Measuring Standard of Living in the UK - An Application of Sen's Functioning Approach Using Structural Equation Models

preliminary

do not quote without permission of the author

Wiebke Kuklys*

February 25, 2004

Abstract

This paper contributes to the multidimensional welfare measurement literature inspired by Sen's functioning approach. After reviewing the different statistical techniques used in multidimensional welfare measurement, we suggest structural equation modeling as an appropriate alternative to measure and model the achievement of welfare. Functionings are conceptualised as latent variables which can only be measured with error. We assess what determines the achievement of these functionings, and compare the numerical functionings values with income in a simple poverty analysis.

Keywords: welfare measure, capability approach, structural equation modelling, poverty analysis

JEL Classifications: C43, D63, I31

*University of Cambridge and Max Planck Institute of Research Into Economic Systems, Jena, Germany. Correspondence to kuklys@mpiew-jena.mpg.de

1 Introduction

Multidimensional welfare measurement in terms of standard of living has recently gained importance as a complement to standard welfare measurement in terms of income or expenditure. For example, the UK government publishes every year 15 standard of living indicators to assess the progress of their Sustainable Development Strategy[1]. These indicators measure the progress in areas such as economic output, employment, social exclusion, health and housing, etc. The results show that since the 1980s health inequalities have grown strongly in the UK. Overall life expectancy has increased over this period by three to four years, but mostly owing to an increase of years lived in poor health. The housing indicators show that in 1996 almost half of the UK population lived in non-decent housing, and in 2001, this proportion still amounts to one third. The increase of GDP per capita or the relatively stable income distribution during the same time cannot mirror in any way the deterioration in health inequalities or slow improvement in housing standards.

Further examples of multidimensional welfare measures are the Basic Needs and Human Development Indexes published by the UNDP [33]. The Human Development Index is an aggregate of three outcome dimensions of standard of living: health (measured by life expectancy at birth), education (measured by adult literacy and educational enrolment rates), and adjusted real GDP per capita, which serves as a *proxy* for the material aspects of welfare. Comparisons of country rankings of this index with GNP per capita show significant differences

Other efforts to measure poverty and inequality based on multidimensional concepts of welfare include Atkinson and Bourguignon ([2], [3]), Bourguignon and Chakravarty ([6], [7]), Hirschberg , Maasoumi and Slottje [10], Klasen [14], Maasoumi ([20], [21], [22]), Maasoumi and Nickelsburg [23], Qizilbash [25], Ram [27] and Sen ([29]:46-69). All of them find significant

[1] see http://www.sustainable-development.gov.uk

differences in poverty and inequality when comparing income-based welfare measures with multidimensional ones.

The philosophical roots of this literature can be found in Kolm [15] and, more recently, Sen's capability approach ([29], [30], [31]), which we will describe briefly in section 2. One very much debated topic in the empirical literature on the capability approach is how to measure and aggregate the different dimensions of welfare, since aggregation can help to avoid double counting of similar dimensions and to minimise measurement errors (see Hirschberg, Maasoumi and Slottje [10]).

In this paper, we will focus on the measurement and aggregation of the dimensions housing and health, as these seem to be important dimensions of welfare in the UK government report on sustainable development. Our aim is to critically review the existing measurement techniques and suggest a new method, namely structural equation modelling, which to our knowledge has not been used for welfare analysis based on the capability approach. This method is then applied to measure, explain and compare the achievement of standard of living in terms of housing and health between 1991 and 2000. For these purposes, housing and health are conceptualised as unobserved variables, which can be measured by three or four observable indicators each, and explained by the resources at the individual's disposal. The numerical values of the latent variables are estimated and used in inequality and poverty analysis to illustrate the differences between welfare achievement in terms of standard of living and in terms of income. Our results confirm the tendencies for health and housing in the government report on Sustainable Development, and find that income by itself is not a good *proxy* for multidimensional welfare as measured in this paper.

The next section introduces formally Sen's approach and explains briefly how it is related to standard economic welfare analysis. Section 3 reviews measurement and aggregation techniques typically used in standard of living measurement based on Sen's approach, while section 4 suggests a structural equation model of welfare achievement as an alternative. Section 5 justifies the variables and the model used in our application on housing and health. The results are presented in section 6.

2 Conceptualising Welfare: Sen's Approach

Sen's approach is mainly developed as an alternative to poverty and inequality analysis in money metric terms.[2] The core concepts of Sen's approach are functionings and capabilities. Sen ([32]:5) defines functionings as an achievement of a person, i.e. what he or she manages to do or to be. Hence, functionings comprise an individual's activities and states of being, e.g. being in good health, being well-sheltered, moving about freely, being employed, being educated. Capability is a derived notion, and contains the various functionings he or she can *potentially* achieve, i.e. involves the person's freedom to choose between different ways of living. In this paper, we concentrate only on the space of functionings.[3]

Formally, and following Sen ([29]:7-10), the evaluation of an individual's welfare involves the analysis of a vector of achieved functionings, $\mathbf{b}_i$ of individual i

$$\mathbf{b}_i | \mathbf{b}_i = f_i \left(c \left(\mathbf{q}_i \right), \mathbf{z}_i \right) \quad \forall \quad f_i \in F_i \text{ and } \forall \quad \mathbf{q}_i \in Q_i \tag{1}$$

where $\mathbf{q}_i$ is a vector of market and non-market goods and services chosen by the individual, $c(\cdot)$ is a function that maps goods into the space of characteristics[4], $\mathbf{z}_i$ is a vector of personal characteristics and societal and environmental circumstances, f_i is a function that maps characteristics of goods into states of being or activities $\mathbf{b}_i$, conditional on $\mathbf{z}_i$. Q_i is the resource constraint.

[2] The capability approach can also be used for policy analysis (see e.g. Alkire [1]). In this paper, however, we will focus on the measurement of the level of individual welfare as used in poverty and inequality analysis.

[3] The measurement issues addressed in this paper are a problem of functionings measurement rather than capability measurement. For literature on capability measurement see Alkire [1], Burchard and Le Grand [8] and Kuklys [16]

[4] in the sense of Gorman [9] and Lancaster [18].

The space of functionings $\mathbf{b}_i$ is the space of states of being and activities, two of which might be being healthy and being well sheltered. The functioning space is related to the goods and characteristics space through the personal conversion function f_i.

The principal differences between Sen's approach as described here and the standard income or expenditure-based approach to individual welfare evaluation are (1) that the vector $\mathbf{q}_i$ includes non-market as well as marketable goods and services, and (2) that individuals with the same resources can achieve different levels of standard of living $\mathbf{b}$, because they have different conversion factors or needs $\mathbf{z}$.[5] For example, the housing standard does not only depend on an individual's income or access to building materials, but also on climatic conditions and access to reliable builders. An individual's health does not only depend on the type of health care and nutrition he or she can afford, but also on genetic dispositions and environmental circumstances.

3 Measurement, Aggregation and Modelling of Functionings Achievement

There are three main problems involved in measuring individual welfare levels in terms of functionings. These are related to the absence of an established measurement unit for each functioning, a missing natural aggregator for the different functionings, and measurement error problems.

