Happiness Under Uncertainty

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Abstract

By explicitly allowing for 'uncertainty' in model space and variable selection, in this paper we re-examine the empirical strategies and conventional results related to best predictors of happiness. We attempt to bridge the gap between prevalent theory and existing empirical foundation of happiness research by emphasizing on the instrumental role of stochastic environment governing our optimal choice. Drawing on various disciplines, first, we incorporate a very large set of predictors of happiness and adopt an estimation strategy in Bayesian domain which account for both model and variable selection uncertainties. The robust set of predictors of happiness is chosen then by Bayesian Model Averaging approach. Second, the marginal responses of the chosen determinants are studied in a semi-nonparametric ordered probit environment in order to accommodate possible non-linearities in the effects of determinants. Examination of four waves of European Social Survey data between 2002 through 2008 for the United Kingdom illustrates that social capital variables are robust predictors of happiness in addition to relative income, marital status, religion, and the state of discrimination. Study of transitional dynamics of happiness over time underlines the importance of social capital as the core determinants of happiness. Finally, estimation of effects in a non-linear environment supports the theoretical prediction about complex nature of happiness perception.

Key Words: Happiness, uncertainty, social capital,
Bayesian model averaging, semi-nonparametric ordered probit

JEL Classifications: C12, C14, D78, Z13

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"Recent research on happiness around the world confirms the stable patterns in the determinants of happiness. It also shows that there is a remarkable human capacity to adapt to both prosperity and adversity... the bottom line is that people can adapt to tremendous adversity and retain their natural cheerfulness, while they can also have virtually everything - including good health - and be miserable. One thing [of course], people do have a hard time adapting to is uncertainty."
- *Carol Graham, The Economist, Feb 1st, 2010*

1 Introduction

Over the past few decades theoretical and empirical research on happiness have experienced an interesting turning point: from being considered as only a subjective element outside the economic decision making process, the study of happiness has appeared to be at the center of recent development policy programs.[1] An in-depth survey of the extant research evidence that three key tenets can summarize the main research questions and results on happiness and economic growth: (i) evolution of the definition of happiness and study of consequences of competing theories,[2] (ii) building of testable empirical models and comparing/choosing determinants of happiness in relation to associated theories[3], and (iii) estimation of the direction and magnitude of causality (between happiness and per capita income). Most research that has taken issue with any of these points have done so by focusing on any given tenet before dealing with another. Strategies that can tackle numerous empirical issues at the same time are therefore warranted as they may provide better insights into the process through which happiness is realized (either as a short-term or long-term objective).

The current study's aim is to address tenets (i) and (ii) in simultaneous fashion while keeping an eye on (iii). This is empirically interesting as it can be seen as a step toward encouraging the choice of robust set of determinants of happiness from the multidimensional perspectives of the concept. Abstracting from the conventional empirical strategy where the presence of 'too many regressors' appeared to be the main limitation, we draw on the useful properties of Bayesian mechanism and perform estimation in a stochastic environment by allowing explicitly both parameter and model uncertainties. In the process we choose the best set of predictors of happiness among several thousand model specifications and numerous variables. The conventional approach also suffers from an important limitation in that it assumes linear relationship between happiness and its co-variates, which in reality may not be the case and which has limited policy implications.

As it stands, point (i) evolves around the problems of 'association and causation' between happiness and utility. In conventional research, happiness and utility are assumed to represent the same thing. However, attempts have been made in recent years to bridge the gap between

[1]The Sarkozy commission in 2008 called for a worldwide effort to develop measures of wellbeing that went beyond those based on income (see Stiglitz et al. 2008). UK is one of the many countries to join in the effort to build well-being indicators to national statistics (see for example, Dolan et al. 2011).

[2]The concept and definition of happiness have evolved especially after Tversky and Kahneman's (1992) classic analysis of prospect theory. Kimball and Willis (2006) provide interesting insights by challenging key aspects of Tversky and Kahneman (1992).

[3]Majority of the empirical research have adopted 'open-ended' approach: i.e., to consider all possible aspects of happiness (viz., labour market, psychology, health and medicine, economics, etc) and study them separately. Jointness of determinants from different disciplines have appeared infrequently in the existing research.

the two concepts. Kimball and Willis (2006) argued that the assumed equivalence between felt happiness and utility as a flow concept is empirically untenable. Instead it has been argued that a large component of happiness can be regarded more as recent change or innovation in life time utility than it is like flow utility. Intuitively, happiness is understood to be a sum of short-run (or transitory) response to good and bad news and a long-run (or permanent) response of mood to circumstances that is distinct from utility. Whereas short-run happiness, also denoted as 'elation' (as in Kimball and Willis, 2006), is short-lived and may depend on factors such as changing economic environment, the long-run or baseline mood is influenced by factors such as health, nutrition, entertainment, and social ties, etc.

Accordingly, we enlarge the scope of the theoretical model of happiness and develop a new empirical strategy where a specific empirical model and predictors of happiness are not set *a priori*. Rather we estimate the same using the Bayesian model averaging (BMA) technique and allow for both parameter and model uncertainties in a way that enables the researcher to choose the best set of determinants among several thousands models s/he estimates in the presence of persistent uncertainty. The strategy can provide useful results once one distinguishes between long- and short-run happiness. An interesting starting point in happiness research, of course, is to separate out utility (which is a reflection of people's choice) from happiness (which is a reflection of people's feelings). Long-run happiness is a valuable commodity which cannot be purchased directly, and therefore, is not directly determined by market forces. However, the inputs to long-run happiness can be purchased and are determined by market mechanism. When the extent of uncertainty in a socio-economic-political environment is very high, it affects both short-run and long-run happiness. Nevertheless, such uncertainties tend to leave a permanent impact on the way individuals perceive long-run happiness. Uncertainties matter for flow utility, short-run and long-run happiness, but the way they have been addressed in happiness literature remains far from satisfactory.

With respect to point (ii), it appears that the conventional empirical analysis of happiness treats 'uncertainty' as a constant and under such an assumption, study of determinants of happiness becomes a simple and routine exercise. However, when 'uncertainty' is endogenized and explicitly considered in the model space, empirical analysis of happiness turns out to be far more complex. In this setting, the modeler constantly faces the risk of choosing a wrong model of happiness. Indeed the choice of best set of determinants and models under uncertain environment gives rise to empirical model where the researcher is required to obtain consistent, unbiased and efficient of parameters for the determinants which minimize uncertainty. The minimization problem is beset with the problem of the presence of large set of predictors, models and most possibly with a complex set of variables having highly non-linear interactions. Thus, the study of happiness under uncertainty involves an empirical test of determinants of happiness within a framework which makes robust use of information by including large number of predictors and explicitly consider model, parameter uncertainty and possibility of non-linear interaction. Predictors obtained from such optimization process may lend to relevant policy implications. In this regard, the BMA mechanism for model and variables selection out of a fairly large number of predictors can be put to optimal use.

Following the above, in the current study we adopt a two-pronged strategies. First, we make use of Bayesian mechanism for model and variables selection and solve - to a reasonable extent - the amount of parameter and model uncertainties on the one hand and endogeneity issues on the other. Second, a non-semiparametric ordered response model is employed to gauge the extent and direction of effects the chosen 'robust' set of determinants have on happiness. Non-linear interaction is allowed for and the functional form of the correlation between happiness and its determinants is left open.

The rest of the paper is structured as follows. Synoptic overview of the literature and determinants of happiness are presented in Section 2. In Section 3 we provide an illustration of the effect of stochasticity on model and parameter choice in a conventional utility/happiness maximization framework. In Section 3, we motivate the choice and usefulness of BMA approach and discuss in brief the properties of semi-nonparametric ordered probit model required for quantification of the effects of chosen determinants while allowing for non-linearity in the interaction process. Data characteristics and preliminary results are presented in Section 5. Main empirical results are discussed in Section 6. Section 7 concludes with some discussion and suggestions for further research.

2 What determines happiness? Insights from the literature

In this section, we draw on the existing literature of subjective well-being (SWB) and happiness to bring out the likely determinants of happiness. Over the past decades, the various conceptual aspects and discussion on the determinants of happiness and subjective well-being have received in-depth treatment from many disciplinary perspectives viz., psychological (e.g., Diener et al., 2003), sociological, medical and economics (e.g., Easterlin, 1974, 2001; Easterlin et al., 2010; Blanchflower and Oswald, 2004; Rayo and Becker, 2007; Kahneman et al., 1999; Oswald and Wu, 2010, Kahneman and Deaton, 2010, Kahneman and Krueger, 2006, and others). Moreover, a substantial methodological literature has also developed on the reliability, validity, and comparability of answers to questions on happiness and SWB from various surveys (Diener, 1984; Frey and Stutzer, 2002). Our purpose in this section will be to present in brief the different classes under which the conventional and modern literature on happiness and SWB have been discussed. Before looking at each category of determinants and their relative positioning in the literature, it is important to understand what lies at the core of happiness perception among individuals. Other determinants, which characterizes individual's position in the society and the varied influences he receives revolve around the core determinants of happiness.

- **The core of happiness**

Rayo and Becker (2007) argue that three key innate characters (which remain constant across cultures, societies, individuals, and time) form the core of 'happiness'. *First*, the hedonic impact of sustained changes in economic conditions has a tendency to diminish over time, such as becoming accustomed to an expensive life style or another with subdued life which under current socio-economic conditions cannot be changed. This reflects on 'habit formation' and 'habit persistence' aspect of an individual's life. New situations bring new rules to life. An unchanged socio-economic rule enforces individuals to adapt to a specific habit. It is not necessary though that the individual would be absolutely happy under new circumstance even if s/he had adjusted to the new situation.

