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Measuring well-being: a multidimensional index integrating subjective well-being and preferences

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Lin Yang

London School of Economics and Political Science, London WC2A 2AE

l.yang10@lse.ac.uk

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Abstract

Policymakers have begun looking for multidimensional alternatives to income-based measures for assessing well-being in societies. The Human Development Index and related composite indices have been widely criticised in the welfare economic literature, yet are still some of the most influential income-alternatives in the research and policy arena. What are the theoretical links that bridge the gap between these composite indices and the criticisms levelled at them? This paper introduces the "preference index approach", a multidimensional measure bringing together the "equivalence approach" and the "distance function" in welfare economic theory. It retains convenient similarities with HDI-type composite indices, but assesses well-being in a way that reflects interpersonal differences in preferences between dimensions of well-being, whilst retaining comparability of well-being levels between individuals. The approach is applied empirically with data from the British Household Panel Survey to estimate different preference types between well-being dimensions. The empirical application finds that preferences differ by age, education level and unemployment status, and finds a weaker preference for the health and income dimension within older groups. Across all groups, health is strongly prioritised over income. When preference heterogeneities are taken into account, the picture of well-being looks quite different than that painted by standard welfare measures.

JEL classification: D63, I31

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Introduction

There has been a recent surge in interest in the question of how to move beyond purely income-based measures of welfare and towards measuring multidimensional well-being. The idea of well-being as a multidimensional concept is not new, however (Rawls, 1971; Sen, 1985; Stewart, 1985). In Sen's (1985) prominent conceptual framework for the "capability approach", an individual's well-being is given by her capabilities, reflecting the combinations of valuable and interrelated functionings (or "beings and doings" Sen (1992, p.39)) that she can attain in various domains of life. At a practical level, the capability approach is often associated with the UNDP Human

Development Index (HDI) – a multidimensional index, comprised of population-level indicators of income, health, and education. With its formulation as a geometric mean aggregation of average population-level indicators, the HDI has been criticised as being "a pale reflection of the general and ambitious methodology proposed by the capability perspective" (Fleurbaey and Blanchet, 2013, p. xiv). However, despite this and the many other criticisms levelled at the HDI (in particular see McGillivray and White (1993); Sagar and Najam (1998); Ravallion (2012)) it is still perhaps the most influential measure of multidimensional well-being, being cited extensively in policy and research and inspiring a proliferation of new measures with similar aggregation methodologies.[1] Since 2010, a notable revision has been incorporated into the HDI formulation and an Inequality-adjusted HDI has been introduced. These are discussed in Section 1.

Objections have been raised against the methodology of these types of multidimensional indices in general, both from a welfarist perspective because they use purely 'objective' information without considering individuals' subjective satisfaction, and from a non-welfarist perspective because the aggregation procedure is such that ethically relevant information about cumulative advantage and disadvantage in multiple well-being dimensions is lost. This paper argues that these objections to the formulation of the HDI and similar indices can be overcome by adopting the following two modifications: 1) altering the sequencing of the aggregation procedure, which the Inequality-adjusted HDI already takes a step towards, and 2) adopting a preference-driven weighting scheme. The resulting measure, introduced in this paper as the "preference index", coincides with a special case of the "equivalence approach" (Pazner and Schmeidler, 1978) and can be interpreted as a distance function concept (Deaton, 1979, 1980). The purpose of this paper is to make this theoretical link explicit, and to illustrate the preference index approach with an empirical application. The equivalence approach has been most notably applied recently in proposals of the "equivalent income" as a preference-sensitive measure of individual well-being (Fleurbaey and Gaulier, 2009; Fleurbaey, 2011; Fleurbaey and Blanchet, 2013), and therefore the preference index also shares similarities with this measure, with some key differences which will be discussed.

The rest of the paper is structured as follows. Section 1 first reviews the methodology of HDI-type multidimensional indices before introducing the modifications that result in the "preference index" approach. This section also discusses the relationship between the proposed preference index and the equivalence approach, and its advantages and disadvantages compared

[1] A recent UNDP inventory (Yang, 2014) details 101 international composite measures of well-being and social performance.

to the "equivalent income" implementation of the equivalence approach. Section 2 provides an empirical application of the preference index approach, including a comparison of different types of preferences found in the British Household Panel Survey (BHPS), and how the picture of well-being painted by the preference index contrasts with that of other welfare measures. Section 3 concludes.

1 Multidimensional Indices and the Preference Index Approach

1.1 *Theoretical framework*

Consider a simple framework in which each individual i considers m dimensions of life that matter for her well-being. Attainment in dimension k for individual i is given by a positive real number x_{ik}, and the personal attainment bundle of individual i is an m-dimensional vector $x_i = (x_{i1}, x_{i2}, ..., x_{im})$. Attainment bundles are defined along a normalised scale following a commonly used min-max goalpost approach (Lugo, 2005; UNDP, 2013) such that $x_{ik} = \frac{\widetilde{x_{ik}} - x_k^{\min}}{x_k^{\max} - x_k^{\min}}$, where $\widetilde{x_{ik}}$ is the raw attainment value in dimension k, $x_k^{\min}$ is a minimum lower bound value and $x_k^{\max}$ a maximum upper bound value. Each individual i has well-defined preferences over personal attainment bundles x_i belonging to the potential attainment set $X \subseteq \mathbb{R}_+^m$. Let R_i denote individual i's complete preference ordering over the set X. Preferences are assumed to be complete and transitive. When i prefers bundle x_i at least as much as bundle x_i', this is denoted by $x_i R_i x_i'$. Strict preference is denoted by $x_i P_i x_i'$ and indifference by $x_i I_i x_i'$. Note that here, x is assumed to be cardinal. In practice, some empirical literature has treated ordinal data as cardinal for tractability and model flexibility (see, for example, Allan (1976) and Harwell and Gatti (2001)), or because this can provide additional insights into useful relationships (Moses *et al.*, 1984). In the empirical application that follows, the education dimension will be treated in this manner.