To understand the nature of the first two problems, let us have a closer look at the standard money metric assessment of individual welfare in terms of utility. This approach can be interpreted as multidimensional, with utility being a one-dimensional, composite welfare indicator and goods being the dimensions. Utility is derived from goods only, and since (under the standard assumptions) the relative market prices of these goods represent the

[5] For an extensive analysis of how Sen's approach is related to standard economic welfare analysis see Kuklys and Robeyns [17].

individual's relative valuation of the goods in terms of utility, these prices can be used to aggregate goods to a composite measure of individual welfare, i.e. the budget constraint. Utility is hence ordinally equivalent to expenditure, which can be conveniently measured in currency units, compared among individuals and used in poverty or inequality analysis.

In contrast, functionings measurement and aggregation is more difficult, because there is no established measurement scale for functionings (e.g. quantity of being healthy or being well sheltered), nor do there exist relative valuations between functionings which could be used for aggregation that are generally accepted and well-established.[6]

No consensus exists in the literature how to address these problems. The Human Development Index, for example, is calculated by scaling each variable indicating health, education and material wealth into a 0-1 interval for measurement purposes, and averaging these scaled dimensions for aggregation purposes. It is assumed that life expectancy at birth and GDP measure health and material wealth respectively without measurement error. Education, however, is measured by the average of two indicators (adult literacy and school enrolment rate) to minimise measurement error, as neither of the two indicators is considered to capture well enough the notion of educational achievement. While adult literacy neglects the latest developments at the school level, the enrolment rate neglects adult welfare in terms of education. An average of the two might more truthfully reflect the overall achieved level of education in the country.

In the empirical literature on the capability approach, the measurement error problem is usually solved by aggregating low-level functionings (such as different health problems or measures of education) to higher-level, broader

[6]Of course, when conceptualising welfare as utility defined over functionings, relative marginal utilities of functionings would correspond to relative shadow prices of functionings, and a shadow expenditure as a composite welfare measure could be derived. However, Sen's approach goes beyond conceptualising welfare as utility defined over functionings. Also, see Kuklys and Robeyns [17] for the difficulties of calcuating shadow prices of functionings appropiately.

functionings (such as being healthy or being educated). Denote the latent broader functioning j of individual i by b_i^j, and assume that it can only be measured with error, so that $b_i^j = b_{is}^j + \varepsilon_{is}$, where b_{is}^j is an indicator for the functioning, and ε_{is} is an i.i.d. error term. Measurement error is minimised by aggregating several b_{is}^j to one b_i^j as in

$$b_i^j = h\left(b_{i1}^j, ...b_{iS}^j\right), \tag{2}$$

where $h()$ is some aggregator function. The function h can take the form of a weighted sum so that

$$b_i^j = \sum_{s=1}^{S} w_s b_{is}^j, \tag{3}$$

where w_s is a weight. A function like h can also be used to aggregate functionings to a one-dimensional composite welfare indicator of welfare. We focus in this paper on the aggregation from low-level to broader functionings. Subsection 3.1 reviews the methods used to determine w_s and the measurement units of b_j^i. Section 3.2 briefly introduces the regression approach to measure functionings achievement.

3.1 Empirical Approaches to Functionings Measurement and Aggregation

Let us now turn to an examination of the methods used for measurement and aggregation of low-level functionings to broader functionings. In table 1 we give an overview over both non-statistical and statistical methods employed in the empirical literature on the capability approach.

The non-statistical methods comprise scaling (as employed in the HDI) and an extension of it, namely fuzzy sets theory. They have in common that the measurement unit is defined as a proportion of the maximum achievable (or achieved) level of a particular indicator. The advantage of this is that the numerical values of the latent functionings can be easily interpreted as a proportion of the maximum achievable functioning level. However, the difficulty lies in determining the maximum achievable level in the first place. The aggregation weights w_s are based on subjective evaluations, either by the analysts or by the individuals covered by the study, they do not use information contained in the data.

The statistical methods comprise, factor analysis, and principal components analysis, and time series clustering. In factor and principal component analysis, the latent functioning b_i^j is measured in terms of the factor scores, i.e. the unit of measurement is defined in relation to a combination of the indicator variables b_{is}^j. Unless all indicator variables are measured on the same scale, the measurement unit of the scores is difficult to interpret. The aggregation weights w_s are based on the covariance or correlation matrix of the indicators b_{is}^j. This has the advantage that information from the data itself is used to determine the weights, but the disadvantage that these weights might not reflect the individual's or the analyst's relative valuations of the functionings. Time series clustering is used to determine potentially distinct functionings by comparing the distances between functionings distributions. Statistically similar functionings indicators are aggregated to a new, broader functioning. The weights for this aggregation are based on entropy measures of the distance between functionings. The measurement units are defined by standardising the observable indicators to have zero mean and variance one.

Time Series clustering as applied by Hirschberg, Maasoumi and Slottje [10] can deal well with discrete data, and has the advantage of taking into account the entire distribution of data, not only first and second moments of it. However, it requires long time series of the indicators, which is rarely available when measuring functionings on the individual level. Factor and principal component analysis as applied in this line of research suffer from two problems. On the one hand, the covariance matrices on which the aggregation weights are based are not adjusted for the ordinal measurement of most of the indicator variables b_{is}. On the other hand, the methods are not useful for

Table 1: Methods for Measurement and Aggregation of Functionings

	Studies	**Measurement Unit**	**Weighting/ Aggregation**
Non statistical methods			
Scaling	UNDP [33]	% of maximum achievable level	subjective valuation (weighted sum)
Fuzzy Sets Theory	Chiappero Martinetti [24] Qizilbash [25]	% of maximum achievable level	subjective valuation (logical operators)
Statistical methods			
Factor Analysis	Lelli [19], S&O [28]	relative to combination of indicators	covariance based
Principal Component Analysis	Klasen [14], Ram [27]	relative to combination of indicators	covariance based
Time Series Clustering	Hirschberg et al. [10]	standardised variables	entropy based

testing whether the implied model is appropriate for the data, i.e. hypothesis test cannot be performed, or only very limited hypothesis tests (such as the calculation of Kronberg's α) are possible. This is particularly relevant as the numerical values of latent functioning scores are often used for further analysis as described in the next subsection.

3.2 The Regression Approach to Modelling Welfare Achievement

In the standard approach to welfare economics, it is not customary to combine inequality or poverty analyses with the estimation of statistical models *explaining* household income levels, say, Mincer equations. In analyses based on the capability approach, however, often estimations of so-called functionings production functions are reported (see Chiappero Martinetti [24], Klasen [14], Lelli [19], Schokkaert and Van Ootegem [28]). These are simple statistical representations of the conversion function in equation (1), usually in regression form

$$\widehat{\mathbf{b}_i^*} = f\left(y_h, \mathbf{z}_i, \mathbf{z}_s, \mathbf{z}_e\right) + \varepsilon_i, \tag{4}$$

where $\widehat{\mathbf{b}_i^*}$ is a vector of achieved functionings for each individual i measured by the estimated factor scores or first principal component of the variable matrix $[\mathbf{b}_i]$, y^h is the household income of the household in which individual i lives, and $\mathbf{z}_{i,s,e}$ are individual, social and environmental conversion factors, usually measured by a range of sociodemographic characteristics of the individuals, ε_i is a vector of error terms. In other words, the scores derived in confirmatory factor analysis or principal component analysis are regressed on household income and a range of sociodemographic characteristics. Unfortunately, this two-step procedure is neither statistically efficient nor is it apt for testing whether the conversion function as a whole is adequate to reflect the structure of the data. In the next section, we present a method that is related to standard confirmatory factor analysis but (1) includes a procedure to take into account ordinal measurement of variables (2) is statistically more efficient by estimating both the factor model and the regression model in one single step, and (3) is set in a statistical framework which allows for hypothesis testing and testing for model adequacy, namely, structural equation modelling.