This brings into fore the *second* innate character of happiness. It is influenced by the individual's prior expectations concerning his own success. This is also affected significantly by 'peer comparisons' (which in modern day economics of happiness research has been discussed as the effect of 'relative income on happiness' [the Easterlin paradox[4]]).

Third, while happiness is volatile, it tends to revert over time to a relatively stable long-term mean. This characteristic of happiness refers to the long-term determinants, such as social relationships, recreative values, leisure activities, social cooperation, etc., which are aspects of social capital, social inclusion and participation. It is suggested that, individuals are mainly concerned not with his absolute level of success, but rather with the difference between his success and a benchmark that changes over time. Changes may take place in economic circumstances, that make some people richer, others socially and economically alienated, and some individuals belonging to particular groups and places discriminated against. The research on happiness that we summarize below characterizes these 'innate' aspects either with an approach that evaluates cognitive evaluation of life or present a psychological aspect which represents emotional state of an individual conditional on certain prior expectations. We discuss below the implications of recent research surrounding these core characteristics.

- **Habit formation (Adaptive capability effects)**

There are basically two notable research in this context, viz., the dynamic equilibrium model (Headey and Wearing, 1992) and hedonic treadmill theory (Brickman and Campbell, 1971). The adaptive capability, habit formation and the corresponding evolutionary approach of happiness has been recently investigated in Rayo and Becker (2007) and Easterlin (2005). According to the dynamic equilibrium model, although an event in one's life can influence an individual's SWB, the individual will eventually adapt to the change experienced and return to his or her biologically determined 'set point' or level of adaptation. Similarly, the 'hedonic treadmill' theory states that Individuals adapt quickly to changes in their lifestyles and return to their baseline levels of happiness, a theory which is consistent to the dynamic equilibrium model. Extensive and rigorousness analysis of the effects of baseline happiness has appeared in Kimball and Willis (2006) who has challenged the well-known results of prospect theory (as in Tversky and Kahneman, 1992) and solve some of the well-known puzzles of happiness research by diving them into short-run and long-run objectives.

Although research evidence seems to support the theory of happiness having a genetic component, as well as the concept of adaptation, Diener et al. (1999) have suggested that these theories, whilst useful, provide an incomplete explanation of why and how individuals adapt. Also, whilst genes may predispose a person to behave in a certain way within certain contexts, a person's level of SWB is not uncontrollable. Rayo and Becker (2007) also reflect on the idea that a person's adaptive capability to new socio-economic order may not necessarily reflect the true happiness s/he desires.

[4]Simply stated, the happiness - income paradox is this: at a point in time happiness varies directly with income, but over time happiness does not increase when a countrys income increases (Easterlin, 1974).

- **(Prior) expectations of success**

How one thinks about his or her life also plays a part in determining one's SWB. This has been adequately explicated in Rayo and Becker (2007) who argue that an individual's prior expectations of his or her own success matter for subjective well-being. In empirical application, surveys seek to infer from individuals' responses with respect to 'how happy they were yesterday or how anxious they are today'. For instance, recent surveys in the UK Office of the National Statistics (ONS) have adopted such questions in their Annual population survey. Studies (e.g., Diener et al, 1999) have found that optimism (the expectation that more good things will happen in the future than bad), internal locus of control (the belief that one has control over his or her life) and self-esteem (i.e., 'how much value one places on themselves, their self-worth and their capabilities') were personality traits that correlated significantly with SWB.

- **Social capital**

Many empirical studies (e.g., Diener and Seligman, 2004) argue that a fulfilling social life and a network of close social support with family and friends are strongly correlated with SWB. Social capital is a multi-dimensional concept that verily encompasses other concepts such as trust (Coleman, 1988); civic engagement, social norms and reciprocity (Putnam, 1993); features of social structures and networks (Lin, 2001); and the resources embedded within them (Bourdieu, 1986). Social scientists, policy makers and clinicians have seized upon it as a panacea for the post-modern disintegration of grand social theory. The effects of access to social opportunities, having someone to confide in, associational membership and feelings of trust are all used as indicators of the quality of a person or communities' social interactions. Leisure and recreation in this context have been found to have beneficial short-term effects on SWB (Argyle, 2001).

At the heart of long-term happiness, as has been argued in Kimball and Willis (2006), social capital/social ties play crucial role. It has been found that people in some places are happier or have better (mental) wellness than people in other places. This is arguably, not just because of their genetic vulnerability, the physical environment or their socioeconomic status. It also reflects the fabric of society - the way in which communities are set up and people live. Correlations between social capital and health outcomes have been researched and there is good evidence that more socially cohesive societies are healthier with lower mortality (Woolcock, 2001; Kawachi and Berkman, 2001; Putnam, 2001). Although the mechanisms by which this social capital is beneficial to health are not clearly delineated, but social networks are believed to promote better health education, better access to health services, informal caring and enforcing or changing societal norms that impact on public health. Kroll (2011) uses European Social Survey (ESS) data and demonstrates in case of UK how social capital is correlated in different ways with the social well-being of men, women, parents, and non-parents. The author concludes that the social context of well-being varies considerably by gender and parental status.

- **Labor market and demographic characteristics**

Research suggests that people who have jobs tend to be happier than those who are unemployed, and what's more, skilled workers seem to be happier than their unskilled counterparts (Argyle, 2001). Warr (1999) suggested that SWB can be attributed to work which effectively matches one's skills, talents and preferences, allows for some amount of autonomy or 'decisional discretion', provides variety in the tasks, provides supportive supervision, as well as opportunities for interpersonal contact with colleagues. He suggested further that the position should have some value in society, and provide financial and physical security. Nevertheless, being employed does provide more of an opportunity to engage the mind and connect with others than being unemployed, where unemployment can lead to higher distress and lower life satisfaction (Oswald, 1997).

Recent research (such as Mastekaasa, 1994; Myers, 2000) also demonstrate that married people are generally happier than those who are unmarried, whether they are separated, divorced or single (Myers, 2000). He also found that the unhappiest people are those stuck in unhappy marriages. One explanation of the link between marriage and happiness is the range of benefits that marriage brings in terms of intimacy, companionship, sharing etc. It can be argued that friendship and commitment are quite important in a marriage. One would also think that co-habiting couples who seem to experience the same benefits as married couples, would therefore have similar correlations with SWB as the married couples. However, Diener and Seligman (2002) found that this was not the case, finding instead that married couples were happier than non-married couples, especially in collectivist cultures such as India. Having said this, within individualistic cultures such as the U.K., this trend is changing and the SWB of co-habiting couples are rising to levels in line with those of the married couples.

3 The role of stochastic environment in the determinants of happiness

Due to the very broad conceptual/definitional encompassing of happiness, it is natural to assume that an individual is likely to be faced with uncertainty arising either from health, social, economic, or environment related factors. Some insightful theoretical models (such as Rayo and Becker, 2007) emphasize on these, however, the empirical constructs have been limited to the conventional inference on the choice of models and variables selection, and on the representativeness of estimated parameters to the true parameter values. Stochasticity affects an individual's short term and long-term decisions and this is one important reason why conventional empirical models need to encompass uncertainty explicitly. A simple framework can be put forward to elucidate the argument.

Assume that a set of individuals $i = 1, ..., N$ are governed by the environment they live which ultimately determine their perception about short-run and long-run happiness. Further assume that a stochastic shock, ϵ_t occurred at time t and this affects individual i over time. The effect of ϵ_t can be either transitory or permanent. A sequence of transitory shocks can leave a long lasting impact on individuals in the sense that they would not be able to predict the pattern of the foreseeable future. This leaves the researcher under an environment of uncertainty where they would be struggling to determine the best model of happiness at time $t+1$. Although there is a dynamic interdependence between happiness between time t and $t+1$, such dependence may not predict any specific pattern in the face of uncertainty. The effect of stochastic shocks on individual's choice can be represented in equation (1) which is described below.

A transformational utility function as in (1) is assumed to represent happiness of an individual where sub-utility classes such as $u_1(.), u_2(.), u_3(.)$ along with stochastic shocks form an indirect utility function $V(.)$. The transformation needs a medium, which can be broad such as economy and environment and which clearly influence the individual's perception about being happy at time t and $t+1$. In equation (1), the sub-utility functions within the utility function represent various classes linked to economic (i.e., absolute and relative income), sociological (i.e., social capital factors such as living in a cohesive society, ability of free communication in a friendly environment, and time for leisure, etc.), health related (i.e., long term/persistent illness), etc. We follow Clark et al. (2008) but extend the utility function with the mentioned classes in the form of sub-utilities and introduce a stochastic environmental term which can affect sub-utilities over time.

$$U = V(u_1(y, y^r), u_2(S), u_3(H); \zeta, \gamma) \tag{1}$$

where $V(.)$ is an indirect utility function of two sub-utilities: $u_1(.)$ being the function of own income (y) and relative income (y^r). The sub-utility function $u_2(.)$ is dependent on social positioning of the individual. The latter takes into account the wide theoretical research in sociology and psychology. Moreover, recent research in economic development also points at the capital importance of 'social capital' as precursor to individual happiness. The sub-utility $u_3(H)$ represents health related factors which can affect the overall utility (hence happiness). In combination with social capital variables, these are likely to affect happiness in the long-run. In the equation, ζ is a stochastic shock, which can influence both relative and own income of the individual and social standing. For simplicity, we assume that $\zeta \sim N(0, \sigma^2)$. The distribution of ζ is allowed to depend upon the stage of development (γ) of the society where i^{th} individual belongs. It is assumed that $\gamma \in (0, 1)$ so that stages of development can be defined: socially alienated and underdeveloped economy is defined when $\gamma = 0$, developed and socially cohesive society has $\gamma = 1$. Transition societies lie somewhere between 0 and 1.[5]

In the absence of any stochastic shock such as ζ, the properties of equation 1 has been investigated in Clark et al. (2008). The presence of non-mean zero stochastic shocks enforces individuals' social comparisons where perception about significant bias in the relative income may give rise to social alienation. The 'adaptive' capability of individuals in the process of social comparisons and adjustment to new situations (could be good or bad) can also be explained by the direction and the magnitude of the stochastic shocks as in (1). The empirical application of (1) may appeal to both current values of income and other co-variates or may include dynamic patterns if substantial data is available.

