income. As a result of the high correlation, if a quadratic in income is used, the coefficient on income becomes much less significant, and is sometimes very different from the coefficient when only income is used.

4.2 Panel fixed effects analysis

We can now turn to the fixed-effect analysis of the two panel surveys. Using panel data we can expect to obtain more accurate results, as we can control for fixed individual heterogeneity in temperament (underlying utility) and in the origin of the reporting scale[16]. Most importantly, the use of a fixed-effects analysis allow us to correct for a correlation between the fixed individual heterogeneity and the regressors. Thus, for example, we may be concerned that naturally happy individuals will typically get higher paying jobs, thereby creating a correlation between income and reported happiness that does not imply a *ceteris paribus* effect of income on utility. Using panel fixed-effects we control for such long-run effects running in the direction from happiness to income, and can therefore be more confident in our own causal interpretation[17].

In the fixed-effects methodology we in fact looking at *deviations* in reported happiness as a function of *deviations* in income. If measurement error is important we can expect the fixed effects estimate of the slope coefficients to be downward biased. If short-run income effects are important we could expect the opposite. The results are reported in Figure 2 and Table 3, in analogy to the pooled cross-section results of Section 4.1. The results are similar to the ones obtained using pooled cross-section methodology, and are consistent with the linear model of Equation 9.

[Figure 2 about here.]

[Table 3 about here.]

4.3 Analysis of curvature

We can finally consider the curvature of the impact of income on utility. In public economics this is more important than the size of the impact of income on utility, since what matters is the ratio between the marginal utilities at different levels of income. For example, if the marginal utility for the poor is 10 times that for the rich, the case for redistribution is exactly the same whether the size of the marginal utilities is large or small.

To explore the curvature more rigorously than in Section 4.1 we seek to estimate the coefficient of risk aversion ρ of Equation 10. To do this we re-run the OLS regression for different values of ρ and compute the log likelihood $L(\rho)$. As in Section 4.1 observations with extreme income values in the top or bottom 5% are excluded.

[16] If a person consistently reports higher utility than we would otherwise expect, this could either be due to a happy personality, or to a positive reporting bias. While a panel methodology does not allow us to distinguish between the two, it does allow us to benefit from the improved explanatory power.

[17] In an annual time series variations in annual happiness are unlikely to be a major cause of variation in income.

Figure 3 shows the log likelihood for each value of ρ. These results are then analysed quantitatively in Table 4, which shows the maximum likelihood estimate and likelihood ratio statistics[18]. The the best overall fit is for $\rho = 1.3$, which is an excellent fit for all the individual surveys. While this value is significantly different from 1, the log formulation remains a good approximation[19].

[Figure 3 about here.]

[Table 4 about here.]

5 Compression of the reported well-being scale

At this point however we need to raise the following question: Is the scale which respondents use in reporting their utility the *true* scale (up to an arbitrary positive affine transformation), or some non-linear transformation of it? In the terms of Equation 7 is f a linear function?[20]

In particular, there comes from psycho-physics the suspicion that reports using bounded scales (e.g. 0-10) may be a concave function of the true scale of utility. In reports of physical sensations this often seems to happen, since replies on bounded scales are generally concave with respect to the use of unbounded scales. For example respondents have been asked to report the duration of noises of differing length(Stevens, 1975, p. 229). In one experiment, a bounded scale of 1 to 7 was offered and respondents were exposed to different durations (the shortest and longest durations being exhibited first). Respondents assigned a category to each duration. These values turned out to be a concave function of the true durations. By contrast when respondents were offered an unbounded scale, their replies were roughly proportional to the true durations.

One could argue that findings relating to the sensation of external physical stimuli are irrelevant to the reporting of utility. When people report their utility they are reporting not on their experience of an external stimulus, but directly on their internal state. Thus, there may well be a non-linear relationship between external circumstances and utility (as we suggest for the case of income), but there is no obvious reason why the relationship between utility and reported happiness should be non-linear. In fact, there is evidence from the neuroscience of physical sensation (Johnson *et al.*, 2002) that the relationship between neural activity and verbal reports is linear. If we are willing to assume that subjective experience is linear in neural activity this evidence implies that verbal reports

[18]The likelihood ratio statistics for ρ is asymptotically distributed as χ^2 with one degree of freedom. The 5% significance point is 3.84.

[19]The World Values Survey was excluded from the combined analysis, because the income data is not as reliable as in the other surveys.

[20]Loosely speaking, of course. Since utility reports are discrete, whereas true utility is real, the function f cannot strictly be linear. But if we think of the reports as the rounding off to the nearest point on the scale of a continuous function of utility we can give precise meaning to the notion of f being linear or else a non-linear concave function.

are linear in subjective experience. Finally, while many people would agree on the meaning of intervals in reported happiness, there is no sense in which we can talk of zero happiness[21]. So presenting people with an interval scale seems to be a natural way to proceed.

Even so, we should allow for the possibility that the mind plays tricks and that people report their reported happiness on a scale that is concave with respect to their actual experience. We explore this issue in three different ways. We maintain throughout the assumptions of Section 3.4, and in particular assume that real utility is linear in the regressors, even if reported happiness is not. The specific hypothesis we are interested in is that the function f of Equation 7 relating utility u to its reports h is concave:

$$h_i = f(u_i), \quad (f' > 0, f'' < 0) \tag{11}$$

The assumptions of Section 3.4 together with Equation 11 imply the following predictions, as can be readily checked by simulation:

1 Spline: If we combine the regressors into a single prediction variable, and then run separate OLS regressions of reported happiness on each half of the sample, the slope should be higher for low values of $\hat{h}_i$ and lower for high values of $\hat{h}_i$.

2 Variance of the residuals: If utility reports, h_i, are estimated with a single OLS regression, the residuals $\hat{\epsilon}_i$ will have lower variance at high values of the predictions, $\hat{h}_i$ than at lower values.

3 Ordered probit/logit cut points: The cut points of ordered probit and ordered logit will be convex with respect to reported happiness (implying a concave transformation from true utility to its reports).

In the next three sections we show that these predictions in fact hold, and for the variance of the residuals and the ordered probit/logit cut points tests we also compute the corrected estimate of ρ. The corrected estimate turns out not to be too different from the OLS estimate of Section 4.3, and in Section 5.4 we give the intuition for why that is the case.

5.1 The spline test

The spline test is based on the idea that if the function f linking reported utility, h, with true utility, u, is linear, then the relationship between h and the OLS predictions $\hat{h}$ should have the same slope of 1 independently of the value of $\hat{h}$.

[21] People may be able to classify instantaneous sensations as pleasant or unpleasant, and in that sense zero can stand for neither pleasant nor unpleasant. However, when people consider the overall quality of their experience they may be more or less happy with their life, but there is no comparable notion of zero happiness.

