Subjective well-being, income and relative concerns in the UK

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12 November 2010

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Abstract

We present an empirical model aimed at testing the relative income hypothesis and the effect of deprivation relative to mean income on subjective well-being. The main concern is to deal with subjective panel data in an ordered response model where error homoskedasticity is not assumed. A heteroskedastic pooled panel ordered probit model with unobserved individual-specific effects is applied to micro-data available in the British Household Panel Survey for 1996-2007. In this framework, absolute income impacts negatively on both completely satisfied and dissatisfied individuals, while relative income affects positively the most satisfied ones. Such an effect is asymmetric, impacting more severely on the relatively poor in the reference group. We argue that our results buttress the validity of the relative income hypothesis as an explanation of the happiness paradox.

Keywords: Subjective Well-being, Relative Income, Absolute Income, Deprivation, Panel Data, Discrete Choice Models.

JEL: C33, C35, D6, D31, I31

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1 Introduction

In recent years a new stream in the economic literature has boomed, which is mainly focused on explaining happiness determinants. In 1974 Richard Easterlin moved the first step towards a new conceptualization of happiness, overcoming the existing approaches built upon income-based measures of individual well-being. Indeed, research focused on the relationship existing between material goods and personal satisfaction- intended as a synonym for happiness- finds that economic factors affect only 10% of the variation between individuals' well-being. Therefore, the 'Easterlin Paradox' or 'Happiness Paradox', i.e. the fact that in developed countries income is increasing while happiness levels are constant or decreasing, is a puzzle to unravel by complementing income-based measures of welfare with other measures, such as health, employment status, marital status and other observable characteristics of interest (e.g. demographic and sociological factors).

We aim at uncovering the Easterlin Paradox by pursuing an empirical analysis with British data, based on the intuitive consideration that individuals' happiness depends not only on personal wealth but also on neighbors'[1] material achievements.

Existing evidence suggests that income matters for happiness if compared to a benchmark (Easterlin, 1995, 2003; Blanchflower and Oswald, 2004a, 2004b; Firebaugh and Tach 2000; Clark, Frijters and Shields, 2008). Easterlin (1974) envisages a consumption behavior in societies: individuals measure their own achievements in comparison to a general standard of living- the eponymous 'keeping up with the Joneses'.[2] According to this view, given that both objective conditions and social status symbols vary across countries and regions, even more prosperous countries may be no happier than poorer ones.

Relative concerns on material circumstances could then constitute an explanation for the Easterlin paradox, as argued by Ferrer-i Carbonell (2005), among others, and provide a justification for our interest in estimating the effect exerted by relative income on happiness. The present study drives at contributing to the empirical literature on the importance of interdependent preferences for individual

[1] We use the term 'neighbors' for indicating people included in the individual's reference group, i.e. people supposed to be confronted with the individual in her daily life.

[2] The comparison could be made against an internal benchmark, rather than against a social one, depending on personal beliefs.

well-being. Specifically, the main contributions of this paper are ascribable to testing the relative income[3] hypothesis, and the effect of deprivation relative to mean income on subjective well-being by using micro-panel data in an ordered probit framework when the homoskedasticity assumption is relaxed. Indeed, dealing with subjective data we see fit to control for heteroskedasticity due to heterogeneity in choices. In particular a heteroskedastic pooled panel ordered probit[4] (HPPOP, henceforth) augmented to control for unobserved individual-specific effects is estimated and a large number of control variables (i.e. health, both at the subjective and objective levels, marital status, having children, age, gender, and employment status) are included. This way flexibility in the analysis of marginal probability effects is gained, revealing that absolute income impacts negatively on the probability of being generally unhappy as well as on the probability of being completely happy. Relative income, instead, has a positive influence on self-reported well-being, meaning that comparison income is negatively related to the level of self-reported satisfaction: in each reference group the (relatively) rich and the (relatively) poor are both less satisfied if the comparison income increases. Such an effect is asymmetric. In fact, including a deprivation measure,[5] we find that the mean income impact is severer for the poor, *ceteris paribus*. Lastly, health, marital status and employment status are very influential variables in the regression, thus representing other important drivers of individual well-being.

The remainder of the present paper is laid out as follows: Section 2 provides a review of the literature, where we summarize the most significant contributions on the explanation of the happiness-income relationship; Section 3 consists of the econometric analysis; Section 4 is devoted to data description and overviews hypotheses and specification; Section 5 is dedicated to the estimation results; Section 6 concludes.

[3]Intended as the difference between individual income and average income in a specified comparison group.

[4]The heteroskedastic ordered probit is also known as heterogeneous choice/ location-scale ordinal probit. We conied the term heteroskedastic pooled panel ordered probit for synthesizing the features of the model we use: an ordered probit, pooled, but still allowing more robustness than cross-sectional analyses (panel), and controlling for potential heteroskedasticity (heteroskedastic).

[5]The deprivation measure consists of a multiplicative term which includes a dummy and relative income. The dummy takes on the unity when personal income is below the reference one.

2 Subjective Well-Being in the Economics Literature

A proved fact in the happiness-related economics literature is that the satisfaction of human greed for material goods cannot intuitively represent the sole determinant of well-being, intended as "the disposition to feel good about oneself and one's own corner of the world" (Lykken and Tellegen, 1996). For this reason, the interest of economists has been captured by other factors supposed to be playing an important role for individual satisfaction with life, e.g. health, marital status, ethnicity, civic trust and, lately, the so called relational goods, which are referred to social aspects of life. Besides, economists are conscious that personal preferences for material goods are influenced by personal characteristics as well as by contextual effects that pertain to the social substrate and the environment individuals live in; hence similar factors cannot be ignored.

As to the designate variables capable of capturing these concepts, psychologists started using questionnaires reporting subjective well-being for studying happiness a long time ago, while it is only recently that economists have started relying on such assessments. The contributions of Sen's capability approach (1995) and Kahneman's work on objective happiness (1999) have been of crucial importance in this perspective. Their work juxtaposes to modern economics mainstream, departing from standard utility theory and welfarism. Indeed, focusing the analysis on subjective well-being surveys means taking into account preferences directly expressed by individuals rather than the canonical revealed ones, and takes us back in time to the earliest conceptions of utility.[6] In turn, surveying people's life satisfaction constitutes a more direct way of observing their behavior; besides, it overcomes likely discrepancies between individual wills and individual choices,

[6] In his Introduction to the Principles of Morals and Legislation, Bentham (1789) states that utility refers to pleasure and pain, the "sovereign masters" that "point out what we ought to do, as well as determine what we shall do" and that "by utility is meant that property in any object, whereby it tends to produce benefit, advantage, pleasure, good, or happiness, (all this in the present case comes to the same thing) or to prevent the happening of mischief, pain, evil, or unhappiness to the party whose interest is considered: if that party be the community in general, then the happiness of the community: if a particular individual, then the happiness of that individual." Kahneman et al. (1997) call it 'experienced utility' as opposed to the modern 'decision utility', which is inferred from observed choices and is in turn used to explain choices.

the latter being possibly not perfectly related to the former because of bounded rationality.[7]

In general, surveys consist of questions of the type: "How satisfied (or happy) are you with your life overall?".[8] The range of possible responses is defined over a scale that varies between datasets (one to four, one to seven, or one to ten), the lowest grades indicating a poor level of life satisfaction. The result is an ordered assessment of individuals' life satisfaction. As to the interpretation of such answers, this is classically conducted under the following main hypotheses.

Firstly, life satisfaction is thought of as being a good proxy for welfare, a more general concept the researchers actually focus on.[9] Specifically, the former is assumed to be a monotonic transformation of the latter.

Secondly, life satisfaction is presumed to be ordinally comparable between individuals. Loosely speaking, we can recognize if any two individuals are better off, worse off or equally well off in terms of welfare. This implies that happiness is a concept perceived much the same way. Being life satisfaction a monotonic transformation of welfare, we are able to discern happier individuals from less happy ones.

Lastly, a cardinal comparability of life satisfaction (preferences) between individuals is assumed to be possible. This means assuming that the difference between any two consecutive scores in the satisfaction scale is the same regardless of the rank. Such a hypothesis is not very widespread for its perversity to the standard microeconomic theory. Indeed, a controversy on happiness (or utility) cardinal measurability exists in this literature. Ng (1996) argues that such a difference of

[7]In the analysis of the link between social behavior and rationality in people's choice, Sen (1995) suggests similar arguments. He argues that there are many situations in which a choice cannot be expected to reveal a preference or to be rational, i.e. to obey the Weak Axiom of Revealed Preferences or alpha/beta properties. The resulting capability-based approach applied to the study of poverty, for instance, explains why poor people might be limitedly capable of making some kind of choices or actions.