4 Methodology

In this section, we introduce Bayesian model averaging (BMA) technique to account for some of the common problems that arise in determining best predictors of happiness under uncertainty.

[5]The three stages of development exert distinct effect on individual's perception about happiness when being associated to a particular society. In a cohesive society, for instance, individuals emphasize on social capital as important determinants of happiness, whereas alienated societies tend to emphasize on relative income and economic situation (uncertainty and volatility, democratic setting, etc). Transition societies' standing are more complex, yet it cannot be denied that social capital still lies at the core of happiness perception.

In the face of many variables drawn from a variety of disciplines, establishing the optimal set of regressors and most important determinants of happiness is challenging both methodologically and intuitively. Indeed, by choosing a specific set of determinants for understanding evolution and co-evolution of happiness, recent research seem to have overlooked a relatively large and varied set of predictors cut across social groups and variables such as health, social ties, nutrition, etc. These empirical models can be argued to contain less information than desirable for the purpose of finding true parameter estimates, with efficiency and consistency. In empirical research of happiness, incorporating more, rather than limited information helps in understanding the true nature of evolution of perception of happiness across individuals.[6]

Moreover, recent research does not treat uncertainty explicitly in empirical construct of happiness function. Let's assume that a researcher is motivated by the usefulness of rich information content and wishes to include as many variables as possible in the regression where happiness is the dependent variable. Statistically, inclusion of such large predictors in the regression multiplies both parameter and model uncertainty. Under the backdrop of persistent uncertainty in model selection and variables, the question then one asks is how to identify the correct model and right set of regressors among the numerousness. In this section we briefly present BMA approach, which have been employed for the purpose of identification of robust set of determinants of happiness.[7]

4.1 Identification, uncertainty and model selection

The BMA methodology can be directly drawn from the model of an individual's choice under uncertainty. Following Rayo and Becker (2007), assume that an individual's happiness (y) is determined by the state of physical environment around him s, and a set of actions x he selects. The combination of s and $x \in X$ then randomly determines the level of y so that the function describing conditional probability distribution $f(y|x, s)$ is known to the agent.

Since the observation about the world around any individual (s) is imperfect and since prevalence of incomplete information due to uncertainty and persistent stochasticity is a possibility, then the action the individual chooses may vary with the variation of s. The modeller then would not be able to choose the correct model, i.e., it would be difficult to choose the right set of predictors of y that would give the representative individual (in the model) highest level of satisfaction (both elation and baseline mood in the sense of Kimball and Willis, 2006). This problem also compounds the extent of parameter uncertainty as the size of the model increases. Indeed, under uncertainty the researcher is virtually faced with very large set of models with as many parameters. In this circumstance, instead of estimating a specific model to characterize happiness, it might be useful to choose those predictors which possess highest probability of affecting the individual's perception of happiness. BMA methodology is very useful in this regard.

The properties of this methodology can be found in Raftery et al. (1997), however, for the present purpose, we outline in brief the main idea of this approach. Since theory on happiness

[6]Choice of specific group of determinants by researchers can be defended on statistical ground, viz., inclusion of a large set of variables in the regression reduces the degrees of freedom and causes problems of multicollinearity if the explanatory variables are qualitative in nature.

[7]The BMA approach is also getting increasingly employed in modern empirical economic growth and political science which, like happiness outcome in the present study, also faces a large set of explanatory variables.

is ambiguous about the set X_k of explanatory variables to include, we are confronted with a classical situation of model uncertainty concerning the covariates which should enter the model. If the estimate of the coefficient of interest depends on the covariates entering the model, we will eventually overestimate the degree of precision of our estimate if we do not account for this particular source of uncertainty. Bayesian Model Averaging (BMA) addresses model uncertainty in a canonical regression problem such as finding robust determinants of happiness. Following convention if we denote X as $n \times k$ matrix of all independent variables theorized to be predictors of outcome Y. Then by standard analysis it is assumed that one assumes a linear model structure between y being the dependent variable (in our case, happiness), α a constant, β the coefficient with

$$y = \alpha + X\beta + \epsilon \tag{2}$$

where $\epsilon \sim N(0, \sigma^2 I)$, X $n \times k$ matrix of all independent variables (which in our case includes labor market and demographic, (macro) economic, sociological, psychological, medical and political factors) theorized to be predictors of outcome Y then a natural problem a researcher faces is which of the variables from X should be included and how important are they? The direct approach to do inference on a single linear model that includes all variables is inefficient or even infeasible with a limited number of observations. Contrarily, even if a researcher has a pre-conceived set of regressors (such as social capital, macroeconomic, medical and sociological, etc.) which she wishes to study, it is possible that these regressors are significant. However, it does not solve the problem of uncertainty, which the researcher took the risk of choosing from the possible large set of predictors. BMA tackles the problem by estimating models for all possible combinations of X and constructing a weighted average over all of them. If X contains K potential variables, this means estimating 2^K variable combinations and thus 2^K models. [8] In the standard econometric approach the practice is to choose one (or a very limited number) of model among this very large number of probable models. In contrast, in Bayesian Averaging settings all the potential models are taken into account in the computation of the estimates of the parameters of interest, thus accounting for model uncertainty.

We begin by assigning a prior probability distribution to the model parameters β and σ^2 and the models M_k. The model, M_k, is assumed to come from the prior probability distribution $M_k \sim \pi(M_k)$ and the vector of model parameters is generated from the conditional distributions $\sigma^2 | M_k \sim \pi(\sigma^2 | M_k)$ and $\beta_w | \sigma^2, m_k \sim \pi(\beta_w | M_k, \sigma^2)$, where $\Omega = w_1, \ldots, w_p$ represents a vector of zeros and ones indicating the inclusion (or exclusion) of variables in model M_k. Assuming that models and parameters are random variables, the rules of probability imply:

$$E(y^* | X) = \sum_{nj1}^{K} p(M_k | X) E(y^* | X, M_k) \tag{3}$$

Using normal linear regression framework, the estimated model is specified as follows. Consider a set of variables $\mathbf{X}_{it}$ evaluated at time t for country i, which are potentially (linearly) related to happiness in country i for the period t to $t+1$, so that the stylized specification considered

[8] In the present context given that we have 74 potential explanatory variables of happiness this would mean 1.88895×10^{22} models.

appears as

$$y_{it+\tau} - y_{it} = \alpha + \sum_{j=1}^{k} \beta_j x_{j,it} + \varepsilon_{it}, \tag{4}$$

where y_{it} refers to happiness of individual i at time t, $x_1, \ldots, x_n$ are n variables which belong to the set $\mathbf{X}$ and ε is an error term assumed uncorrelated across cross-sectional units and with constant variance σ^2. When dealing with model uncertainty, the size of the model, n and the identity of the regressors in (4) are not assumed to be known, and are treated as objects to be estimated.

In Bayesian framework, dealing with model uncertainty simply requires to put a prior distribution over the model space M. So,

$$P(M_j) = p_j, j = 1, 2, ..., 2^K, \tag{5}$$

with $p_j > 0$ and $\sum_{j=1}^{2^K} p_j = 1$ The posterior model probability is, in turn, a function of the prior probability of the model and its marginal likelihood, and is given by:

$$P(M_j|y) \propto l_y M_j P(M_j), \tag{6}$$

where $P(M_j)$ is the prior probability, y is the response variable and $l_y(M_j)$ the marginal likelihood of model M_j.

The BMA technique allows a computation of the posterior inclusion probability (PIP) of each of the K variables. The PIP represents the sum of the posterior probability of models which includes a given variable, and can be interpreted as the probability that this variable belongs to the true model.[9] The technique allows us to compute the posterior means and the posterior standard deviations of each of the potential explanatory variables as follows:

$$E(\beta_j|Y) = \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y) E(\beta_j|Y, M_l) \tag{7}$$

and

$$\begin{aligned} \mathrm{var}(\beta_j|Y) \quad &= \quad \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y) \mathrm{var}(\beta_j|Y, M_l) + \\ &\quad + \sum_{l=1}^{card(\mathcal{M})} P(M_l|Y)(E(\beta_j|Y, M_l) - E(\beta_j|Y))^2 \end{aligned} \tag{8}$$

where β_j is the parameter of interest and $E(\beta_j|Y, M_l)$ is the OLS estimator of β_j for the constellation of $\mathbf{X}$- variables implied by model M_l. The posterior probability that a given $\mathbf{X}$-variable is part of the true regression model can be computed as the sum of posterior model probabilities of those models containing the variable of interest.

[9]The posterior inclusion probability is routinely interpreted as the robustness of a variable as a determinant of the phenomenon under investigation.

BMA is particularly helpful when a researcher wishes to assess the evidence in favor of two or more competing measures of the same theoretical concept, especially when there is also significant uncertainty over control variables. Additionally, when there is uncertainty over control variables, researchers can use BMA to test the robustness of their estimates systematically than is possible under a frequentist approach. Indeed, when dealing with model uncertainty, the size of the model and the identity of the regressors are not assumed to be known, and are treated as objects to be estimated. It is one of the important reasons why BMA method is particularly suited for our purpose.