4 A Structural Equation Model of Functionings Achievement

Structural equation modelling was developed by Joereskog and Goldberger ([13], [11]) as an efficient tool to deal with errors in variables problems, and has been widely applied in social psychology and sociology (see e.g. Bentler and Weeks [5]). Recently, economists have started to use this method also for the measurement of latent concepts in economic applications, e.g. institutional change in Eastern Europe (DiTommaso, Raiser and Weeks [26]). A full structural equation model can deal with measurement error in both endogenous and exogenous variables, i.e. each exogenous or endogenous variable is in itself unobservable (latent), but can be imperfectly measured by a range of indicator variables. The full model corresponds to a regression model where both dependent and independent variables are measured with error. The most basic structural equation model is a standard confirmatory factor model with one factor. In this paper, we focus on so-called multiple-cause multiple-indicator (MIMIC) models, which are characterised by a latent endogenous variable, but no measurement error in the independent variables. The latent endogenous variable corresponds to the unobserved functioning being healthy or being well sheltered, each measured by a range of indicator variables. The independent variables correspond to resources and conversion factors as explained in section 2.

In this section, we first present the specification of a typical MIMIC model, following closely DiTommaso, Raiser and Weeks' notation. In subsection 4.2 we refer to the specific requirements in case of ordinal variables in the model. Subsection 4.3 explains how the coefficients and latent variable scores are being estimated.

4.1 Model Specification

We estimate two models, one for being well sheltered (Housing), one for being healthy (Health), each for 1991 and 2000. The structure of each model of functionings achievement is as follows. Let y_j^f be one of $j = 1, ..., m$ indicators of the latent functioning y^f, $f =$ (Health, Housing), such that we can write

$$y_j^f = \mathbf{\Lambda}_j^{y_f} y_f^* + \varepsilon_j^f \tag{5}$$

where $\mathbf{\Lambda}^y = \left\{\Lambda_1^{y_f}, ..., \Lambda_m^{y_f}\right\}'$ denotes an $m \times 1$ parameter vector of factor loadings, representing the expected change in the respective indicators following a one unit change in the latent variable. ε_j^f is an error term with mean zero and covariance matrix Θ_{ε^f}; we assume that $cov\left(\varepsilon_i^f \varepsilon_j^f\right) = 0 \ \forall \ i \neq j$, such that any correlation across the indicators is driven by the common factor y_f^*. Under this assumptions equation (5) is a confirmatory factor analysis model for the observable indicators $\mathbf{y}_f = (y_{1f}, ..., y_{mf})'$ with common factor y_f^* and unique factor ε_j^f Let τ denote the $m \times 1$ vector of diagonal elements of Θ_ε.

We assume further that functionings achievement is linearly determined by a vector of observable exogenous variables $\mathbf{x} = (x_1, ..., x_s)'$, and a stochastic error η, such that

$$y_f^* = \gamma_1^f x_1 + \gamma_2^f x_2 + ... + \gamma_s^f x_s + \eta_f. \tag{6}$$

The model hence comprises two parts: the measurement model in equation (5), which specifies how the observed endogenous variables are determined by the latent functioning, and the structural model in equation (6), which specifies the relationship between the functionings achievement and its causes. In terms of other applications of the capability approach, equation (5) corresponds to the factor analysis model, equation (6) to the regression model as in equation (4). However, the estimation of structural equation models differs significantly from this procedure as we will see shortly.

Since y_f^* is unobserved it is impossible to recover direct estimates of the structural parameters γ. However, if we combine equations (5) and (6) and solve for the reduced form representation, we can write

$$\mathbf{y}_f = \pi \mathbf{x} + \mathbf{v}_f \tag{7}$$

where $\pi = \mathbf{\Lambda}^{y_f} \gamma'$ is then the $m \times s$ reduced form coefficient matrix and $\mathbf{v}_f = \mathbf{\Lambda}^{y_f} \eta_f + \varepsilon_f$ is the reduced form disturbance with covariance matrix

$$\mathbf{\Theta}_{v_f} = E\left[\left(\mathbf{\Lambda}^{y_f} \eta_f + \varepsilon \right) \left(\mathbf{\Lambda}^{y_f} \eta_f + \varepsilon \right)' \right] = \sigma_\zeta^2 \mathbf{\Lambda}^{y_f} \mathbf{\Lambda}^{y_f\prime} + \mathbf{\Theta}_\varepsilon. \tag{8}$$

σ_η^2 is the variance of the structural stochastic error η.

The estimation of the free parameters ω^f in γ^f, $\mathbf{\Lambda}^f$,and $\mathbf{\Theta}_{v_f}$ is achieved by minimising the distance between the covariance matrix implied by the model $\Sigma\left(\omega^f\right)$ and the sample covariance matrix Σ^s of the observed data. This will be explained in detail in section 4.3 below.

One problem that has to be solved by appropriate specification is the indeterminacy of equations (7) and (8), which is due to the fact that the reduced form parameters are invariant to a transformation (multiplication or division) by a scalar. This follows from the fact that functionings are not directly observable, and have no defined unit of measurement. In order to be able to interpret parameter estimates it is necessary to define the origin and unit of measurement. This can either be achieved by standardising the latent variables to have unit variance, or by fixing a non-zero coefficient in $\mathbf{\Lambda}^{y_f}$. We chose the latter option because we are interested in using the scores later on in inequality analysis. Standardising the scores to have unit variance would be counterproductive in this case.

Another problem is whether or not the model is actually identified, i.e.

whether sufficient restrictions are imposed on the model to guarantee the absence of underidentification. A necessary condition for identification of all parameters, p is

$$p \leq \frac{1}{2}(m+s)(m+s+1) \tag{9}$$

where m is the number of indicators for functioning y_f^* and s is the number of independent variables. For the model to be exactly identified there exists one and only one combination of the independent parameters in $\mathbf{\Lambda}^y, \gamma$, and $\mathbf{\Theta}_\varepsilon$, which generates covariance matrix implied by the model. A sufficient condition for the MIMIC model to be identified is that $m \geq 3$ and $s \geq 1$.[7]

4.2 Ordinal Measurements

In the previous section we have implicitly assumed that all variables in the model are continuous. However, often household survey data is of qualitative nature, measured on ordinal scales such as Likert scales or measured by binary variables, such as answers to yes/no questions. An application of structural equation models, including standard factor models to these types of data is inappropriate if the ordinal measurement is not taken into account.

The principal problem is that ordinal variables do not have an origin or a unit of measurement, and therefore means, variances and covariances of these variables have no real meaning. As the estimation relies heavily on the covariance matrix, equation (5) does not represent a valid measurement equation in the presence of ordinal or binary variables.