1.2 *HDI-type multidimensional indices*

HDI-type multidimensional indices use only information about the attainments x_{ik}, and not the preference relations R_i. The general formulation for these indices is:

$$HDI(\overline{x_{ik}}, w_k) = \begin{cases} \left(\sum_{k=1}^{m} w_k \left(\overline{x_{ik}}\right)^{\rho} \right)^{\frac{1}{\rho}} & \rho < 1, \rho \neq 0 \\ \prod_{k=1}^{m} \left(\overline{x_{ik}}\right)^{w_k} & \rho = 0 \end{cases}, \quad (1)$$

which is defined as a weighted generalised mean of order ρ, where $\overline{x_{ik}}$ is a population-level average of attainments in dimension k, and w_k is the weight assigned to dimension k, where $\sum_{k=1}^{m} w_k = 1$. In all versions of the HDI, dimensions are equally weighted so that $w_1 = ... = w_m = \frac{1}{m}$. In the pre-2010 HDI, $\rho = 1$ so that Equation (1) reduces to a weighted arithmetic mean with perfect substitutability between dimensions. The 2010 revision to the HDI modifies this to $\rho = 0$, which equates to a weighted geometric mean, introducing a degree of imperfect substitutability between dimensions. In both HDI formulations the population-level averages $\overline{x_{ik}}$ are defined as the arithmetic mean of individual attainments x_{ik} in dimension k. The Inequality-adjusted HDI (IHDI) uses the 2010 HDI formulation, and in addition redefines $\overline{x_{ik}}$ as the geometric mean of individual attainments to capture attainment inequality in each dimension k.

A key objection to the HDI formulations and similar indices is that they are insensitive to inequality among individuals and to cumulative advantage and disadvantage across dimensions. This is a consequence of first aggregating over individuals – the aggregation embodied in $\overline{x_{ik}}$ – and then aggregating over the m dimensions. To overcome this weakness, an index must carry out this aggregation sequence in reverse and first aggregate over dimensions for each individual i, and then aggregate these individual-level measures over the population. The IHDI circumvents this issue by invoking the Foster and Shneyerov (2000) path independence property. The IHDI consists of a symmetric double geometric mean aggregation, and therefore satisfies the property that either sequencing of aggregations – whether aggregation is first carried out over individuals or over dimensions – yields the same result. Practically speaking, the advantage of this is that there is no need to rely on a particular sequencing, or on one single data source to compute the index.

The IHDI does not, however, overcome a second key objection – that the equal and identical weighting scheme implicitly assumed across individuals imposes an unacceptable degree of perfectionism and paternalism, and unrealistic and arbitrary trade-offs between dimensions (Ravallion, 2011, 2012; Decancq and Lugo, 2013). This critique can be viewed from the welfarist perspective that the subjective satisfaction of individuals is important, and that individual preferences should be respected. Indeed, interest in welfarism has seen a renewal, in tandem with a surge in interest in empirical studies measuring subjective well-being (SWB) and its covariates. The approach proposed in this paper does not align with the view among some authors (for example, Diener, 1994; Helliwell, 2003; Layard, 2005; Graham, 2011) that raw measures of

SWB provide an operational form for welfarism.[2] However, it does use the lines of argumentation presented in Schokkaert (2007) and Decancq *et al.* (2015a) that useful components of the SWB approach can be combined with a non-welfarist concern for the underlying distribution of attainments in dimensions of well-being.

The following sections presents a theoretical proposal for how the gap between HDI-type multidimensional indices and these key objections can be bridged, and how the resulting "preference index" can be implemented in practice. An empirical analysis implementing the preference index using SWB regression is presented in Section 2.

1.3 *A preference-sensitive multidimensional well-being index*

In contrast to the indices described in the previous section, a preference-sensitive index of multidimensional well-being addresses the objections of paternalism and arbitrary trade-offs between dimensions by using the preference relations of individuals themselves, R_i, as the theoretical basis for specifying preference-specific trade-offs as defined by the weighting scheme and functional form for aggregating dimensions. In practice, the persuasiveness of this preference-based aggregation will be determined by how realistic the computed marginal rates of substitution (MRS) between dimensions are in empirical applications of the approach, and this is investigated in Section 2.

The other objections of insensitivity to inequality among individuals and to cumulative advantage and disadvantage across dimensions are addressed by using a formulation that first aggregates over dimensions for each individual i, and then aggregates these individual-level measures over the population – reversing the sequencing of HDI-type indices. Inequality-sensitivity can be integrated into the second aggregation step by using an Atkinson-Kolm-Sen equally distributed equivalent measure for aggregating over the population, which captures welfare loss due to well-being inequality. In particular, selecting the Atkinson family of measures retains the generalised mean formulation for this aggregation step, in-keeping with the analogous (but differently sequenced) aggregation in HDI-type indices. Since the application of Atkinson-Kolm-Sen and other unidimensional inequality measures is not the main innovation of the preference index approach and commands its own extensive literature,[3] the rest of the paper focuses exclus-

[2]Readers are referred to the abundant literature critiquing welfarism and subjective welfarism, much of which originates from Sen (1985), who identifies the problems of "valuation neglect" and "physical condition neglect". These recognise respectively that welfarism focuses on psychological states and feelings rather than people's reflective valuations, and that individuals may exhibit feelings of optimism or pessimism that do not necessarily reflect their objective circumstances.

[3]See Cowell (2011) for an overview of the literature.

ively on the first step of the aggregation procedure – namely, the aggregation over dimensions for each individual.

Given the theoretical framework of Section 1.1, an individual-level index of well-being, $\phi(x_i, R_i)$, can be specified according to her preference ordering R_i over m-dimensional bundles x_i, where ϕ is increasing, continuous and concave in x_i. For comparability across dimensions, the well-being level at the minimum and maximum attainment bundles in the potential attainment set $X \subseteq \mathbb{R}^m_+$ are normalised to $\phi(x_{\min}) = 0$ and $\phi(x_{\max}) = 1$, respectively, for all R_i. If we make the simplifying restriction to the domain of homothetic R_i, *i.e.* $x_i R_i x_i^{'} \Leftrightarrow \alpha x_i R_i \alpha x_i^{'}$, we have that $\phi(x_i, R_i)$ will be homogeneous and ordinally equivalent to:

$$\phi(x_i, R_i) = \begin{cases} \left(\sum\limits_{k=1}^{m} w_{ik} \left(x_{ik}\right)^{\rho} \right)^{\frac{1}{\rho}} & \rho < 1, \rho \neq 0 \\ \prod\limits_{k=1}^{m} \left(x_{ik}\right)^{w_{ik}} & \rho = 0 \end{cases} . \tag{2}$$

for dimensions $k = 1, ..., m$, where w_{ik} captures the relative weights given by individual i to each of the dimensions. With this homotheticity restriction, $\phi(x_i, R_i)$ can therefore be represented by a generalised mean, akin to the analogous aggregation in HDI-type indices. The restriction imposes the property of constant elasticity of substitution (CES) between dimensions. The restrictiveness of this in practice is examined in the empirical application in Section 2, where the CES property is relaxed to investigate its empirical repercussions.

