



1004

**Disentangling the Circularity in
Sen's Capability Approach – An
Analysis of the Co-Evolution of Functioning
Achievement and Resources**

by

**Martin Binder
Alex Coad**

The *Papers on Economics and Evolution* are edited by the
Evolutionary Economics Group, MPI Jena. For editorial correspondence,
please contact: evopapers@econ.mpg.de

ISSN 1430-4716

Max Planck Institute of Economics
Evolutionary Economics Group
Kahlaische Str. 10
07745 Jena, Germany
Fax: ++49-3641-686868

© by the author

Disentangling the Circularity in Sen's Capability Approach - An Analysis of the Co-Evolution of Functioning Achievement and Resources[☆]

M. Binder^a, A. Coad^a

^aMax Planck Institute of Economics, Evolutionary Economics Group, Kahlaische Str.10, 07745 Jena, Germany

Abstract

There is an ambiguity in Amartya Sen's capability approach as to what constitutes an individual's resources, conversion factors and valuable functionings. What we here call the "circularity problem" points to the fact that all three concepts seem to be mutually endogenous and interrelated. All three are entangled and it can be conjectured that some functionings are resources for the achievement of other functionings, some resources can be conceived to be actually valuable functionings, and both could be conversion factors in the achievement of other functionings. To econometrically account for this interdependency we suggest a panel vector autoregression approach. We analyze the intertemporal interplay of the above factors over a time horizon of fifteen years using the BHPS data set for Great Britain, measuring individual well-being in functionings space with a set of basic functionings, comprising "being happy", "being healthy", "being nourished", "moving about freely", "being well-sheltered" and "having satisfying social relations". We find that there are indeed functionings that are resources for many other functionings (viz. "being happy") while other functionings are by and large independent, thus shedding light on a facet of the capability approach that has been neglected so far.

Key words: capability approach, vector autoregressions, functioning selection, co-evolution of functionings, circularity problem

JEL-classification: I12, I31, R15

1. Introduction

Despite initial doubts on its practical applicability, Amartya Sen's capability approach has spawned a huge array of empirical works trying to measure functioning achievement on

[☆]The authors are grateful for having been granted access to the BHPS data set, which was made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-Social Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here. We thank Tom Broekel for helpful comments and suggestions. Remaining errors are ours.

Email address: binder@econ.mpg.de (M. Binder)

an either micro or macro basis (Sen, 1984, 1985a,b): the empirical literature on functioning measurement has happily focussed on different, often *ad hoc* ranges of functionings and established several competing ways of measuring how well individuals are able to convert their resources into functioning achievement (see Kuklys, 2005, for a quite recent survey on the plethora of different studies). These exercises have not been slowed by still ongoing debates on unresolved issues of what to consider as valuable functionings or whether and how to aggregate several of them into one comprehensive measure of achieved functioning.

There is, however, a vexing problem that has so far been neglected, which results from the way key concepts in the capability approach are related to each other: one central tenet of the approach is that individuals achieve valuable functionings through the conversion of resources they command, subject to intervening conversion functions (and conversion factors). While conceptually clear cut, the relation between resources, functionings and their conversion is empirically less clear, since some functionings might be considered resources for other functionings, some resources might be actually considered functionings and so on. This problem, which we call the “circularity problem”, refers to an entanglement (or endogeneity) of these concepts that cannot easily be resolved. Consider the functioning “being in good health.” Clearly, an individual’s health seems to be influenced by that individual’s material resources (Smith, 1999; Gardner and Oswald, 2004). But then, achievement in this dimension would also affect the individual’s resources (sick individuals might not be able to pursue a job, see Arrow, 1996). Similarly, “being in good health” has an influence on “being happy”, but the reverse also holds (Easterlin, 2003).

Now consider the functioning “being educated”. Here, too, an individual’s education can be conjectured to be influenced by resources. But education can also have an influence on resources (individuals having invested in higher education tend to have better jobs and earn more money, see Becker, 1964). Moreover, the achievement in this dimension might strongly influence functioning achievement in the health dimension (better educated individuals tend to live healthier life-styles, see Grossman, 2005). This entanglement is exemplary for the more general problem that it is not altogether clear what an individual’s functionings are and what the individual’s resources are. The more functionings one looks at, the more interdependencies between them and the resources side can be expected (this also pertains to conversion factors that might be considered either resources or functionings in different contexts). Econometrically speaking, this creates the difficulty of deciding which factors should be on which side of the regression equation.

The preceding discussion highlights two important insights: First, in exploring individuals’ functionings achievement, one has to deal with a complex interplay of causal relationships, which are often badly understood. Second, the dynamic interplay of these factors has to be analyzed in more detail. While existing research mainly focuses on a limited set of functionings, it neglects the complex interaction between these and other variables, especially their intertemporal development. We may need to consider several different time lags to appreciate the richer structure of the dynamics of individual functioning achievement and possible feedback effects. While the circularity problem has been recently recognized as troubling the empirical measurement literature (Anand et al., 2005, p. 53), to our knowledge we are the first to offer a suitable methodology to address this issue.

What we suggest is using a framework to analyze the leads and lags in the interplay between different functionings, conversion factors and resources. Panel studies exist in the

capability literature, and are important because they allow us to remove individual-specific effects, thus providing more reliable identification of individual responses to changes in lifestyle and living conditions. This paper combines these two elements — time lags and panel data techniques — using ‘reduced-form’ vector autoregressions, a technique that has not been applied previously to the capability approach. By looking at what functioning, conversion factor or resource at one point in time has an influence on what functioning or resource at later points in time, we are able to analyze the lead and lag associations and hence examine the co-evolution of the variables in question.

Examining the bigger picture of this complex co-evolutionary process, we describe the dynamics of resources, conversion factors and functionings. A related contribution of this paper lies thus in its focus on human life experiences as complex evolving processes. We consider functionings and resources to be interdependent and mutually endogenous. We look at the co-evolution of a relatively large number of variables, allowing each to be associated with each other over a number of time lags. In this way, we take a more global view on the sources, processes, and dynamics of well-being in functionings space.

The paper is structured as follows. In section 2 we briefly present the capability approach. Section 3 is devoted to a discussion of the circularity problem and a methodology we deem well-suited to deal with it, namely a vector autoregressions approach. Section 4 then presents an empirical illustration of our approach. We use the British Household Panel Survey data set (BHPS) because it offers a rich variety of indicators for functioning achievement over a large temporal interval. For this exposition, we use well established and uncontroversial resources (income), conversion factors and (basic) functionings such as “being happy”, “being healthy”, “being nourished”, “moving about freely”, “being well-sheltered” and “having satisfying social relations” (of which the latter two are only available for a shorter time interval in our model). We explore the dynamics of these functionings and test the robustness of our findings for different subgroups. Section 5 concludes.

2. The Capability Approach

Amartya Sen’s capabilities and functionings approach is an evaluative framework to assess individual welfare (Sen, 1984, 1985a,b, 1992). In this account, living is seen as consisting of a set of functionings, which could be described as different aspects of life, or the achievements of an individual. They give us information about what a person is and what she does. For an assessment of a person’s well-being, Sen proposes not only “being happy” (as in the utilitarian tradition) but other intrinsic values as well: other functionings are for example “being nourished”, “avoiding premature mortality” (Sen, 1992, p. 39) or “being in good health”, “being well-sheltered”, “being educated” or “moving about freely” (Kuklys, 2005, p. 10), making the approach multi-dimensional as a person’s state of being (and her individual activities) is a vector of functionings. This intuition has been formalized by Sen (1985a):¹ a vector of functionings can be described in set-theoretic notation as

$$\vec{b} = f_i(c(\vec{x})|\vec{z}_i, \vec{z}_e, \vec{z}_s) \quad (1)$$

¹We follow Kuklys (2005) in notation.

where \vec{b} , the vector of functionings is defined by the following elements: $\vec{x} \in X$ is a vector of commodities out of the set of all possible commodities (or more generally: resources) X . This includes *expressis verbis* non-market goods and services as well. \vec{x} is mapped into the space of characteristics (Lancaster, 1966) via the conversion function $c(\bullet)$ so that $\vec{c} = c(\vec{x})$ would be a characteristics vector of a given commodity vector \vec{x} . The characteristics of a commodity do not vary across individuals, i.e. they are the same for everyone. What does vary, however, is the way individuals can benefit from the characteristics of a commodity. Think of a person who possesses a loaf of bread. Someone suffering from a parasitic disease would benefit less from the characteristic “caloric content” than someone being well-fed (Sen, 1985a, p. 9). This is reflected by the conversion function of an individual $f_i \in F_i$ that maps a vector of characteristics into the space of functionings (F is the set of all possible conversion functions). This conversion is influenced by the conversion factors \vec{z}_k , where we can distinguish individual (\vec{z}_i), social (\vec{z}_s) and environmental (\vec{z}_e) influences (Kuklys, 2005, p. 11). Individual factors could be gender, intelligence, physical (dis)abilities, etc. Social influences are legal regulations, population density, etc. Examples for environmental factors include climate, environmental pollution and so on. These conversion factors can be seen as non-monetary constraints an individual faces. Note that selection of some of the conversion functions is part of an individual’s capability to function while, of course, some conversion functions are just not eligible, e.g. being female or male, and thus outside an individual’s control (Sen, 1985a).