On the other hand, if f is concave, the slope estimates based on low values of $\hat{h}$ should be higher than the slope estimates based on high values of $\hat{h}$.

We first estimate the OLS predictions $\hat{h}$ using the entire sample. In the second stage we regress h on the values of $\hat{h}$ obtained in the first stage, allowing for separate slope estimates for the part of the sample below the median of $\hat{h}$ and the part above it:

$$h_i = \begin{cases} b_1 \hat{h}_i & \hat{h}_i < \text{median}(\hat{h}) \\ b_2 \hat{h}_i & \hat{h}_i \geq \text{median}(\hat{h}) \end{cases} \tag{12}$$

The results in Table 5 are consistent with the non-linear transformation hypothesis.

[Table 5 about here.]

5.2 Variance of the residuals

A second approach involves a fundamental assumption about what it is we want to measure in public economics. We are concerned with the impact of the outside world upon how people feel. If a person notices no difference in how he feels, that should count as no difference in happiness. And the natural units in which to measure changes in happiness is the "just noticeable difference" (JND). This has been much used in the study of physical sensation, and is variously defined — for example, as the difference that in repeated observations would be noticed 50% of the time[22].

However, we cannot assume that, when people use a response scale from 0 to 10, they make the differences between each point on the scale represent a given number of JNDs. A way to investigate this is by repeatedly asking an individual about his or her happiness (with no change of circumstances or mood available to explain any change in the answer). In such a test-rest situation we would not expect the same answer every time unless the JND was vanishingly small. But we would want the variance of the replies to be independent of the person's position on the scale of happiness — implying that units of the scale reflect the same number of JNDs at all points on the scale.

We would therefore like to retest individuals in unchanging circumstances. But we have no such data. We can, however, use panel data from the GSOEP to look at the root mean squared prediction error for each individual, and how this related to their predicted happiness. In Figure 4 we group individuals into 20 groups with ascending average predicted reported happiness, and plot for each group the average value of their root mean squared prediction error σ_i. This shows clearly that the errors are smaller for higher values of reported happiness.

[22]Ref: Thurston and Stevens(Stevens, 1975)

[Figure 4 about here.]

This could be for a number of reasons. It could reflect test-retest errors (as discussed above). The test-retest error variance for true utility should be the same at all points on the scale. If we find that the test-retest error variance is lower at the upper end of the reported happiness scale. This indicates that at the upper end the reported scale is a compressed version of the true scale.

However, the findings shown in Figure 4 could also reflect fewer mood swings among people at the upper end. There is some evidence for this, since, if we exclude people who are ever ill, the difference in error variances is somewhat reduced. So, when we assume below that all differences in error variances come from test-retest error, we are implying an upper bound to the extent to which the scale is compressed at the upper end.

We can use this finding to produce a corrected scale of true utility. Our psychological assumptions are:

1 True utility, u, should be measured using a scale with constant standard errors.

2 Reported happiness, h, has variable units which are proportional to the measured standard errors.

Thus, to convert intervals on the h scale to units on the u scale we deflate them by $\sigma(h)$, or for purposes of normalisation by $\sigma(h)/\sigma_0$, where σ_0 is the error variance at a reference point h_0, where true utility will be defined as equal to reported happiness:

$$du = \frac{dh}{\sigma(h)/\sigma_0} \tag{13}$$

We can now use the individual data underlying Figure 4 to estimate the following relationship:

$$\frac{\sigma_0}{\sigma(h)} = 1 + c(h - h_0) \tag{14}$$

where $c > 0$.

To find the relationship between u and h, we substitute Equation 14 into Equation 13 and then integrate. Normalising around $h = h_0$ gives us the following:

$$u - h_0 = (h - h_0) + \frac{c}{2}(h - h_0)^2 \tag{15}$$

This relationship is shown in Figure 5. Note that $h_0 = u_0$ by definition.

[Figure 5 about here.]

With these definitions, at h_0 the slope of u is the same as the slope of h (Figure 5). Thus, u is convex with respect to h, and the relation between u and income is less concave than the relation from between h and income. Clearly, if the relationship between u and h is sufficiently convex (c large enough), the relationship between u and income could actually be convex(Oswald, 1996). However, the evidence which follows goes against this.

The key issue is how far the true marginal utility ($\partial u/\partial y$) declines with income. Suppose, for example, that the reported happiness equation has the following form:

$$h = \alpha \log y + \text{etc.} \tag{16}$$

In this case the elasticity of marginal reported happiness with respect to income ($d\log(\partial h/\partial y)/d\log y$) is unity. So what is the elasticity of marginal true utility with respect to income? When h and u are set equal to h_0 the elasticity of marginal true utility with respect to income is $1 - \alpha c$. When the estimate $\hat{\rho}$ of the coefficient of risk aversion is different from unity the formula is slightly more complicated[23].

To find c we estimate Equation 14 using the GSOEP data on individuals and set $h_0 = 6$. The resulting estimate[24] is $\hat{c} = 0.2431$ (se=0.0022). From Table 2 we have the estimate $\hat{\alpha} = 0.52$, and so the appropriate correction factor for the OLS estimate of Section 4.1 is 0.874, reducing the estimate of ρ from 1.3 to 1.14[25].

5.3 Ordered probit/logit

Ordered probit and ordered logit provide significantly improved fit as compared with OLS. For example, in the case of the European Social Survey, the log likelihood difference between OLS and ordered logit is 14,612. This result provides *prima facie* evidence for a non-linear transformation between u and h. However, part of the better fit may have nothing to do with the concavity of the transformation, and is simply due to the fact that OLS is fitted using integer valued responses, rather than a continuous variable. It is therefore also useful to look at the maximum likelihood cut points.

The ordered logit cut points are displayed in Figure 6, and are consistent with the proposed concave transformation between reported happiness and true utility. These results cannot be explained by a linear model with heteroscedasticity that could in principle account for the observed relationship between the root mean squared prediction errors and the predictions.

[23]The correction factor is then $(1 - \alpha c y^{1-\hat{\rho}}/\hat{\rho})$ (see Appendix D for the derivation).

[24]Excluding 1% of outlier observations with $\sigma(0)/\sigma_0 > 5.3$.

[25]$\hat{\rho} = 1.3$ was determined using a grid search, and is not an accurate measure. Consequently we can update our estimate to the region of 1.1 to 1.2, but not more accurately than that.

[Figure 6 about here.]

The log likelihood procedure used in Section 4.3 for estimating the coefficient of risk aversion ρ implicitly assumes that the function f linking true utility with its reports is linear. As a result, if f is not in fact linear the resulting estimate of ρ may be biased. Using ordered logit, however, we can repeat the same procedure allowing for an arbitrary monotonic transformation f. The results of this procedure are shown in Figure 7 and Table 6. The resulting estimate of $\hat{\rho} = 1.2$ is only marginally different from the linear regression estimate of Section 4.3.