It is possible, however, to construct a meaningful covariance matrix Σ^s of the observed data, even if they are measured on ordinal scales. For these purposes, assume that a latent continuous variable underlies every ordinal variable. For example, if the observed variable is health status, measured on a five-point Likert scale (e.g. excellent, good, fair, poor, very poor) it can be reasonably assumed that an underlying continuous variable exists. The

[7] For a derivation of these conditions see Bentler and Weeks [5].

respondent makes his choice on the scale depending on an implicit threshold observational rule, e.g. if his health status is worse than a certain threshold h^1, it is very poor, if it is worse than h^2, but better than h^1, it is poor. Is it better than h^4, his health status is excellent. These thresholds can be estimated, and based on these and a distributional assumption about the underlying variable, correlation coefficients of the underlying continuous variables can be estimated.

More formally, and following Joereskog [12], letting y^o and y^c denote respectively the ordinal variable with k categories and the underlying continuous counterpart respectively, the observational rule may be written as

$$y^o = \mathbf{1}\left(y^c \leq a_1\right) + \mathbf{1}\left(a_2 \leq y^c \leq a_3\right) 2 + ... + \mathbf{1}\left(a_{k-1} \leq y^c \leq a_k\right) k \qquad (10)$$

Thresholds $a_j,\ j = 1, ...k$ can be estimated once we assume a distribution for y^c, which in the case of a standard normal distribution generates thresholds

$$a_j = \Phi^{-1}\left(\sum_{i=1}^{j} \frac{N_i}{N}\right), \ j = 1, ...k \qquad (11)$$

where $\Phi^{-1}(.)$ is the inverse of the standard normal distribution function and N_i is the number of observations in category i. Once these k thresholds have been estimated for each ordinal variable, it is possible to calculate the correlation coefficients between the underlying continuous variables, say y_1^c and y_2^c each as follows. Let y_1^o and y_2^o have k categories each. Their marginal distribution can be represented by a contingency table with typical element $[n_{ij}]$ where n_{ij} is the number of cases in category i on y_1 and in category j on y_2. The underlying variables y_1^c and y_2^c are each assumed to be standard normally distributed so that it is reasonable to assume that y_1^c and y_2^c are distributed standard bivariate normal with correlation ρ. This ρ is called the polychoric (tetrachoric if $k = 2$) correlation. Let $a_1^1, ...a_k^1$ be the thresholds for y_1 and $a_1^2, ..., a_k^2$ the thresholds for y^2. The polychoric correlation can be estimated by maximising the log likelihood for the multinomial distribution,

$$\ln L = \sum_{k_1} \sum_{k2} n_{ij} \log \pi_{ij} (\theta) , \tag{12}$$

where $\pi(\theta) = \Pr[y_1 = i, y_2 = j] = \int_{a_{i-1}^1}^{a_i^1} \int_{a_{i-1}^2}^{a_i^2} \phi_2(u,v)\, dudv$ and ϕ is the standard bivariate normal density with correlation ρ.

Correlations between an observed continuous variable, and a continuous counterpart of an ordinal variable are called polyserial correlation coefficients. In case two continuous variables are present in the sample, the standard Pearson correlation coefficient can be used; these are the typical elements of Σ^s.

In summary, the estimation of model parameters when ordinal variables are involved generates the following stages: i) estimation of threshold values according to equation (11); ii) estimation of latent correlations (polychoric/polyserial) given estimated thresholds according to equation (12) and iii) estimation of model parameters conditional upon i) and ii) as described in the next section.

4.3 Estimation

The fundamental hypothesis for a structural equation model is that the covariance matrix of the observed variables, Σ^s, may be parameterised based upon a given model specification with parameter vector ω. A general form of a measure of fit between Σ^s and $\Sigma(\omega)$, may be written as

$$\begin{aligned} F(\omega) &= (s-\sigma)' W^{-1} (s-\sigma) \\ &= \sum_{g=1}^{k} \sum_{h=1}^{s} \sum_{i=1}^{k} \sum_{j=1}^{i} \omega^{gh,ij} (s_{gh} - \sigma_{gh}) (s_{ij} - \sigma_{ij}) , \end{aligned} \tag{13}$$

where $s = (s_{11}, s_{21}, ..., s_{kk})'$ is a vector of the elements of the lower half of $\mathbf{\Sigma}^s$ and $\sigma = (\sigma_{11}, \sigma_{12}, ..., \sigma_{kk})$ is the corresponding vector of $\mathbf{\Sigma}(\omega)$. $\omega^{gh,ij}$ is a typical element of a positive definite matrix $\mathbf{W}^{-1}$ of order $q \times q$, where $q = m + s$. In the context of weighted least squares $\omega^{gh,ij}$ is a consistent estimate of the asymptotic covariance between s_{gh} and s_{ij}. If the original variables are distributed multivariate normal then the general form for the asymptotic covariance matrix of Σ^s may be written

$$\lim_{n\to\infty} cov\left(s_{gh}, s_{ij}\right) = \left(\frac{1}{N}\right)\left(\sigma_{gh}\sigma_{hj} + \sigma_{gj}\sigma_{hi}\right) \tag{14}$$

Under normality, model parameters are estimated based upon minimising the function

$$F = \ln\left|\Sigma\left(\omega\right)\right| - \ln\left|\Sigma^s\right| + tr\left(\Sigma^s\Sigma\left(\omega\right)^{-1}\right) - \left(m+s\right) \tag{15}$$

In this paper, we estimate a variant of this model, where Σ^s contains the polychoric/polyserial correlations calculated as described in the previous section.

Once the parameters of the model are estimated, the latent variable scores y_i^{*f} for each individual i can be obtained by minimising

$$\begin{aligned} F &= \sum_{i=1}^{N}\left(\mathbf{y}_i^f - \widehat{\mathbf{\Lambda}^{yf}}y_i^*\right)'\widehat{\Theta_\varepsilon^{-1}}\left(\mathbf{y}_i^f - \widehat{\mathbf{\Lambda}^{yf}}y_i^*\right) \\ &\quad \text{subject to} \\ cov\left(y^{*f}\right) &= \frac{1}{N}\sum_{i=1}^{N} y_i^{*f}y_i^{*f}, \end{aligned} \tag{16}$$

where $\widehat{}$ indicates that estimated values of the parameters are used.

5 The Data

In this section, we provide a description of the data that enter both the measurement and the structural models. We first describe the data source, the

British Household Panel Survey (BHPS) and the characteristics of the data set used in this paper. In subsection 5.2, we justify the selection of indicators for measuring the two functionings, health and housing. In subsection 5.3, we take a closer look at the causal factors employed in the structural model to explain functionings achievement. In subsection 5.4 the tetrachoric correlation matrices between indicators and causal factors are presented.

5.1 The BHPS

The data used in this study are taken from the British Household Panel Survey (BHPS). Since 1991, the BHPS has been conducted as an annual panel survey of a representative sample of approximately 10,000 individuals over the age of 16 in more than 5,000 households. A household questionnaire is answered by the head of household and individual questionnaires answered by all individuals over 16 which are members of this household. In case of individuals which cannot be contacted directly or are too ill to fill in their own questionnaires a much shorter *proxy interview* is conducted with a family member. In case a person cannot be contacted otherwise, a telephone interview is used. Both proxy and phone interviews are eliminated from the present analysis as they do not provide the required data.