1.4 *The equivalence approach*

A graphical representation demonstrates how such a specification captures differences in preferences between dimensions of well-being, and how the equivalence approach allows comparisons of the well-being levels of individuals with such preference differences. In Figure 1, the indifference curves of the individuals i and j cross due to differences between their preference orderings R_i and R_j over bundles of two-dimensional attainments in dimensions $dim1$ and $dim2$. Their situations at x_i and x_j cannot therefore be unambiguously compared, as would be the case if their indifference curves did not cross (the individual on the higher indifference curve would always be considered as faring better than the individual on the lower indifference curve). Instead, we have here an ambiguous situation where i's indifference curve is higher in the portion of the graph where bundle x_i is situated, whereas j's indifference curve is higher in the portion where bundle x_j is situated.

The equivalence approach, initiated by Pazner and Schmeidler (1978) and developed in the work of Fleurbaey (2005, 2011); Fleurbaey and Maniquet (2011), ranks the well-being levels of individuals on the basis of the intersections of their indifference curves with a monotone reference path (Decancq *et al.*, 2015b). The points of intersection between the reference path and indifference curves give the attainment bundles that would be deemed equally as good by the individuals as their respective bundles x_i and x_j. The approach therefore compares individuals in a hypothetical situation in which they are just as satisfied as in their actual situation, but in which their attainment bundles are situated along the defined reference path. By defining this path as the ray through the minimum and maximum attainment bundles as in Figure 1, this ray is defined exactly by Equation (2) and represents fractions of the maximum attainment bundle. The path defined in this way can be viewed in terms of a "distance function", as investigated by Deaton (1979) in the context of consumer theory, applied here in the context of non-market dimensions of well-being. The distance function, defined here on R_i and $x_{\max}$, is the amount by which $x_{\max}$ must be divided in order to bring it on to the indifference curve representing the preference ordering R_i. Geometrically, this is the ratio $\phi(x_{\max})/\phi(x_i, R_i)$, where $\phi(x_{\max})$ is normalised to 1, and so this becomes $1/\phi(x_i, R_i)$. The preference index can therefore be interpreted as an inverse distance function concept. Interpersonal comparisons are made between individuals with heterogeneous preferences along the reference path as defined, and in the example in Figure 1 it is deemed that $\phi(x_j, R_j) > \phi(x_i, R_i)$.

[Figure 1 about here.]

In comparison to HDI-type indices, which aggregate dimensions using population-level averages without a clear theoretical basis for the aggregation procedure (described by Ravallion (2010) as "mashup" indices), the equivalence approach uses individuals' own preferences as the theoretical basis for aggregating dimensions. Importantly, this avoids a paternalistic definition of well-being, for which there may be no consensus among the population. Furthermore, the preference index application of the equivalence approach results in a specification (Equation (2)) that is closely related to the population-level mean aggregation typical of HDI-type indices. The practical advantage of this is that it provides a measure that can conveniently be expressed in a similar way to the existing indices, which have arguably endured due to their simplicity. At the same time, the approach bridges an important gap in the theoretical basis of such measures.

1.5 *Relationship to related well-being measures*

As an anonymous referee pointed out, it is important to note that the normalisation parameters chosen to scale attainment values in each dimension can have a substantive impact on the computed well-being levels, since changing these parameters would shift the reference path. However, this issue of reference-dependence exists in many established methods of well-being evaluation, and often simply goes unnoticed because the reference parameters are not always made explicit. For example, conventional income poverty measures take mean or median income as the reference parameter and calculate a percentage of this to arrive at the poverty threshold – this has no explicit justification, and indeed measured poverty would be different if this reference was to be chosen in another way. Even the choice of market prices as the reference prices for computing GDP can be questioned, and indeed the choice of appropriate reference prices for imputing the value of non-market goods in GDP has often been contentious. While it is certainly possible to motivate the choice of reference parameters on normative, theoretical and empirical grounds, there is no coherent theory of reference parameters in the literature. No claim is made to fill this gap in this paper; however, motivations for the selection of reference parameters in the empirical application are given in Section 2.2. It is also worth first exploring how existing applications of the equivalence approach differ with respect to setting reference parameters.

Decancq *et al.* (2014) use a reference ray, similar to the preference index, to derive a class of preference-sensitive multidimensional poverty indices based on a poverty threshold vector z, which identifies an individual as poor if she prefers z to her actual attainment bundle. By setting the poverty vector to 60% of median attainment in each dimension and discarding information about individuals with well-being above this vector, the authors avoid explicitly defining the parameters of the reference ray for scaling the dimensions. However, these parameters are implicitly pinned down by z relative to the distribution of dimension attainments in the population; anchoring z to a different point in the distribution or according to some other criteria would change the reference poverty evaluations. This observation is analogous to the one made in relation to conventional poverty measures.

The equivalent income approach, which has been introduced in the recent welfare economic literature,[4] defines reference parameters for each non-income dimension of well-being (with more recent proposals to define different sets of parameters specific to each individual) that represent the optimal level of attainment in that dimension. This choice is motivated by a normative

[4] See the references contained in Section 1.4

argument that it is ethically defensible to compare the situations of individuals, irrespective of their preferences, when they achieve their optimal levels of attainment. Equivalent income is then defined as an individual's actual income adjusted down for her loss in well-being associated with less-than-optimal attainment in each non-income dimension. It can be interpreted as the individual's actual income minus her willingness give up to reach her optimal level of attainment in other dimensions. The corresponding interpretation for the preference index is an individual's willingness to sacrifice relatively high dimension attainments in order to raise lower attainments and obtain an equally distributed balance of attainments across well-being dimensions. It is not claimed that the reference path defined in the preference index approach is preferable on normative grounds to the one defined in the equivalent income approach. However, the main point is that on pragmatic grounds, defining the reference path in this way coincides with bridging a significant gap in the theoretical basis of HDI-type indices.

As another point of comparison, the reference ray as defined in the preference index approach results in a measure that varies along the dimension-neutral unit space rather than along the income space. This departure from a monetary metric has the advantage that it does not rely on income being part of an individual's definition of well-being and is generalisable to any combination of cardinally measurable well-being dimensions. For example, under "Buddhist" preferences which place no weight on income, it is not possible for a money-metric well-being measure to be implemented, since income is unable to capture the trade-offs between dimensions of well-being. The results of the empirical estimation of preferences in Section 2.4 find that two preference types indeed place no statistically significant weight on income. Therefore, abandoning money as a well-being metric allows an approach to well-being measurement that is not reliant on a particular dimension being present in the definition of well-being, expanding the types of preferences that can be captured.