[8]A word of caution is in order at this stage. Some criticism might arise about the difference between 'happiness' and 'life satisfaction'. Indeed, while meaning and comparability are arguable, some studies have shown that questions on happiness and satisfaction with life are so closely correlated that reflect the same abstract concept (Graham and Pettinato, 2002; Blanchflower and Oswald, 2004a).

[9]Here, again, it is lapalissian that Kahneman's approach has played a fundamental role, in that welfare is based on objective happiness. In Kahneman's theory, the construct is 'objective happiness' and the measure is a temporal integral of moment-based happiness reports.

opinion arises from the fact that the term 'utility' is used to measure both individual subjective satisfaction (thought of as being cardinally measurable) and the preference rankings of an individual (where only the orderings or ordinal utility is relevant). "While the latter concept is relevant to the positive theory of consumer choice under certainty, the former is relevant for many other purposes". Also, "modern economists are trained to regard utility (a measure of the degree of preference satisfaction) as only ordinally measurable. This is so because ordinal utility is sufficient for the positive analysis of behavior. A given set of indifference curves will give the same demand curves irrespective of the cardinal utilities assigned as long as the ordering is the same. Thus, for positive economics, cardinal utility is unnecessary. However, for problems of public policy or social choice[...] we do not only need to know how many individuals are made better off and how many made worse off, we also need to know better off and worse off by a lot or by only a little bit. Thus, cardinal utility is necessary." (Ng, 2008). Ferrer-i Carbonell and Frijters (2004), instead, produce evidence that the assumption of cardinality of life satisfaction scores has a negligible impact on empirical results. Indeed, we argue that such an assumption is closely related to the econometric method used for the empirical analysis, and that when ordinal discrete models are used, cardinality is not a major concern.

From a methodological viewpoint, surveys are susceptible to be biased due to several factors, such as unobservable conditions, situations or events and personal idiosyncrasies. The econometrician faces the difficult task of controlling for all these problems at once. The use of panel data, thanks to both the temporal and cross-sectional dimensions, does permit to control for the aforementioned issues, for example by including fixed effects or *ad hoc* dummies. Nevertheless, as we will see hereafter, few are the studies in which econometricians hazard the implementation of panel data methods in discrete choice models, especially the ordered ones.

As extensively discussed by Ferrer-i Carbonell and Frijters (2004), the econometric models under the hypothesis of ordinal comparability generally present an ordinal latent-variable specification. The error term may be assumed to be either Normal or Logistic, this leading respectively to an ordered probit or logit. This framework is the most popular (for example, ordered probit analyses are pursued, among others, by Clark and Oswald (1994); Blanchflower and Oswald (2001); Frey and Stutzer 1999,2000, while Winkelmann and Winkelmann (1998); Blanchflower and Oswald (2004b); Alesina et al. (2004), rely on ordered logit models). Usually fixed effects are not directly included in the regression, provided the estimates obtained are inconsistent (Maddala, 1983).

Noteworthy studies are the ones by Winkelmann and Winkelmann (1998), where a conditional maximum likelihood estimator for a fixed effects logit model is implemented dichotomizing the dependent variable, and by Ferrer-i Carbonell and Frijters (2004), who augment the Winkelmann and Winkelmann estimator with individual specific thresholds, disregarding the hypothesis of cardinal comparability between responses.

In alternative to the frameworks presented so far, other contributions assume a structural relationship existing between time-invariant variables and time-varying ones (Mundlak 1978; Chamberlain 1984- general studies) or include individual random time-invariant effects in ordered response models (Ferrer-i-Carbonell 2005). This last strand is the one we take inspiration from.

Relying on the achievements of the literature surveyed, some general guidelines can be traced for the design of future analyses on the nexus between happiness and income. In consideration of the ordinal nature of life satisfaction data, we argue that analyses based on ordered discrete choice models should provide a better fit. In addition, we think that individual fixed effects as well as heteroskedasticity in choices need to be controlled for.

3 The Econometric Analysis

As described in Section 2, numerous are the empirical studies exploring the happiness relationship with income. However, many of them have their pitfalls in the cross-sectional nature of the analysis, which does not allow to control for individual specific traits; some others are either specified in such a way too many observations are dropped or do not take into account fixed-effects in ordered response model settings. The use of panel data as well as the development of suitable micro-econometric techniques allow us to take a further step towards the achievement of sounder evidence on the satisfaction link with income.

First of all, we presume that it is appropriate to keep the ordered structure of the dependent variable 'Life Satisfaction', rather than conforming to other panel data analyses where the same variable is dichotomized, because ordinal variables embed more information than binary ones. Furthermore, given the strong heterogeneity of people surveyed exacerbated by the psychological nature of the question, the econometric analysis needs to account for unobservable individual effects and potential heteroskedasticity. Therefore, in the remainder we specify a HPPOP model, which is augmented to account for unobserved time-invariant individual effects. We control for unobserved effects which are neither considered as parameters to estimate nor as having a certain distribution and being independent from all covariates, accommodating the model by Mundlak (1978) to our case. In this way we do control for fixed effects, as Mundlak (1978) shows in his original article, where a modified random coefficients model leads to a 'within' estimator identical to the fixed effect estimator of the basic specification when unobserved effects are assumed to be normally distributed conditional on the covariates.

Lastly, we want to avoid the assumption that error variances are the same for all cases, which might entail biased parameter estimates. Heterogeneous choice models explicitly specify the determinants of heteroskedasticity in an attempt to correct for it, which requires the researcher to arbitrarily choose the potential sources of heterogeneity. This leads to joint estimation of the explanators of heterogeneity and the explanators associated with choices.

3.1 Baseline Setting

Hereinafter, we explain the basic pooled panel ordered probit (PPOP, henceforth) in its standard form. Formally, the ordered categorical outcome for the variable life satisfaction S_{nt} is coded in a rank preserving manner:

$$S_{nt} \in \{1, 2, ..., j, ..., J\}$$

where we implicitly assumed repeated measurements ($t = 1, ..., T$) for a sample of N individuals ($n = 1, ..., N$). The vector of covariates $\mathbf{x}$ is, say, of dimension $(1 \times k)$. The cumulative probabilities of the outcome are linked to a single index of independent variables as follows:

$$\Pr(S_{nt} \leq j|\mathbf{x}_{nt}) = \Phi(\alpha_j - \mathbf{x}_{nt}\boldsymbol{\beta}),$$

where α_j and β are unknown parameters and Φ is the standard normal cumulative density function.

Well-defined probabilities are ensured if $\alpha_j > \alpha_{j-1}$, $\alpha_J = \infty$ such that $\Phi(\infty) = 1$ and $\alpha_0 = -\infty$ such that $\Phi(-\infty) = 0$. Ordered response models are expressed by means of an underlying continuous latent process S^*_{nt} and a response scheme:

$$\begin{aligned} S^*_{nt} &= \mathbf{x}_{nt}\beta + \epsilon_{nt} \\ S_{nt} &= j \text{ iff } \alpha_{j-1} < S^*_{nt} = \mathbf{x}_{nt}\beta + \epsilon_{nt} < \alpha_j,\ j = 1, 2, ..., J, \end{aligned} \tag{1}$$

where S^*_{nt} represents the real line that is discretized in J categories by the threshold parameters α_j and it is in linear relation with observables and unobservables, the latter assumed to be distributed as a standard normal, $\Phi(\epsilon_{it})$. The estimated parameters are to be interpreted as indicative of the sign but not the magnitude of the effect. Indeed, conditional probabilities are crucial in this kind of analyses; they read as follows[10]:

$$\Pr(S = j|X = \mathbf{x}) = \Phi(\alpha_j - \mathbf{x}\boldsymbol{\beta}) - \Phi(\alpha_{j-1} - \mathbf{x}\boldsymbol{\beta}).$$

For identifying the parameters we need to assume that $\mathbf{x}$ does not contain a constant, this aimed at fixing the location of the arguments in Φ (Boes and Winkelmann, 2006b).

We are interested in understanding how a marginal variation in one covariate produces a change in the cumulative distribution of the dependent, thus a variation in all the outcome probabilities. For a continuous regressor x_h the marginal effects are computed as follows:

$$M_{jh}(\mathbf{x}) = \frac{\partial \Pr(S = j|X = \mathbf{x})}{\partial x_h} = \left[\phi(\alpha_{j-1} - \mathbf{x}\boldsymbol{\beta}) - \phi(\alpha_j - \mathbf{x}\boldsymbol{\beta})\right]\beta_h,$$

[10] Henceforth in this subsection we disregard subscripts for expositional neatness; the specification refers to individual n at period t.

where $\phi(\cdot)$ is the standard normal probability density function. If the regressor is discrete, we compute the variation in probability before and after the discrete change:

$$\Delta \Pr(S = j|X = \mathbf{x}) = \Pr(S = j|X = \mathbf{x} + \Delta x_h) - \Pr(S = j|X = \mathbf{x}).$$

The size of the effects on the outcome probabilities depends on the values that the n^{th} observation takes on.