4.2 Quantification of effects

Once a researcher finds robust determinants of happiness by employing BMA approach, the next step is to quantify their effect while accounting for possible non-linearity in the functional relationship between happiness and its predictors. The standard procedure to quantify effects of chosen determinants of happiness is to employ parametric ordered probit or logit methodologies (used in recent research, viz., Kroll, 2011). By doing so, linear functional relationship between happiness and the relevant determinants is imposed a priori. However, a more appropriate approach would be to recognize that a misspecified model may lead one to conclude that a variable is relevant when in fact it is not. We take a step forward in this direction by considering conditional variable uncertainty with full blown specification uncertainty. We use recently developed nonparametric model selection techniques to deal with nonlinearities in the functional relationship between happiness and its predictors.

To briefly outline the procedure, assume now that we have L set of variables, the effects of which we are interested in quantification. On the assumption that happiness is an ordered response variable (that is, respondents of a survey on happiness answering 0 for being extremely unhappy and 10 for extremely happy), the conventional approach is to use an ordered probit or ordered logit model and calculate the marginal effects of the chosen variables (see for instance Kroll, 2011). Following our objective, because happiness, takes on finitely many different values which renders a meaningful ordering, one can use ordered probit and ordered logit model. The (ordered) probit and (ordered) logit models require specific distributional assumptions, namely $\epsilon|x_i \sim iidN(0,1)$ and $\epsilon|x_i \sim LOG(0,1)$ respectively. In case of the former, if we assume y_i as the answer of the respondents to the question about 'how happy they are', then we can present the following relationship:

$$y_i^* = \beta' x_i + \epsilon_i \tag{9}$$

with $\epsilon|x_i \sim iidN(0,1)$, then

$$y_i = \begin{cases} 1 & \text{if } \alpha_0 < y_i^* < \alpha_1 \\ 2 & \text{if } \alpha_1 < y_i^* < \alpha_2 \\ . & . \\ . & . \\ . & . \\ J & \text{if } \alpha_{J-1} < y_i^* < \alpha_J \end{cases}$$

The y_i^*'s and α_i's can be interpreted as $P(y_i = j|x_i) = P(\alpha_{j-1} y_i^* \leq \alpha_j|x_i)$. Thus, y_i^* can be seen as person i's perception of happiness on a scale from $-\infty$ to ∞. The higher is y_i^*, the higher is this perception about happiness. We can now rewrite $P(y_i = j|x_i)$ in the following way:

$$\begin{aligned} P(y_i = j|x_i) &= P(\alpha_{j-1} y_i^* \leq \alpha_j|x_i) \\ &= P(\alpha_{j-1} - \beta' x_i \leq \epsilon \leq \alpha_j - \beta' x_i|x_i) \\ &= \Phi(\alpha_j - \beta' x_i) - \phi(\alpha_{j-1} - \beta' x_i) \end{aligned} \tag{10}$$

For ordered logit model, all specifications remain the same except the distribution of error which is specified as a logistic distribution: $\epsilon_i|x_i \sim LOG(0, 1)$. For identification, we set the intercept parameter at 0, essentially indicating that we eliminate the constant term from the model. Also we set standard deviation, σ of $\epsilon_i|x_i$ at 1. The α and β coefficients in the ordered probit and logit models are calculated using the method of conditional maximum likelihood.

In the ordered probit and logit models, the distribution of the error terms are known and a priori specified. But actually, the distribution of the error terms is unknown meaning that the assumption might affect the results significantly. Therefore, we will investigate whether this distributional assumption indeed influences the outcome of the ordered probit. To this end, we will employ a semi-nonparametric method to estimate the unknown density of the conditional error terms. Semi-nonparametric estimations partly impose a parametric form on the density while keeping other parts of the density non-parametric. By doing so, we also allow the functional form of the distributions unknown.

Gabler et al. (1993) use the semi-nonparametric estimator of Gallant and Nychka (1987) to approximate the distribution of the error terms in a binary choice model. They found that semi-nonparametric estimation is rather efficient and outperforms the probit estimation in non-normal samples. Stewart (2005) compares, among other semiparametric estimators, the semi-nonparametric estimator of Gallant and Nychka (1987) with the standard ordered probit estimator. Applying the method to job satisfaction data, it was found that the semi-nonparametric estimator outperforms the normal ordered probit estimate.

Gallant and Nychka (1987) approximate an unknown density using the product of a squared polynomial and a normal density. Here the squared polynomial is nonparametric while the normal density is parametric, the approximation therefore is semi-nonparametric. The approximation is specified as

$$f_K(\epsilon) = \frac{1}{\theta} \left(\sum_{k=0}^{K} \gamma_k \epsilon^k \right)^2 \phi(\epsilon) \tag{11}$$

where $\phi(\epsilon)$ is the standard normal density function and where $\theta = \int_{-\infty}^{\infty} \left(\sum_{k=0}^{K} \gamma_k \epsilon^k \right)^2 \phi(\epsilon) d\epsilon$ so that $f_K(\epsilon)$ integrates to 1. From this the cumulative density function is derived as

$$F_K(v) = \int_{-\infty}^{v} \frac{1}{\theta} \left(\sum_{k=0}^{K} \gamma_k \epsilon^k \right)^2 \phi(\epsilon) d\epsilon \tag{12}$$

The required distribution function is therefore specified as

$$F_K(v) = \frac{\int_{-\infty}^{v} \left(\sum_{k=0}^{K} \gamma_k \epsilon^k \right)^2 \phi(\epsilon) d\epsilon}{\int_{-\infty}^{\infty} \left(\sum_{k=0}^{K} \gamma_k \epsilon^k \right)^2 \phi(\epsilon) d\epsilon} \tag{13}$$

This defines a family of semi-nonparametric (SNP) distributions for increasing values of K, the polynomial order. To obtain estimates for β, α_i and the parameters of the approximation of the unknown density by using the method of maximum likelihood conditional on K. The standard model selection procedures will be used to choose between different (integer) values of K. The pseudo-likelihood function we will maximize is

$$\log L(\alpha, \beta) = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij} \log[F_K(\alpha_j - \beta' x_i) - F_K(\alpha_{j-1} - \beta' x_i)] \tag{14}$$

where $y_{ij} = 1$ if $y_i = j; 0$, otherwise, and F_K is the approximation of the unknown density given above.

5 Preliminary data analysis

Data quality is an important factor in understanding the true nature of happiness. Recent research clearly emphasize on new data and flexible empirical models to entangle the complex dynamics of happiness.[10] In particular, Di Tella and MacCulloch (2006) suggest that 'to provide more help to the policy makers, researchers have to be more specific about the distributional details of the proposed policies'. For the purpose of our empirical analysis, we measure happiness and overall life satisfaction, the response to the question "All things considered, how satisfied are you with your life as a whole these days". We use the four waves of the European Social Survey (ESS) data from 2002 through 2008 for the United Kingdom (UK). The variables include socio-economic, psychological, health and other factors defining broadly the classifications viz., short- and long-run happiness. In The BMA methodology is employed in two steps. First, we employ BMA technique for the entire four waves of ESS data for UK. The entire sample comprises of 8600 individual respondents. Second, to study how the determinants of happiness have evolved over the time, we have applied BMA to each of the four waves. The scientific rigor and comparability of the ESS makes it a unique resource to exploit for the study of the determinants of mental health and has been extensively used in research and policy forums.

The variable 'happiness' is an ordered response variable, the values of which range from 0 (very unhappy) to 10 (very happy).[11] The distribution of happiness is presented in Figure 1,

[10]See for example, Kroll, 2011; Easterlin and Angelescu, 2009; Webber and Huxley, 2007.

[11]Due to technical requirement of the empirical analysis we have re-coded this variable where response of 'very unhappy' is coded as 1 and very happy is coded as 11. The re-coding does not affect our conclusions.

which shows the number of respondents that have given a certain answer. It appears that the society is divided in the happiness perception: respondents answering 4-6 in the 0-10 point scale are about 16% of the total. Similarly, about 28.7% respondents have answered 8 and 18.13% answering 10 in the happiness scale of 1 to 10. Only 0.31% responded to extremely unhappy perception, whereas 11.24% respondents appeared to be extremely happy.

In line with Easterlin (1974) and many others, if distribution of income, in addition to other social capital, economic and labor market variables determine the extent of happiness perception, then the above findings on happiness perception (between extremely happy and unhappy) is intuitive given that UK's Gini coefficient (measuring income inequality) as of 2010 is 0.36 (reflecting relative equi-distribution of resources). However, the perceptions about happiness (Table 1) and about how satisfied the respondents are in life as whole (Table 2) feature distinct classes: there are three classes common to both tables cluster 1: (7,8,9), cluster 2: (3,4,5,6) and cluster 3: 10 indicating the possibility that different clusters of individuals enjoy different socio-economic benefits. Ensuring transition from cluster 1 to cluster 3 is not easy as long as the socio-economic environment is uncertain and volatile. Moreover, it is hard to determine a priori which variables would influence their likely transition from cluster 1 to 3, but both in a socially cohesive (like UK) and socially segregated society (for instance some developing countries), social capital is an important determinant, which directly influences perceptions about stability and sustainability in socio-economic relations.

In Figure 1, we looked at how perceived happiness among respondents is distributed for the entire sample range: 2002-2008. In Figure 2 we move a step forward and study the evolutionary characteristics of happiness for each ESS round 2002 through 2008. The thick lines in each graph represent Kernel density of happiness for ESS1 (2002) through ESS4 (2008), whereas the thin lines represent the normal density plots. The mean value for the normal density plots for each ESS round is around 7.5 in 0-10 point scale. The standard deviation for ESS1 (2002) is 1.79 which is lower than ESS2, ESS3 and ESS4, implying the possibility that individuals' have been facing increasing volatility in the perception of happiness.

An interesting characteristics of the density plot for all ESS rounds merits attention: there is a visible existence of multi-modality in the distribution of happiness for all periods, sharper for ESS rounds 1, 2 and 3 for the lower tail of the distribution. For these three survey periods, significant bi-modality in the happiness distribution indicates that the prevalent socio-economic conditions have given rise to a class of individuals whose mean happiness perception value lies in the range between 0 to 5 and another class the same lies around 8.5 in the scale of 0-10. The implications of these two cluster of individuals could be far reaching. However, the deterministic density estimates such as presented in Figure 2 do not account for probabilistic nature of happiness perception and their transition over evolutionary path, i.e., the number of people who evince 'transition' from unhappiness to happiness.