[Figure 7 about here.]

[Table 6 about here.]

It is important to note, that the ordered logit model assumes that the errors are symmetrically distributed, and that this assumption may fail if the unobserved variables have a skewed distribution. In particular, many unobserved variables may have the majority of the observations to the right of the mean, and a much longer tail to the left. For example, most people's health is about average, but a substantial minority are very unhealthy. If this is typical for the most important unobserved variables affecting utility, the overall distribution of the error in reported happiness can be significantly skewed even if f is linear. If this is the case, an ordered logit model may result in a better fit using a transformation that is more concave than the true f. Consequently, the correction implied by the ordered logit model is probably too great, and so the real value of ρ probably lies between 1.2 and 1.3.

5.4 Why the scale compression matters so little

For the non-linear scale compression to have a big effect two conditions must hold:

1 Rich and poor people should typically be found at significantly different points of the real utility scale.

2 The curvature at these points should be substantially different.

In reality, however, neither of these conditions hold. First, income is only moderately correlated with utility. For example, in the GSOEP the simple regression of well-being on log income is only 0.7, so that roughly speaking a quadrupling of income is necessary to lift a person one unit on the 0-10 utility scale[26]. For it to have a significant effect over common income differences, the curvature of the relationship between real utility and its reports would thus have to be substantially different over intervals of less than 1 on the utility scale. Second, the curvature is in reality quite modest. Taken together, these facts imply that rich and poor people are typically found at points on the utility scale in which

[26]The simple correlation between reported happiness and log income is about 0.2.

the reporting curvature is very similar. Thus, although we have found evidence for a non-linear relationship between real utility and its reports, this non-linear relationship has only a modest impact on the results of Section 4.

6 Conclusion

We have been studying a key parameter for any policy analysis using the principles of public economics. This is the elasticity of the marginal utility of income with respect to the level of income. We have used 6 different surveys, including country studies of USA, Britain and Germany, and multi-country studies involving all first-world countries and in one case third-world countries also.

We find considerable degree of agreement in the answers. If we take respondents' answers at face value as cardinal measures of utility, we find that the estimated elasticity in all 6 surveys is around 1.3. If it was exactly 1, the marginal utility would be inversely proportional to the level of income. Thus the estimates suggest that marginal utility declines somewhat faster than that.

However, there is the obvious question, Do the answers correspond to the true level of utility, or do respondents in their replies use a scale which is convex or concave with respect to their true utility? We investigate this in three ways, with similar results. In each case true utility is convex with respect to reported utility, so that true marginal utility declines less fast than reported marginal utility. However, we can also compute the size of the difference. It turns out that the elasticities reported earlier need only be reduced to about 1.2.

We have thus confirmed one of the key assumptions of nineteenth century political economy, and are able to provide those who do cost-benefit analysis with a scientifically-based set of weights to apply to income changes at different levels of income.

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Appendices

A Reported happiness survey questions

The subjective well-being survey questions are listed in Table 7. Basic descriptive statistics are shown in Table 8, and the histograms of the reports are in Figure 8. Allowing for the different range the histograms are remarkably similar in the different surveys for both happiness and life satisfaction.

It is interesting to note that there are many replies in the middle of the scale and at its extremes, and to some extent this may be an artefact of reporting along a scale. If this is the case then it contributes somewhat to the measurement error, but does not have a significant effect on our results.

[Table 7 about here.]

[Figure 8 about here.]

[Table 8 about here.]

B Happiness and life satisfaction questions

Some surveys ask about overall happiness, while others ask about satisfaction with life. These two questions are obviously very similar, but before lumping them together we wanted to test their similarity empirically. Table 9 shows the coefficient on log income and the overall R^2 in the regression for happiness, life satisfaction, and a combined variable when both questions were asked in the same survey. There are doubtless some significant differences, with life satisfaction more correlated with income, and also with most other regressors (as evidenced by the higher R^2). At the same time, the combined variable is typically as or more correlated with income, and the overall regression fit is as big or larger. These results suggest that combining the two variables results in a substantial reduction in measurement error.

[Table 9 about here.]

We should note that the findings of all surveys in which questions are asked about "happiness in general" give different answers from studies of instantaneous utility. For example, Kahneman et al. (Kahneman *et al.*, 2006) studied a group of working women from Columbus, Ohio. The method was to reconstruct the events of the previous day into roughly 15 episodes and then ask questions about positive and negative affect in each episode (the Day Reconstruction Method, DRM). When each person's happiness over the day was computed, this was found to be uncorrelated with any of the standard variables analysed in our surveys (such as income, employment status and marital status). The authors argue that this disagrees with the results of general questions on happiness due to "focusing illusion" — including apparently focusing on many obvious external circumstances of life. This whole issue clearly requires more study, but one might alternatively ask whether the day reconstruction method leads to excessive focus on the contribution of current activities to happiness, and inadequate attention to a person's underlying mood.

C Why income equivalisation scales are not used

When considering the relationship between utility and income we should think of the entire income, without deductions for choices the person has made. This argument extends to the choice of how many children to have, and therefore equivalised income scales are inappropriate for our purposes.

It is nonetheless interesting to look at the regression results when equivalised income is used. Table 10 compares the coefficients and overall R^2 in a regression with log household income and log equivalised household income in the European Quality of Life Survey. Household income clearly has more explanatory power than equivalised income. Furthermore, controls for the number of adults and kids add little to regressions with household income[27].

[Table 10 about here.]

It thus seems that for both theoretical and empirical reasons it is better not not normalise income by household size when considering the relationship between utility and income.

D Derivation of the correction factor for $\hat{\rho}$ using the constant variance of the residual method

We assume that the relationship between reported happiness and income is described by a constant relative risk aversion function with coefficient ρ_h:

$$h = \begin{cases} \frac{y^{1-\rho_h}-1}{1-\rho_h} & \rho_h \neq 1 \\ \log y & \rho_h = 1 \end{cases} \tag{17}$$

And so we obtain the following partial derivatives:

$$\frac{\partial h}{\partial y} = y^{-\rho_h} \tag{18}$$

[27]Results on the European Quality of Life Survey are particularly clean, but the results from other surveys are consistent with the same conclusions.

$$\frac{\partial^2 h}{\partial y^2} = -\rho_h y^{-(1+\rho_h)} \tag{19}$$

Using Equation 15 we can compute the first and second partial derivatives of true utility u with respect to income in terms of partial derivatives of reported happiness:

$$\frac{\partial u}{\partial y} = (1 + c(h - h_0))\frac{\partial h}{\partial y} \tag{20}$$