The values at which the partial effects are to be evaluated are the means of the independent variables. Theoretically, we obtain the so called 'average marginal effects' by computing the expected value with respect to the covariates. The way to consistently estimate the average partial effects is to replace the population parameters with the estimates obtained by maximum likelihood and compute the average over the whole sample of observations.

A note is due on the limits of the ordered response models, because the ratio between the marginal probability effects of two different continuous regressors on the same response choice remains constant across individuals. Moreover, due to the shape of the normal distribution, we observe that the sign of marginal probability effects changes only once from the lowest to the highest category, being first negative and then positive or *vice versa*. Indeed, it is difficult to understand the effects for the categories included between the first and the last.

3.2 Extensions to the Baseline Setting

We operate two main adjustments to our baseline setting by introducing unobserved individual effects and controlling for potential heteroskedasticity of the errors.

Specifically, when unobserved individual specific effects are assumed to exist, the specification of the PPOP model changes as follows:

$$\begin{aligned} S^*_{nt} &= \xi_n + \mathbf{x}_{nt}\boldsymbol{\beta} + \epsilon_{nt} \ , \\ n &= 1, ..., N; \quad t = 1, ..., T. \end{aligned} \tag{2}$$

In a linear model ξ_n would be eliminated by a first difference estimation or by a within- transformation. The ordered probit, instead, given its non-linear form, does not permit similar methods. Applying a dummy variable approach is not advisable either, mainly for two reasons: too many degrees of freedom are lost in this case and the incidental parameters problem[11] would lead to inconsistent estimators.

What we do for taking into account unobserved individual effects is modeling the conditional distribution of such a term with respect to the covariates:

$\xi_n|\mathbf{x}_n \backsim N(\overline{\mathbf{x}}_n\boldsymbol{\gamma}, \sigma^2_{\varpi})$, where $\overline{\mathbf{x}}_n$ is the average over time of $\mathbf{x}_{nt}$, and σ^2_{ϖ} is an unknown parameter. In other terms, $\xi_n = \overline{\mathbf{x}}_n\boldsymbol{\gamma} + \varpi_n$, where ϖ_n is an orthogonal error with $\varpi_n \mid \mathbf{x}_n \backsim N(0, \sigma^2_{\varpi})$.

In practice, we extend the approach *à la* Mundlak (1978) to an ordered setting. Mundlak originally proposes a modified random coefficients model in which unobserved effects are assumed to be normally distributed conditional on the mean of the covariates, thus obtaining a 'within' estimator in the random effects framework. In Mundlak's specification the error distribution is symmetrical, thus the resulting GLS estimator is identical to the fixed effect estimator of the basic specification. Therefore it is unbiased (Hsiao, 1986).

The other adjustment regards the error term. We model the error variance structure, as suggested in the literature on heterogeneous choice models, assuming that $\epsilon_{nt}|\mathbf{x}_{nt} \backsim iiN(0, \sigma^2_{\epsilon})$, where $\sigma^2_{\epsilon} = \exp(\mathbf{z}_{nt}\boldsymbol{\vartheta})^2$. The vector $\mathbf{z}_{nt}$ can contain all the variables that the researcher considers as possible sources of heteroskedasticity, even variables already included in the set of regressors. Such a method should avert potential heteroskedasticity to bias our results. Heteroskedastic models like this one have been frequently used to explore heterogenous behaviors (Alvarez and Brehm, 1997, 1998, 2002; Busch and Reinhardt, 1999; Gabel, 1998; Lee, 2002; Krutz, 2005). So far, heteroskedastic probit and heteroskedastic ordered probit models are the most used tools in investigating discrete heterogenous choices. The advantage of these models is the ability to cure probit with non-homogeneous error variances or to test hypotheses about heterogenous choices that immediately relate to σ^2_{ϵ} (Keele and Park, 2006).

[11] In fixed effects models, the number of parameters increases with the number of individuals, because we estimate them as unknown parameters. When n becomes large, but T is finite, the maximum likelihood estimator is inconsistent.

Back to our model, all parameters are now scaled by

$$(\sigma_{\epsilon}^{2}+\sigma_{\varpi}^{2})^{-1/2}=(\exp(\mathbf{z}_{nt}\vartheta)^{2}+\sigma_{\varpi}^{2})^{-1/2}$$

that will be denoted with $\Omega_{nt(z)}$. By assuming that the individual-specific effects are normally distributed conditional on the individual means of time-varying covariates, we end up with a sum of normal variables; the response probabilities for individual n at period t, $p_j(\mathbf{x},\mathbf{z})=\Pr(S=j\mid X=\mathbf{x},Z=\mathbf{z})$, look like:

$$\begin{aligned}
&p_1(\mathbf{x},\mathbf{z})=\Phi\left[(\alpha_1-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]\\
&p_2(\mathbf{x},\mathbf{z})=\Phi\left[(\alpha_2-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]-\Phi\left[(\alpha_1-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]\\
&\ldots\\
&p_{J-1}(\mathbf{x},\mathbf{z})=\Phi\left[(\alpha_{J-1}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]-\Phi\left[(\alpha_{J-2}\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]\\
&p_J(\mathbf{x},\mathbf{z})=1-\Phi\left[(\alpha_J-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right].
\end{aligned}$$

The joint distribution of $(S_{n1},...,S_{nT})$ conditional on the explanatory variables is obtained by integrating ϖ_n out in the response probabilities:

$$f\left(S_{n1},...,S_{nT}\right)=\int_{-\infty}^{+\infty}\prod_{t=1}^{T}\prod_{j=1}^{J}p_j(\mathbf{x},\mathbf{z})^{\mathbf{1}(S_{nt}=j)}\frac{1}{\sigma_{\varpi}^{2}}\phi\left(\frac{\varpi_n}{\sigma_{\varpi}^{2}}\right)d\varpi_n.$$

The parameters $\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\vartheta}$ and σ_{ϖ}^{2} are estimated by maximum likelihood, the total partial log-likelihood function reading as:

$$\ell(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\vartheta},\sigma_{\varpi}^{2}\mid\mathbf{x},\mathbf{z})=\sum_{n=1}^{N}f\left(S_{n1},...,S_{nT}\right).$$

Without further assumptions, a robust variance matrix estimator is needed to account for serial correlation in the scores across the time periods. Indeed, we adjust robust standard errors for clustering at the individual level, i.e. correct for correlation between responses of the same individual across time periods.

As to the marginal partial effects, it is straightforward to see how their magnitude and sign are dependent on the inclusion of a function for modeling the error variance. The first case to be considered is that of continuous variables included in $\mathbf{z}$ when such vector is a subset of $\mathbf{x}$. Consider the marginal effect of $x_h \in \mathbf{z} \subseteq \mathbf{x}$:

$$\begin{aligned} M_{jh}(\mathbf{x}) &= \frac{\partial \Pr(S=j|X=\mathbf{x},Z=\mathbf{z})}{\partial x_h} = \\ &= \phi\left[(\alpha_{j-1}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]\left\{\beta_h\cdot\Omega_{(z)}+\theta_h\cdot(\alpha_{j-1}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\exp(\mathbf{z}\boldsymbol{\vartheta})^2\mathbf{z}\boldsymbol{\vartheta}\right\} \\ &\quad -\phi\left[(\alpha_{j}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\cdot\Omega_{(z)}\right]\left\{\beta_h\cdot\Omega_{(z)}+\theta_h\cdot(\alpha_{j}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\exp(\mathbf{z}\boldsymbol{\vartheta})^2\mathbf{z}\boldsymbol{\vartheta}\right\}, \end{aligned} \tag{3}$$

where the mean component for x_h is considered to be negligible. This way it is easy to understand how the structure imposed to the model allows the marginal effects to be non-trivial. Different from the basic model, the ratio of marginal probability effects of two distinct continuous covariates on the same outcome is not constant across individuals and the outcome distribution. Moreover, marginal probability effects may change their sign more than once when moving from the smallest to the largest outcome. Therefore, while the standard model precludes a flexible analysis of marginal probability effects by design, when turning our attention to the effects on the full distribution of outcomes this extension appears to be more appropriate.