We chose to perform a comparative analysis of achieved functionings between 1991 and 2000, the first and last waves of the BHPS available at the time this paper was written. Covering almost a decade of governmental housing and health policy, the analysis will allow us to assess the differences in welfare achievement in the beginning of the 1990s compared to the beginning of the 21st century. We consider the waves as independent cross sections, i.e. we are not comparing welfare of the same cohort across the decade, but rather of two independent samples to separate the policy effect from a potential cohort effect. We chose only those individuals for the analysis who actually report income; the sample size for 1991 is 8870 individuals, for 2000 it is 7702. Missing data amounting to ca. 2%-4% of the data is considered missing at random.

The level of analysis chosen is the individual. In case of housing, the values of the indicator variables are projected onto the individual level, i.e. members living in the same household will have the same housing achievements.

5.2 Health and Housing

In this subsection, we describe the indicators used for the measurement of each functioning. For the selection of indicators, we applied the following criteria. a) The choice of indicators should be informative to the subject of analysis, i.e. variables referring to health problems should be used to indicate health, and variables referring to housing problems should be used to indicate housing. Though seemingly an obvious criterion, it is important to scrutinise the indicators for their relevance, as otherwise, spurious correlations between indicators can lead to a misinterpretation of the latent variable. b) The indicators should comprise a range of information, i.e. not cover only one area of the functioning (e.g. only physical health problems that affect mobility). a) and b) refer to the fact that the chosen range of indicators has to be both narrow enough to indicate the functionings they are supposed to indicate, and wide enough to cover most or all aspects of the functioning. c) We follow the literature on functionings measurement by using self-reported indicators of two types: those which are objectively verifiable (e.g. mobility problems) and those which are not (e.g. subjective health status). Finally, d) practical considerations concerning the availability of indicators in the household survey for the chosen years under analysis.

Most of the chosen indicators were dichotomous, indicating, e.g. the presence or absence of a particular health or housing problem. We chose to dichotomise the remainder of the indicators as well to measure all indicators on the same scale and avoid problems in the calculation of the correlation matrices as described in section 4.2 above. All variables are coded such that a 1 indicates absence of a problem, and a 0 indicates presence of a problem. This makes interpretation of the factor loadings and the structural parameters of the model straightforward.

Table 2 shows a summary of the indicators used in our analysis, and how they are dichotomised. For the health functioning we chose the indicators a) physical illness affects daily activity (such as walking for more than 10 minutes, going up the stairs, dressing) b) visits to the doctor (General Practioner) during the past year c) self-assessed health status. To indicate welfare in terms of housing, we chose a) problems with condensation, b) problems with rot in windows or floor, c) problems with heating (cannot keep the home warm), d) problems with space.

Table 2: Indicators for Health and Housing Functionings

	Coding	
Indicator	original code	dichotomous code
visits to doctor in past year	0, 1-2, 3-4, 5-10, >10	1 if ≤ 2, 0 otherwise
health limits daily activities	yes, no	1 if no, 0 otherwise
self-assessed health status over past 12 months	excellent, good, fair, poor, very poor	1 if excellent or good, 0 otherwise
problems with home: condensation	yes, no[/a]	1 if no, 0 otherwise
problems with home: keeping it warm	yes, no[/a]	1 if no, 0 otherwise
problems with home: rot in wood	yes, no[/a]	1 if no, 0 otherwise
problems with home: no space	yes, no[/a]	1 if no, 0 otherwise

[/a] in 1991, the original coding was "no problem, small problems, big problems"; we chose to recode 1 if no problem, 0 otherwise. This did not produce substantially different results from when the original coding was used.

In table 3 we present descriptive statistics for the health indicator for 1991 and 2000. In 2000, a higher proportion of individuals reports a worse self-assessed health status than in 1991, however, the amount of visits to GP remains the same.[8] More individuals also report that they are limited in their daily activities, which indicated that health overall has decreased.

Table 3: Distribution of Health Indicators 1991 and 2000

	1991		%	2000	
health indicator	0	1		0	1
health status	26.4	73.6		31.0	69.0
visits to GP	37.8	62.2		38.6	61.4
limits to daily activities	13.4	86.4		16.3	83.7

Table 4 shows descriptive statistics for the housing indicator for 1991 and 2000. We observe a sharp decrease in all problems related to housing over the analysed period, with the exception of space problems. While the absence of condensation and cold problems could possibly be explained by different climate in the particular year, this is not the case with a long-term problem such as rot in the floors or windows. Therefore, a real improvement in housing quality seems to have taken place.[9]

Table 4: Distribution of Housing Indicators 1991 and 2000

	1991		%	2001	
housing indicator	0	1		0	1
condensation	33.2	66.8		13.6	86.4
cold	22.9	77.1		4.7	95.5
rot	21.6	78.4		6.9	93.1
no space	22.7	77.3		22.0	78.0

[8] This is confirmed when studying the originally coded variable (no. of visits to GP) as well.

[9] A different explanation might be that our recoding of small and big problems into the category "problems" in 1991 is inadequate. Using the original coding, however, lead to substantially the same results as the recoded dichotomous variable.

5.3 The "causal" factors

Recall from equation (1) that the achievement of functioning b_i^j by individual i is linked through the conversion function f_i to resources $\mathbf{q}$ available to the individual and depends on personal, social and environmental characteristics, $\mathbf{z}$

$$b_{ij} = f_i \left(c \left(\mathbf{q}_i \right), \mathbf{z}_i \right).$$

This conversion function is used to motivate the explanatory variables in our model. Although it is beyond the scope of this paper to estimate a *functioning production function* in the technical sense for each of these functionings, we expect to find significant effects of resources and circumstances on the achievement of housing and health. These tell us how welfare achievement is related to income and socioeconomic background, even if we cannot interpret the coefficients as strictly causal relationships.

Resources are understood in a wide sense, i.e. financial income and capital as well as non-market resources, such as education. We use equivalised household income and education as resource variables. We expect that all resource variables have a positive impact, both on health and housing. It can be expected, however, that housing, which is more related to material welfare, is more sensitive to household income than health, which is also determined by unobservable genetic factors.

Personal and environmental characteristics can influence the conversion from resources into achievements and hence welfare. Among the causal factors we include therefore personal attributes such as gender, age, job status and whether an individual lives in the London area. Descriptive statistics for these variables are presented in tables 5 and 6. slightly more than half of the respondents are female, possibly because more male individuals respond by phone or proxy interview, which are excluded from the sample. 41.9% of the sample are either self-employed or employed in 1991, compared to 39.5% in 2001. Similarly, the marriage or cohabiting rate has slightly decreased in

2000, down 1% from 34.7% in 1991. The amount of individuals with higher education has strongly increased from 24.5% to 39.3% of the sample in 2000. Finally, the percentage of individuals living in London is slightly reduced in 2000, with about 8.6% of the individuals living in the capital.