When choosing what way of life to live, a person chooses, depending on her idiosyncratic preferences, from different functioning vectors. The set of all feasible functioning vectors for a person i is this person’s *capability set* Q_i . It is a derived notion and represents the person’s opportunities to achieve well-being, reflecting the various functionings that are potentially achievable (given her constraints X_i, \vec{z}_k). This set can now be defined as

$$Q_i(X_i) = \left\{ \vec{b}_i \mid \vec{b}_i = f_i(c(\vec{x}_i) \mid \vec{z}_i, \vec{z}_e, \vec{z}_s) \forall f_i \in F_i \wedge \forall \vec{x}_i \in X_i \right\} \quad (2)$$

The capability approach has been devised with a certain openness regarding the selection of a set of valuable functionings. While Sen favours this openness and stresses the deliberative social dimension that is involved in choosing a set of valuable functionings, other authors have promoted lists of functionings that supposedly reflect a common consensus of what is valuable (e.g. Nussbaum, 2000). Note that this indeterminacy of the approach has resulted in an empirical measurement literature that often measures welfare over an *ad hoc* range of different functionings. Moreover, most of the empirical approaches do not work at an individual level but use macro level data. A second difficulty lies in measuring the actual *capability* to function (for an attempt to do so see Anand et al., 2005; Anand and Hees, 2006), but also the empirical examination of conversion factors and functions has received comparatively less attention in the literature (but see Binder and Broekel, 2008; Deutsch et al., 2003).

3. Vector Autoregression Methodology

What most of the literature on the capability approach crucially neglects is the fact that all of the main variables, functionings, resources and conversion factors, are in fact inter-related and mutually endogenous. As stated in the introduction, the achieved functioning

“being in good health” seems to be influenced by an individual’s resources (Smith, 1999; Gardner and Oswald, 2004), but the achievement in this dimension would also affect the individual’s resources (Arrow, 1996). Similarly, an individual’s education might be influenced by resources, but education has also an influence on resources as individuals with higher education tend to earn more money. Moreover, the achievement in this dimension might strongly influence functioning achievement in the health dimension (better educated individuals tend to live healthier life-styles, see Grossman, 2005).

Similar interdependencies seem to exist for all conceivable functionings: it is well understood that “being happy” is associated with the functioning “having fulfilling social relations” (e.g., Myers, 1999), with marriage being the most important (one could also think of marriage as a conversion factor of an individual, however). Similarly, happiness is associated with being in good health (Easterlin, 2003) and to a certain degree happiness also seems to depend on an individual’s resources (Oswald, 1997; Stevenson and Wolfers, 2008). But this one-way identification would neglect that “being happy” is itself an important determinant of how healthy we are, how successful we are in social relations, and probably even how large our resources (income) are (Graham et al., 2004; Lyubomirsky et al., 2005). Basically, when examining any of the relationships between the above variables, there are competing hypotheses as to which direction the causal arrow points and explanatory hypotheses exist that could explain both directions. Coming back to our earlier example regarding the interplay between “being happy” and “being healthy”, Easterlin (2003) notes that it is not sure “which way the causal arrow runs: from health to life satisfaction or from life satisfaction to health” (p. 11177).

In fact all these variables are interrelated and mutually determined. It is our opinion that it is not realistic to view one variable as the exogenous stimulus and the other as the outcome. While an individual’s well-being is the outcome for some variables, it is also a determinant of other variables. It would be better to view different variables as inextricably linked together and co-evolving over time. We aim to take a more complete, comprehensive view of the phenomenon in question by considering interactions between all of these main variables. We aim to better describe the procedures and dynamics of individual functioning achievement and the channels through which life events affect well-being in functionings space. In this context of complex interactions and mutually endogenous variables, we argue that an appropriate statistical technique for such a system would be a reduced-form vector autoregression. While a vector autoregression approach has been recently employed in the subjective well-being literature to analyze the interplay between happiness and social relations and various other factors (Becchetti et al., 2008; Binder and Coad, 2009), we want to make a case that this methodology can also be of considerable use within a broader, more complex, welfare framework such as the capability approach. Following on from the preceding discussion and our outline of the capability approach in section 2, we will later identify a system of interdependent variables (to wit, a set of “basic functionings”, resources and the most common conversion factors), to which we will apply a vector autoregression model in order to better describe the co-evolution of these variables.

While we are guided by theory in selecting these resources, conversion factors and functionings, the techniques we employ do not force us to assume specific causal relationships. We thus analyze how changes in these variables are *associated* with changes in the other variables. Although our focus on intertemporal associations is similar in spirit to ‘Granger-causality,’

we cannot guarantee the true causal nature of the relationships between the variables.² In macroeconomic applications of VARs, a precise understanding of the causal relations between variables is required to ensure that an exogenous policy shock to one variable will have the expected effects on other variables. In this paper, however, we have no strong policy recommendations concerning how an exogenous stimulus to one variable will affect other variables. Instead, we merely seek to describe the dynamic processes of the evolution of functionings and resources over time. At this preliminary stage of investigation, this methodology seems to be judicious.

3.1. Time-invariant individual effects and time lags

While early studies on functioning achievement were mostly cross-sectional analyses, scholars are becoming increasingly aware of the drawbacks of making inferences from cross-sectional data (Anand et al., 2005). One of the main statistical problems facing this body of research stems from the existence of time-invariant individual-specific components (also known as ‘fixed effects’) in outcome variables. Fixed effects are an important feature in contexts where most of the variance in functioning achievement is between individuals at a specific cross-section in time, rather than within individuals over time (this plays a role for functionings such as “being happy”, see Lykken and Tellegen, 1996). As a result, a longitudinal approach is to be preferred to a cross-sectional one, and individual-specific fixed effects need to be allowed for. In this paper, we control for fixed effects by taking first differences of the main variables: functioning achievement for individual i at time t can be broken down into a time-invariant fixed effect μ_i and a transitory component ϵ_{it} :

$$\text{Functioning achievement: } b_{it} = \mu_i + \epsilon_{it}. \quad (3)$$

By taking first differences, we can remove the influence of the time-invariant effect μ_i and thus remove any misleading influence that μ_i might have on the regression results. This is not unimportant in the case of achieved functionings such as “being happy” since subjective well-being does not only have state-like but also trait-like properties (Diener et al., 1999, pp. 279-80), thus being dependent not only on situational influences but also on stable personality and genes (Lykken and Tellegen, 1996).

While levels of functioning achievement are affected by both the fixed effect μ_i and the transitory component ϵ_{it} (equation (3)), changes in functioning achievement can be expressed purely in terms of changes in the transitory component (i.e., $\Delta\epsilon_{it}$; see equation (4)).

$$\Delta b_{it} = b_{it} - b_{i,t-1} = (\mu_i + \epsilon_{it}) - (\mu_i + \epsilon_{i,t-1}) = \epsilon_{it} - \epsilon_{i,t-1} = \Delta\epsilon_{it}. \quad (4)$$

²In fact, if we were to insist on identifying the true causal relationships between the variables, we would need to identify the instantaneous (i.e. ‘within-the-period’) influences of each variable on each other, and whatever methodology we pursued would be complicated and rather controversial. One approach would be to base ourselves on restrictive theoretical assumptions, but we would not be comfortable with this because theoretical assumptions are not always entirely realistic, and furthermore the capability approach is, at present, not sufficiently developed with respect to causal relationships between resources and functionings to guide empirical work. Alternatively we might pursue an empirical approach to establishing causality through the use of instrumental variables, but no suitable instruments are available to us in this particular case.