Despite its simple statistical properties, one can still argue that existence of multiple-equilibria in the form of many convergence blocks with regard to happiness perception, implies a divided society. Unchanged nature of multi-modality across the survey periods implies that the society is becoming increasingly volatile. As evident from Figure 1, multi-modality in happiness distribution in 2008 has replaced bi-modality in the ESS round 1 through 3. The overall implication is that individual respondents have been facing more stochastic and uncertain environment in the current ESS round than before.

Figure 1: Distribution of happiness

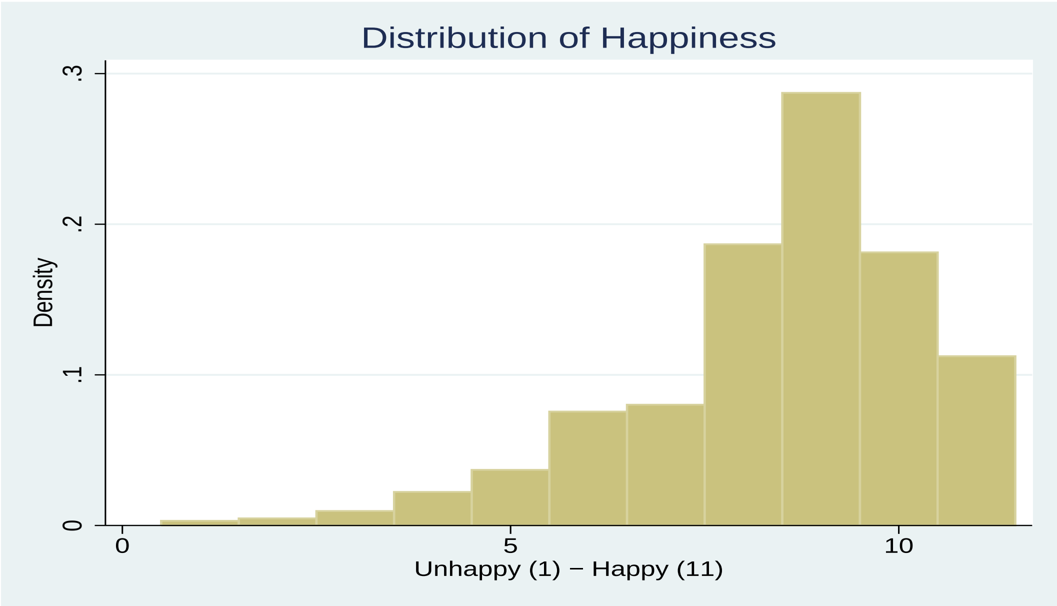

Figure 2: Evolution of happiness

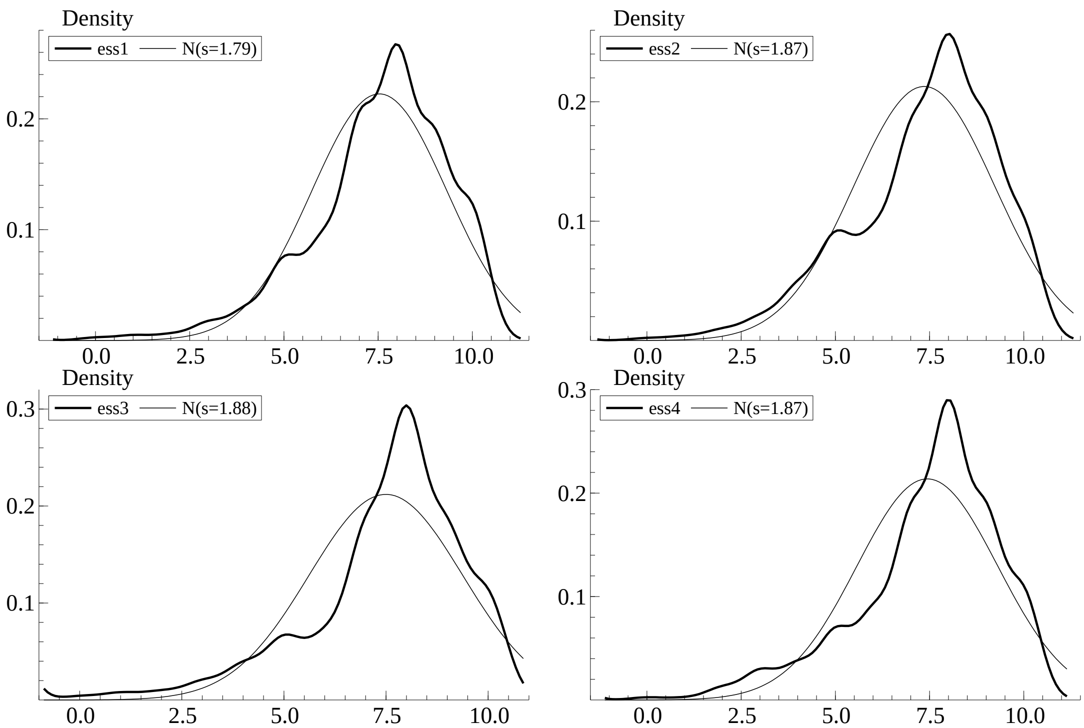

Table 1: How happy are you?

		Freq.	Percent	Cum.
Extremely unhappy	0	19	0.31	0.31
	1	29	0.47	0.78
	2	59	0.96	1.74
	3	137	2.23	3.97
	4	227	3.69	7.66
	5	465	7.56	15.22
	6	493	8.02	23.24
	7	1,148	18.67	41.91
	8	1,766	28.72	70.63
	9	1,115	18.13	88.76
Extremely happy	10	691	11.24	100
	Total	6,149	100	

Table 2: How satisfied with the life as a whole?

		Freq	Percent	Cum.
Extremely dissatisfied	0	50	0.81	0.81
	1	43	0.7	1.51
	2	76	1.24	2.75
	3	228	3.71	6.46
	4	309	5.03	11.48
	5	633	10.29	21.78
	6	553	8.99	30.77
	7	1,182	19.22	49.99
	8	1,719	27.96	77.95
	9	780	12.68	90.63
Extremely satisfied	10	576	9.37	100
	Total	6,149	100	

6 Main results

The results presented in this section correspond to the broad research questions outlined and discussed in the preceding section: first, how to choose determinants of happiness among a set of very large predictors where parameter and model uncertainty is so pervasive, and second, once robust determinants are identified, how to quantify their likely impact on happiness while allowing flexible distribution of error term and assuming a non-linear interaction among variables. The first set of results we present below corresponds to the first question: the results of Bayesian estimation. Quantification of the effects of the chosen determinants arrived at by the BMA approach will be performed in semi-non-parametric environment. This will address some of the concerns in the second set of questions raised above.

6.1 Bayesian model averaging results

Before discussing the results of the Bayesian model averaging (BMA) some comments are noteworthy with respect to the choice of prior. The standard practice in the literature is to choose a fixed value for the Zellner's g prior and then test the robustness of the results by changing the value. The g-prior for the parameter estimates has been widely adopted because of its computational efficiency in evaluating marginal likelihoods and model search, and perhaps most importantly, because of its simple, understandable interpretation arising from the analysis of a conceptual sample generated using the same design matrix X as employed in the current sample. However, as shown by Feldkircher and Zeugner (2009) fixing g may come at a cost. Indeed, the higher g, the more closely posterior mass will concentrate on the few best-performing 'super models' (Feldkircher and Zeugner, 2009). In other words, a large value for g will favor a single model. To overcome this issue the authors propose a method that put a prior distribution on g, known as the hyper-g prior. In contrast to the 'default' prior framework that embodies overly confident prior beliefs, the hyper-g prior offers an approach that features the virtues of prior input and predictive gains without incurring the risk of misspecification.[12] To compute the results of our Bayesian exercise we adopt the hyper-g prior.

We present two sets of BMA results, first we estimate the full model, without pre-specifying any set condition (in our case social capital) and identify the robust set of regressors determining happiness. In the second stage, we fix social capital and estimate the full model, so that the conditional distribution of other variables can be gauged. The idea of the latter approach is to provide a robustness check to our estimation. For both steps, we use the BMA settings described above using the Markov Chain Monte Carlo Model Composition (MCMC) for the computation of the posterior probability of the different model specifications in the model space. We adopt a binomial-beta distribution as a prior on model size, by setting the prior mean model size equal $K/2 = 37$, where K, the number of potential explanatory variables is equal to 74. Given the number of potential explanatory variables at 74, there are 2^{74} potential models. We first consider the case where all the potential models are allowed. Then for the robustness check of our results we also experiment with various model sizes. Table 1 summarizes the main results. There are basically two components in the results: first, the posterior inclusion probability (PIP) represents the likelihood of including a variable averaged across thousands of model estimated. Second, the ratio of posterior mean to posterior standard deviation of the parameter (PM/PSD) associated to each one of the covariates measures the precision of the estimate. The results are presented for 500, 1000, and 5000 best models in order to understand the robust effects selected determinants have on happiness.

From Table 1 it can be observed that 14 out of the 74 potential explanatory variables have PIP higher than 0.5 (37/74), thus indicating that these variables have high posterior probability inclusion. From these results it could be seen that social capital variables (*viz*, pplfair, pplhlp, sclmeet, sclact and inmdisc) are among seven variables with posterior inclusion probability equal 1. Moreover, the social capital variables have high degree of precision in the estimation of their effects, judging from the ratio PM/PSD. Their associated model averaged parameters are positive, thus implying that an increase in social capital increases the probability of being happy. The other variables with high posterior inclusion probability are marital status (married), feeling about household income (hincfel), source of income (incinvest and socbenefit), discrimination (dscrgrp), religion (rlgdgr), importance in seeking fun/pleasureful activities (impfun), importance in helping people and care for others wellbeing (iphlppl) and importance of new ideas/creativity (ipcrtiv).