And

$$\frac{\partial^2 u}{\partial y^2} = (1 + c(h - h_0))\frac{\partial^2 h}{\partial y^2} + c(\frac{\partial h}{\partial y})^2 \tag{21}$$

Evaluating Equations 20 and 21 at $h = h_0$ and inserting the values from Equations 18 and 19 we obtain:

$$\frac{\partial u}{\partial y}|_{h=h_0} = \alpha y^{-\rho_h} \tag{22}$$

$$\frac{\partial^2 u}{\partial y^2}|_{h=h_0} = -\alpha\rho_h y^{-(1+\rho_h)} + c\alpha^2 y^{-2\rho_h} \tag{23}$$

We can now compute the coefficient of risk aversion for true utility:

$$\rho_u = -\frac{(\partial^2 u/\partial y^2)}{\partial u/\partial y} y = \frac{\rho_h \alpha y^{-(\rho_h+1)} - c\alpha^2 y^{-2\rho_h}}{\alpha y^{-\rho_h}} = (1 - \alpha c y^{1-\rho_h}/\rho_h)\rho_h \tag{24}$$

And so the correction factor is $1 - \alpha c y^{1-\rho_h}/\rho_h$, which simplifies to $1 - \alpha c$ in the case of $\rho_h = 1$.

Figure 1: The partial relationship between reported happiness and log income in pooled cross-section regressions

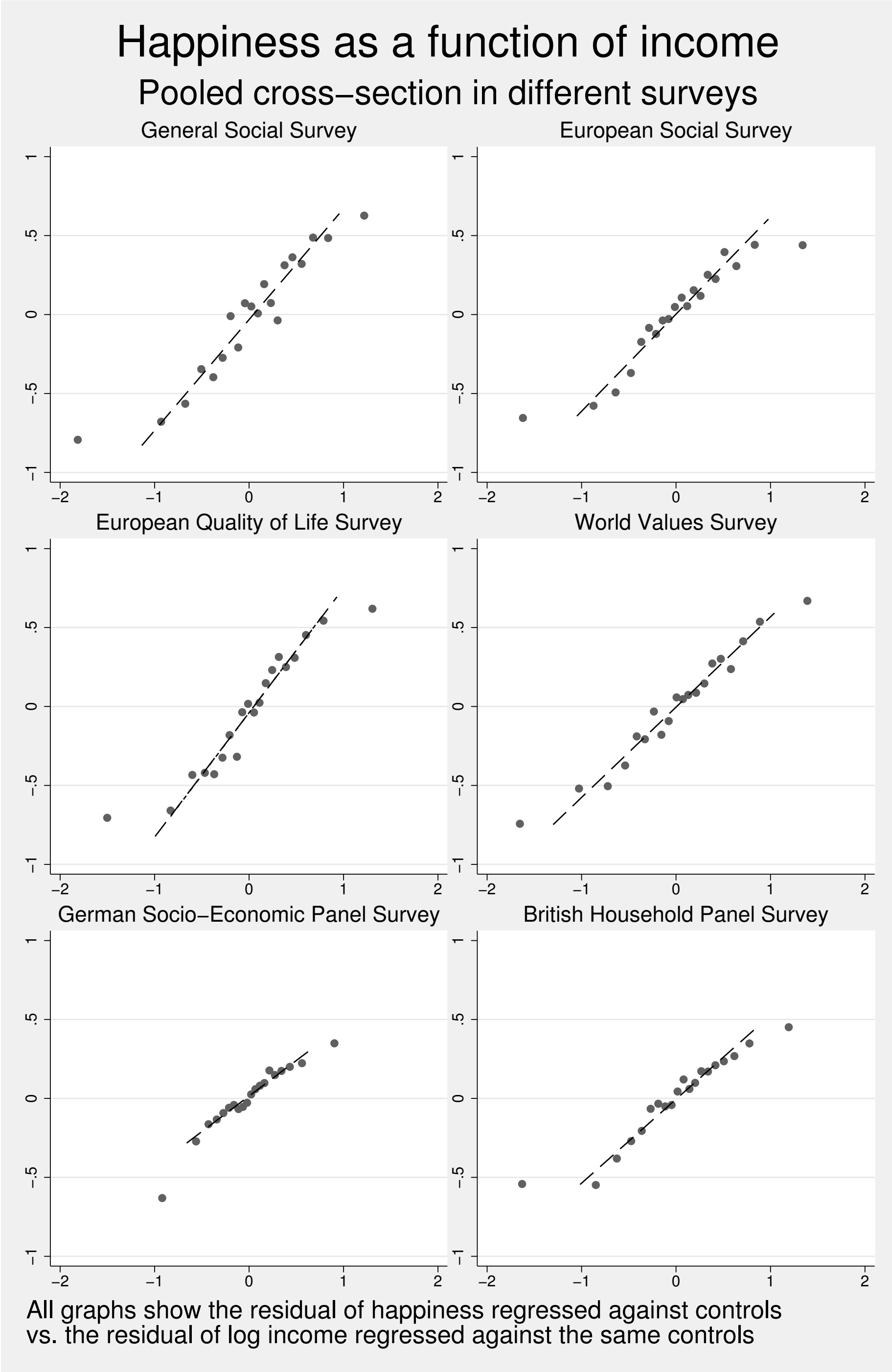

Figure 2: The partial relationship between reported happiness and log income in panel datasets. The two columns compare pooled cross-section analysis (left column) with panel fixed effects analysis (right column).

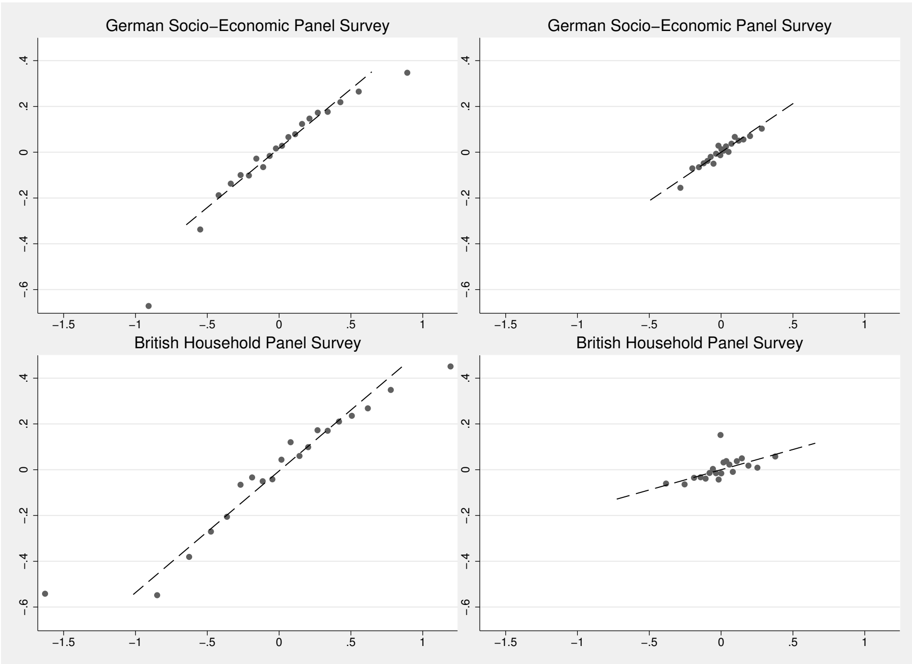

Figure 3: OLS estimates of the coefficient of relative risk aversion, as obtained in regressions of reported happiness on a CRRA function of income, and on other regressors. The figure shows the log likelihood for each value of ρ. The $y-$scale cannot be compared between surveys.