Removing the fixed effect in this way can be problematic if there is measurement error in the variables, because taking differences may amplify the noise to signal ratio in the data set. As a result, there may be a small downward bias in the magnitudes of our coefficient estimates. Nonetheless, in our data set we have a large number of observations which should help in the identification of the coefficient estimates. In addition, in section 4.3 we investigate the robustness of our results in a number of directions.

When moving from cross-sectional to longitudinal data sets, the study of the time lags between key variables should also receive increasing attention. This might shed light on different dynamics present in the functionings variables, for example the effects of rising aspirations levels regarding some achievements or adaptation to achieved functionings levels. A case in point would be the functioning “being happy”: as is well known from happiness research, individuals easily adapt to the happiness that good things bring them over time (Frederick and Loewenstein, 1999). As a result, both short-term and longer-term effects need to be investigated. It is important to note that the traditional approaches mentioned in the previous subsections are restricted to the analysis of one dependent variable (such as achieved functioning “x”) without the possibility of endogenizing more variables in the same integrative framework, as would be allowed with the VAR methodology suggested in the present paper. Our analysis includes a number of time lags both before and after life events in order to appreciate the richer structure of the dynamics of individual well-being in functionings space.

3.2. The model

Our regression equation is the following:

$$b_{i,t} = \alpha + \sum_{\tau=t-s}^{t-1} \beta_{\tau} b_{i,\tau} + \gamma \cdot X_{i,t-1} + \varepsilon_{i,t}, \quad (5)$$

where b is a vector containing our main endogenous variables in functionings space ($t - s$ referring to the number of lags examined): X corresponds to a vector of control variables that are supposedly exogenous (i.e. age, gender, region, year dummies, etc.). β is a matrix of dimension 5×5 (7×7 in the model using the shorter time-period) and contains our main coefficients of interest. The coefficients in γ , relating to the control variables, are estimated in all regressions, but for the sake of space they are not reported in our results tables. ε corresponds to the usual residual error term. Put differently, each of the main variables has a turn at being the dependent variable, with lags of all main variables among the independent variables. Each variable is seen as a function of lagged values of itself and each other variable.

4. Data and Findings

4.1. Data set and functioning selection

The British Household Panel Survey (BHPS) is a longitudinal survey of private households in Great Britain, undertaken by the ESRC UK Longitudinal Studies Centre with the Institute for Social and Economic Research at the University of Essex, UK (BHPS, 2009). Its aim is to track social and economic change in a representative sample of the British population (for the following and more information on the data set, see Taylor, 2009). The BHPS started

as a nationally representative sample of 5,000 households, where adults (being of age sixteen and over) were interviewed and tracked over the years. The sample comprises about 15,000 individual interviews. Starting in 1991, up to now, there have been 17 waves of data collected with the aim of tracking the individuals of the first wave over time (there is a percentage of rotation as some individuals drop out of the sample over time and others are included, but attrition is quite low, see Taylor, 2009). The BHPS data contains information on various areas of the respondents' lives, ranging from income to jobs, household consumption, education, health, but also social and political values. In contrast to many approaches in the capability literature, we are thus using micro level data in our analysis.

We have already hinted at the theoretical problems related to selecting a list of functionings. From an empirical point of view, it has to be noted that there is quite a large amount of overlap between the different lists of functionings that are suggested in the literature; what often differs are indicators selected to capture functioning achievement, due to different data availability (Qizilbash, 2002).³ In constructing a suitable set of functionings, we face a trade-off between being able to track individuals in the panel over a long time horizon versus increasing the breadth of the set of functionings examined. The BHPS offers a rich variety of indicators for different functionings, but many indicators for functionings have not been elicited in many different waves. We have thus chosen to examine two different model specifications, one that tracks individuals and their functionings achievement in a smaller number of functionings over the full sample horizon (model 1) and a model specification that includes additional functionings but only over about half the sample horizon (model 2).

To construct a set of “basic functionings” we chose different indicators for the six functionings “being happy”, “being healthy”, “being nourished”, “moving about freely”, “being well-sheltered” and “having satisfying social relations”, of which the latter two are only available for the shorter model. All of these have been always prominent candidates in empirical studies on the capability approach and figure in many multidimensional welfare measures (Alkire, 2002b,a; Anand et al., 2005). We also examine “material well-being”, which can be a functioning, or as it is seen most often, it can be the proxy for the commodity vector in the capability framework (see section 2). Another functioning that is often used in the approach and that has a high theoretical plausibility is “being educated”. Although we would have liked to include this as a functioning in our analysis, the indicator that could be used to capture it (an individual's highest education level, see below) exhibits only the tiniest variance in its rate of change in the sample. While it would be inappropriate to use it as a dependent variable (i.e. expressed in differences), we use the education level as a control variable, thus treating it effectively as a conversion factor of an individual.

We will now discuss the indicators chosen to reflect our functionings as well as control variables that represent different conversion factors. Table 1 gives an overview of the descriptive statistics for the more extensive (longer) model specification.⁴ As we are using unbalanced panel data from 1991 to 2006 (waves 1 to 16), we have a total of 154,300 obser-

³This might also explain the finding by Ramos and Silber (2005) that the exact specification of a set of functionings does not seem overly critical for the resulting multidimensional welfare measure. The authors have demonstrated a great (empirical) similarity of the different approaches in their study (also using the BHPS data set).

⁴We have relegated the descriptive statistics for model 2 in the appendix (see Table 5).

variations after cleaning the panel: we had to drop one year because the coding of one of the variables was changed, and we discarded individuals who have not reported the indicators we use, leaving us effectively with 15 waves of data. Taking the changes in variables, we have 112,765 observations, yielding 59,927 observations for use in the regressions with the long model of lag length 2. Due to the nature of the data set, first differences are between years so that the lag structure is on an annual basis.

Table 1: Summary statistics of variables, model 1

Variable	Mean	Std. Dev.	Min.	Max.	N
Δ happiness	-0.068	5.244	-36	36	112,765
Δ log(inc)	0.015	0.458	-10.148	9.622	112,765
Δ health	-0.007	1.145	-7.805	8.142	112,765
Δ food	0.096	1.417	-10	10	112,765
Δ mobility	0.012	0.475	-3	3	112,765
age	45.185	18.501	15	99	154,300
gender	1.532	0.499	1	2	154,300
education	2.975	1.738	1	7	154,300
d_disabled	0.075	0.264	0	1	154,300
d_unemployed	0.038	0.192	0	1	154,300
d_sepdivwid	0.181	0.385	0	1	154,300

To assess “being happy” (*happiness*), we have decided on using the well-known GHQ-12 measure which tracks the individual’s assessment of “mental well-being” as a proxy of happiness or subjective well-being.⁵ This concept of mental well-being is relatively similar to the better known happiness measures. It is, however, more encompassing as it also relates to mental health. It is an index from the ‘General Health Questionnaire’ of the BHPS, composed of the answers to 12 questions that assess happiness, mental distress (such as existence of depression or anguish), and well-being. This subjective assessment is measured on a Likert scale from 0 to 36, which we have recoded to values of one (lowest well-being) to 37 (highest scores in mental well-being). This proxy is widely used in the psychological literature (for more details on this indicator see, e.g., Gardner and Oswald, 2007; Shields and Wheatley Price, 2005; Clark and Oswald, 2002). Note that we implicitly interpret our well-being measure as cardinal in using an OLS regression in the panel VAR (besides we use OLS for the income variables and continuous health, social and shelter variables in the models). This is justified for two reasons. First, such an interpretation is common in the psychological literature on well-being, and it has been shown that there are no substantial differences between both approaches in terms of the results they generate (Ferrer-i Carbonell and Frijters, 2004).⁶ Second, as our measure of well-being has 37 outcomes, the supposition

⁵The BHPS also asks for individuals’ life satisfaction scores. We have decided against using these for two reasons. First, the question was only introduced halfway into the sampling period, resulting in considerably lower observations. While we could have included it for the shorter model, we wanted to keep the composition of the functionings in both models constant. Second, there seem to be order effects in the way the question was elicited in the survey, casting some doubt on the validity of the answers.