Table 5: Distribution of Causal Factors (dichotomous)

	1991		%	2000	
variable	0	1		0	1
gender (1 female)	47.4	52.6		47.2	52.8
job status (1 if self-employed)	41.9	58.1		39.5	60.5
married (1 if married, cohabiting)	34.7	65.3		33.8	66.2
education (1 if higher qualification)	75.5	24.5		60.7	39.3
london (1 if living in London)	90.1	9.9		91.4	8.6

The average age of the sample has slightly increased over the 10 year period under analysis. This might explain some of the bigger health and mobility problems which are suggested in table 3. The income variable is equivalised net income, inflated to 2001 prices, as provided by Bardasi et al. [4]. Average annual equivalised net household income in 1991 is GBP 15,899, which increases to GBP 19,079 in 2001.

Table 6: Descriptive Statistics of Causal Factors (continuous)

	1991		2000	
variable	mean	s.d.	mean	s.d.
age	44.65	18.48	46.17	18.46
income (GBP, prices of 2001)	15899	9295	19079	11952

5.4 Correlation Matrices

In tables 7 and 8 we present the tetrachoric correlation matrices of the health and housing indicators for 1991 and 2000. As we have described in section

4.2, tetrachoric correlations between dichotomic variables correspond to the standard correlation coefficients between the latent, continuous variables underlying each of the indicators. They can be interpreted just as standard correlation coefficients.

The correlations between the different health indicators in 1991 are high, between 0.55 and 0.72, allowing the conclusion that a close relationship between these variables exist. Similarly, the correlations between the different housing indicators are high, with the exception of the correlation between problems with rot and problems with space. As can be reasonably expected, the correlation between housing and health indicators is low. This picture is mirrored in 2000, with similarly high correlation coefficients within both health and housing indicators, and low correlations between housing and health indicators.

Table 7: Tetrachoric Correlation Matrix of Indicators 1991

	Health			**Housing**			
	limits	visits	status	cond	cold	rot	space
Health							
limits daily activities	1.00						
visits to doctor	0.55	1.00					
health status	0.72	0.60	1.00				
Housing							
condensation	−0.05	0.01	0.07	1.00			
cold	0.10	0.10	0.17	0.43	1.00		
rot in wood	−0.01	0.01	0.05	0.37	0.41	1.00	
no space	−0.10	−0.04	−0.03	0.24	0.13	0.15	1.00

In tables 9 and 10 we observe the tetrachoric and polyserial correlation coefficients between the indicators for health and housing and the independent variables for 1991 and 2000. Polyserial correlations are those correlations between an observed continuous variable such as income, and the latent

Table 8: Tetrachoric Correlation Matrix of Indicators 2000

	Health			**Housing**			
	limits	visits	status	condens	cold	rot	space
Health							
limits daily activities	1.00						
visits to doctor	0.54	1.00					
health status	0.70	0.60	1.00				
Housing							
condensation	0.04	0.05	0.05	1.00			
cold	0.09	0.06	0.11	0.44	1.00		
rot in wood	0.07	−0.01	0.09	0.57	0.38	1.00	
no space	−0.00	0.03	0.03	0.26	0.30	0.15	1.00

continuous variable which underlies an ordinal variable. The health indicators are negatively correlated with gender, i.e. women seem to have more health problems, especially, they go to the doctor more often than men. As expected, the health indicators are negatively correlated with age, i.e. the older the individuals the more health problems they report. The correlation with education is positive, indicating that individuals with a higher degree have less health problems, possibly owing to less work-related health risks than blue-collar workers. The correlation between having a job and health is positive, as is the correlation between health and income. While it is plausible that higher income opens the door for better health care and hence better health, it is more probable that health problems have a negative impact on the employability of the individuals and hence their income. The effect of income and employment in the structural model for health below has therefore to be interpreted with special care, as the variables might be endogenous.

The housing indicators in 1991 are hardly correlated with gender, marriage or education. They are positively correlated with age, and negatively correlated with living in London. The indicators condensation and cold seem to be correlated with income, while rot and lack of space seem to be problems independent of income.

Table 9: Polychoric/Polyserial Correlations of Indicators and Causes 1991

	gender	age	job	married	edu	ln(in)	london
Health							
limits daily act.	−0.10	−0.41	0.52	0.10	0.18	0.21	−0.06
visits to doctor	−0.29	−0.17	0.33	0.04	0.12	0.14	0.02
health status	−0.10	−0.21	0.35	0.08	0.22	0.21	−0.02
Housing							
condensation	−0.01	0.17	−0.05	−0.02	0.04	0.10	−0.03
cold	−0.02	0.14	0.10	0.12	0.10	0.22	−0.02
rot	0.03	0.16	−0.05	0.00	−0.07	0.03	−0.08
no space	0.01	0.32	−0.17	−0.13	0.00	0.02	−0.05

The correlations of the health indicators in table 10 mirror closely those for 1991. In terms of housing, however, we observe a strengthening of the negative correlation with living in London, and of the positive correlation with income. Rot problems are no longer correlated with age, but rather with income. The correlations with gender, job, marriage and education remain small.

6 Results

This section is structured as follows: In subsection 6.1, we present the results for the measurement and structural model, and subsection 6.2 takes a closer look at the distribution of the latent variable scores as our measure of welfare as compared to the income measure. This permits a comparison with the traditional welfare measure, income, as well as an assessment of changes in achievements over the decade under analysis.

Table 10: Polychoric/Polyserial Correlation of Indicators and Causes 2000

	gender	age	job	married	edu	ln(in)	lond
Health							
limits daily act.	−0.09	−0.34	0.54	0.07	0.22	0.20	−0.02
visits to doctor	−0.30	−0.18	0.33	0.03	0.15	0.12	0.04
health status	−0.07	−0.25	0.35	0.05	0.21	0.17	0.02
Housing							
condensation	−0.03	0.16	0.01	0.04	0.03	0.14	−0.13
cold	−0.01	0.16	−0.02	0.10	0.09	0.21	−0.03
rot	−0.01	0.03	0.02	0.09	−0.05	0.12	−0.23
no space	−0.01	0.26	−0.11	−0.06	−0.03	0.07	−0.12

6.1 Results for Measurement and Structural Model

The results for the measurement model for 1991 and 2000 are presented in table 11. We observe high factor loadings, between 0.70 and 0.93 in the model for the health functioning, for both years under analysis. The explanatory power of each indicator for the latent variable ranges between 0.50 and 0.86. We also observe that in this case, a simple averaging of the indicators would not have led to a good approximation of the underlying latent functioning; too different are the contributions of each indicator to the health functioning.

The factor loadings for the housing functioning range between 0.29 for rot and 0.72 for space problems. The explanatory power of each indicator is lower than in the measurement model for health, but still acceptable. The low contribution of rot problems in 1991 is raised in the model for 2000. In the housing model for 2000, the factor loadings have converged to a range between 0.47 and 0.68, whereas the explanatory power ranges between 0.22 and 0.46. All factor loadings are significant at the 1% level.