2 Multidimensional Well-being in the UK

2.1 *Methodological discussion*

To operationalise the preference index approach empirically, the following steps are required:

1. Use ordinal and interpersonally non-compariable information about individual preferences to estimate the indifference curves of individuals for the chosen dimensions of well-being – model fit statistics can be used to investigate the implications of imposing or relaxing the

homotheticity restriction on preferences at this stage, as discussed in Section 1.3.

2. For each individual use Equation (2), with the choice of parameter ρ informed by the estimations in step 1, to compute the equivalent bundle on the reference path defined in Section 1.4 that corresponds to her actual bundle of (normalised) multidimensional well-being attainments – these are the preference index values.

3. Use these preference index values to rank the actual situations of individuals, providing interpersonal comparability between individuals with different preferences and different levels of attainment in dimensions of well-being.

The rest of this section implements the preference index approach following to these steps, selecting three dimensions of well-being for analysis: income, health, and education. A detailed description of these variables is given in Section 2.2. Section 2.3 explains the estimation of preferences in step 1 using a life satisfaction regression approach, a method suggested by Schokkaert (2007) and implemented in Decancq *et al.* (2015a), using micro level data from twelve waves of the BHPS. Section 2.4 discusses the parameters of the preference index derived from the life satisfaction model to implement step 2, and presents an analysis of different parts of the preference-sensitive well-being distribution once individuals are ranked according to step 3.

2.2 *Description of the British Household Panel Survey and well-being variables*

The BHPS is a representative sample of individuals aged over 16 in the UK. New entries and attrition means that the panel is unbalanced, with an average of 6 panels per individual. Wave 6 in 1996 marked the introduction of an additional self-completion questionnaire to the BHPS, asking individuals to indicate on a scale from 1 to 7 (very dissatisfied to very satisfied respectively) their satisfaction with various domains of life and life overall. Therefore, data from 1996 to the final wave in 2009 is used, excluding 2001 which omitted this life satisfaction question. This encompasses all waves of the BHPS containing the variables necessary for the analysis.

The three chosen dimensions – income, health, and education – appear frequently as objective policy outcomes in both theoretical and policy applications evaluating well-being across multiple dimensions. The HDI perhaps set the precedent for incorporating education and health into comparisons of living standards. Inspired by this, a large body of work has grown out of this framework for measuring multidimensional well-being outcomes (Yang, 2014), identifying a shared view on the key dimensions of human well-being across the international community. Following in this vein, a focus on the chosen outcomes helps to frame the analysis consistently with this literature. All three indicators are treated as cardinal variables, though as acknowledged in Section 1.1, this treatment of education is not as satisfactory as the other dimensions due to the small number of education levels. Analysis is conducted using normalised variables using the normalisation procedure proposed in Section 1.1 so that results that follow are interpretable with respect to a $[0, 1]$ unit scale as defined in the previous theoretical framework, though in practice no individual receives normalised dimension attainments of zero. The normalisation parameters are discussed below.

Income

Attainment in the income dimension is measured by equivalised household income, calculated by taking total annual household income and dividing by the square root of number of household members. This adjusts household income to account for the economies of scale gained from sharing resources among additional household members, and makes household income comparable at the individual level. Other more complex equivalisation scales are available; however, the widespread use of square root equivalisation facilitates comparability with other studies – this is the recommended scale for users of the Luxembourg Income Study, Eurostat, and more recently the OECD and many other individual countries (Chanfreau and Burchardt, 2008; OECD, 2013). $x_k^{\max}$ for the income dimension is defined as £52,500; $x_k^{\min}$ is defined as £100. The choice of $x_k^{\min}$ is motivated by the empirical bunching of values below £100, which is implausibly low given that these figures include state benefit payments, and therefore may be the result of reporting error. The choice of maximum at £52,500 is motivated by the findings of Kahneman and Deaton (2010), using 2008 Gallup data, that there is virtually no gain in well-being from income per capita above this level (converted from dollars using 2008 purchasing power parity). Such a level of income can therefore be seen as an optimal level of attainment from which comparisons can defensibly be made across individuals, similar to the rationale behind reference parameter choices for equivalent income. This choice is also consistent with current HDI methodology.

Health

For the health dimension, a composite indicator is derived using BHPS binary health indicators. Subjective health satisfaction is not used as a direct measure of health, since this risks endogeneity with the life satisfaction responses as discussed by Ferrer-i Carbonell and Frijters (2004). The measure is derived using the predicted linear index from an ordered logit model of subjective health satisfaction. The choice of $x_k^{\max}$ and $x_k^{\min}$ reference parameters are given by the maximum and minimum possible values of the health index, again motivated by using deviations from an optimal level of attainment from which to make comparisons across individual situations. Details of the derivation are provided in the Appendix.

Education

Although education has appeared in many lists of basic well-being dimensions and on many policy agendas, the effect of educational attainment on SWB has been a subject of contention (Dolan *et al.*, 2008; Michalos, 2008). The coefficient on education has often been found to be indeterminable (for example, Luttmer (2005), Ferrer-i Carbonell (2005) and Decancq *et al.* (2015a)), and MacKerron (2012, p. 721) concludes in a survey of the SWB literature that "the impact of education varies between studies: in some it has no significant effect, whereas in others highest [SWB] is variously associated with lower, higher, and intermediate levels of education." While some evidence points to a small positive association between education and life satisfaction (Veenhoven (1996); Frey and Stutzer (2002); Oswald and Powdthavee (2007)), contradictory findings in other studies have been suggested to be the result of raised aspirations that are unfulfilled or by the higher educated taking on more high-stress occupations later in the life course (Stutzer (2004); Ferrante (2007); Sebates and Hammond (2008)). From these findings, it is tempting to conclude that education does not improve individuals' SWB.

The use of individual fixed effects minimises the indirect life course effects through income and aspirations, since this narrows the time frame under consideration to the preceding year by using within-individual variation. This is in contrast to making comparisons of education levels between individuals, which confounds the effects of prior education that have manifested themselves indirectly later in the life course, either through positive income effects or negative aspiration effects.

Furthermore, as an alternative strategy, a binary indicator is used for the education dimension in the life satisfaction regression, indicating whether an individual has received a new qualification in the preceding year. Vocational qualifications, such as nursing and apprenticeships, are included as well as academic qualifications. While vocational qualifications may have an academic-equivalent value in certain professions, they do not necessarily follow a clear continuous progression as academic qualifications do, i.e. GCSE, then A Level, then first degree and so on. This makes it difficult to identify any effect using a typical 'highest qualification' indicator in a life satisfaction regression where highest qualification is treated as a cardinal variable. On the other hand, treating it as a categorical variable may lead to insufficient variation between categories to identify these effects in a demanding individual fixed-effects specification, as in Section 2.3. Using the binary education indicator, the estimated coefficient is then used to derive the relative weight of the education dimension for the preference index computations.