[12]Simulation exercises show that flexible priors (the hyper-g prior) outperform fixed g settings in terms of forecasting accuracy and exhibit a more stable structure of posterior model and inclusion probabilities as noise varies (see Feldkircher and Zeugner, 2009 for more detailed discussion).

These variables, with the exception of socbenefit, iphlppl and rlgdgr, also have high degree of precision in the estimation of their effects. Being married, living comfortably on present income (hincfel), belonging to a religious group (rlgdgr) and importance of fun and pleasureful activities (impfun) all have the intuitively expected model-averaged positive parameter. The associated model-averaged parameter for being member of a group that is discriminated against (dscrgrp) and income from investment (incinvest) is negative. Although this is intuitively expected from the former, the negative sign of the latter warrant an explanation. Indeed, if the only/main source of income of the individual is through income from investment then this income is likely to be affected by market fluctuations. This income volatility in turn can affect the mood and thus the happiness of the individual.[13] Additionally, it can be noted that the chosen determinants remains consistent across the size of best models specification (viz., 500, 1000, and 5000 best models).

In addition to experimenting with different 'best' model sizes, as in Table 1, to ensure robustness of the results we try another proxy of happiness based on the standard of life (as a dependent variable).[14] The five social capital variables (pplfair, pplhlp, sclmeet, sclact and inmdisc) remain robust predictors of happiness, both in terms of their posterior probability inclusions and the degree of precision in the estimation of their effects. Being married, living comfortably on present income, belonging to a religious group also remain robust predictors. Three new variables that, previously, were not important now appear to be robust in explaining standard of life; these are: total income form all sources, unemployment benefit and trust in people. These findings could suggest that, although happiness and standard of living are closely related, they are explained by different set of elements.

It is also interesting to note that both dependent variables share social capital as a robust explanatory variable. Additionally, we have also run BMA with social capital variables fixed and found that there are seventeen variables which have posterior inclusion probability greater than 0.5. As such, there is no significant difference in the result, which points at the importance of social capital variables in happiness perception.

[13]The variables that have moderate probability inclusion (viz closed to 0.5) such as unempbenefit, pensions, ipfrule (importance of following established rules) can be seen as marginally explaining happiness in terms of their probability inclusion. However, they have low degree of precision in the estimation of their effects.

[14]Results not presented here, but available upon request.

Table 3: BMA estimation without social capital conditioning

100 best models			500 best models			1000 best models			5000 best models		
variables	PIP	PM/PSD	variables	PIP	PM/PSD	variables	PIP	PM/PSD	variables	PIP	PM/PSD
dscrgrp	0.992	-4.294	dscrgrp	0.992	-4.269	dscrgrp	0.992	-4.273	dscrgrp	0.992	-4.279
hhmmb	0.423	0.777	hhmmb	0.426	0.782	hhmmb	0.423	0.778	hhmmb	0.420	0.773
hincfel	1.000	14.461	hincfel	1.000	14.460	hincfel	1.000	14.460	hincfel	1.000	14.461
impfun	0.900	2.277	impfun	0.898	2.260	impfun	0.899	2.269	impfun	0.900	2.273
incinvest	0.999	-4.860	incinvest	0.999	-4.856	incinvest	0.999	-4.867	incinvest	0.998	-4.852
inmdisc	1.000	7.529	inmdisc	1.000	7.530	inmdisc	1.000	7.529	inmdisc	1.000	7.528
ipcrtiv	0.639	1.175	ipcrtiv	0.639	1.174	ipcrtiv	0.638	1.172	ipcrtiv	0.639	1.175
ipfrule	0.485	0.876	ipfrule	0.483	0.873	ipfrule	0.485	0.876	ipfrule	0.485	0.876
iphlppl	0.837	1.841	iphlppl	0.837	1.842	iphlppl	0.836	1.837	iphlppl	0.836	1.839
married	1.000	10.195	married	1.000	10.182	married	1.000	10.194	married	1.000	10.202
pensions	0.490	0.879	pensions	0.497	0.891	pensions	0.493	0.884	pensions	0.487	0.875
pplfair	1.000	6.019	pplfair	1.000	6.023	pplfair	1.000	6.019	pplfair	1.000	6.019
pplhlp	1.000	6.149	pplhlp	1.000	6.152	pplhlp	1.000	6.150	pplhlp	1.000	6.149
rlgdgr	0.979	3.464	rlgdgr	0.979	3.449	rlgdgr	0.980	3.464	rlgdgr	0.980	3.470
sclact	1.000	6.046	sclact	1.000	6.045	sclact	1.000	6.046	sclact	1.000	6.045
sclmeet	1.000	9.589	sclmeet	1.000	9.587	sclmeet	1.000	9.589	sclmeet	1.000	9.590
socbenefit	0.658	-1.206	socbenefit	0.656	-1.201	socbenefit	0.657	-1.202	socbenefit	0.662	-1.214
unempbenefit	0.487	0.865	unempbenefit	0.494	0.875	unempbenefit	0.490	0.870	unempbenefit	0.484	0.860

Table 4: BMA estimation with social capital conditioning

Variables	PIP	Variables	PIP
pplfair	1.0000	impdiff1	0.0421
pplhlp	1.0000	ipshabt1	0.0386
sclmeet	1.0000	impfree1	0.0377
sclact	1.0000	dscrlng	0.0367
married	1.0000	dscrrce	0.0355
hincfel1	1.0000	ipmodst1	0.0311
inmdisc1	0.9993	dscrsex	0.0290
rlgdgr	0.9962	eastmidlands	0.0248
ppltrst	0.9498	imptrad1	0.0228
hinctnt	0.9278	incself	0.0198
unempbenefit	0.8982	southeast	0.0192
hhmmb	0.7918	impenv1	0.0191
incinvest	0.6917	ipstrgv1	0.0186
impfun1	0.6125	gndr	0.0180
dscrgrp	0.5691	ipudrst1	0.0174
socbenefit	0.5583	scotland	0.0167
dscrage	0.5214	wales	0.0161
dscroth	0.4744	ipeqopt1	0.0160
dscrdsb	0.4555	widowed	0.0159
iphlppl1	0.2924	unmarried	0.0158
eduyrs	0.2838	eastengland	0.0158
wkhtot	0.2634	dscrgnd	0.0156
dscrrlg	0.2376	incmisc	0.0154
dscretn	0.2037	imprich1	0.0151
ipbhprp1	0.1810	brncntr	0.0148
wkhct	0.1744	impsafe1	0.0146
iplylfr1	0.1477	ipadvnt1	0.0145
northireland	0.1249	ctzcntr	0.0140
ipcrtiv1	0.1007	northwest	0.0138
ipfrule1	0.0945	iprspot1	0.0137
wagesalary	0.0854	yorkshirehum	0.0134
ipgdtim1	0.0797	london	0.0134
ipsuces1	0.0568	northeast	0.0133
pensions	0.0526	southwest	0.0132
dscrntn	0.0458	westmidlands	0.0132
age	0.0454	divorced	0.0127
		separated	0.0124

6.2 Quantification of effects and non-linearity

To what extent social capital variables affect happiness among individuals? To answer this question, we estimate ordered probit/logit models both with parametric and semi-parametric methods. The dependent variable is ‘happiness’ and the explanatory variables are pre-set to the number found from BMA analysis. However, we have also added the ’age’ variable in the regression so as to test the hypothesis: if happiness monotonically increases with age. Research on this aspect mainly find that happiness can be ’U-shaped’ over the life-cycle.

Some researchers have also argued that since older cohorts are more in control of their resources and time, they are observed to be happier than younger cohorts. In addition to the age variable, we have also added two more variables (dscroth: Discrimination of respondent’s group - other grounds; and dscrdsb: Discrimination of respondent’s group - disability), which were in the borderline of 0.5, the posterior inclusion probability (see Tables 3 and 4). As pointed out before, to understand the likelihood and extent of effect of these variables, we will be using ordered logit and probit models (using both parametric and non-parametric methods). Moreover, since the happiness as the dependent variable is expected to vary across individual perceptions, we expect some degree of heteroscedasticity. In the presence of the latter, a regular probit or logit application will mis-specify the means function. To correct for this problem, we perform a robust estimation of ordered probit (OP) and ordered logit (OL) models. The results are presented in Table 5.

As can be observed, all variables except *hinctnt* (household's total net income), *unemp-benefit* (unemployment benefit), *dscroth* (discrimination of respondent's group: other ground) and *dscrdsb* (discrimination of respondent's group - disability) are significant at 5% level (exception being *dscrage*, which is significant at 10%). The coefficient of 'age' is negative significant, whereas the square of this variable, capturing experience effect is positive and significant. The implication is that as experience grows, people tend to be happier over the life cycle given a stable socio-economic environment. The likelihood ratio (LR) test statistic of the OP model (not reported in the table) is 1268.20 and is $\chi^2(21)$ distributed under the null hypothesis that all variables together have no influence on the answer to the question about perception of happiness. The pseudo-R^2, which measures goodness of fit for OP model is 0.056 which is slightly greater than that of OL model (0.053). It should be noted that the value of pseudo-R^2 in general decreases as the number of choices in the dependent variable increases. Alternatively speaking, in a model with more choices the probabilities involved are smaller than in a model with fewer choices. Comparing both OP and OL models with respect to log-likelihood and pseudo-R^2, the OP model appears to fare better in terms of fit. The subsequent analysis, therefore will be based on OP model and its extension, in the non-parametric domain.