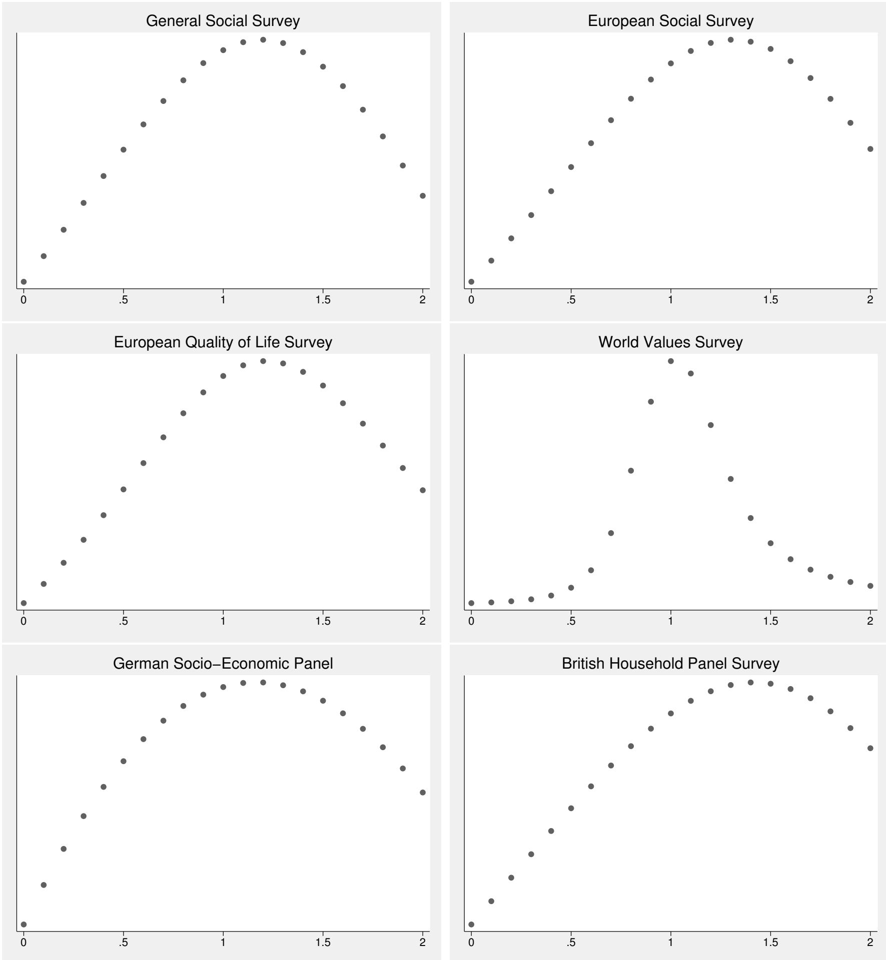

Figure 4: Root mean squared prediction error as a function of mean prediction in a fixed effects regression in the German Socio-Economic panel. Includes only subjects who responded to 10 or more survey rounds.

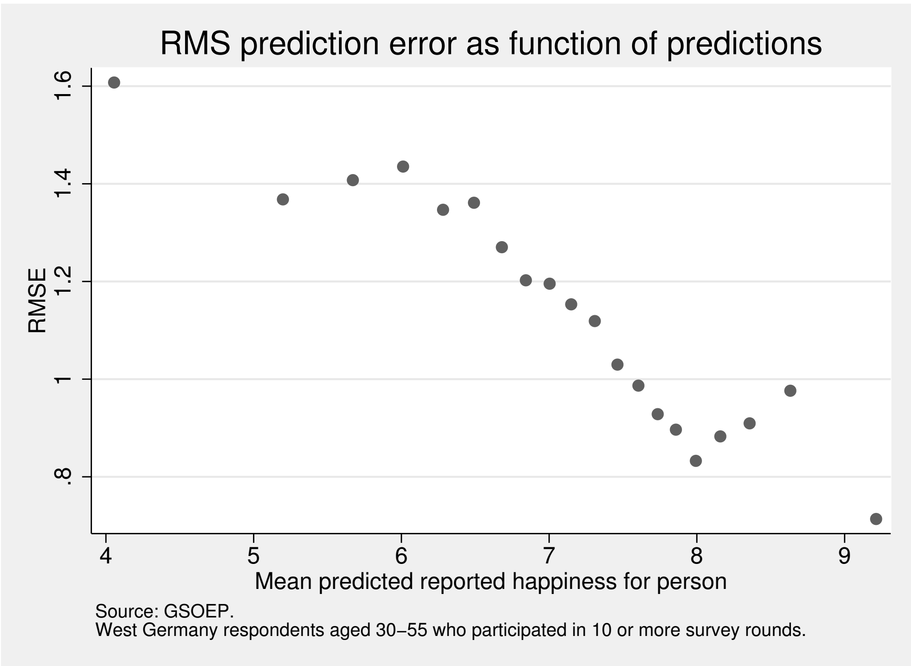

Figure 5: Qualitative illustration of how the relationship between true utility, u, and income, y, differs from the relationship between reported happiness, h, and income. Both functions are normalised so as to intersect at $h_0 = 6$ and also have the same slope at the point. The difference is that the curvature of the function relating u and y is less than that relating h and y, and hence the coefficient of risk aversion is lower.