While the estimation strategy uses a binary indicator, attainment in the education dimension *is* measured by an individual's highest qualification (academic or vocational). Each qualification is assigned to one of the following six academic-equivalent qualification levels: no education, no completed qualifications, GCSE or equivalent, A Level or equivalent, first degree or equivalent, and higher degree or equivalent. The resulting measure is treated as a cardinal measure in the range $[1, 6]$, with the caveat that this is not ideal due to the small number of qualification levels. However, without more detailed information about educational attainment, it is difficult to do better. $x_k^{\max}$ is defined as 6, corresponding to the value for an individual having a higher degree or equivalent, and $x_k^{\min}$ is defined as 1, corresponding to the value for no education. In practice, the qualification levels are assigned so that all individuals fall into the category of no completed qualifications and above, since even individuals who have no qualifications in the UK will have received some minimal schooling – this means that no individual receives a normalised attainment of zero in the education dimension. Again, the reference parameters are chosen so that comparisons are made against an optimal level of attainment – though it must be acknowledged that the choice of higher degree as the optimal level of education is less clear-cut than the choices for other dimensions.

2.3 *A life satisfaction approach to estimating preferences*

The proposed index of well-being requires the estimation of individuals' preferences between dimensions of well-being. These preferences can be derived by estimating a "refined (or cleaned) measure of satisfaction with life", as suggested by Schokkaert (2007), to extract the relevant information from the life satisfaction responses using the following life satisfaction equation:[5]

$$S_{it}^* = \alpha_i + \gamma_t + (\beta + \Lambda D_{it})'\Phi(X_{it}) + \delta' Z_{it} + u_{it} \tag{3}$$

[5] An overview of existing life satisfaction regressions with the BHPS can be found in Clark and Oswald (2002).

S_{it}^* is the latent life satisfaction variable underlying the observed discrete responses S_{it} of individual i in year t, such that reported life satisfaction $S_{it} = q$ for $q = 1, 2, ..., 7$ if S_{it}^* falls between thresholds $\eta_{i(q-1)}$ and η_{iq}, where the η_{iq} are individual-specific and time-invariant. S_{it}^* is a function of attainment in dimensions of well-being and individual characteristics: X_{it} is the vector of attainment in the ℓ well-being dimensions of interest, in this case income, health and education; Z_{it} contains observed socio-demographic variables such as cohort, employment and marital status. The error term u_{it} is assumed to follow a standard logistic distribution. To allow estimation of preference heterogeneity between dimensions of well-being for different partitions of individuals, interaction effects between X_{it} and a vector of dummy variables D_{it} are included. In theory one could conceive of using ever finer partitions to move closer towards estimating heterogeneity at the individual level; however, it is arguably more insightful from an analytical perspective to understand how preferences vary with observable socio-demographic characteristics of individuals. The vectors β and δ capture direct effects and matrix Λ capture the interaction effects to be estimated. Φ is a function to be estimated, capturing the degree of elasticity of substitution between dimensions given by ρ in Equation (2). α_i and γ_t capture unobserved individual and time fixed effects respectively, such as personality traits or aggregate shocks to the population.

Individual fixed effects are captured using a method approximating the "fixed effect ordered logit" developed by Ferrer-i Carbonell and Frijters (2004), and further discussed by Frijters *et al.* (2006). In practice, this is estimated as a modification of the Chamberlain (1980) binary conditional fixed-effects logit model, with the modification allowing for an individual-specific rather than common life satisfaction threshold for each individual. This results in a much smaller loss of information compared to the original Chamberlain model since all individuals with any variation in satisfaction over time can be included, not just those with variation crossing over a fixed threshold. The resulting model results in a loss of only 8% of the observations. A Hausman test confirms that fixed effects rather than random effects are appropriate, in line with a finding in the SWB literature that most panel studies examining determinants of life satisfaction have rejected the random effects assumption *i.e.*, the unobservable individual effects have been found in fact to be correlated with the explanatory variables (Frijters *et al.*, 2006).

In order to pin down a suitable Φ, a generalised additive model (GAM) of specification ((3)) is first fitted using spline functions for the dimension variables to allow for the possibility of flexible functional forms. Note that splines cannot be fitted to the education indicator since it is a binary variable, and must enter the model linearly. In a second step, the fit of this non-parametric model is compared to a parametric model in which an optimal power transformation is estimated for each continuous dimension, allowing the transformation parameter for each dimension to vary independently. This is done by searching over a fine m-dimensional grid of values. In this case $m = 2$ for the two continuous dimensions, income and health. Finally, the fit of this parametric model is compared to a restricted parametric model in which the optimal power transformation is defined to be common across dimension. Such a specification allows a CES representation of the preferences to be estimated in accordance with Equation (2). A comparison of the model fits resulting from the last two steps allows an assessment to be made of how restrictive the assumption of CES preferences is, as opposed to allowing a more flexible and data-driven estimation of preference elasticities.

Table 1 presents the model fit statistics under each of these specifications, with higher log likelihood values indicating better fit. In the range $[-2, 2]$ of Box-Cox power transformation parameters tested, a parameter of 0.2 for income and 0.5 for health gives the best-fitting model, and produces a better fit than the non-parametric GAM model. This model is then also compared to those with the closest common integer-value transformation parameters of 0 and 1, which give naturally interpretable approximations to the transformation parameters. A value of 0 reduces to a logarithmic transformation whereas a value of 1 equates to a linear relationship. The log likelihood values indicate that the linear specification provides a better fit for the data than the log specification. However, informed by the widely recognised criticism of unrealistic perfect substitutability between dimensions implied by linearity, the second best-fitting logarithmic approximation will be used in the rest of the analysis for the substitution elasticities of both the continuous dimensions, health and income. The loss in log likelihood shows, however, that there is an empirical loss in imposing the more tractable but restrictive CES assumption.

[Table 1 about here.]