For a continuous variable x_h in $\mathbf{x}$ but not in $\mathbf{z}$, the marginal partial effect is much simpler:

$$\begin{aligned} M_{jh}(\mathbf{x}) &= \frac{\partial \Pr(S=j|X=\mathbf{x},Z=\mathbf{z})}{\partial x_h} = \\ &= \left[\phi(\alpha_{j-1}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})-\phi(\alpha_{j}-\mathbf{x}\boldsymbol{\beta}-\overline{\mathbf{x}}\boldsymbol{\gamma})\right]\beta_h\cdot\Omega_{(z)}. \end{aligned} \tag{4}$$

Finally, for discrete variables in $\mathbf{z}$ the partial effect is easy to compute and similar to the baseline case:

$$\Delta p_j(\mathbf{x},\mathbf{z}) = \Pr(S=j|X=\mathbf{x}+\Delta x_h, Z=\mathbf{z}+\Delta x_h) - \Pr(S=j|X=\mathbf{x}, Z=\mathbf{z}),$$

while for discrete variables in $\mathbf{x}$ but not in $\mathbf{z}$ the partial effect is exactly the same as in the baseline setting.

4 Data

4.1 The Life Satisfaction Variable

The BHPS is a longitudinal panel survey of households in Great Britain. The first wave of data was collected in 1991,[12], originally including 5,500 households. Members of these households who were aged 16 years and over in 1991 have been interviewed every year, and their children included as respondents when older than 16, as well as any new member of the household. About 10,300 individuals are interviewed every year from 1996 to 2007 on the general question "How satisfied are you with life overall?".[13] They can choose based on an ordinal scale from 1 to 7, where 1 means 'not satisfied at all' and 7 'completely satisfied'. The dependent variable is therefore a 1 to 7 ordered response variable denoted as 'Satisfaction with Life Overall' and is meant to measure subjective well-being. By means of a single question it is possible to register individuals' self-reported level of happiness. The person surveyed makes a cognitive assessment on her own perceived quality of life, and we are driven by the belief that these data are significantly reliable for disclosing individuals' state. Studies on subjective well-being generally take two main perspectives referred to the concept they want to capture by means of the satisfaction variable: *hedonism* and *eudaimonia*. Hedonism can be expressed as the pursuit of satisfaction by self-gratification or pleasure, thus well-being is merely related to the material goods and the immediate enjoyment of such goods. Eudaimonia refers to the human desire for overall fulfillment- originally eudaimonia ($\varepsilon\upsilon\delta\alpha\iota\mu o\iota\nu\iota\alpha$, ‹‹happiness›› etymologically) was a concept belonging to greek philosophy[14] which considered happiness as the final goal, the moral perfection of the human-being achieved by means of the *Virtus*, and for this reason material circumstances were conceived to be only corollary to pure happiness. By interpreting

[12] The number of waves an individual is surveyed may change due to several reasons, such as death, immigration and attrition or because new individuals become part of the household.

[13] We drop all the non-full interviews. From Wave 7 (1997) there is oversampling of low income people for comparability with the European Community Household Panel. Moreover, many more observations have been sampled for Scotland and Wales. In order to maintain comparability with previous waves and random sampling, we keep only observations belonging to the original sample.

[14] Socrates was the first philosopher using this term; Aristoteles and Plato contributed to develop the concept in relationship with the moral and political disciplines.

the meaning of eudaimonia for the present society, we might consider it as the multidimensional actualization of the *self* and a commitment to socially-shared goals. Despite the fact that both are considered separately as inputs into subjective well-being, for the purposes of this work we focus on the concept of 'eudaimonia', given the use of variables other than income in our analysis of well-being determinants.

4.2 Income, Relative Income and Deprivation

Our main interest is to assess the importance exerted by material circumstances on individual well-being. For this reason, such regressors play a crucial role in the analysis and deserve a special mention.

The variable income is meant to capture the consumption capacity of the person surveyed. It is intended as the compound of annual nominal household labour income and household non-labour income both deflated at the UK CPI[15] (basis year: 2005). We opt for household rather than individual income for the simple reason that life tenor depends on the familiar monetary wealth more than on the individual one.

Relative income, instead, is computed as the ratio between the real household income and the average income in the neighborhood.

In the following digression we will explain in which way relative income is thought of proxying a measure of social comparison and what is the definition of neighborhood used.

In line with the economic literature on subjective well-being, we assume that happiness responses give us a perception of individuals' preferences. In practice, we hypothesize that individuals make a cognitive assessment of their overall situation and express their self-measured level of satisfaction deriving from the utility function maximization.

Let us consider a function of the form:

$$\begin{aligned} U_{nt} &= S^*_{nt}\left[(y_{jt}),(y_{jt}/y^*),\mathbf{x}_{nt}\right], \qquad (5)\\ n &= \text{individual, } j=\text{household, } t=\text{time.} \end{aligned}$$

[15] Source UK National Statistics (http://www.statistics.gov.uk/hub/index.html)

where U stands for utility, y_{jt} is real household income and y^* is a specific benchmark income, also called comparison income. Finally, $\mathbf{x}_{nt}$ is a vector of covariates- in our case, demographic and socioeconomic variables.

The term that includes relative income expresses social comparison. Since Duesenberry (1949), the relative income hypothesis- i.e. that people care about what their income is compared to other people in the same country more than their absolute one- has been used in many speculations on individual preferences and reciprocity. Nevertheless, it is only recently that the happiness economics literature focuses on the importance of material comparison for individual well-being. In particular, neighborhood more than country effects are thought of playing a role in these regards. Neighborhood effects are in general defined as "social interactions that influence the behavior or socioeconomic outcome of an individual", Dietz (2002). They include influences on individual behavior or outcomes due to the characteristics of an individual's neighbors and neighborhood, and spatial aspects of the neighborhood (the spatial relationship is defined with respect to location of residence). However, a measure of social distance may also be appropriate. Therefore, how choosing the reference (or comparison) group is of crucial importance for measuring social and economic interdependencies correctly. The main question here is whether the size of the neighborhood, as *a priori* determined by the researcher, influences the conclusions of the study. At present, there are no convincing answers to such a question. In our specific case the neighborhood delineation is driven by limitations of the data set. Specifically, we select reference groups based on sub-region and age-cohort, lacking of theoretically motivated definitions of neighborhood. If this presents an estimation bias is not known with certainty, given that no studies in the neighborhood effects literature exist which empirically test the effect of different neighborhood definitions. The common sense suggests that individuals are likely to compare with people they are in contact with in everyday life, and who share similar characteristics, e.g. are same-aged and live in the same area. As regards the geographical area, two options were available using the BHPS: either considering the so called 'Primary Sampling Units' (PSU's) or UK sub-regions. The former contain, at minimum, 500 households and are stratified into an ordered listing by region and three socio-demographic variables. The latter refer to 18 sub-regions. Considering PSU's defined neighborhoods would mean having very small groups in most of the cases, as well as too much variability in the size of the different groups. That is the reason why we opt for grouping by 18 sub-region, and 6 age-cohorts, singling out 108 neighborhoods. In this last case, in fact, we increase the size of each neighborhood and minimize its within-region variability. Furthermore, we assume within neighborhood effects only, i.e. that the neighborhood has no spillover characteristics. Thus, neighborhoods with identical characteristics but dissimilar neighboring neighborhoods are considered equivalent. In attempting to embed the educational dimension into the neighborhood choice we encountered a problem of collinearity with the income variable, which is present in the estimation as well.

Finally, we imagine that income comparisons are not symmetric, affecting the poor more than the rich. For this reason a deprivation relative to mean income measure is introduced, leading the empirical function to be conceived as follows[16]

$$S^*_{nt} = \xi_n + \ln(y_{jt})\beta_1 + \ln(y_{jt}/y^*)\beta_2 + D \cdot \ln(y_{jt}/y^*)\beta_3 + \underset{1\times k-3}{\mathbf{x}_{nt}} \boldsymbol{\beta}_k + \epsilon_{nt} \qquad (6)$$

where

$$D = \begin{cases} 1 \text{ if } y_{jt} \leq y^* \\ 0 \text{ otherwise} \end{cases},$$

and S^*_{nt} is the conditional expected value of individual well-being. If $\beta_2 > 0$, an increase in the comparison income reduces the well-being of those with an income above the mean. An increase in the reference income produces a worsening in well-being for individuals with a given income below the mean if $\beta_2 + \beta_3 > 0$. Finally, if $\beta_3 > 0$ the comparison income has a greater effect on the poor.[17] Gravelle and Sutton (2009) introduce the same measure for studying the relationship between perceived health and income in the UK. We find its design appropriate to our purpose as well, because we want to test for asymmetries in the impact that relative income might have on the relatively poor and the relatively rich in the comparison group.

[16] Notice that equation (6) represents the latent random utility model, as in equation (2).