⁶It seems that individuals convert ordinal response labels into similar numerical values such that these

of a cardinal underlying latent variable does not really seem problematic.

Turning to our measure of “material well-being” (*income*), which can be either seen as resource or functioning achievement, we have decided to use net equivalised annual household income (in British Pound Sterling), before housing costs and deflated to price level of 2008, as provided and detailed by Levy and Jenkins (2008). As equivalence scales, we have opted for applying the widely accepted McClements scale (McClements, 1977).⁷ Such an income measure has been extensively discussed in our context of the BHPS (Burchardt, 2005; Kuklys, 2005). In accordance with practice in the literature, we use the *logarithm* of the income measure in our analysis, assuming that it is the relative proportional change in income, rather than the absolute change in the amount of income, that is the relevant quantity for relating changes in income to changes in other variables.

To measure “being healthy” (*health*), we have chosen to use a mixture of subjective and objective indicators of health. For the former, we focus on an individual’s subjective assessment of health (during the last 12 months). This is ordinally scaled on a five point Likert scale, ranging from ‘excellent’ (five) to ‘very poor’ (one).⁸ Subjective assessments of health seem to predict objective health quite well in some cases (e.g., regarding morbidity). Whether objective health is sufficiently well captured by subjective health assessments is still debated (Johnston et al., 2007). In order to account for more objective aspects of individual health, we also included the number of days spent in hospital, the number of visits to a general practitioner as well as the number of serious accidents in the previous year (see the extensive descriptive statistics in Table 8 in the appendix).

While the aggregation of different indicators into one comprehensive functioning achievement measure is by no means trivial, we have opted for a simple Principal Component Analysis (PCA) for the aggregation exercise. Such a type of analysis has been used in the capability literature to aggregate functioning indicators as well as multiple functionings (e.g., Roche, 2008; Lelli, 2005; Klasen, 2000). Using this type of analysis is very convenient in our context, as this econometric procedure allows the data to determine the weights when aggregating the indicators for our functionings, thus not forcing us to stipulate *ad hoc* some artificial weighting scheme about which indicators should be given which weight. Via PCA, we can summarize the information of different indicators into one measure that contains the largest possible part of the variance of the indicators; in other words, it accounts for the

cardinal values equally divide up the response space (Praag, 1991; Clark et al., 2008). As opposed to this, the differences in results between model specifications that account for fixed effects and those which do not are substantial (Ferrer-i Carbonell and Frijters, 2004).

⁷The choice of an appropriate equivalence scale also seems to matter much when assessing poverty or income inequality (Buhmann et al., 1988). Future research could thus examine to what extent our results are robust with regard to the choice of such a scale. A second issue would be to assess to what extent noncash incomes such as subsidies for education or health services distort an individual’s income (Smeeding et al., 1993). Such transfers are to a degree already reflected in the way our income measure is calculated (see Levy and Jenkins, 2008).

⁸As in the case of well-being, we have reversed the numerical order of the Likert scale to consistently use higher values for higher ‘achievement’ in these domains. The original coding in the BHPS codes a value of one to be excellent health and five to be very poor health. Note further that in the 1999 wave, a different coding of this indicator has been used. Since comparability between the different scalings is nontrivial, we have chosen to discard the observations of this wave to have a more consistent panel at our disposal.

(empirically) largest share of variation in all components.⁹ The overall functioning “being healthy” is thus a continuous variable, derived from a PCA. With this measure, we can account for $\rho = 44.43\%$ of the underlying indicators’ variance. To further explore its goodness of fit, we calculated the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for the indicator (0.6227), which is acceptable. Finally note that these proxies are similar to the ones employed in other studies on functioning achievement (e.g., Lelli, 2001; Kuklys, 2005).

The functioning “being nourished” (*food*) can be approximated by the household weekly expenditure on food and grocery items. In the BHPS, this is measured in 12 categories (ranging from “under 10” to “160 or over” in GBP).¹⁰ This is admittedly a crude indicator, but it nevertheless offers a first approximation of this functioning which is otherwise not easily captured in this data set (on the relevance of this functioning see also Qizilbash, 2002, p. 468).

The functioning “moving about freely” (*mobility*) can be approximated by information on whether the household members have access to a car or van to move about at leisure. The number of cars available to household members is measured semi-cardinally on a scale from 0 to 3, where numbers correspond to numbers of cars except for the highest category, which denotes three or more cars. The same measure has been used by Robeyns (2006, p. 262).

For the two additional functionings “being well-sheltered” (*shelter*) and “having satisfying social relations” (*social*), we have again computed a composite measure using PCA. For “being well-sheltered”, we also use a mix of objective and subjective indicators. We use an individual’s satisfaction with her housing situation as a proxy. This is measured on a seven point Likert scale, where 1 denotes “not satisfied at all” and 7 denotes the individual is “completely satisfied”. A second subjective indicator would be whether an individual “likes the present neighbourhood” (binary variable). The objective indicators comprise the number of rooms of the individual’s house or flat as well as a variety of 11 possible housing problems. Such indicators are often used in the literature to approximate the underlying functioning (see Deutsch et al., 2003; Kuklys, 2005; Robeyns, 2006). While the BHPS is a rich source for assessing the quality of a person’s home based on answers to questions concerning “lack of space”, “rot in walls, floors etc.”, “leaky roof” and so on, such an indicator alone would have only a small variance and thus would not be suited for the analysis (the low variance might be due to overall quite favourable housing conditions in Great Britain).¹¹ Our measure

⁹While we are aware of possible drawbacks of such a procedure, viz. neglecting parts of the variance inherent in the indicators, we feel justified on ignoring these concerns in the present context. The main aim of our paper lies elsewhere, and we allow ourselves to remain agnostic on the concrete aggregation of indicators. Other measures might be equally appropriate, something which merits future research. There is also some discussion in the literature to what extent a standard Principal Component Analysis provides flawed estimates for discrete proxy variables. This is based on the contention that a Pearson correlation matrix, as is used in a standard PCA, would not make much econometric sense when it comes to binary or ordinal variables, hence different types of variables necessitate different types of correlation matrices to be used in a PCA. We follow the reasoning of Kolenikov and Angeles (2009), who argue that this is unnecessary in the case of ordinal variables, especially when the number of ordinal categories is five or more. Empirically, there tend to be only small differences between using a PCA with polychoric correlations and just treating ordinal variables as cardinal in a PCA. We therefore did the calculations with a standard (Pearson) PCA.

¹⁰In the first year, these expenditures were asked in continuous amounts of GBP, which could be easily transformed into these 12 categories by the authors, however.

¹¹See Table 8 in the appendix for more information on the housing conditions.

of “being well-sheltered” accounts for $\rho = 40.13\%$ of the indicators’ variance. Overall, our measure of housing quality also exhibits an acceptable KMO measure of 0.5976.

The final functioning we look at is “having satisfying social relations” (*social*) and we use an individual’s satisfaction with her social relations as an indicator for functioning achievement in this dimension, as well as two questions regarding the amount of contact to family, friends and neighbours (an index based on similar questions is used by Lelli, 2001; Ramos and Silber, 2005; Robeyns, 2006). The former is measured on a seven point Likert scale, where 1 denotes “not satisfied at all” and 7 denotes the individual is “completely satisfied”. The latter are ordinal scaled variables regarding the “frequency of talking to neighbours” and the “frequency of meeting people” (0 to 5, ranging from “never” to “on most days”). One could also include further objective indicators like the number of activities in organizations or answers to questions on whether the individual has persons to rely on in times of stress (e.g., as in the studies of Deutsch et al., 2003; Ramos and Silber, 2005), however, these indicators are only available for short time spans in the BHPS. Our overall functioning measure is again computed via PCA and accounts for $\rho = 41.29\%$ of the indicators’ variance. It yields an acceptable KMO measure of 0.5471.

The last category of variables concerns the (mostly individual) conversion factors, which we include in our analysis. These comprise of gender, age, and age² (note that we use the squared difference between age and mean-age instead of age² in order to avoid problems of multicollinearity) as well as some dummies regarding disability, being unemployed and individual marriage status (focussing on being separated, divorced or widowed) as a selection of some of the most important individual factors influencing achieved functioning (a similar set of factors was used also by Chiappero-Martinetti and Salardi, 2007). We have also added year dummies and a regional control variable for environmental conversion factors (the regional control variable distinguishes former Metropolitan Counties and Inner and Outer London areas). Of our sample, 53.2% were female. The mean age is 45.185 years (s.d. 18.501) with maximum age at 99 years and minimum age at 15 (younger individuals were not interviewed in the BHPS).