2.4 *Results and comparison with other measurement approaches*

The estimation results first without preference heterogeneity are presented in the first column of Table 2 as a comparative "representative agent" approach, using the logarithmic specification discussed as a representation of Equation (2) with $\rho = 0$. The second column reports the significant interaction effects between the vector of dummy variables D_{it} and well-being variables X_{it} when included in the regression, following specification (3). These dummy variables identified whether individuals have higher education, are male, living in an urban area, unemployed, or young (first observed in the sample at age 36 or younger, corresponding to being born on or after 1960 in the first wave). The pseudo R^2 values for both models are small, but in line with other fixed-effects studies of SWB using the BHPS (Burchardt (2005), for example).

[Table 2 about here.]

Most significantly, the direct coefficient of income under the heterogeneous model shows that income does not have a statistically significant effect on life satisfaction for the older, lower educated group. Though surprising, this does triangulate with the analysis of FitzRoy *et al.* (2011), who find that "own income becomes insignificant for those over 45" in the BHPS sample. Sensitivity testing of the partition definition for the "young" dummy confirms the FitzRoy *et al.* (2011) result using our model, and shows that the effect of income begins to display statistical significance for individuals with a first-sampled age of 32 or younger. The effect of income is positive and significant for all other groups, and plays a greater role for the young and the higher educated.

The interaction effect of age and health highlights another surprising result, showing that the life satisfaction of older people is less influenced by given improvements or deteriorations in health compared to younger people. This may be less counterintuitive than at first sight. In a Taiwan panel study by Collins *et al.* (2007) of 3,363 older persons, the authors find similar results suggesting that higher life satisfaction and optimism may indicate the presence of adaptive coping mechanisms. In other words, individuals may expect to have worse health as they age, and adapt by transitioning to less busy lifestyles, for example, that are less susceptible to interruption by changes in health. In the heterogeneous model, sensitivity analysis indicates that age-related preferences over health begin to turn towards being less concerned by given changes in health after the age of 68.

A comparable analysis in Decancq *et al.* (2015a) finds the opposite health result using Russian data – a larger weight on health is found for the preferences of the old. Far from being a problematic inconsistency, these contrasting findings highlight the central argument for taking account of heterogeneous preferences. Whilst the well-being of older people living in the UK is less affected by changes in health status than that of younger people, in Russia older people are more affected by health status than the young. The underlying fundamentals of health care and ageing in these two countries provides some insight to this result. Russia's social programmes and care for the elderly are plagued by meagre pensions and poor access to healthcare services; in the UK on the other hand, a high quality National Health Service and state and occupational pensions provide assurance for the health of the elderly. This resonates with the observation of Deaton (2008) that whereas in the United States and Britain, health satisfaction actually improves with age after 50, in the the former Soviet Union health satisfaction falls very rapidly in the elderly. This is a difference that this preference-sensitive approach is able to capture.

[Table 3 about here.]

Table 3 shows the coefficients of the heterogeneous model, listed by preference type, and the homogeneous model, equivalent to modelling a representative agent, after linearly rescaling each row to sum to 1. This allows the relative importance of each dimension under the different preference types to be directly compared with the equally weighted HDI approach and the income-only approach. For all preference types except the young, higher educated types, income receives the lowest relative weight. This result is consistent with the observation made in Deaton (2008, p. 54) that "many studies comparing people within countries have found only a small effect of income on life satisfaction relative to other life circumstances".

Health, on the other hand, receives a very high weight. Again this squares with similar findings in the literature on health and SWB, for example those of Campbell *et al.* (1976) that health was rated by subjects in the US as the most important factor for happiness. Calculating the MRS between income and health for an older, higher educated, unemployed individual using the weights in Table 3, an individual with mean attainments in income and health would be willing to give up £4,983 in equivalised household income to eliminate on average one problem from the BHPS list of twelve health problems: limbs, vision, hearing, skin conditions, chest or breathing, heart or blood pressure, stomach or digestion, diabetes, anxiety or depression, addiction, epilepsy, or migraines. For a younger, lower educated, employed individual, this MRS would be £18,949.

Note, however, that older and unemployed individuals have lower mean health attainment than younger and employed individuals. This will affect the observed distribution of MRS values in the data, since there exists diminishing MRS at higher attainments in the chosen geometric mean specification for the preference index. Therefore if we carry out the same MRS calculations using mean attainments specific to the older, higher educated, unemployed group and the younger, lower educated, employed group, we obtain MRS values of £6,936 and £16,220 respectively. On the other hand, if the dimensions are equally weighted according to the HDI approach, the computed MRS for an individual with mean income and health attainments is just £1,977. As a comparison, the review of willingness-to-pay and health-status by Reed Johnson *et al.* (1997) finds estimates (valued in 1993 dollars) ranging from \$1.18 per day, or \$430.70 per year, for a mild cough, to \$164.99 per day, or \$60,221.35 per year, for severe heart-related chest pain (angina). Another more recent review (European Chemicals Agency, 2016) finds values (in 2012 euros) of €2,000-€12,000 per year for severe skin inflammation (chronic dermatitis) and €35,803 per year for chronic kidney disease. Clearly there is wide a range of estimates in the health literature for a spectrum of health conditions and severities. The estimates implied by the preference index fall within a very reasonable position within that range, while the HDI weighting produces a relatively low estimate.

[Figure 2 about here.]

Figure 2 illustrates two groups of indifference curves – the older, higher educated, unemployed group and the younger, lower educated, employed group. This illustrates the point empirically that taking account of heterogeneous preferences is important when measuring well-being. Consider an individual situated at the attainment bundle marked by the black circle. If this individual was older, higher educated, and unemployed (dashed indifference curves), this would be a position of lower preference satisfaction than if the individual was younger, lower educated, and employed (solid indifference curves) and situated at the same bundle. We can see this by comparing the two thick indifference curves, which represent the same level of well-being since they intersect at the same point on the diagonal ray. In contrast to conventional measures of well-being, with the preference index it is possible that two individuals with identical attainment can have differing ideas about their level of well-being.

To get a better idea of how the picture of well-being using the preference index measure corresponds with a number of other popular measures of welfare, some comparisons are presented in the following tables. Table 4 contains a cross-tabulation of quintiles of the preference index with quintiles of income. It is immediately obvious on inspection of the diagonal that there is limited agreement between the two measures on the rankings of individual well-being positions. At best, just under half of individuals in the highest income quintile also rank in highest quintile of the preference index. Table 5 expands the number of measures compared to include the "representative agent" specification with no preference heterogeneity (2), the equal

HDI weighting (3), and the raw life satisfaction score (5), focusing on the policy-relevant task of identifying the least well-off. In-keeping with common practice, this is defined as those individuals with $< 60\%$ of median attainment in the 2008/9 wave according to each measure. Let those identified as least well-off according to the preference index measure be referred to as the 'preference poor'. The first row shows the percentage of individuals who fall below the criteria of $< 60\%$ of median attainment according to each measure, the next three rows show the mean equivalised income, health score and life satisfaction score of these individuals, and the last five rows show what percentage of these individuals are male, young (first observed in the sample at age 36 or younger), higher educated, living in an urban area, and unemployed. As a comparison benchmark, the last column of Table 4 contains these descriptive statistics for the pooled 2008/9 sample including those with 60% of median attainment and higher.