[17] A person whose income is 20 000 GBP, and confronts herself with a reference income of 30 000 GBP, experiences the same relative deprivation of an individual having 90 000 GBP per year and a comparison income of 100 000 GBP.

4.3 Control Variables

A large number of control variables is included among the regressors for rendering the analysis more robust.

First of all, we think that health status could strongly drive the happiness response. In order to capture the impact of the health status on life satisfaction, we first make use of a self-reported measure of subjective health. Data were collected by registering answers to the question "How would you define your health status over the last 12 months" on a 1-5 scale (from excellent to very poor). We dichotomize the variable by assigning it value 1 if the original were 1 and 2, and value 0 otherwise, by relying upon the median point to group responses into good or bad health status. Criticism may arise on the endogeneity of such variable: an individual saying she is happy can subjectively consider herself in a good health status and the other way around. This is why we repeat the analysis by replacing this measure for health with the variable 'Limits in Activities of Daily Life (ADL)'. This is a dichotomous variable that takes on value 1 if individuals say that a list of health problems limit their daily activities (doing the housework, climbing the stairs, getting dressed, walking more than 10 minutes, limits in type or amount of work) and 0 otherwise. We argue that in this way it is possible to synthesize individuals' health objectively, by taking into account the possible consequences of several factors, such as illness, obesity and injuries. Our aim is to check that the results obtained under a subjective measure of health status are not too dissimilar from those obtained by including a more objective proxy, which rules out possible psychological interferences.

Marital status is indicated by the binary variable 'Married'. We include both legally married and living-as-a-couple individuals, given that we are interested in the effect of sharing everyday life with someone rather than the importance of the mere relationship type. 'Children' is a dummy indicating the presence of own children in the household, while 'Employed' is a binary variable that indicates being in-paid employed.

Age is calculated from the date of birth, and is included in the regression squared and cubed, in order to control for potential non-linearities in the relation with happiness.

Finally, we include gender, ethnicity, year and geographical dummies. In this case, compared to what we have done for computing the relative income, we group geographical regions into macro-areas: Southern England, Northern England, London, Scotland, and Wales.

Although the BHPS offers a good range of educational variables, only one suited our purposes, specifically a qualitative variable on educational attainment. Nevertheless, even when properly modified, we faced the problem of collinearity between this variable and the income one, which makes good sense if we consider income as a proxy for education. Therefore, we could not explicitly include any educational variable.

4.4 Potential Sources of Heteroskedasticity

A last note is due on the choice of the variables to be included in the set of potential heteroskedasticity sources, i.e. the vector $\mathbf{z}$ in $\sigma_\epsilon^2 = \exp(\mathbf{z}_{nt}\vartheta)^2$. We mentioned that the vector $\mathbf{z}$ can contain either some or all the regressors, or variables which are not included among the explanatories, or a mixture of both. In our case, we have selected income, sex, age and ethnicity to appear in the variance structure, this leading $\mathbf{z}$ to be a subset of $\mathbf{x}$.

Income has been chosen for taking into consideration the possibility that an increase in income has a greater impact for poor people than for rich ones. Therefore, given the high correlation between poverty and low self-reported well-being, we are driven to think that the variation in income might cause the perceived satisfaction to vary more for the poor than for the rich. Loosely speaking, a very poor person who rated herself as completely unsatisfied and experiences ameliorations in her income might change her response by one unit, for example. The same variation might not cause a similar reaction for a rich individual who rated herself as satisfied 'six' on a one-to-seven scale, simply because more income does not matter for being one score happier. A similar behavior, which is likely to bias our results, is not controllable otherwise, neither the inclusion of unobservable individual effects can assure that we properly account for it . Heterogeneity can arise due to several factors. For example, it may be the by-product of different levels of perception about a choice: certainty about if and how much satisfied one is with her life might depend on mental sophistication,[18] cultural heirloom, personal ambition. In fact, age, gender and ethnicity dummies are added for capturing some more variation in choices, even though we have included them also in the main regression. Again, the point is to relate heterogeneity in choices, therefore potential error heteroskedasticity, with its plausible causes, and we are persuaded that those variables are indeed good factors for explaining human complexity and heterogeneity.

4.5 Descriptive Statistics

Figure 1 displays the percentage of the responses to the subjective well-being question. In accordance with the literature exploring individual well-being in western countries, about 75% of the people surveyed assert to be very satisfied (between 5 and 7).

Figure 1 about here

The transition matrix reported in Table 2 gives us a rather clear perception of how responses change over time. Probabilities located on the main diagonal are quite high, meaning that choosing the same response is frequent, especially for 'very satisfied' people; higher volatility is observed for responses from 1 to 3. A reasonable interpretation for this is that individuals who consider themselves very unsatisfied could find an improvement in their lives more significant than already 'happy' individuals, as already discussed in the previous subsection.

Table 1 about here

As a preliminary clue on the nature of the relationship between life satisfaction and real income, let us notice that, according to Figure 2, real average household income has significantly increased while life satisfaction has been on average fairly constant. Not surprisingly, what we find in our data is adherent to what other studies on western economies have already found.

Figure 2 about here

[18] For instance, men and women have different sensibility and ambitions, as it is well-known.

Table 3 shows some descriptive statistics. Given that the regressors are mainly binary variables, we have computed the mean level of life satisfaction and how it varies when individuals surveyed are women or men, married or not, in good or bad health status, employed or unemployed, have babies or not, have an income above/below the average in their neighborhood or in the whole sample. Individuals with a good perceived health have an average satisfaction 0.61 units higher than the average of the whole sample; such a difference in the mean may be quite important. Who lives as a couple has a higher level of average satisfaction, while women and men in the sample have almost the same average level of life satisfaction. Moreover, people older than the average are happier than younger respondents.

Average life satisfaction is higher for individuals with a household income greater than the average, both in the reference group and in the whole sample, and lower for those lagging behind the others. At this first attempt, we are inclined to think that our guess on relative concerns is correct and that other factors rather than income itself are at work to determine increases in happiness.

Table 2 about here

5 Estimation Results

Tables 3 and 4 display the HPPOP and PPOP estimates, both with and without individual effects, using respectively a subjective health measure (Health) and a more objective one (ADL, limits in Activities of Daily Life). The first question we address is whether one of the models presented uses the information inherent in the data optimally. For this purpose, we perform information criteria comparisons between each model: a smaller value indicates a better fit while penalizing for the escalation of parameters. Akaike, Hannan-Quinn and Schwarz Bayesian criteria are reported at the bottom of both Table 4 and Table 5. It can be observed that all these criteria suggest the HPPOP model with individual-specific effects should be favored to all the others. That is why such a model is considered as the benchmark. For completeness reasons, though, the other models estimates are included in our comments.

All our results show that income and relative income are both significant, but they exert an opposite effect on happiness: specifically, absolute income is in negative relationship with happiness, while relative income has a positive link with it. Therefore, the total effect of absolute income, obtained by summing the coefficients of absolute and relative income, is almost null. As to the deprivation measure, when subjective health is considered, it is significant and positive in sign only in the benchmark model, i.e. in the HPPOP with unobserved individual effects. In the objective health estimation, it is instead always significant and positive. Such results mirror what conjectured: when the temporal dimension is added, absolute income matters very little for happiness, because of adaptation and income shock absorption in the long run. The positive coefficient attached to the relative income variable, instead, signals that an increase in the comparison income reduces the well-being of those with a household income above the mean. Furthermore, the sum between the relative income and the deprivation measure coefficients is positive, meaning that an increase in the reference income produces a worsening in well-being for individuals with a given income below the mean. Finally, the deprivation coefficient is positive, thus the comparison income has a greater effect on the poor than on the rich, relatively to the neighborhood they belong to. We argue that this explanation could constitute a solution to the Easterlin Paradox in that the impact of absolute income is compensated from the one of reference income, leading happiness to depend more on material social comparison than on household wealth itself. While this idea is not new in the subjective well-being literature, yet our methodological analysis renders such findings more reliable.

Not surprisingly, the most relevant variables for subjective well-being are health and marital status. As to the role played by health status, a good perceived health positively and substantially affects happiness. Intuitively, limits in ADL have a negative effect on life satisfaction. The marital status is found to exert a positive effect on happiness as well, while the number of children has a negative effect on the whole sample of individuals. Finally, employment status is in positive relation with happiness, but shows a smaller impact than health and marital status.

The variable age is included squared and cubed in order to determine the nature of its relation with the dependent variable and to allow for potential non-linear patterns. Our estimates suggest that age can be related to life satisfaction through a convex decreasing relationship. It is interesting to mention that several cross-sectional or random-effects analyses highlight a U-shaped pattern (e.g. Oswald, 1997; Blanchflower and Oswald, 2004a; Lelkes, 2006b). However, the marginal effect of an additional year in the age distribution is typically small.