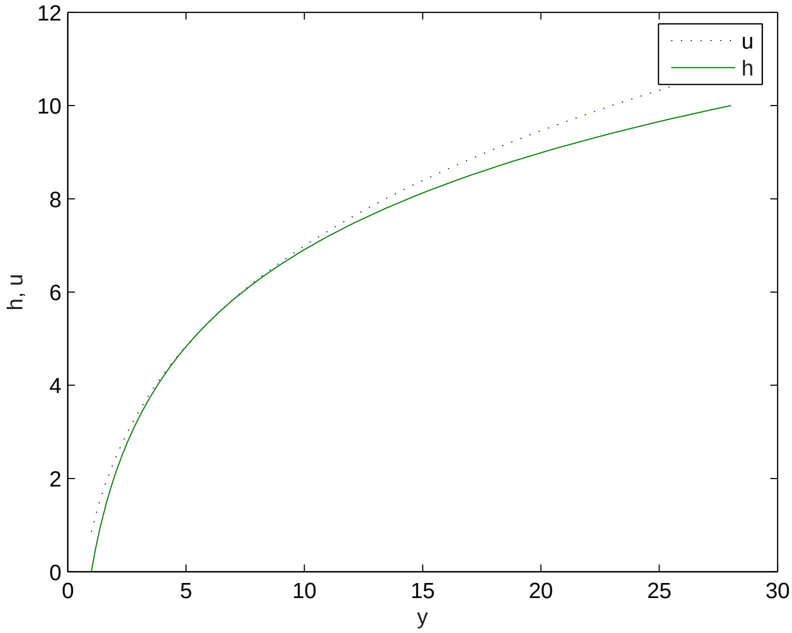

Figure 6: Ordered logit cut points in a model of reported happiness. The cut points of ordered probit are virtually indistinguishable.

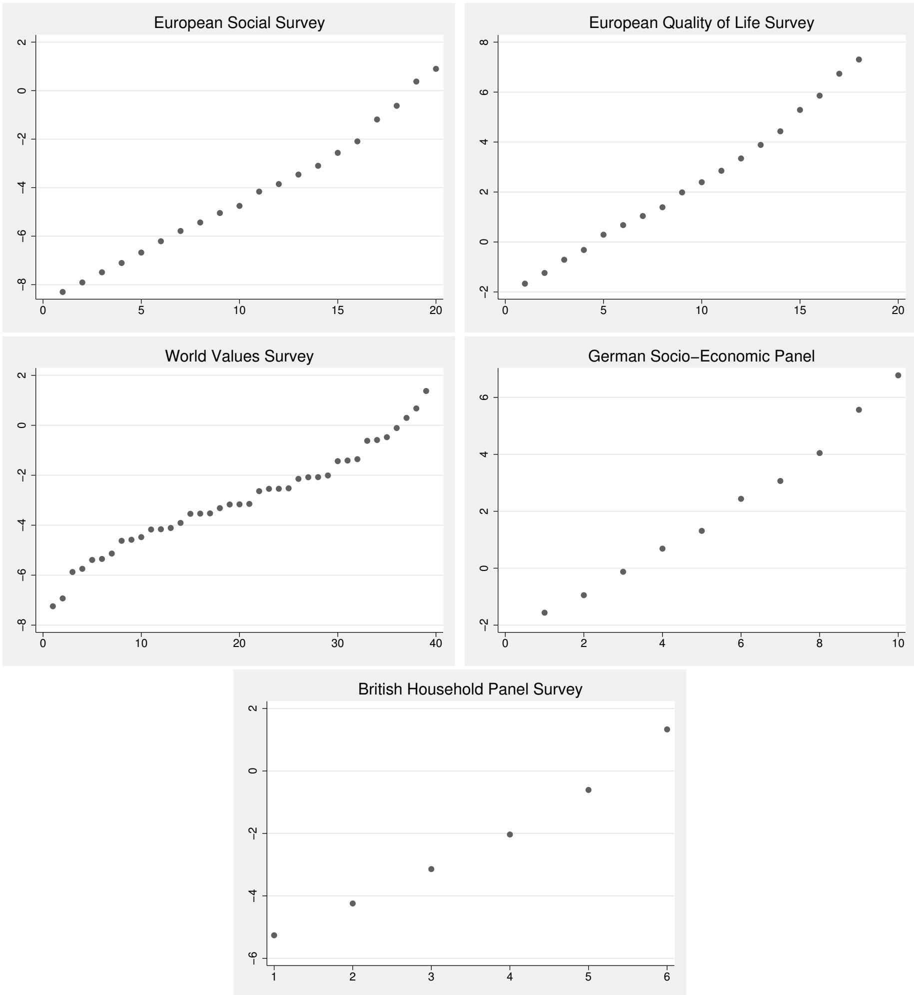

Figure 7: Ordered logit estimates of the coefficient of relative risk aversion, as obtained in regressions of reported happiness on a CRRA function of income, and on other regressors. The figure shows the log likelihood for each value of ρ. The $y-$scale cannot be compared between surveys.

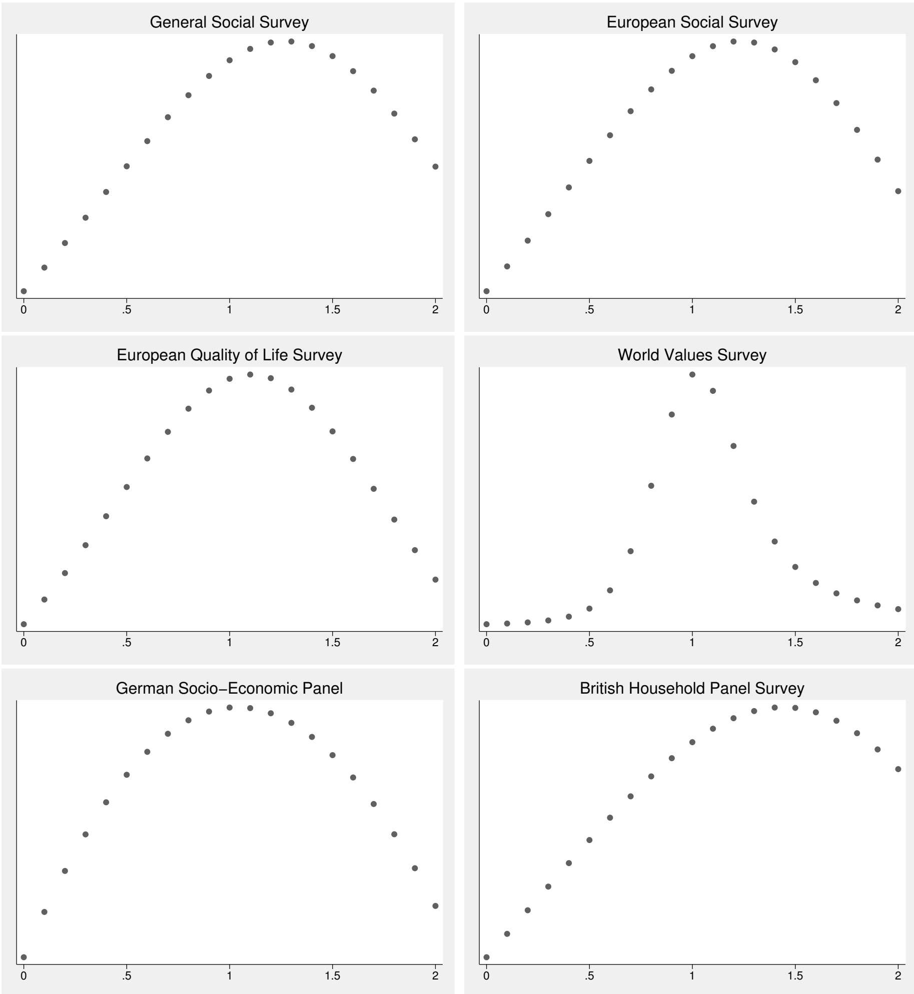

Figure 8: Histograms of answers to reported happiness questions.