In terms of dimension attainments, those identified as preference poor in column (1) are characterised by the lowest average health scores, particularly compared to the income poor in column (4), reflecting the priority of health across all preference types. Being income poor has much lower bearing on health status, to the extent that there is little difference between average health among the income poor in column (4) and average health across the pooled sample including the non-poor in column (6). The preference poor tend to have lower average life satisfaction than the income poor, with little difference again in average life satisfaction among the income poor and the pooled sample. Income has least bearing on the life satisfaction measure in column (5), with those attaining $< 60\%$ of median life satisfaction scores receiving equivalised incomes of £17,094 on average. The preference index, representative agent approach and HDI approach seem to capture poor attainments across income, health and life satisfaction. The income measure is ineffective at capturing poor health and life satisfaction, while the life satisfaction measure is ineffective at capturing low income and to some extent poor health compared to the pooled averages in column (6).

Comparing the characteristics of the least well-off according to each measure to average characteristics of the pooled sample including the non-rich, all measures indicate that older, female, lower educated, urban and unemployed individuals are overrepresented in the least well-off members of society. However, though the frequencies of these characteristics are disproportionately high among the least well-off groups according to each measure, these groups are comprised of different *individuals*. In fact, there is no agreement at all across all five measures that any single individual in the 2008/9 sample is among the least well-off, and only 19.9% agreement for individuals who are identified as both preference poor and income poor (analysis available upon request). As one would expect, the dimension attainments and characteristics of the preference poor in column (1) are closest in line with those of the least well-off according to the representative agent measure in column (2). Yet there is still imperfect agreement – 85.2% – between the preference index and the representative agent measure about who the least well-off *individuals* are. This shows that a well-being measure taking account of preference heterogeneity provides a distinct assessment of well-being compared to a representative agent approach that assigns an average of population preferences to all individuals.

[Table 4 about here.]

[Table 5 about here.]

3 Summary

The main objective of this paper was to formulate a preference-sensitive multidimensional index of well-being that makes explicit the theoretical link between widely-criticised HDI-type composite indices and theoretically and normatively-driven approaches to making well-being comparisons. The end goal was not to prescribe a definitive well-being measure or make definitive conclusions about quality of life. Rather, the aim was to identify how this gap in theory between these two approaches to multidimensional well-being measurement could be bridged, and the valuable analysis possibilities that the resulting "preference index" approach provides.

The preference index was shown to coincide with a special case of the "equivalence approach" (Pazner and Schmeidler, 1978) and to be interpretable as a distance function concept (Deaton, 1979, 1980). The similarities and differences of the preference index in relation to existing implementations of the equivalence approach were discussed, and an empirical application of the preference index showed how it could be implemented and used for types of analysis that standard welfare measures cannot offer. Operationalising the approach using BHPS data, interaction and individual fixed effects were used to uncover different preference types by age, education level and unemployment status. Calculations of MRS between income and health were used to assess the persuasiveness of the estimated preference parameters.

Among the most interesting findings were that less educated individuals placed no statistically significant importance on income, and that younger individuals placed more importance on changes in health status compared to older individuals. It was also shown how considerations of multidimensionality and preference heterogeneity change our understanding of well-being and the characteristics of the least well-off in society compared with assessments using unidimensional measures such as income and SWB. This has potentially important ramifications for the design of welfare policy, especially in the context of ongoing efforts in the UK to integrate alternative measures of well-being into public policy decision-making processes.

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About the author

Dr Lin Yang is a Research Officer at the Centre for Analysis of Social Exclusion at the London School of Economics and Political Science. Her research focuses on the multi-dimensional measurement and analysis of well-being, inequality and poverty. She received her BSc from University College London in 2011, and her MSc and PhD from the London School of Economics and Political Science in 2012 and 2017 respectively.

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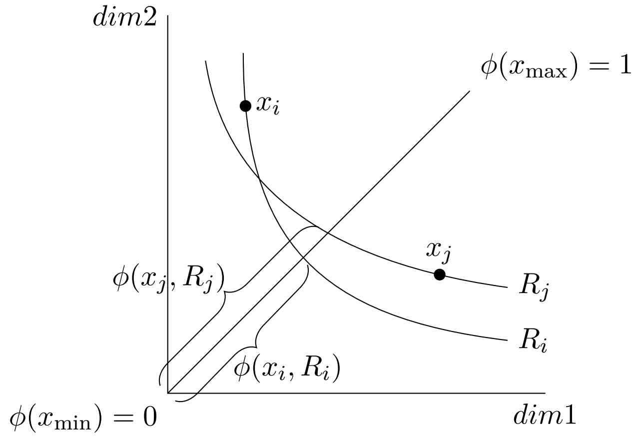

Figure 1: Illustration of the preference index implementation of the equivalence approach

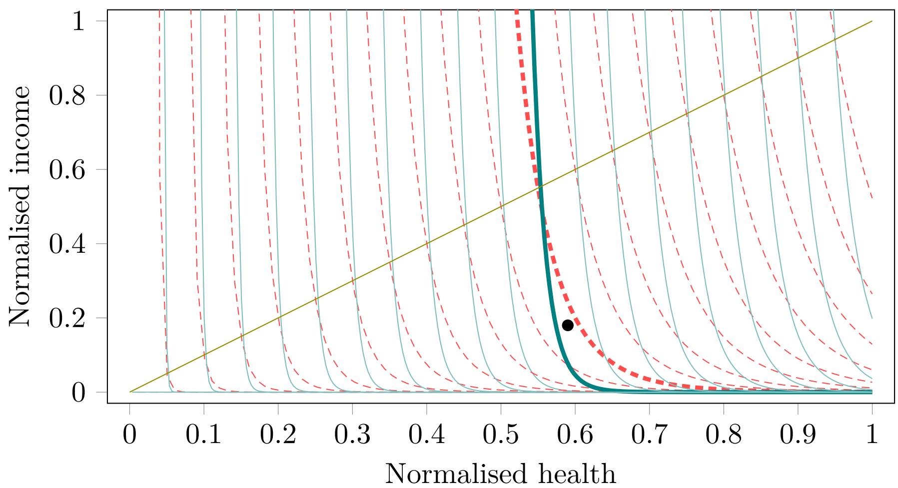

Figure 2: Indifference curves of an older, higher educated, unemployed individual (dashed indifference curves) and younger, lower educated, employed individual (solid indifference curves). The two thick indifference curves represent the same level of well-being since they intersect at the same point on the diagonal ray.