As alluded to above, we also conceive of “being educated” as a conversion factor represented by an individual’s highest level of education. This is measured ordinally, ranging from one (‘none of these’) to seven (‘higher degree’), giving intermediate values to the middle education levels.¹² This scale is widely used in the literature and education certainly seems to be an important functioning (Kuklys, 2005; Chiappero-Martinetti and Salardi, 2007; Ramos, 2008), the fact of which is highlighted by its prominent role of being one of the indicators of development in the HDI (UNDP, 2006). However, using first differences of education levels in preliminary analyses has shown that this measure lacks the requisite variance to be meaningfully applied within our regression framework. In other words, in our sample which focuses on British adults, education levels were empirically quite stationary and did not change much.¹³ We feel thus justified in treating education predominantly as a conversion factor that influences the other functionings but is rather not influenced (over the time period under consideration) by achievement in the other dimensions. This can be seen as

¹²For more information see Taylor (2009), App.2, pp. 18-9.

¹³Moreover, the coding of this variable is arguably quite “crude” (Robeyns, 2006, p. 256).

a first result of our co-evolutionary methodology, intended to clarify the interplay between different factors.

Table 2: Contemporaneous correlations in differences, model 1

Variables	Δ happiness	Δ log(inc)	Δ health	Δ food	Δ mobility	age	gender	education
Δ happiness	1.0000							
obs.								
Δ log(inc)	0.0076 (0.0111)	1.0000						
obs.	112765							
Δ health	0.1426 (0.0000)	0.0095 (0.0014)	1.0000					
obs.	112765	112765						
Δ food	0.0149 (0.0000)	0.0786 (0.0000)	0.0064 (0.0323)	1.0000				
obs.	112765	112765	112765					
Δ mobility	0.0073 (0.0139)	0.0972 (0.0000)	0.0094 (0.0016)	0.1520 (0.0000)	1.0000			
obs.	112765	112765	112765	112765				
age	0.0003 (0.9326)	-0.0068 (0.0229)	-0.0233 (0.0000)	-0.0041 (0.1727)	-0.0361 (0.0000)	1.0000		
obs.	112765	112765	112765	112765	112765			
gender	-0.0000 (0.9993)	0.0018 (0.5506)	0.0047 (0.1182)	0.0003 (0.9110)	-0.0034 (0.2602)	0.0353 (0.0000)	1.0000	
obs.	112765	112765	112765	112765	112765	154300		
education	0.0016 (0.5984)	0.0031 (0.3044)	0.0090 (0.0025)	0.0091 (0.0022)	0.0159 (0.0000)	-0.3424 (0.0000)	-0.0739 (0.0000)	1.0000
obs.	112765	112765	112765	112765	112765	154300	154300	

In Table 2, we report pairwise correlations between our indicators for the changes in the main and control variables. The correlations of most of our indicators, except for gender, are highly statistically significant. The correlations in differences are rather small in effect, the highest two correlations being between change in health and change in well-being ($r = 0.1426$), possibly due to the incorporation of some (mental) health aspects in the concept of mental well-being. There is also a high correlation between change in mobility and being nourished ($r = 0.1520$).¹⁴ It is noteworthy that all (significant) correlations between our main variables (changes in subjective well-being, health, income, being nourished and mobility) are positively associated. This is different with the control variables, where age is negatively correlated with most of the main variables (except for change in well-being, where the correlation is not significant), while education is positively correlated with the main variables (except for change in well-being, where the correlation is not significant). The gender control variable shows no significant association with any of our many variables.

Note that the correlations in Table 2 are in differences (pairwise correlations of *levels* can be found in Table 7 in the appendix). The pairwise correlations in levels are quite similar to those found in other studies (on the same data set, see Deutsch et al., 2003; Ramos and Silber, 2005). The low correlation of log equivalised income with some of the other variables shows that these other dimensions of well-being do indeed capture important information on

¹⁴The other comparatively high correlation in that table is between education and age ($r = -0.3424$), two of our control variables of which we report only levels, not differences. An explanation why age is negatively associated with education could be that the sample contains a large proportion of older individuals who do not hold as many high academic degrees as might be usual today.

individuals' well-being that cannot be captured by income variables. Such low correlation also suggests that income might not be an important resource for many relevant other functionings (however, income and both food and mobility functionings show high positive correlation, of which at least the former correlation might be explained by the way we measure functioning achievement "being nourished", i.e. via food expenditures). Due to the simplistic nature of this correlation analysis, this can be only a first approximation and one should probably not put too much emphasis on these correlations. For instance, these simple correlations do not include the relevant control variables. Moreover, note the differences between the pairwise correlations in both different model specifications (Table 2 and Table 6).

As an additional investigation of potential multicollinearity, we inspected the VIF diagnostics for the following VAR(2) model, which were all satisfactory. This lends further support to the validity of our regression methodology.

4.2. Results and discussion

The main findings of our vector autoregressions are summed up in Table 3 (for the long model 1) and in Table 4 (the short model 2). While we report the three-lag specification for model 1 in the appendix (Table 9), we focus in our interpretation of the results on the two-lag specification and disaggregate the findings by gender (Table 10 and Table 11 in the appendix). Although the results table may appear daunting at first sight, it is nonetheless easy to read. Each row of the results table corresponds to a regression, with the dependent variable being indicated in the first column. For example, the first row shows a regression in which the dependent variable is change in "being happy", and the independent variables are changes in happiness, income, health, food status and mobility, which are included as explanatory variables, at both one and two lags. Towards the end of the row, coefficients for some control variables can be found as well as the corresponding R^2 statistic. The dependent variable for the second row is change in income, and so on.

Due to the exploratory nature of our study, focusing on the signs instead of the absolute coefficient magnitudes seems to be the conservative choice. To begin with, the results are quite similar in the variables we have common in both model specifications. Throughout our data, we also observe negative autocorrelation for each of our variables.¹⁵ This is exhibited on the diagonals of the tables. If, for example, well-being increased the previous period, it is less likely to increase this period. This can be interpreted as evidence for adaptation effects, where individuals adjust to their new sources of well-being so that further increases are less likely (Frederick and Loewenstein, 1999). This is consistent with the view that happiness is not a random walk, but characterized by fluctuations around an individual-specific level, the so-called set-point theory of happiness (Lykken and Tellegen, 1996).

¹⁵Negative autocorrelation in differenced variables in VAR models has also been observed in other cases, such as firm growth (e.g. Coad, 2010).

Table 3: Regression results of a two-lag vector autoregression, full sample period, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***). The equations where changes in “being nourished” and “moving about freely” are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). For each regression we have 59,927 observations.

	β_{t-1}										β_{t-2}										sex	(pseudo-) R^2
	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi	qfachi	age	age2				
Δ hap	-.5645*** (.0059)	-.1561** (.0509)	.0393* (.0198)	-.0388* (.0159)	.0153 (.047)	-.2785*** (.0057)	-.1177* (.0486)	-.0226 (.0195)	-.0544*** (.0155)	-.0092 (.0458)	-.0016 (.0114)	.0003 (.0014)	-.0003*** (.000006)	-.0016 (.0114)	-.0003*** (.000006)	-.0016 (.0114)	-.0003*** (.000006)	-.0003*** (.000006)	-.0516 (-.0372)			
Δ inc	.0013*** (.0004)	-.4105*** (.0133)	-.0021 (.0016)	-.001 (.0015)	.0076 (.0046)	.0013* (.0004)	-.1952*** (.0109)	.0001 (.0016)	-.0031* (.0014)	.0109* (.0045)	-.0004 (.0009)	-.0008*** (.0002)	.00003*** (6.00e-06)	-.0004 (.0009)	.00003*** (6.00e-06)	-.0004 (.0009)	.00003*** (6.00e-06)	.0001 (.0032)	0.1603			
Δ hl	.0099*** (.001)	-.0307** (.0104)	-.4984*** (.0054)	.0067* (.0034)	.0026 (.0097)	.0062*** (.001)	-.0306** (.01)	-.2536*** (.005)	.0045 (.0033)	-.0242** (.0094)	-.0009 (.0025)	-.0021*** (.0003)	-.00004** (1.00e-05)	-.0009 (.0025)	-.00004** (1.00e-05)	-.0009 (.0025)	-.00004** (1.00e-05)	.018* (.0083)	0.2125			
Δ food	.0035*** (.001)	.0399*** (.0121)	-.0088* (.0041)	-.3926*** (.0044)	.1066*** (.011)	.002 (.001)	.0212 (.0115)	-.0016 (.0041)	-.1764*** (.0039)	.0627*** (.0106)	.005 (.0026)	-.0004 (.0003)	-.00009*** (1.00e-05)	.005 (.0026)	-.00009*** (1.00e-05)	.005 (.0026)	-.00009*** (1.00e-05)	.0061 (.0087)	0.0611			
Δ mobi	.004** (.0013)	.0872*** (.0155)	.0091 (.0054)	.0384*** (.0048)	-1.0229*** (.0151)	.002 (.0013)	.0682*** (.0151)	.0131* (.0054)	.0355*** (.0048)	-.5127*** (.0145)	.002 (.0034)	-.0028*** (.0005)	-.0001*** (.00002)	.002 (.0034)	-.0001*** (.00002)	.002 (.0034)	-.0001*** (.00002)	.0044 (.0115)	0.0984			