In the extended ordered probit model, the assumption $\epsilon|x_i \sim iidN(0,1)$ is relaxed by estimating the real density of $\epsilon|x_i$. From Table 6, we can compare the estimated density characteristics between ordered probit and extended ordered probit using non-parametric methods (SNP). The degree of polynomial allowed in our case is limited to 10 keeping in mind the number of (ordered) responses of the dependent variable, happiness. We have estimated SNP using values of K, the order of polynomial assuming odd numbers (for instance, $K = 3, 5, ...$) In Table 6, we have presented results up to $K = 7$. It can be observed that the LR-test rejects the ordered probit model for all value of K. Moreover, we have also obtained AIC and BIC test values (not reported in the table) for both ordered probit and extended ordered probit models. Both test values reject the selection of OP model. Thus it can be concluded that extended ordered probit model outperforms the ordered probit model. Although the likelihood ratio test for all values of K depict significant differences from OP model, we select the model with $K = 5$, based primarily on the least bias (skewness value for $K = 5$ is $0.766 < 0.851$ $(K = 3) < 0.972$ $(K = 7)$. Given that skewness in the distribution can affect severely the choices an individual faces and inclines the society towards alienation, we would normally expect the distribution to possess zero skewness and Kurtosis = 3. However, in the extended probit model (with $K = 5$), there is positive skewness and Kurtosis = 4.427 (which is also less than other order of polynomials). Positive skewness means, the peak of the distribution is at the left of the center, while a higher Kurtosis means that the distribution is less flat.

Comparing the results of OP and extended OP, we find that all social capital variables are significant in both models, however, extended OP model reports lower values than OP model. The marginal effect and the odds ratio derived from lower coefficient would also reflect smaller partial effects conditional on other social capital variables. Additionally, extended OP model has higher likelihood than OP, thus indicating the better fit for the former than the latter. On the whole, it appears that extended OP model has outperformed simple OP model. Moreover, the significant coefficients for polynomial of order 1,2, and 3 imply that there is overall non-linearity among social capital variables which comply with the theoretical prediction in sociology, psychology and recent economic development literature.

Table 5: Ordered logit (OL) and ordered probit (OP) estimation: Dependent variable: Happiness (*Note*: ***: significant at 1%, **, significant at 5% and *: significant at 10% levels.)

	OL		OP	
Variables	Coef.	Z	Coef.	Z
age	-0.040	-4.870	-0.022	-4.720
agesq	0.000	5.520	0.000	5.420
pplfair	0.071	4.890	0.038	4.720
pplhlp	0.094	6.810	0.049	6.260
sclmeet	0.167	9.800	0.091	9.490
sclact	0.147	5.500	0.082	5.450
married	0.657	11.450	0.380	11.510
hincfel1	0.846	12.460	0.464	12.120
inmdisc1	0.634	6.950	0.336	6.550
rlgdgr	0.038	4.550	0.022	4.580
ppltrst	0.030	2.270	0.016	2.180
hinctnt	0.010	0.950	0.005	0.750
unempbenefit	0.086	1.030	0.041	0.860
hhmmb	0.058	2.590	0.032	2.470
incinvest	-0.477	-4.300	-0.239	-3.890
impfun1	0.268	5.590	0.155	5.610
dscrgrp	-0.205	-2.360	-0.114	-2.270
socbenefit	-0.317	-2.440	-0.149	-2.030
dscrage	-0.301	-1.780	-0.139	-1.450
dscroth	-0.192	-1.240	-0.140	-1.560
dscrdsb	-0.243	-0.930	-0.162	-1.080
Happiness = 1	-2.655***		-1.180***	
Happiness = 2	-1.703***		-0.814***	
Happiness = 3	-0.859***		-0.456***	
Happiness = 4	0.041***		-0.036***	
Happiness = 5	0.810***		0.349***	
Happiness = 6	1.688***		0.819***	
Happiness = 7	2.291***		1.160***	
Happiness = 8	3.306***		1.759***	
Happiness = 9	4.683***		2.584***	
Happiness = 10	5.967***		3.304***	
N. obs	6140		6140	
Log Likelihood	-11143.453		-11118.053	
Pseudo-R^2	0.053		0.056	

Table 6: Semi-nonparametric (SNP) estimation of ordered probit (OP): happiness models for different values of K. (*Note*: ***: significant at 1%, **, significant at 5% and *: significant at 10% levels.)

	OP Coef. (s.e.)	SNP(K=3) Coef. (s.e.)	SNP(K=5) Coef. (s.e.)	SNP(K=7) Coef. (s.e.)
age	-0.0222***	-0.138***	-0.021***	-0.022***
agesq	0.0002***	0.0001***	0.000***	0.000***
pplfair	0.0382***	0.050***	0.044***	0.047***
pplhlp	0.0487***	0.051***	0.051***	0.054***
sclmeet	0.0913***	0.091***	0.087***	0.091***
sclact	0.0824***	0.102***	0.096***	0.103***
married	0.379***	0.342***	0.355***	0.371***
hincfel1	0.4637***	0.466***	0.459***	0.482***
inmdisc1	0.3360***	0.384***	0.354***	0.376***
rlgdgr	0.0218***	0.023***	0.022***	0.024***
ppltrst	0.0163***	0.023***	0.022***	0.024***
hinctnt	0.0046***	0.014***	0.011***	0.013***
unempbenefit	0.0409***	0.093***	0.077***	0.083***
hhmmb	0.0319***	0.032***	0.026***	0.025***
incinvest	-0.2391**	-0.255**	-0.279**	-0.288**
impfun1	0.1549*	0.122*	0.112*	0.116*
dscrgrp	-0.1135***	-0.125***	-0.128***	-0.133***
socbenefit	-0.1489***	-0.177***	-0.183***	-0.193***
dscrage	-0.1392**	-0.161**	-0.178**	-0.179**
dscroth	-0.1403	-0.061	-0.052	-0.062
dscrdsb	-0.1619	-0.063	-0.068	-0.080
Thresholds:				
happiness = 1	-1.1802***	-1.180***	-1.180***	-1.180**
happiness = 2	-0.8138**	-0.901***	-0.748***	-0.758 ***
happiness = 3	-0.4556***	-0.602**	-0.367***	-0.369**
happiness = 4	-0.0358***	-0.234***	0.045***	0.060***
happiness = 5	0.3492**	0.110***	0.409***	0.439**
happiness = 6	0.8190**	0.538***	0.839***	0.887***
happiness = 7	1.1599***	0.852**	1.147***	1.208***
happiness = 8	1.7585***	1.416**	1.690***	1.776***
happiness = 9	2.5843***	2.256**	2.493***	2.628***
happiness = 10	3.3035***	3.189***	3.393***	3.591***
Polynomial				
1		-0.537***	-0.216	-0.241
2		0.166***	-0.092*	-0.019
3		0.053***	0.055*	-0.068
4			0.018***	-0.001
5			-0.000	-0.005
6				0.001
7				0.000
8				
9				
log likelihood	-11118.053	-11090.326	-11077.719	-11076.925
Standard deviation	1	1.141	1.111	1.210
Skewness	0	0.851	0.766	0.972
Kurtosis	3	4.338	4.427	5.023
LR-test: OP against SNP		106.253***	131.469***	133.056***

6.3 Robustness exercise: evolution of happiness

The empirical analysis in the previous section was performed by pooling happiness data for four waves of survey beginning 2002 through 2008. But do the results reflect on the broad conclusions of each ESS round? More specifically, one may be interested in knowing how the determinants of happiness have evolved over the years. In this section, we perform as a robustness check, whether the variables determining happiness have more or less remained constant over various ESS rounds. This exercise also would reflect on the theoretical conclusions of Rayo and Becker (2007), who consider a time-varying reference point or performance benchmark of the happiness function. The benchmark is updated over time so that habits and peer comparisons can arise as a special case of the updating process. As Rayo and Becker (2007) argue, this updating can give rise to volatility in the level of happiness that can impede the process of reversion to long-run mean. Implications of this interesting result can be gauged from Figure 2 where we have found transition from bi-modal structure of happiness to multi-modality. Indeed, presence of multi-modality in the happiness distribution reflects undergoing socio-economic changes which make decision making process - in our case happiness - volatile. As long as stochastic shocks as in (1) remain significant and grow over time, they are likely to affect happiness function both in the short and long-run. Overall, the choice of the best model and best of determinants become tricky.

For the above purpose, we have estimated happiness function by employing the BMA approach discussed in the preceding section to each of the four waves of the ESS data for UK. The results are presented in Table 7. Note that the posterior inclusion probability (PIP) of each variable is computed as before by summing the posterior probabilities of models including that variable. To gauge implications of PIP for the variables in Table 7, it may be recalled that we have set a cut-off value of 0.5 since we assume equal prior inclusion probability assumed across all model specifications. Therefore, posterior inclusion probabilities above 0.5 imply that, after observing the data, our belief that the variable belongs in the true model has increased. In order to interpret the standardized posterior estimates of the parameter, a rule-of- thumb threshold is given by Masanjala and Papageorgiou (2008), who define those variables where the ratio of posterior mean to posterior standard deviation is above 1.3 in absolute value as effective covariates.