Table 12 contains the results of the structural equations, i.e. an approximation of the conversion functions. The structural equations for Health are very similar for 1991 and 2000. Gender, age, and living in London all

Table 11: Parameter Estimates Measurement Model

Measurement Equation[a]				
	1991		2000	
	Λ^b	R^2	Λ^y	R^2
Health				
limits daily activities	0.930	0.865	0.935	0.876
visits to doctor	0.703	0.494	0.694	0.481
health status	0.840	0.705	0.822	0.676
Housing				
condensation	0.631	0.499	0.571	0.326
cold	0.542	0.294	0.581	0.338
rot	0.289	0.084	0.474	0.225
no space	0.721	0.520	0.685	0.469

[a] all loadings significant at 1% level

influence negatively the achievement of health. Employment has a positive coefficient, but given the potential endogeneity of this variable we cannot interpret this as a positive effect of employment on health achievement. A more careful analysis which we consider beyond the scope of this paper is necessary to establish such a claim. The same is true for the negative coefficient of marriage which indicates that married people are generally less healthy than non-married. Self-selection of the sick into couples or a lower propensity to get divorced could explain this negative relation as well.

For housing, we observe significant differences between the models for 1991 and 2000. In 1991, housing achievement was influenced positively by age, and negatively by marriage and living in London. The other variables were not significant. In 2000, however, we observe in addition a strong influence of income on housing achievement. Similarly, employment and being male has a significantly positive effect on housing achievement, which was not the case in 1991. The R^2 for all four models are in line with or exceeding

Table 12: Parameter Estimates Structural Model 1991 and 2000

	Structural Equation							
	1991				2000			
	Health		Housing		Health		Housing	
	γ^{health}		$\gamma^{housing}$		γ^{health}		$\gamma^{housing}$	
Variable								
log(income)	0.013		0.019		0.013		0.203	***
sex	−0.106	***	−0.022		−0.071	***	−0.049	***
age	−0.089	***	0.402	***	−0.063	***	0.367	***
education	0.042	*	0.046		0.029		0.036	
job	0.410	***	0.030		0.522	***	0.083	***
london	−0.052	*	−0.082	***	−0.093	***	−0.247	***
married	−0.102	***	−0.166	***	−0.144	***	−0.171	***
R^2	0.252		0.178		0.192		0.320	

*, **, *** denote significance at 10%, 5% and 1% level respectively

the values for score regressions reported in the literature.

Table 13 gives an overview over the overall goodness of fit measures of the model. The χ^2-values exceed the critical value (49 in both cases) by far; however in microanalyses this is often the case as the χ^2 depends on the sample size, which is very large in this sample. Neither of the models manages to fall below the critical value of the root mean square error approximation (RMSE; critical value 0.05), but the values are close to the critical value. Both the goodness of fit index (GFI) and the adjusted goodness of fit index (AFGI) indicate a good overall fit of the models.

To summarise, our approximated conversion functions explain satisfactorily the achievement of health and housing. The role of material resources (income) is negligible, with the exception of housing achievement in 2000, while conversion factors such as gender, age and region of living have a significant impact. In this context, we are aware that several potentially important variables are not taken into account for lack of data, in particu-

Table 13: Goodness of Fit Measures

Measure	1991	2000
χ^2	1084.20	1486.88
RMSEA	0.0613	0.0582
GFI	0.988	0.989
AGFI	0.974	0.977

lar unobservable variables such as the genetic resources of an individual, or quality and quantity of nutrition for the health functioning.

6.2 Functioning Scores and Income in Comparison

In this section, we use the factor scores for housing and health to compare welfare achievement across the last decade of the 20th century, and to illustrate how the conclusions of a functioning-based analysis differ from a money-metric one. For these purposes, we use the scores estimated from the measurement model only.

Given that social policy is often directed to relieve the situation of the most deprived, we will illustrate the use of functionings analysis for this subgroup of society. In table 14 we present the distribution of functioning scores for each year (in %), according to certain sociodemographic subgroups. We only study the poorest decile of each functioning, i.e. those individuals who find themselves in the first decile of each of the functionings. To interpret the numbers correctly, the percentage for each functioning should be compared with the corresponding percentage in the overall sample. For example, while we have 46.4% of male individuals in the sample, we find only 38.6% of male individuals with health scores in the first decile. One could say, women are more than proportionately health-poor. The percentage of health-poor women increases over the decade by about 5 percentage points, while the overall sample composition hardly changes. This indicates that gender inequality in terms of health has increased from 1991 to 2000. The distribution of housing scores in the lower decile, however, seems in accordance with the sample distribution. This might be because housing is a household level variable, and in case of families, is automatically equally distributed between males and females. The same would however be true for household income, which shows an even stronger gender inequality in favour of men than the health functioning. While this income inequality can be explained by the fact that lone mothers or widows often have lower income than male singles, it seems that this does not have any impact on the housing quality of the different subgroups.

When studying the scores distribution according to age classes, we observe -as can be expected- that a disproportionate amount of older individuals finds itself in the lower health decile, while the young are underrepresented. This is stable across the decade. In terms of housing, however, the young are those with a more than proportionate representation in the poor decile. Income shows a similar picture, with the young overrepresented in the poor decile. Interestingly, it is the over 75s who are also overrepresented in the poor decile. Thus, it does not seem to be the pension age, which throws individuals into poverty, but something that happens ten years later.

Married and cohabiting individuals are slightly underrepresented in the lower decile of both health and housing in 1991, i.e. they are better off than their non-married counterparts, but this is compensated for both functionings in 2000. For income, however, married and cohabiting people are very much underrepresented in the lower income decile.

Interesting is also the distribution according to education. Individuals with a higher degree are underrepresented in all functionings in the lower decile; while this can be expected for income, it is interesting that this is also the case for health. The underrepresentation in the first housing decile, which is clearly present in 1991, is compensated for by 2000.

Table 14: Distribution of Functioning Scores and Income

	Sample		Health		Housing		Income	
Variable	1991	2000	1991	2000	1991	2000	1991	2000
male	46.4	45.9	38.6	33.9	43.8	44.8	38.7	40.5
female	53.6	54.1	61.5	66.1	56.2	55.2	61.3	59.5
age 16-25	16.9	14.7	6.7	6.9	23.7	17.4	19.7	22.5
age 26-35	20.9	19.2	7.7	16.8	28.1	24.6	19.9	14.2
age 36-45	18.5	20.2	11.6	17.4	17.9	22.1	13.3	16.0
age 46-55	14.7	16.2	17.7	18.3	11.8	13.7	9.7	11.0
age 56-65	11.9	12.4	18.9	15.3	7.1	10.0	10.2	10.9
age 66-70	6.1	4.8	12.1	5.4	3.9	2.8	6.5	3.3
age 71-75	3.9	3.5	8.4	5.7	2.6	3.5	5.0	5.3
age > 75	7.1	9.0	16.9	14.1	4.9	5.8	15.8	17.0
London	10.4	8.9	11.7	9.3	9.7	11.2	9.3	7.0
not London	89.6	91.1	88.3	90.7	90.3	88.8	90.7	93.0
married/coh.	65.5	66.1	58.9	65.8	61.0	65.5	44.8	44.6
not married	34.5	33.9	41.1	34.2	39.0	34.5	55.2	55.4
higher degree	23.9	38.9	15.1	28.5	17.8	36.7	10.6	20.2
no high. deg.	76.1	61.1	84.9	71.5	82.2	63.3	89.4	79.8
employed	58.0	60.4	19.7	25.2	49.8	56.6	23.9	27.9
not employed	42.0	39.6	80.3	74.8	50.2	43.4	76.1	27.1