Table 4: Regression results of a two-lag vector autoregression, short sample period, additional functionalings, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***). The equations where are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). Control variables are included in the regressions but not reported here. For each regression we have 15, 587 observations.

	β_{t-1}												β_{t-2}					(pseudo-) R^2
	l-Δ hap	l-Δ inc	l-Δ hl	l-Δ food	l-Δ mobi	l-Δ social	l-Δ shelter	l-Δ hap	l-Δ inc	l-Δ hl	l-Δ food	l-Δ mobi	l-Δ social	l-Δ shelter				
Δ hap	-.5622*** (.0118)	-.2326* (.1009)	-.058 (.0407)	-.0308 (.0317)	.0334 (.0995)	.1026* (.045)	.0553 (.0477)	-.294*** (.0112)	-.119 (.1025)	-.0363 (.0396)	-.0367 (.0294)	-.0063 (.0926)	-.1097* (.044)	-.0055 (.0479)	0.2547			
Δ inc	.0014 (.0007)	-.3978*** (.0234)	-.0008 (.0032)	.0001 (.0028)	-.013 (.0083)	-.0018 (.0035)	.0067 (.0036)	.0015* (.0008)	-.1786*** (.0183)	.0012 (.0032)	-.0024 (.0027)	.0093 (.0081)	-.0058 (.0036)	-.0001 (.0036)	0.1430			
Δ hl	.0072*** (.0019)	-.0503* (.0199)	-.4883*** (.0109)	.0036 (.0062)	-.0079 (.0188)	-.0147 (.0094)	.0042 (.0101)	.0044* (.0019)	-.0461* (.0208)	-.2502*** (.0098)	.0044 (.0062)	-.0085 (.0189)	.0142 (.0094)	.0035 (.0104)	0.2041			
Δ food	.0021 (.002)	.0828*** (.0249)	-.0072 (.0086)	-.3967*** (.0085)	.084*** (.0217)	-.0036 (.01)	.0183 (.0109)	-.003 (.002)	.0453* (.0221)	-.0074 (.0083)	-.1809*** (.0075)	.0466* (.0213)	-.0055 (.01)	-.0104 (.0102)	0.0641			
Δ mobi	.005* (.0026)	.1073*** (.028)	.0242* (.0112)	.03** (.0092)	-1.0273*** (.0303)	-.0069 (.0127)	.0052 (.0138)	.0018 (.0026)	.1077*** (.0304)	.0281** (.0107)	.0229* (.0092)	-.5042*** (.0302)	-.018 (.0128)	-.0008 (.0133)	0.0982			
Δ social	.0037* (.0016)	-.0195 (.0196)	-.0044 (.0071)	-3.00e-06 (.0055)	-.0158 (.0161)	-.5775*** (.009)	.0241** (.0089)	.0033* (.0016)	.0222 (.0196)	-.0076 (.0069)	-.0073 (.0054)	-.0044 (.0157)	-.2658*** (.0091)	.0178* (.0084)	0.2649			
Δ shelter	-.0012 (.0017)	-.0044 (.0207)	.0025 (.0071)	.0172*** (.0056)	.0012 (.0178)	-.0066 (.0085)	-.4703*** (.0128)	-.0028 (.0017)	.0296 (.0195)	-.0065 (.0068)	.0015 (.0055)	-.0236 (.0172)	-.0186* (.0084)	-.1914*** (.0103)	0.1953			

When turning to the functioning “being happy”, we can confirm several findings from the happiness literature: perhaps quite strikingly, positive changes in this functioning have a positive effect on the other functioning achievements in subsequent periods (this effect is more pronounced for the first than the second lag). This is consistent with recent results on the beneficial effects of happiness on important life domains (Lyubomirsky et al., 2005; Binder and Coad, 2009). In the context of the capability approach, we can add that one’s subjective well-being is in a certain sense also a resource for an individual when it comes to higher functioning achievement for the health, food and mobility functionings. Positive changes in happiness are also followed by increases in income, however, this effect disappears in the disaggregation when focussing only on the female subsample. The positive influence of subjective well-being on health is also strikingly robust over all models and time lags. This can also be due, in part, to the fact that our well-being variable measures a broad mental well-being construct.

On the other hand, positive changes in the other functionings are followed by a decrease in mental well-being, except in the case of health and the social functioning in our model 2. Thus, while it can be seen that changes in mental well-being are positively and significantly related with all other functionings (see the contemporaneous correlation table, Table 2), the introduction of a time lag into the analysis shows that this does no longer hold in the intertemporal context, presumably due to adaptation processes related to the adjustment of well-being.

While income is mostly treated as a resource in the capability framework, our analysis reveals that (log equivalised) income is itself influenced by the changes in the achievement of other functionings. Beside the above-mentioned positive influence of increases in mental well-being on income (both in the first and second lag), individuals’ income is positively associated with positive changes in the mobility functionings (lags 2 and 3). Scoring higher on the mobility dimension has thus beneficial consequences for individuals’ financial situation (mobility is a resource to achieve higher “material well-being”). This effect cannot be found in the male subsample, but is present for females. An explanation of this finding could be a mobility gender gap. If males have already achieved high levels of functionings achievement for mobility, additional improvements would no longer have an impact on their financial situation. In other words: you might get a (better) job if you have (at least) one car at your disposal, but additional cars have no longer an effect here. Such an explanation is in line with existing findings that less women have access to cars than men (Robeyns, 2006), and it is also observed in our panel data, where the mobility functioning (approx. the number of cars) for men is on average 1.32 and for women 1.15.

Increases in the functioning “being nourished” are, on the contrary, negatively associated with changes in (log) income (also pertaining only to lags 2 and 3). Here this effect is robust with respect to the male subsample but not the female subsample. It is not at all clear how such improvements in one’s food functioning should negatively bear on one’s financial condition.¹⁶

Finally, and in accordance with existing literature, changes in income have manifold

¹⁶One could speculate that this is an effect of “overachievement” in the food dimension, such as obesity, that then negatively impacts on individuals’ ability to earn their living, but this speculation is not borne out by the data as we can see no negative relation between food and health achievements.

effects on changes of the other functionings: increases in income do positively influence the aforementioned food and mobility functionings (over most lags and in a quite robust fashion). This is not surprising and does not warrant much explanation: higher incomes of an individual can be used to purchase larger quantities of higher quality food. A similar rationale holds regarding mobility. On the other hand, increases in income are followed by decreases in health and happiness. For the latter, this points to an explanation in terms of hedonic adaptation or rising aspiration levels that accompany increases in income (Frederick and Loewenstein, 1999). Why increases in income should be also associated with a deterioration of an individual's health in this intertemporal fashion is less clear. It might be possible that one's focus on work and having a career (and thus rising incomes) leads to a comparative neglect of health issues. But this explanation cannot account for the finding that the negative association between changes in income and health is absent in the male subsample but present for the female subsample. Further research might fruitfully explore this phenomenon.