Interesting results emerge from Table 7. In comparison with the BMA results from pooled data for all survey periods which provided fourteen best set of predictors of happiness, the same with individual rounds evince significant differences. In fact, in ESS round 1, there are sixteen variables which have PIP of 0.5 or more. With same PIP levels, there are 17 variables in ESS round 2, 9 in round 3 and 8 in round 4. Despite the significant drop in the number of determinants over time, what is notable is that individuals seem to be more confident about the long-term benefits of social capital variables (in ESS round 3 and 4). For instance, in all ESS rounds, it is found that being married (married), feeling about household income currently (hincfel1), social meeting (sclmeet), fair attitude of people towards each other (pplfair) and engagement in social activities (sclact), etc., have PIP more than 0.5. A striking change is observed: survey respondents in the earlier ESS rounds (2002 and 2004, i.e., waves 1 and 2) appeared to be more open to the choice of determinants which include variables such as unemployment benefit (unempbenefit), member of a group discriminated against in the country (dsrgrp), discrimination corresponding to gender (dscrage), number of people living in a household (hhmmb), and the being religious (rlgdgr), etc. Variables which have also been important in the waves 1 and 2 include household's total net income (hintctnt) and people's trust (ppltrst).

Two broad conclusions can be drawn from Table 7. First, even under uncertainty, the relevance of social capital variables as core determinants of happiness, has remained unchanged. Second, the evolutionary pattern of happiness determinants also points at a very important aspect of psychology which is often stressed in this stream of happiness research: in the presence of uncertain environment when individuals possess income with which they can maintain a reasonable living standard, then short-run components of happiness do not find prominent place in their perspective of happiness goal. If uncertainty and volatility were to continue and if the social cohesion continues to erode, people's desire to revert back to these primitive objectives remain unchanged. This is what is also reflected in the type of determinants in Waves 3 and 4 (2006 and 2008 respectively). Interestingly also, the evolutionary features of happiness over years present another important dimension of economics of happiness research: under relative stability of socio-economic order, respondents are likely to report and choose many factors which may not be directly related to social capital. But when volatility becomes a persistent phenomenon in the society, stable and primitive determinants such as social capital turns out to be most important determinants of happiness.

Table 7: Evolution of happiness over time

Wave 1		Wave 2		Wave 3		Wave 4	
Variables	PIP	Variables	PIP	Variables	PIP	Variables	PIP
pplfair	1.000	pplfair	1.000	hincfel1	1.000	married	1.000
pplhlp	1.000	pplhlp	1.000	sclmeet	1.000	hincfel1	1.000
sclmeet	1.000	sclmeet	1.000	married	1.000	sclmeet	1.000
sclact	1.000	sclact	1.000	pplfair	0.999	pplhlp	0.999
rlgdgr	1.000	married	1.000	sclact	0.949	inmdisc1	0.982
married	1.000	hincfel1	1.000	incinvest	-0.862	pplfair	0.970
hincfel1	1.000	inmdisc1	0.999	socbenefit	-0.776	sclact	0.593
inmdisc1	1.000	rlgdgr	0.996	ipsuces1	0.761	incinvest	-0.516
ppltrst	0.987	ppltrst	0.950	inmdisc1	0.719	imptrad1	0.431
unempbenefit	0.954	hinctnt	0.928	dscrgrp	-0.451	widowed	-0.264
hinctnt	0.951	unempbenefit	0.898	iphlppl1	0.429	impfun1	0.264
hhmmb	0.880	hhmmb	0.792	dscrrce	-0.371	northeast	0.195
impfun1	0.745	incinvest	0.692	unempbenefit	0.295	rlgdgr	0.176
incinvest	0.711	impfun1	0.613	northwest	-0.286	socbenefit	-0.132
dscrgrp	0.569	dscrgrp	0.569	pplhlp	0.256	iplylfr1	0.104
socbenefit	0.559	socbenefit	0.558	dscroth	0.234		
dscrage	0.483	dscrage	0.521	ipshabt1	-0.162		
dscroth	0.449	dscroth	0.474	ipadvnt1	0.153		
dscrdsb	0.439	dscrdsb	0.455	rlgdgr	0.139		
iphlppl1	0.260	iphlppl1	0.292	wagesalary	0.137		
dscrrlg	0.240	eduyrs	0.284	wales	0.129		
eduyrs	0.221	wkhtot	0.263	hhmmb	0.112		
wkhtot	0.217	dscrrlg	0.238				
dscretn	0.163	dscretn	0.204				
ipbhprp1	0.130	ipbhprp1	0.181				
wkhct	0.117	wkhct	0.174				
		iplylfr1	0.148				
		northireland	0.125				
		ipcrtiv1	0.101				

7 Conclusion

Choice of best determinants of happiness is a leading research issue which has been inadequately explored in the literature. Despite its immense methodological and policy values, the study of choice of determinants of happiness under uncertainty has rather been overwhelmed lately by research related to definitional, measurement, and evaluation of implications of standard theoretical and econometric models of happiness. In this paper, we have attempted to overcome issues concerning selection of best set of predictors and models under uncertainty by making optimal use of Bayesian mechanism.

It was noted in the paper that conventional empirical construct of happiness employed widely in the extant research suffer from the limitation of failing to use large set of predictors of happiness, which is normal in view of the implications of happiness research in various disciplines. In the conventional framework, we observed that empirical estimation of happiness models were based on *a priori* assumption of selected variables belonging either to the set of economic, social, political, or to the cross-product of some of these factors. We argued that existing empirical studies of happiness suffered heavily in terms of model and parameter uncertainty, which while ignored made estimated parameters unreliable. Our empirical specification was based on the well-known theory of happiness, especially the ones which characterized happiness with respect to three innate features such as peer comparisons and relative income, comparison with own expectations and success, and habit formation. Since, these innate characters control for both subjective well-being and psychological aspects of happiness, expectation of the presence of large predictors are natural. Combined with this situation, if the individuals face stochastic shocks which may not be mean-converging in the long-run, we demonstrated that a herding outcome of pseudo-representation of happiness score may appear. However, as we showed, in an increasingly uncertain environment given that the individual's baseline needs are met, they tend to look for 'social capital' variables as long-term happiness objectives.

We found that as happiness distribution evolved over time, individuals tended to be consistent and content with social capital variables as the most important determinants of happiness. The evidence of multi-modal structure of happiness also reflect that uncertain socio-economic environment in UK has created distinct classes of individuals who are trapped under various 'happiness scores' and a transition can only break the cycle. The effect of social capital variables were quantified by employing semi-non-parametric ordered response approach where high degree of non-linearity with respect to the functional forms and variables were allowed. It was found that social capital variables possess high predictive probabilities and serve as robust determinants of happiness. The result is consistent with recent findings. The quantification of effects of ordered probit model carried out in non-parametric domain suggested that the latter outperformed the former. Our finding of significant non-linearity in model and variables, further vindicate that perception of happiness is exceedingly complex involving the greater socio-economic and demographic dynamics.

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Appendix

Table 8: Definition of Variables

Variables	Definitions
brncntr	Born in country
cntbrth	Country of birth
ctzcntr	Citizen of country
ctzship	Citizenship
dscrage	Discrimination of respondent's group: age
dscrdk	Discrimination of respondent's group: don't know
dscrdsb	Discrimination of respondent's group: disability
dscretn	Discrimination of respondent's group: ethnic group
dscrgnd	Discrimination of respondent's group: gender
dscrgrp	Member of a group discriminated against in this country
dscrlng	Discrimination of respondent's group: language
dscrna	Discrimination of respondent's group: no answer
dscrnap	Discrimination of respondent's group: not applicable
dscrntn	Discrimination of respondent's group: nationality
dscroth	Discrimination of respondent's group: other grounds
dscrrce	Discrimination of respondent's group: colour or race
dscrref	Discrimination of respondent's group: refusal
dscrrlg	Discrimination of respondent's group: religion
dscrsex	Discrimination of respondent's group: sexuality
edlvgb	Highest level of education, united kingdom
edulvl	Highest level of education
eduyrs	Years of full-time education completed
empl	Employment status
gndr	Gender
happy	How happy are you
health	Subjective general health
health1	Subjective general health (ordering reversed)
hhmmb	Number of people living regularly as member of household
hincfel	Feeling about household's income nowadays
hincsrc	Main source of household income
hinctnt	Household's total net income, all sources
impdiff	Important to try new and different things in life
impenv	Important to care for nature and environment
impfml	Important in life: family
impfrds	Important in life: friends
impfree	Important to make own decisions and be free
impfun	Important to seek fun and things that give pleasure
	Continued on next page

Table 8 – continued from previous page

Variables	definition
implsrt	Important in life: leisure time
imppol	Important in life: politics
imprich	Important to be rich, have money and expensive things
imprlg	Important in life: religion
impsafe	Important to live in secure and safe surroundings
imptrad	Important to follow traditions and customs
impvo	Important in life: voluntary organisations
impwrk	Important in life: work
inmdisc	Anyone to discuss intimate and personal matters with
ipadvnt	Important to seek adventures and have an exciting life
ipbhprp	Important to behave properly
ipcrtiv	Important to think new ideas and being creative
ipeqopt	Important that people are treated equally and have equal opportunities
ipfrule	Important to do what is told and follow rules
ipgdtim	Important to have a good time
iphlppl	Important to help people and care for others well-being
iplylfr	Important to be loyal to friends and devote to people close
ipmodst	Important to be humble and modest, not draw attention
iprspot	Important to get respect from others
ipshabt	Important to show abilities and be admired
ipstrgv	Important that government is strong and ensures safety
ipsuces	Important to be successful and that people recognize achievements
ipudrst	Important to understand different people
married	Legal marital status
pplfair	Most people try to take advantage of you, or try to be fair
pplhlp	Most of the time people helpful or mostly looking out for themselves
ppltrst	Most people can be trusted or you can't be too careful
regiongb	Region, united kingdom
rlgdgr	How religious are you
rship2	Second person in household: relationship to respondent
sclact	Take part in social activities compared to others of same age
sclcptp	Social club etc., last 12 months: participated
sclmeet	How often socially meet with friends, relatives or colleagues
stflife	How satisfied with the life as a whole
unempbenefit	Unemployment benefit
wkhct	Total contracted hours per week in main job (overtime excluded)
wkhtot	Total contracted hours per week in main job (overtime included)
yrbrn	Year of birth