Finally, the ethnicity dummies are significant only for white and black individuals, essentially because they are the most numerous groups. The magnitude of the impact on the response probabilities is approximately the same.

Notice how the individual-specific time-invariant effects standard errors are smaller when the variance is structured as described in the previous sections. This means that, although the coefficients relative to the **z** variables are meaningless *per se*, still we are able to capture some more error variation and, perhaps, to correct upward/downward biases. Besides, it is only in the HPPOP with individual effects that the deprivation measure shows significance in the main model specification (with subjective health).

In order to better understand the magnitude of the effect that such variables exert on life satisfaction, as well as to know how the impact changes across categories, we now turn our attention to average marginal probability effects of the income variables on happiness (Tables 5 and 6).

First of all, let us focus on the absolute household income variable in Table 5.[19] The interpretation of, for example, first column $MPE_5 = 0.0414$ is that a one-percent increase in log-income raises the probability of life satisfaction = 6 by approximately 0.0414 percentage points. A quite striking result of our benchmark model (column 1) is that of a negative marginal partial effect for both low happiness responses and the highest one, meaning that an increase in absolute income actually reduces the probability of being completely satisfied as well as of being generally dissatisfied. Looking at the magnitude of the effects, we can observe that the negative impact on the individuals who rated themselves as the happiest is about -4%, while for the low categories the percentage is on average -0.45%. This would signal that absolute income is not the key variable driving happiness. Only the individuals who perceive themselves as moderately happy (4 and 5 responses) show a positive income impact. Performing the same estimation with no fixed effects (column 2) simply leads to an underestimation of the magnitude for the dissatisfied individuals and an overestimation of the impact on the highest

[19] Marginal partial effects computed as in (3)

categories.

The same behavior cannot be inferred from the PPOP (column 3 and 4), where the effects' sign is allowed to change only once by design. Indeed, the somewhat perverse result in this model is that the high responses are associated to a negative sign and the others to a positive one.

On the contrary, the results are unambiguous regarding relative income:[20] a positive variation in this variable due to either an increase in absolute income, or a decrease in reference income, or both, increases the probability of rating oneself very happy or completely happy of about 0.9% and decreases the probability of being dissatisfied or moderately happy of approximately 2% on average. Such a result is confirmed for all the models, where accounting for fixed effects allows to avoid, again, overestimation.

Finally, variations in the deprivation variable follow, intuitively, those in relative income, and have to be interpreted as "getting less deprived" increases the probability of being very/completely happy , while decreasing the one of being less happy. Fixed effects are crucial to have significant results, for both HPPOP and PPOP.

The results displayed in Table 6 mimic those pertaining Table 5 just commented, confirming that using a subjective measure of health instead of an objective one does not spoil the basic variable relationships.

6 Conclusions

In the last 30 years research in economics has experienced a booming in the exciting field of happiness and well-being studies. Many are the unsolved questions about what determines life satisfaction, and economists started focusing on the role of money in people's happiness. The well-known Easterlin Paradox, the economics of happiness milestone, finds that increasing trends in income are associated with flat average levels of life satisfaction in western countries. In a first instance this signals that in developed societies money does not necessarily bring the contentment we might think, thus other factors might be at work. When accounting for other

[20] Marginal partial effects computed for HPPOP as in (4).

determinants such as a good health and family status, cultural and civic trust as well as age and sex, the effect of absolute income may be even negative. At the light of this evidence, research has recently moved its interest towards the effect exerted by relative rather than absolute income. Given the phenomenon of adaptation, individuals are thought of being only temporarily influenced by variations in their income, even when highly positive. This might explain why, despite the significative increase in income, people rate themselves as being as happy as always. The relative position in the social ladder, proxied by relative income, could explain the existence of frustrated achievement or constant self-reported levels of happiness corresponding to higher incomes.

Our work investigates the role of relative income for satisfaction with life making use of frontier econometric methods. Indeed, our primary concern is to perform an analysis tailored on the data at hand, as robust as possible, and taking into due consideration the possible problems arising from subjective micro-data on personal well-being. Furthermore, we try to compute the reference income embedding two distance dimensions between individuals, namely age-cohort and geographical sub-region.

Whether the happiness paradox can be explained by the relationship between relative income and satisfaction is still an open debate. Nevertheless, we argue that a further step is moved towards the comprehension of people's psychology and their perception of what money can buy, based on the conviction that the strategy used is very appropriate for the treatment of such data. With this purpose in mind, we implement an heteroskedastic pooled panel ordered probit with 'quasi-fixed' effects, extending the method *à la* Mundlak (1978) to a non-linear setting where the homoskedasticity assumption is relaxed. Our analysis is based on the assumption that self-reported life satisfaction is a valid measure for well-being, and that current happiness predicts future behavior. In accordance to a number of studies pursued for other countries, we find that health, employment and marital status are very important predictors of well-being. On the one hand, happiness appears to be decreasing in absolute income, even for people that rate themselves as completely satisfied with their life. On the other hand, relative income, i.e. the ratio between household income and average household income in the neighborhood, seems to impact positively on the probability of the self-rated happiest categories. The relative size of their effects is positive, this meaning that the positive impact of an increase in one's income with respect to the reference one overcomes the effect exerted by absolute income. Furthermore, the effect is asymmetric affecting the poor more than the rich.

Our results lead to conclude that relative income should be accounted for when exploring what actually affects people's behavior and their perception of life satisfaction. This could represent a key for the solution of the happiness paradox.

Further analyses could be carried on in the future based on more advanced micro-econometric and time series techniques, for example allowing household income lags to be embedded into the main regression for understanding whether habits have a stronger impact than social comparison.

Appendix. Dataset Features and Statistical Package

Quoting the official BHPS web site "The British Household Panel Survey began in 1991 and is a multi-purpose study whose unique value resides in the fact that:

- it follows the same representative sample of individuals – the panel – over a period of years;

- it is household-based, interviewing every adult member of sampled households;

- it contains sufficient cases for meaningful analysis of certain groups such as the elderly or lone parent families.

The wave 1 panel consists of some 5,500 households and 10,300 individuals drawn from 250 areas of Great Britain". From Wave7 (1997), there is oversampling of low income people for comparability with ECPH. "Moreover, many more observations have been sampled for Scotland and Wales. Additional samples of 1,500 households in each of Scotland and Wales were added to the main sample in Wave9 (1999), and in 2001 a sample of 2,000 households was added in Northern Ireland, making the panel suitable for UK-wide research".

Data in each wave are organized in different macro-groups: INDSAMP includes all sampled individuals (either respondents or not), INDALL is an individual level record for all members of the household, corresponding to the household grid, INDRESP includes responding individuals only. The same applies to household-specific data, collected into HHSSAMP, HHSAMP and HHRESP. Hence, when extracting the individual interview outcome (IVFIO) from INDSAMP/HHSAMP, we are taking more observations than those that we have in INDRESP/HHRESP. They are dropped when dropping according to IVFIO (we drop all the observations where the interview outcome was not 1, i.e. all the non-full interviews). Also, in order to maintain comparability with previous waves and random sampling, we keep only observations belonging to the original sample (MEMORIG=1 for INDRESP and HHORIG=1 for HHRESP), disregarding the data added from 1997, 1999 and 2001 mentioned before.

Here follows a list of BHPS codes for the raw variables used in our analysis, in alphabetical order:

Raw Data			
age	age from birth	biographic	continuos
fihhyl	annual household labor income	derived	continuous
fihhynl	annual household non-labor income	derived	continuous
hgemp	In paid employment - household grid	self-reported	binary
hllte	health no indrance daily activities	self-reported	binary
hlstat	health over last 12 months	self-reported	1-5 ordered
lfsato	satisfaction with life overall	self-reported	1-7 ordered
mastat	marital status	biographic	5 different stati
nchild	number of own children in household	biographic	continuous
race	ethnicity	biographic	5 different races
region	region / metropolitan area	biographic	18 UK sub-regions
sex	gender	biographic	

By means of STATA, the PPOP model has been estimated using the standard command `oprobit`. For the HPPOP model, instead, we have made use of a STATA module by Williams (2006), known as `oglm`.