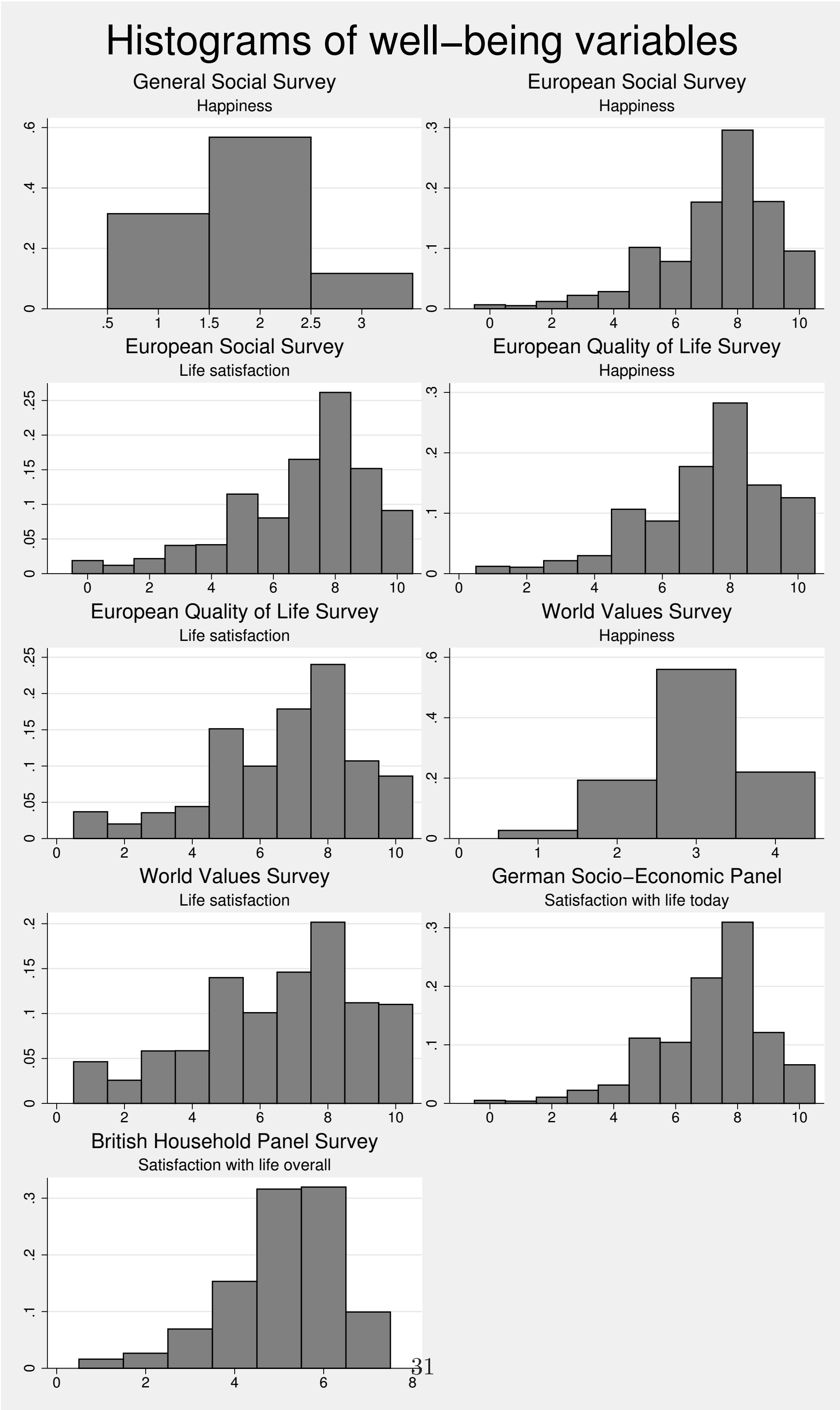

Table 1: Description of surveys as used. Details relate only to the subset of observations used in the regressions. The well-being variable was categorical when levels are indicated and numerical when a range is indicated.

Survey Name	**Type**	**Countries**	**Years**	**Obs.**	**Well-being variable**	**Household income variable**
General Social Survey (GSS)	Cross-section	United States	1972-2004 (25 waves)	19,495	Happiness (3 levels)	Yearly gross
European Social Survey (ESS)	Cross-section	Europe (22 in 1st wave, 26 in 2nd wave)	2002 and 2004 (2 waves)	29,484	Both happiness and life satisfaction (0-10)	Monthly net
European Quality of Life Survey (EQLS)	Cross-section	Europe (28)	2003	9,080	Both happiness and life satisfaction (1-10)	Monthly net
World Values Survey (WVS)	Cross-section	Worldwide (50)	1990-2000 (3 waves)	40,768	Both life satisfaction (1-10) and happiness (4 levels)	Month or year Gross
German Socio-Economic Panel Survey (GSOEP)	Panel	Germany	1984-2003 (20 waves)	92,661 obs.	Life satisfaction (0-10)	Monthly net
British Household Panel Survey (BHPS)	Panel	Britain	1996-2004 (7 waves)	42,075	Life satisfaction (1-7)	Monthly net

Table 2: Coefficients on log relative income and log relative income squared in pooled cross-section regressions of reported happiness. The absolute value of the t-score is shown in parentheses. The coefficient on log relative income is also shown in units of standard deviation of the reported happiness variable in the survey. Relative income is defined as mean income in country/year.

	Regression with $\log(y/\bar{y})$ only		**Regression with quad. coeff.**	
	$\log(y/\bar{y})$	$\log(y/\bar{y})/\sigma_h$	$\log(y/\bar{y})$	$\log(y/\bar{y})^2$
GSS	0.70 (14.6)	0.22	0.66 (12.2)	-0.07 (2.0)
ESS	0.62 (27.0)	0.32	0.61 (26.4)	-0.15 (5.7)
EQLS	0.82 (17.5)	0.39	0.83 (17.3)	-0.07 (1.4)
WVS	0.58 (30.4)	0.26	0.58 (30.3)	0.02 (1.1)
GSOEP	0.52 (26.8)	0.29	0.53 (26.8)	-0.12 (3.1)
BHPS	0.53 (21.6)	0.25	0.52 (20.9)	-0.14 (5.0)

Table 3: Comparison of the coefficients on log relative income in panel fixed effects vs. pooled cross-section regressions of reported happiness. The absolute value of the t-score is shown in parentheses. See text for more details.