Functioning achievement "being healthy" is also a resource for certain functionings. It positively affects mental well-being (although the effect is not robust for the subgroups). Increases in health in lag 2 also are associated with higher mobility in the present, pointing to longer term effects of health on mobility. There is a negative association, however, with health and subsequent food functioning for females. It is difficult to explain this effect from our data and further investigation into this relationship is certainly necessary. The finding is especially puzzling since there is also a reverse effect that increases in food functioning achievement are followed by increases in health (the effect here is stronger for females than males).

The functioning "moving about freely" is (except for the negative autocorrelation) only positively affected by other functionings. Besides the interactions discussed already above, it is worth mentioning that increases in the food functioning in both previous periods lead to an increase in mobility (a finding that is robust through the different subgroups and models). Being adequately nourished is thus also a prerequisite for higher mobility (one could conjecture about an indirect effect here through better health, but since we control for health this effect we capture is a direct one). But the effect is also reverse: increases in the mobility functioning are positively associated with increases in the food functioning. This also is a direct effect (an individual with higher mobility has better access to food).

In contrast to the full sample horizon analysis of model 1, we can see that a shorter analysis with the two more functionings did not add much information. For the functionings common in both models, there are no reversed signs, although some of the significant results of model 1 are not present in the shorter model 2 (e.g., the positive influence of subjective well-being on the other functionings is not as strong in model 2, where "being nourished" and "material well-being", i.e. income, are no longer significantly positively influenced by "being happy"). Moreover, the social and shelter functionings are relatively isolated and do not interact in many ways with the other functionings.¹⁷

For the functioning "having fulfilling social relations", we note that these are associated with a subsequent increase in mental well-being. That is, we find that more social individuals

¹⁷The generally poor results in their case could of course be due to the coding of the variables or the shorter sample horizon, viz. fewer observations, which we cannot rule out completely.

tend to reap benefits in terms of their subsequent happiness, a finding also known from the subjective well-being literature (Myers, 1999). This effect is absent in the male subsample but can be found for females, maybe attributable to gender roles that put relatively more weight on the cultivation of social skills of females. Vice versa, increases in mental well-being are found to be followed by increases in the social functioning. Happier individuals tend to also be more successful in social matters. Interestingly, here the gender disaggregation differs in that this effect is found in the male subsample but not in the female subsample. The interplay of these two functionings over time thus show a marked difference between the two genders. By this we extend a finding of Robeyns (2006), who found a gender gap, with women more socially skilled, in a similarly coded social functioning (in a cross-section of the BHPS). A last finding regarding social functioning achievement is that an increase in living conditions is followed by increases in social achievement, one of the few effects where this functioning interacts with other functionings.

Concerning the aforementioned shelter functioning, it is probably worth noting that for the male subsample, improvement in the functionings “social relations”, “being in good health” and “moving about freely” are followed by decreases in living conditions two periods later, maybe suggesting that males do give higher priority to scoring on these functionings and neglect their dwelling conditions as a consequence (model 2, male subsample, corresponding result table not reported here). But overall, changes in housing thus do not influence — and are not influenced by — the other functionings, probably due to the fact that the housing conditions in the U.K. are already quite satisfactory (which can be seen in the low number of problems that individuals’ flats and houses have, see Table 8, appendix). But this also shows that the functioning “being well-sheltered” can be analysed comparatively better independent of other functionings in our data.

4.3. Robustness analysis

We explore the robustness of our previous findings in a number of ways. A natural way to do so is analysing the co-evolution of our variables of interest for various subgroups. We chose to focus here on subgroup analyses related to subgroups that might be disadvantaged by important life-events. This concerns the disabled, as well as individuals that are separated, divorced or widowed.¹⁸

Overall, the analysis for the latter subgroups suffered from the relatively low number of observations in differences which we had at our disposal. We report the subsample vector autoregressions in the appendix (Table 12 and Table 13) and focus here on a short discussion of some of the findings for the subgroup with disabilities. Studies in the capability literature show that disabled individuals need much higher incomes to achieve comparable levels of functionings achievement as healthy individuals (Zaidi and Burchardt, 2005; Kuklys, 2005). These disparities are not reflected in the equivalence scales applied to such analyses. We can contribute to this by reporting that we cannot find many of the temporal associations that changes in equivalised income on the full sample exhibited (see Table 12, appendix).

¹⁸We also conducted an analysis for the subgroup of unemployed but except for the negative autocorrelation of the individual functionings, no significant results were obtained. We attribute this to the relatively few individuals in this subgroup. In the short model for the unemployed, we only had 348 observations in differences.

This pertains to negative associations (for the disabled, increases in income do lead to lower subjective well-being only with a longer time lag) but also to positive associations (no longer positive effects of income on the food functioning). The positive effect of income on mobility, however, did stay present in this subsample. An explanation for this could lie in the different adaptation level disabled individuals are on: to the extent that they are jaded or hardened by their fate, it takes comparatively higher changes in income to either positively or negatively affect their other functionings (no matter in what direction).

A second observation pertains to the relationship between income and health, where we find that increases in health in lag 2 are followed by a decrease in current income. It could be conjectured that for this disadvantaged subgroup, improvements in health are literally bought at the expense of their material well-being, however, it is not clear how this would come about: even if healthcare is expensive and medical services were not fully covered by health insurance, this might not have a bearing on the income variable as it is used in this study. While these findings also reinforce the findings of the above studies that the disabled need much higher incomes to achieve comparable functioning achievement levels, further research might be necessary to explain this relationship.

To the extent that our robustness tests yield similar estimates as our main models, we think of this as a confirmation of the robustness of the main findings. For the subgroup analyses regarding being disabled, or separated, divorced or widowed, we can summarize our results as showing that these groups do not differ significantly in the ways functioning achievement influences other functionings and resources. That is, none of the intertemporal relationships discussed above are reversed for these subgroups. However, many of the relationships discussed above cannot be reproduced in these subsamples. We hasten to add that the absence of evidence should not be mistaken for evidence of absence, and thus the findings pertaining to effects not present discussed in this subsection might also be a result of the much smaller sample sizes. Furthermore, we have been focussing here on the *intertemporal dynamics* of these variables, not their absolute (or relative) levels. What we thus do not dispute is that these subgroups might exhibit significantly different absolute levels of functioning achievement: achievement levels have been shown to differ significantly for these subgroups in other studies (e.g. Kuklys, 2005).

5. Conclusion

In the present paper, we have argued that the capability approach is incomplete regarding the relation of its key concepts: one central tenet of the approach is that individuals achieve valuable functionings through the conversion of resources they command, subject to intervening conversion functions (and conversion factors). While conceptually clear cut, the relation between resources, functionings and their conversion is empirically less clear, since some functionings might be considered resources for other functionings, some resources might be actually considered functionings and so on. This problem, which we called the “circularity problem”, refers to an entanglement (or endogeneity) of these concepts that cannot be easily resolved. Such an entanglement is exemplary for the more general problem that it is not altogether clear what an individual’s functionings are and what the individual’s resources are. Econometrically speaking, this creates the difficulty of deciding which factors should be on which side of the regression equation. While this circularity problem has been

recently recognized as troubling the empirical measurement literature (Anand et al., 2005, p. 53), to our knowledge we are the first to offer a suitable methodology to address this issue (i.e. reduced-form vector autoregressions).

We have suggested using a framework to analyze the leads and lags in the interplay between different functionings, conversion factors and resources. This paper has combined two elements — time lags and panel data techniques (i.e. taking differences in longitudinal data to remove fixed effects) — using vector autoregressions, a technique that has not been applied previously to the capability approach, to examine what functioning, conversion factor or resource at one point in time has an influence on what functioning or resource at later points in time. By this, we were able to analyze the lead and lag associations and hence examine the co-evolution of the variables in question. Examining the bigger picture of this complex co-evolutionary process, we were able to disentangle the interplay between resources, conversion factors and functionings. In this way, we took a more global view on the sources, processes, and dynamics of well-being in functionings space. While we are guided by theory in selecting these resources, conversion factors and functionings, the techniques we used did not force us to assume specific causal relationships: we analyzed how changes in these variables are *associated* with changes in the other variables.

Using the BHPS data set for a time horizon of fifteen years, we were able to shed light on the diverse interactions between commonly analysed functionings and resources. We found that income is not only a resource but also a functioning that benefits from positive changes in other functionings, for example “being happy”, turning the latter effectively into a resource for the former. On the other hand, there are also functionings that stand more isolated in the analysis, which suggests that these can be more easily analyzed independently of their interactions with other variables. Overall, our analysis shows that it is important to be aware of these intertemporal interactions between resources and functionings in the capability framework in order to better understand the multiple dimensions of human well-being and their co-evolution over time.