7 Conclusion

The aim of this paper was to explore the usefulness of structural equation modelling for the measurement of standard of living or quality of life. We used Sen's capability approach to motivate the use of outcome-based measures to assess individual welfare and to justify their relationship to resources and individual and environmental characteristics. We applied structural equation modelling to the measurement of health and housing levels in the UK over the decade 1991 to 2000, to compare these achievements with traditional income-based measures. We confirm our expectation that resource-based measures cannot capture well what is happening on the standard of living level. When comparing our results with the development of the government's leading indicators for housing and health we can confirm that housing levels have improved. We note, however that health quality is reduced when measured by our indicators, which possibly reflects the increase of life expectancy at the cost of more years lived in poor health. Furthermore, assessment on the individual level allows us to analyse individual poverty in terms of quality of life. We observe for example a high level of gender inequality in terms of health and income. When interpreting these results, however, we have to remember to caveats. Firstly, those living in most precarious housing conditions, the homeless, are not included in the BHPS data. And secondly, we cannot assess child poverty, as only individuals over 16 are included in the survey.

References

[1] Sabina Alkire. *Valuing Freedoms: Sen's Capability Approach and Poverty Reduction*. Oxford University Press, Oxford, 2002.

[2] Anthony B. Atkinson and F. Bourguignon. The Comparison of Multi-Dimensioned Distribution of Economic Status. *Review of Economic*

Studies, 49:183–201, 1982.

[3] Anthony B. Atkinson and F. Bourguignon. Income Distribution and Differences in Needs. In George F. Feiwel, editor, *Arrow and the Foundations of the Theory of Economic Policy*, pages 350–370. Macmillan Press, London, 1987.

[4] Elena Bardasi, Stephen Jenkins, and John A. Rigg. Documentation for Derived Current and Annual Net Household Income Variables, BHPS waves 1-9. *mimeo,University of Essex*, 2001.

[5] Peter M. Bentler and David G. Weeks. Linear Structural Equations with Latent Variables. *Psychometrika*, 45(3):289–308, 1980.

[6] Francois Bourguignon and Satya R. Chakravarty. A Family of Multidimensional Poverty Measures. In D. Slottje, editor, *Advances in Econometrics, Income Distribution and Methodology of Science*. Springer Verlag, London, 1999.

[7] Francois Bourguignon and Satya R. Chakravarty. The measurement of Multidimensional Poverty. *Journal of Economic Inequality*, 1, 2003.

[8] Tania Burchardt and Julian Le Grand. Constraint and Opportunity: Identifying Voluntary Non-Employment. *CASE Working Paper*, (55), 2002.

[9] W. Gorman. A Possible Procedure for Analyzing Quality Differentials in the Egg-Market. *Review of Economic Studies*, 47:843–856, 1980.

[10] Joseph G. Hirschberg, Esfandiar Maasoumi, and Daniel J. Slottje. Clusters of Attributes and Well-Being in the USA. *Journal of Applied Econometrics*, 16:445–460, 2001.

[11] K. G. Joereskog. The Analysis of Covariance Stuctures. *The Scandinavian Journal of Statistics*, 8:65–92, 1981.

[12] K. G. Joereskog. Analysis of Ordinal Variables 2: Cross-Sectional Data. *Mimeo, SSI Website*, 2001.

[13] K. G. Joereskog and Goldberger. Estimation of a Model with Multiple Indicators and Multiples Causes of a Single Latent Variable. *Journal of the American Statistical Association*, 70:637–639, 1975.

[14] Stephan Klasen. Measuring Poverty and Deprivation in South Africa. *Review of Income and Wealth*, 46:33–58, 2000.

[15] Serge-Christoph Kolm. Multidimensional Egalitarianism. *Quarterly Journal of Economics*, 91:1–13, 1977.

[16] Wiebke Kuklys. Measuring Standard of Living in the UK - An Application of Sen's Capability Approach Using Structural Equation Modelling. *Max Planck Institute for Research Into Economic Systems: Papers on Strategic Interaction*.

[17] Wiebke Kuklys and Ingrid Robeyns. Sen's Capability Approach to Welfare Economics. *Cambridge Working Papers on Economics*, (0415), 2004.

[18] K. Lancaster. A New Approach to Consumer Theory. *Journal of Political Economy*, 74:132–157, 1966.

[19] Sara Lelli. Factor Analysis vs. Fuzzy Sets Theory: Assessing the Influence of Different Techniques on Sen's Functioning Approach. *Center of Economic Studies Discussion Paper, KU Leuven*, DPS 01.21, 2001.

[20] Esfandiar Maasoumi. The Measurement and Decomposition of Multi-Dimensional Inequality. *Econometrica*, 54(4):991–997, 1986.

[21] Esfandiar Maasoumi. Composite Indices of Income and Other Developmental Indicators: A General Approach. *Research on Economic Inequality*, 1:269–286, 1989.

[22] Esfandiar Maasoumi. Continuously Distributed Attributes and Measures of Multivariate Inequality. *Journal of Econometrics*, 42:131–144, 1989.

[23] Esfandiar Maasoumi and Gerald Nickelsburg. Multivariate Measures of Wellbeing and an Analysis of Inequality in the Michigan Data. *Journal of Business and Economic Statistics*, 6(3):327–334, 1988.

[24] Enrica Chiappero Martinetti. A Multidimensional Assessment of Well-Being Based on Sen's Functioning Approach. *Rivista Internazionale di Scienze Sociali*, 2, 2000.

[25] Mozaffar Qizilbash. A Note on the Measurement of Poverty and Vulnerability in the South African Context. *Journal of International Development*, 14:757–772, 2002.

[26] Martin Raiser, Maria Laura DiTommaso, and Melvyn Weeks. The Measurement and Determination of Institutional Change: Evidence from Transition Economics. *DAE Working Paper*, 29, 2000.

[27] Rati Ram. Composite Indices of Physical Quality of Life, Basic Needs Fulfillment, and Income: A Principal Component Representation. *Journal of Development Economics*, 11:227–247, 1982.

[28] Erik Schokkaert and Luc Van Ootegem. Sen's Concept of the Living Standard Applied to the Belgian Unemployed. *Recherches Economiques de Louvain*, 56:429–450, 1990.

[29] Amartya K. Sen. *Commodities and Capabilities.* North Holland, Amsterdam, 1985.

[30] Amartya K. Sen. Capability and Well-Being. In Martha Nussbaum and Amartya K. Sen, editors, *The Quality of Life*, pages 30–53. Clarendon Press, Oxford, 1993.

[31] Amartya K. Sen. *Development as Freedom*. Oxford University Press, Oxford, 1999.

[32] Amartya K. Sen. Development as Capability Expansion. In Sakiko Fukuda-Parr and A.K. Shiva Kumar, editors, *Readings in Human Development. Concepts, Measures and Policies for a Development Paradigm*, pages 3–16. Oxford University Press, 2003.

[33] UNDP. *Human Development Report*. Oxford University Press, Oxford, 1990-2002.