Transformation parameters		Log likelihood
Income	Health	
Cubic spline	Cubic spline	-51443.74
0.2	0.5	-51439.59
1	1	-51450.85
0	0	-51465.92

Table 1: Model fit for different curvatures of the well-being dimensions

Satisfaction	Homogeneous model	Heterogeneous model
Equivalised income	0.043***	0.016
	(0.015)	(0.033)
Health	0.335***	0.282***
	(0.016)	(0.033)
Education	0.049*	-0.051
	(0.026)	(0.070)
Young $\times$ *income*		0.051*
		(0.028)
Higher educated $\times$ *income*		0.069**
		(0.031)
Young $\times$ *health*		0.203***
		(0.033)
Unemployed $\times$ *health*		-0.109***
		(0.032)
Young $\times$ *education*		0.110*
		(0.058)
In a couple	0.269***	0.269***
	(0.041)	(0.041)
Separated/widowed	-0.322***	-0.323***
	(0.058)	(0.058)
Unemployed	-0.607***	-0.673***
	(0.035)	(0.082)
Urban	-0.099**	-0.095
	(0.042)	(0.058)
Household size	-0.068***	-0.072***
	(0.011)	(0.011)
Birth cohort	0.165*	0.168*
	(0.095)	(0.094)
Year dummies	yes	yes
Social class indicators	yes	yes
Housing quality indicators	yes	yes
N	115,966	114,874
Pseudo R^2	0.0154	0.0159

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Satisfaction regression (standard errors in parentheses)

Preference type	Income	Health	Education
Young, lower educ, unempl	0.094	0.700	0.206
Young, lower educ, empl	0.078	0.751	0.171
Young, higher educ, unempl	0.197	0.621	0.182
Young, higher educ, empl	0.167	0.679	0.155
Older, lower educ, unempl	0	0.610	0.390
Older, lower educ, empl	0	0.719	0.281
Older, higher educ, unempl	0.195	0.491	0.314
Older, higher educ, empl	0.149	0.612	0.239
Representative agent	0.102	0.783	0.115
HDI approach	0.333	0.333	0.333
Income only	1	0	0
Life satisfaction	-	-	-

Table 3: Preferences

Quintiles of income	Quintiles of the preference index 1	2	3	4	5
1	0.33	0.28	0.18	0.13	0.08
2	0.27	0.23	0.21	0.17	0.13
3	0.23	0.19	0.18	0.20	0.19
4	0.14	0.22	0.29	0.24	0.11
5	0.04	0.07	0.13	0.27	0.49

Table 4: Cross-tabulation of income and preference index quintiles

	Preference index (1)	Represent-ative agent (2)	HDI weighting (3)	Income only (4)	Life satis-faction* (5)	Pooled 2008/9 (6)
< 60% of 2008/9 median attainment (%)	20.6	23.0	17.9	21.2	3.1	-
Income (£)	15,802	15,922	11,394	7,882	17,094	21,278
Health (0-1 scale)	0.22	0.24	0.33	0.63	0.43	0.71
Life satisfaction (1-7)	4.76	4.80	4.85	5.11	1.62	5.23
Male (%)	35.9	36.5	35.9	38.7	40.0	45.1
Young (%)	25.0	25.4	21.2	43.4	51.4	51.6
Higher educated (%)	9.7	11.4	3.2	9.2	15.9	22.1
Urban (%)	70.6	70.4	69.7	68.4	73.6	67.9
Unemployed (%)	19.1	17.7	20.4	15.2	34.8	7.8

* Median life satisfaction is 5, so figures are for those who responded 3 or lower.

Table 5: Characteristics of the least well-off in 2008/9

Appendix

Derivation of the composite health measure

The composite measure derived for the health dimension is estimated using an ordered logit model. Denoting H_{it}^* as the latent health satisfaction variable underlying the observed discrete responses H_{it} of individual i in year t, we observe $H_{it} = p$ for $p = 1, 2, ..., 7$ if H_{it}^* falls between thresholds $\zeta_{(p-1)}$ and ζ_p, where the ζ_p are fixed across individuals and years. H_{it}^* is modelled as:

$$H_{it}^* = \mu_t + \vartheta' B_{it} + \tau' Z_{it} + \varepsilon_{it} \tag{4}$$

Z_{it} is the same vector of observed socio-demographic variables as specification (3); B_{it} is a vector of of binary variables indicating the presence of health problems associated with: limbs, vision, hearing, skin conditions, chest or breathing, heart or blood pressure, stomach or digestion, diabetes, anxiety or depression, addiction, epilepsy, or migraines; μ_t captures year fixed effects. ϑ and τ are vectors of the direct effects to be estimated. The error term ε_{it} is assumed to follow a standard logistic distribution.

The estimation results are presented in Table A1. Predictors of the linear index $\vartheta' B_{it}$ are then rescaled to the $[0, 1]$ interval as suggested by van Doorslaer and Jones (2003), and used as measures of individual health attainment x_{ik}, when dimension k is health, consistent with the theoretical framework introduced in Section 1.1. The rescaling is given by $x_{ik} = \frac{\tilde{x}_{ik} - x_k^{\min}}{x_k^{\max} - x_k^{\min}}$, where $x_k^{\min}$ is the minimum value of the linear index $\vartheta' B_{it}$ and $x_k^{\min}$ is the maximum value.

[Table A1 about here.]

	Health satisfaction	
Limbs	-0.975***	(0.013)
Vision	-0.367***	(0.024)
Hearing	-0.222***	(0.019)
Skin conditions	-0.152***	(0.016)
Chest or breathing	-0.696***	(0.015)
Heart or blood pressure	-0.658***	(0.015)
Stomach or digestion	-0.848***	(0.020)
Diabetes	-0.625***	(0.028)
Anxiety or depression	-1.228***	(0.020)
Addiction	-0.622***	(0.075)
Epilepsy	-0.634***	(0.058)
Migraines	-0.411***	(0.018)
Socio-demographic controls	yes	yes
Year dummies	yes	yes
N	125,484	
Pseudo R^2	0.0744	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Regression for deriving the health measure (standard errors in parentheses, cut-points not reported)