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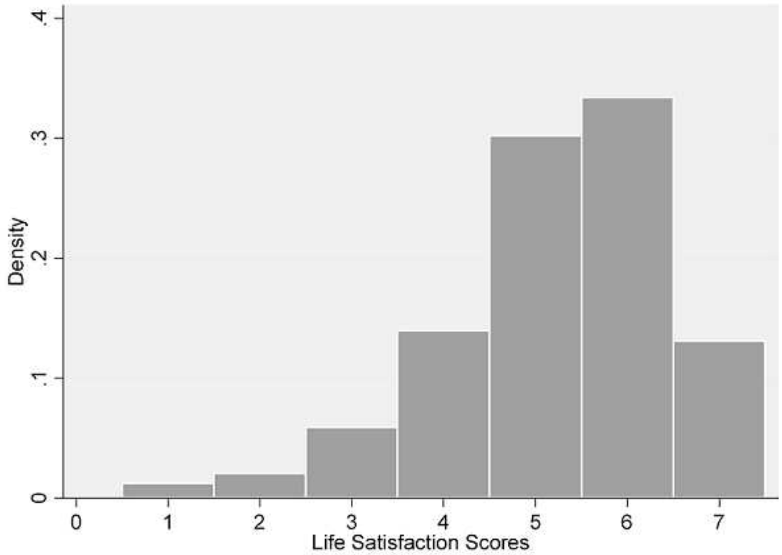

Figure 1: Density of Life Satisfaction Responses

Figure 2: Average Real Household Income and Life Satisfaction Series

Transition Matrix									
		Life Satisfaction in t							
		1	**2**	**3**	**4**	**5**	**6**	**7**	Total
Life Satisfaction in $t-1$	**1**	30.16	14.43	15.52	14.86	12.68	6.56	5.79	100
	2	8.40	18.86	25.79	20.97	15.65	7.50	2.82	100
	3	2.81	9.20	25.38	29.39	21.89	9.11	2.21	100
	4	1.68	3.17	12.22	32.21	34.12	13.40	3.18	100
	5	0.36	1.07	4.58	15.64	46.36	28.19	3.79	100
	6	0.24	0.44	1.57	5.89	26.15	54.93	10.78	100
	7	0.68	0.43	1.27	3.83	9.81	30.28	53.70	100
	Total	1.2	2.05	5.94	13.96	30.57	33.66	12.61	100

Table 1: Transition Matrix for Life Satisfaction, 1996-2007

Descriptive Statistics			
Variable	Obs	Mean	St.Dev.
Life Satisfaction	91494	5.22	1.25
Household Income	93145	30345.45	22830.35
Age	92870	45.07	18.51
Life Satisfaction if income > average in the neighborhood	38259	5.36	1.12
Life Satisfaction if income < average in the neighborhood	52675	5.13	1.33
Life Satisfaction if income > average in the sample	37462	5.29	1.10
Life Satisfaction if income < average in the sample	54032	5.18	1.35
Life Satisfaction if younger than average	48722	5.17	1.18
Life Satisfaction if older than average	40923	5.30	1.33
Life Satisfaction if good health status	58284	5.45	1.08
Life Satisfaction if bad health status	33163	4.84	1.43
Life Satisfaction if employed	57654	5.24	1.12
Life Satisfaction if unemployed	33840	5.20	1.46
Life Satisfaction if woman	49450	5.22	1.29
Life Satisfaction if man	42040	5.23	1.21
Life Satisfaction if married or living-as-couple	60601	5.31	1.19
Life Satisfaction if divorced, widowed or single	30654	5.05	1.36
Life Satisfaction if have children	26167	5.12	1.20
Life Satisfaction if do not have children	65367	5.26	1.27

Table 2: BHPS Descriptive Statistics, 1996-2007

Notation in Tables 3, 4, 5 and 6:

- HPPOP= Heteroskedastic Pooled Panel Ordered Probit; PPOP= Pooled Panel Ordered Probit.
- Dependent Variable LIFE SATISFACTION naturally coded; score 1=very unsatisfied, score 7=completely satisfied.
- 'hhincome' refers to household labor and non-labor income.
- 'comparison income' is determined by age-cohort (16-25, 26-35, 36-45, 46-55, 56-65, 66-75, 75>), and sub-region (Inner London, Outer London, Rest of South East, South West, East Anglia, East Midlands,West Midlands Conurbation,Rest of West Midlands, Greater Manchester, Merseyside, Rest of North West, South Yorkshire, West Yorkshire, Rest of Yorks & Humberside, Tyne & Wear, Rest of North, Wales, Scotland).
- 'Deprivation' is $D{\cdot}\ln$(hhincome/comparison income), where

$$D = \begin{cases} 1 \text{ if hhincome} \leq \text{comp. income} \\ 0 \text{ otherwise} \end{cases}$$

- *Sigma=exp($\mathbf{z}_{nt}\boldsymbol{\vartheta}$).
- AIC= Akaike Information Criterion; HQ= Hannan-Quinn Information Criterion; SC= Schwarz Information Criterion.

Life Satisfaction in the UK,1996-2007				
	HPPOP		PPOP	
Individual Effects	YES	NO	YES	NO
Total Std. Deviation	0.3674		1.0124	
ln(hhincome)	-0.0275***	-0.0649***	-0.0681***	-0.190***
	(0.00821)	(0.0104)	(0.0226)	(0.0282)
ln(hhincome/comparison income)	0.0157*	0.0916***	0.0475*	0.278***
	(0.00949)	(0.0131)	(0.0265)	(0.0342)
Deprivation	0.0207**	-0.00563	0.0416**	-0.0404
	(0.00806)	(0.00946)	(0.0208)	(0.0267)
Health	0.0973***	0.222***	0.274***	0.651***
	(0.00721)	(0.0152)	(0.00933)	(0.0128)
Married	0.0746***	0.114***	0.220***	0.337***
	(0.00776)	(0.00930)	(0.0177)	(0.0171)
Children	-0.00204	-0.0128**	-0.00793	-0.0400**
	(0.00518)	(0.00545)	(0.0150)	(0.0160)
Woman	0.0258***	0.0205***	0.0667***	0.0529***
	(0.00534)	(0.00512)	(0.0146)	(0.0146)
Employed	0.0176***	0.0358***	0.0440***	0.103***
	(0.00583)	(0.00618)	(0.0164)	(0.0164)
Age	-0.0389***	-0.0393***	-0.112***	-0.122***
	(0.00438)	(0.00377)	(0.0103)	(0.00774)
Age×Age/100	0.0806***	0.0731***	0.230***	0.231***
	(0.00887)	(0.00762)	(0.0204)	(0.0166)
Age×Age×Age/1000	-0.00544***	-0.00378***	-0.0155***	-0.0124***
	(0.000595)	(0.000460)	(0.00136)	(0.00108)
Ethnicity: White	0.0265***	0.0237***	0.0735***	0.0635***
	(0.00694)	(0.00666)	(0.0192)	(0.0188)
Ethnicity: Black	0.0322**	0.0297**	0.0999***	0.0865**
	(0.0129)	(0.0127)	(0.0365)	(0.0364)
Ethnicity: Asian	-0.00381	-0.00785	-0.000625	-0.0141
	(0.0190)	(0.0185)	(0.0528)	(0.0524)
Ethnicity: Chinese	-0.0393	-0.0346	-0.0899	-0.0707
	(0.0775)	(0.0764)	(0.218)	(0.213)
Cut Point 1	-2.295***	-1.837***	-6.616***	-5.359***
	(0.210)	(0.153)	(0.438)	(0.291)
Cut Point 2	-2.127***	-1.674***	-6.167***	-4.922***
	(0.203)	(0.145)	(0.437)	(0.290)
Cut Point 3	-1.921***	-1.477***	-5.602***	-4.372***
	(0.194)	(0.136)	(0.436)	(0.289)
Cut Point 4	-1.686***	-1.251***	-4.941***	-3.728***
	(0.185)	(0.127)	(0.436)	(0.289)
Cut Point 5	-1.372***	-0.948***	-4.044***	-2.851***
	(0.174)	(0.116)	(0.436)	(0.289)
Cut Point 6	-0.977***	-0.563***	-2.934***	-1.757***
	(0.163)	(0.106)	(0.436)	(0.290)
ln(sigma*)			-	-
ln(hhincome)	-0.123***	-0.125***		
	(0.00598)	(0.00591)		
Woman	0.0649***	0.0674***		
	(0.00999)	(0.00980)		
Age	0.00346***	0.00367***		
	(0.000278)	(0.000273)		
White	0.0587***	0.0426***		
	(0.00905)	(0.00883)		
Black	-0.0101	-0.000474		
	(0.0274)	(0.0266)		
Asian	0.0559	0.0470		
	(0.0436)	(0.0423)		
Chinese	-0.0469	-0.0574		
	(0.167)	(0.168)		
Year Dummies	YES	YES	YES	YES
Geographical Dummies	YES	YES	YES	YES
Observations	91068	91068	91068	91068
AIC: $[-\frac{2}{N}\cdot loglik+2\frac{k}{N}]$	2.9644	2.9984	2.9900	3.7448
HQ: $[-\frac{2}{N}\cdot loglik+2\frac{k}{N}\cdot\ln(\ln(N))]$	2.9662	2.9998	2.9914	3.2658
SC: $[-\frac{2}{N}\cdot loglik+\frac{k}{N}\cdot\ln(N)]$	2.9704	3.0028	2.9950	7.1357