	Pooled cross-section	**Panel fixed-effects**
Survey	$\log y$	$\log y$
GSOEP	0.52 (26.8)	0.42 (13.5)
BHPS	0.53 (21.6)	0.18 (4.18)

Table 4: OLS estimates of the coefficient of relative risk aversion, as obtained in regressions of reported happiness on a CRRA function of income and on other regressors. The table lists the maximum likelihood estimate $\hat{\rho}$ for each survey and for all the surveys taken together, and the likelihood ratio statistic for $\rho = 1$ ($\log y$) and for $\rho = 1.3$ (the overall maximum likelihood linear regression estimate of ρ).

Survey	$\hat{\rho}$	**LR stat. for** $\rho = 1$	**LR stat. for** $\rho = 1.3$
GSS	1.2	3.77	1.20
ESS	1.3	41.23	0
EQLS	1.2	11.22	1.76
GSOEP	1.2	1.13	0.69
BHPS	1.4	20.53	1.70
Total	1.3	72.56	0

Table 5: Spline test results. The results show the ratio between b_1 and b_2 in Equation 12. The t-score of the significance of different coefficients is in parentheses.

Survey	b_1/b_2
GSS	1.36 (2.34)
ESS	1.48 (6.84)
EQLS	1.21 (2.52)
WVS	1.18 (1.74)
GSOEP	1.38 (6.17)
BHPS	1.28 (2.36)

Table 6: Ordered logit estimates of the coefficient of relative risk aversion, as obtained in regressions of reported happiness on a CRRA function of income and on other regressors. The table lists the maximum likelihood estimate $\hat{\rho}$ for each survey and for all the surveys taken together, and the likelihood ratio statistic for $\rho = 1$ ($\log y$) and for $\rho = 1.2$ (the overall maximum likelihood ordered logit estimate of ρ).

Survey	$\hat{\rho}$	**LR stat. for** $\rho = 1$	**LR stat for** $\rho = 1.2$
GSS	1.3	7.13	0.38
ESS	1.2	19.09	0
EQLS	1.1	2.39	2.06
GSOEP	1.0	0.00	1.25
BHPS	1.4	18.24	5.63
Combined	1.2	37.56	0

Table 7: The survey questions for the reported happiness variables we used.

Survey	Variable	Question
GSS	Happiness	Taken all together, how would you say things are these days would you say that you are very happy, pretty happy, or not too happy?
WVS	Happiness	Taking all things together, would you say you are: Very Happy, Quite Happy, Not very happy, Not at all happy?
WVS	Life satisfaction	All things considered, how satisfied are you with your life as a whole these days? Please use this card to help with your answer. [range of 1-10 with 1 labeled "Dissatisfied" and 10 labeled "Satisfied"]
ESS	Happiness	Taking all things together, how happy would you say you are? Please use this card [card marked from 00, labeled "Extremely unhappy", to 10, labeled "Extremely happy". Other values not labeled.]
ESS	Life satisfaction	All things considered, how satisfied are you with your life as a whole nowadays? Please answer using this card, where 0 means extremely dissatisfied and 10 means extremely satisfied. [card marked from 00, labeled "Extremely dissatisfied", to 10, labeled "Extremely satisfied". Other values not labeled.]
EQLS	Happiness	Taking all things together on a scale of 1 to 10, how happy would you say you are? Here 1 means you are very unhappy and 10 means you are very happy.
EQLS	Life satisfaction	All things considered, how satisfied would you say you are with your life these days? Please tell me on a scale of 1 to 10, where 1 means very dissatisfied and 10 means very satisfied.
GSOEP	Life satisfaction	In conclusion, we would like to ask you about your satisfaction with your life in general. Please answer according to the following scale: 0 means 'completely dissatisfied', 10 means 'completely satisfied'. How satisfied are you with your life, all things considered?
BHPS	Life satisfaction	How dissatisfied or satisfied are you with your life overall? [scale of 1-7 with 1 labeled "Not satisfied at all" and 7 labeled "Completely satisfied".]

Table 8: Sample statistics for happiness and life satisfaction, and the combined variable.

Survey	Variable	Mean	Standard deviation
GSS	Happiness	5.989	3.134
ESS	Happiness	7.367	1.903
ESS	Life sat.	6.944	2.597
ESS	Combined	7.152	1.928
EQLS	Happiness	6.986	2.118
EQLS	Life sat.	6.285	2.426
EQLS	Combined	6.636	2.082
WVS	Happiness	6.576	2.404
WVS	Life sat.	6.177	2.694
WVS	Combined	6.327	2.280
GSOEP	Life sat.	7.126	1.795
BHPS	Life sat.	6.803	2.132

Table 9: The coefficient on log income ($t-$score in parentheses) in units of standard deviation of the subjective well-being variable, and overall regression fit for happiness, life satisfaction, and the combined variable.

Survey	**Variable**	**Coef. on** $\log(y)/\sigma_h$	**Regression** R^2
GSS	Happiness	0.22 (14.6)	0.089
ESS	Happiness	0.28 (22.6)	0.187
ESS	Life satisfaction	0.31 (26.2)	0.251
ESS	Combined	0.32 (27.0)	0.252
EQLS	Happiness	0.32 (13.4)	0.232
EQLS	Life satisfaction	0.39 (17.8)	0.327
EQLS	Combined	0.39 (17.5)	0.325
WVS	Happiness	0.19 (21.0)	0.213
WVS	Life satisfaction	0.25 (28.7)	0.268
WVS	Combined	0.26 (30.4)	0.296
GSOEP	Life satisfaction	0.25 (23.7)	0.056
BHPS	Life satisfaction	0.25 (21.6)	0.055

Table 10: Coefficients in regressions of reported happiness ($t-$scores in parentheses) on log household income or log equivalised household income, with or without controls for the number of adults and children in the household. All regressions included standard controls, as well as country dummies. Source: European Quality of Life Survey.

Income variable	**Log income**	**Adults**	**Children**	R^2
Household income	0.82 (17.53)			0.3248
Equiv. household income	0.65 (15.06)			0.3183
Household income	0.83 (17.53)	-0.03 (0.18)	0.03 (0.29)	0.3251
Equiv. household income	0.83 (17.46)	0.17 (7.53)	0.15 (6.05)	0.3249