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Estimation Results (Subjective Health)

Life Satisfaction in the UK,1996-2007				
	HPPOP		PPOP	
Individual Effects Total Std. Deviation	YES 0.3501	NO	YES 1.0716	NO
ln(hhincome)	-0.0294***	-0.0418***	-0.0840***	-0.131***
	(0.00767)	(0.00979)	(0.0219)	(0.0289)
ln(hhincome/comparison income)	0.0174**	0.0819***	0.0600**	0.274***
	(0.00876)	(0.0126)	(0.0256)	(0.0349)
Deprivation	0.0191***	-0.0150	0.0363*	-0.0861***
	(0.00741)	(0.00925)	(0.0201)	(0.0272)
ADL	-0.0474***	-0.145***	-0.133***	-0.427***
	(0.00731)	(0.0130)	(0.0195)	(0.0257)
Married	0.0672***	0.106***	0.212***	0.331***
	(0.00710)	(0.00893)	(0.0171)	(0.0177)
Children	0.00159	-0.00640	0.00415	-0.0202
	(0.00475)	(0.00527)	(0.0145)	(0.0164)
Woman	0.0162***	0.0149***	0.0423***	0.0400***
	(0.00498)	(0.00490)	(0.0151)	(0.0151)
Employed	0.0490***	0.0568***	0.151***	0.180***
	(0.00663)	(0.00690)	(0.0172)	(0.0171)
Age	-0.0447***	-0.0397***	-0.138***	-0.132***
	(0.00446)	(0.00377)	(0.0101)	(0.00798)
Age×Age/100	0.0806***	0.0733***	0.246***	0.249***
	(0.00853)	(0.00756)	(0.0199)	(0.0171)
Age×Age×Age/1000	-0.00544***	-0.00380***	-0.0166***	-0.0135***
	(0.000573)	(0.000454)	(0.00133)	(0.00111)
Ethnicity: White	0.0235***	0.0232***	0.0703***	0.0648***
	(0.00642)	(0.00629)	(0.0188)	(0.0186)
Ethnicity: Black	0.0258**	0.0251**	0.0820**	0.0728**
	(0.0120)	(0.0118)	(0.0362)	(0.0360)
Ethnicity: Asian	0.00421	0.00384	0.0291	0.0207
	(0.0176)	(0.0174)	(0.0523)	(0.0522)
Ethnicity: Chinese	-0.0776	-0.0611	-0.168	-0.130
	(0.0769)	(0.0739)	(0.222)	(0.218)
Cut Point 1	-1.899***	-1.701***	-5.801***	-5.288***
	(0.193)	(0.148)	(0.452)	(0.299)
Cut Point 2	-1.748***	-1.552***	-5.380***	-4.870***
	(0.187)	(0.141)	(0.452)	(0.299)
Cut Point 3	-1.565***	-1.374***	-4.850***	-4.346***
	(0.179)	(0.133)	(0.451)	(0.298)
Cut Point 4	-1.356***	-1.169***	-4.231***	-3.732***
	(0.172)	(0.124)	(0.451)	(0.298)
Cut Point 5	-1.075***	-0.892***	-3.381***	-2.889***
	(0.163)	(0.114)	(0.451)	(0.298)
Cut Point 6	-0.713***	-0.536***	-2.308***	-1.822***
	(0.155)	(0.104)	(0.451)	(0.298)
ln(sigma*)	ln(hhincome) -0.131*** (0.00613) Woman 0.0666*** (0.0102) Age 0.00396*** (0.000281) White 0.0485*** (0.00873) Black 0.00297 (0.0261) Asian 0.0518 (0.0422) Chinese 0.000190 (0.184)	ln(hhincome) -0.132*** (0.00607) Woman 0.0685*** (0.0101) Age 0.00396*** (0.000279) White 0.0416*** (0.00860) Black 0.00158 (0.0259) Asian 0.0499 (0.0428) Chinese -0.0250 (0.182)	-	-
Year Dummies	YES	YES	YES	YES
Geographical Dummies	YES	YES	YES	YES
Observations	91108	91108	91108	91108
AIC: $[-\frac{2}{N}\cdot loglik + 2\frac{k}{N}]$	3.0458	3.0581	3.0760	3.0886
HQ: $[-\frac{2}{N}\cdot loglik + 2\frac{k}{N}\cdot \ln(\ln(N))]$	3.0476	3.0595	3.0775	3.0898
SC: $[-\frac{2}{N}\cdot loglik + \frac{k}{N}\cdot \ln(N)]$	3.0517	3.0626	3.0811	3.0924

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimation Results (Objective Health)

Marginal Partial Effects (Subjective Health)				
	MODEL			
	(1) HPPOP with FE	**(2) HPPOP no FE**	**(3) PPOP with FE**	**(4) PPOP no FE**
ln(hhincome) MPE's				
1	-0.00388***	-0.00235***	0.00130***	0.00417***
2	-0.00474***	-0.00110	0.00225***	0.00668***
3	-0.00535**	0.00460*	0.00591***	0.0168***
4	0.00832**	0.0252***	0.0104***	0.0284***
5	0.0414***	0.0524***	0.00714***	0.0194***
6	0.00746	-0.0133**	-0.0140***	-0.0383***
7	-0.0432***	-0.0655***	-0.0130***	-0.0371***
ln(hhincome/comparison income) MPE's				
1	-0.000746*	-0.00509***	-0.000906*	-0.00612***
2	-0.00147*	-0.00930***	-0.00157*	-0.00980***
3	-0.00392*	-0.0236***	-0.00413*	-0.0246***
4	-0.00685*	-0.0397***	-0.00726*	-0.0417***
5	-0.00468*	-0.0269***	-0.00499*	-0.0284***
6	0.00923*	0.0534***	0.00981*	0.0561***
7	0.00843*	0.0512***	0.00905*	0.0544***
Deprivation MPE's				
1	-0.000982***	0.000313	-0.000794**	0.000887
2	-0.00194***	0.000571	-0.00138**	0.00142
3	-0.00516***	0.00145	-0.00361**	0.00356
4	-0.00901***	0.00244	-0.00636**	0.00605
5	-0.00616***	0.00165	-0.00437**	0.00412
6	0.0121***	-0.00328	0.00859**	-0.00814
7	0.0111***	-0.00315	0.00793**	-0.00790
Obs	91068	91068	91068	91068
*** p<0.01, ** p<0.05, * p<0.1				

Table 5: Average Marginal Partial Effects (Subjective Health)

Marginal Partial Effects (Objective Health)				
	MODEL			
	(1) HPPOP with FE	**(2) HPPOP no FE**	**(3) PPOP with FE**	**(4) PPOP no FE**
ln(hhincome) MPE's				
1	-0.00521***	-0.00451***	0.00223***	0.00363***
2	-0.00496***	-0.00351***	0.00321***	0.00510***
3	-0.00406*	-0.000436	0.00754***	0.0118***
4	0.0109***	0.0167***	0.0122***	0.0188***
5	0.0427***	0.0465***	0.00821***	0.0126***
6	0.00912**	0.00210	-0.0164***	-0.0252***
7	-0.0485***	-0.0568***	-0.0170***	-0.0267***
ln(hhincome/comparison income) MPE's				
1	-0.00121**	-0.00605***	-0.00159**	-0.00760***
2	-0.00201**	-0.00977***	-0.00230**	-0.0107***
3	-0.00475**	-0.0227***	-0.00538**	-0.0247***
4	-0.00762**	-0.0360***	-0.00869**	-0.0393***
5	-0.00512**	-0.0241***	-0.00587**	-0.0265***
6	0.0102**	0.0483***	0.0117**	0.0529***
7	0.0105**	0.0504***	0.0121**	0.0559***
Deprivation MPE's				
1	-0.00134***	0.00110	-0.000964*	0.00239***
2	-0.00221***	0.00178	-0.00139*	0.00336***
3	-0.00523***	0.00415	-0.00326*	0.00776***
4	-0.00839***	0.00657	-0.00526*	0.0124***
5	-0.00564***	0.00440	-0.00355*	0.00833***
6	0.0112***	-0.00881	0.00708*	-0.0166***
7	0.0116***	-0.00920	0.00736*	-0.0176***
Obs	91108	91108	91108	91108
*** p<0.01, ** p<0.05, * p<0.1				

Table 6: Average Marginal Partial Effects (Objective Health)