Further work would do well to apply this framework to data on developing countries (subject to data restrictions). There would be different themes here. While food expenditures are often associated with obesity in developed countries, they are more closely related to malnutrition in developing countries. Also, opportunities are probably more evenly distributed among individuals in developed countries, but in developing countries it might be the case that the poor are hindered in many ways from leading an economically active life (e.g. prohibitively expensive schooling and healthcare, the caste system, and so on). Further work would also benefit from focusing on younger individuals (so that education is not fixed), given that development at a very early stage in life has long-term effects for later life.

Date: May 18, 2010; ca. 9,600 words

Appendix

Table 5: Summary statistics of variables, model 2

Variable	Mean	Std. Dev.	Min.	Max.	N
Δ happiness	-0.067	5.289	-36	36	47'887
Δ log(inc)	0.014	0.44	-10.148	9.558	47'887
Δ health	-0.003	1.126	-7.805	8.142	47'887
Δ food	0.108	1.432	-10	9	47'887
Δ mobility	0.015	0.465	-3	3	47'887
Δ shelter	0.025	0.979	-10.234	7.556	47'887
Δ social	0.008	0.997	-6.985	6.516	47'887
age	45.759	18.427	15	99	89'640
gender	1.533	0.499	1	2	89'640
education	3.083	1.756	1	7	89'640
d_disabled	0.091	0.288	0	1	89'640
d_unemployed	0.032	0.177	0	1	89'640
d_sepdivwid	0.183	0.386	0	1	89'640

Table 6: Contemporaneous correlations in differences, model 2

Variables	Δ happiness	Δ log(inc)	Δ health	Δ food	Δ mobility	Δ social	Δ shelter	age	gender	education
Δ happiness	1.0000									
obs.										
Δ log(inc)	0.0037 (0.4123)	1.0000								
obs.	47887									
Δ health	0.1507 (0.0000)	0.0080 (0.0807)	1.0000							
obs.	47887	47887								
Δ food	0.0163 (0.0003)	0.0723 (0.0000)	0.0031 (0.4949)	1.0000						
obs.	47887	47887	47887							
Δ mobility	0.0044 (0.3358)	0.0740 (0.0000)	0.0025 (0.5867)	0.1392 (0.0000)	1.0000					
obs.	47887	47887	47887	47887						
Δ social	0.1027 (0.0000)	-0.0032 (0.4849)	0.0216 (0.0000)	-0.0004 (0.9241)	-0.0065 (0.1532)	1.0000				
obs.	47887	47887	47887	47887	47887					
Δ shelter	0.0647 (0.0000)	0.0083 (0.0704)	0.0217 (0.0000)	0.0183 (0.0001)	0.0327 (0.0000)	0.0704 (0.0000)	1.0000			
obs.	47887	47887	47887	47887	47887	47887				
age	-0.0049 (0.2802)	0.0025 (0.5774)	-0.0256 (0.0000)	-0.0036 (0.4361)	-0.0446 (0.0000)	-0.0014 (0.7536)	0.0000 (0.9933)	1.0000		
obs.	47887	47887	47887	47887	47887	47887	47887			
gender	0.0013 (0.7824)	0.0042 (0.3597)	0.0042 (0.3638)	0.0006 (0.8969)	-0.0053 (0.2446)	0.0040 (0.3796)	-0.0012 (0.7846)	0.0252 (0.0000)	1.0000	
obs.	47887	47887	47887	47887	47887	47887	47887	89640		
education	0.0024 (0.5989)	-0.0028 (0.5355)	0.0119 (0.0090)	0.0020 (0.6681)	0.0146 (0.0013)	-0.0047 (0.3021)	0.0008 (0.8575)	-0.3356 (0.0000)	-0.0637 (0.0000)	1.0000
obs.	47887	47887	47887	47887	47887	47887	47887	89640	89640	

Table 7: Contemporaneous correlations in levels, model 1

Variables	happiness	log(inc)	health	food	mobility	education	age	gender
happiness	1.0000							
obs.								
log(inc)	0.0802 (0.0000)	1.0000						
obs.	154300							
health	0.3487 (0.0000)	0.1261 (0.0000)	1.0000					
obs.	154300	154300						
food	0.0512 (0.0000)	0.2129 (0.0000)	0.1265 (0.0000)	1.0000				
obs.	154300	154300	154300					
mobility	0.0871 (0.0000)	0.3554 (0.0000)	0.1898 (0.0000)	0.4545 (0.0000)	1.0000			
obs.	154300	154300	154300	154300				
education	0.0658 (0.0000)	0.3133 (0.0000)	0.1848 (0.0000)	0.1683 (0.0000)	0.2670 (0.0000)	1.0000		
obs.	154300	154300	154300	154300	154300			
age	-0.0461 (0.0000)	-0.0460 (0.0000)	-0.1792 (0.0000)	-0.2175 (0.0000)	-0.2349 (0.0000)	-0.3424 (0.0000)	1.0000	
obs.	154300	154300	154300	154300	154300	154300		
gender	-0.1299 (0.0000)	-0.0656 (0.0000)	-0.1301 (0.0000)	-0.0609 (0.0000)	-0.0993 (0.0000)	-0.0739 (0.0000)	0.0353 (0.0000)	1.0000
obs.	154300	154300	154300	154300	154300	154300	154300	

Table 8: Summary statistics of variables in PCA, time period of model 2 (BHPS variable name in brackets)

Variable	Mean	Std. Dev.	Min.	Max.	N
health	-0.002	1.33	-7.988	1.666	89'640
health status over last 12 months (hlstat)	3.808	0.949	1	5	89'640
no. of visits to gp since 1.9.200x (hl2gp)	3.584	1.199	1	5	89'640
no. of serious accidents since 1.9.200x (nxdts)	4.881	0.387	1	5	89'640
log(days in hospital)	0.18	0.606	0	5.771	89'640
social	0.001	1.11	-5.841	1.839	89'640
satisfaction with: social life (lfsat6)	4.943	1.494	1	7	89'640
frequency of talking to neighbours (frna)	4.057	0.993	1	5	89'640
frequency of meeting people (frnb)	4.296	0.767	1	5	89'640
shelter	0	1.267	-6.701	12.068	89'640
satisfaction with: house/flat (lfsat3)	5.425	1.436	1	7	89'640
number of rooms in accommodation (hsroom)	4.685	1.669	1	60	89'640
likes present neighbourhood (lknbrd)	0.933	0.251	0	1	89'640
accom: shortage of space (hsprbg)	0.21	0.407	0	1	89'640
accom: noise from neighbours (hsprbh)	0.105	0.306	0	1	89'640
accom: street noise (hsprbi)	0.157	0.363	0	1	89'640
accom: not enough light (hsprbj)	0.059	0.236	0	1	89'640
accom: lack of adequate heating (hsprbk)	0.043	0.203	0	1	89'640
accom: condensation (hsprbl)	0.119	0.324	0	1	89'640
accom: leaky roof (hsprbm)	0.036	0.185	0	1	89'640
accom: damp walls, floors etc (hsprbn)	0.075	0.264	0	1	89'640
accom: rot in windows, floors (hsprbo)	0.066	0.248	0	1	89'640
accom: pollution/environmental problems (hsprbp)	0.072	0.259	0	1	89'640
accom: vandalism or crime (hsprbq)	0.17	0.376	0	1	89'640

Table 9: Regression results of a three-lag vector autoregression, full sample period, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***). The equations where changes in “being nourished” and “moving about freely” are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). Control variables are included in the regressions but not reported here. For each regression we have 41,887 observations.

	β_{t-1}						β_{t-2}					
	l- Δ hap	l- Δ inc	l- Δ hl	l- Δ food	l- Δ mobi	l2- Δ mobi	l2- Δ hap	l2- Δ inc	l2- Δ hl	l2- Δ food	l2- Δ mobi	
Δ hap	-0.6172*** (.0072)	-0.1617** (.0621)	0.817*** (.0247)	-0.0455* (.0193)	0.0776 (.0567)	-0.3853*** (.0077)	-0.1976** (.0642)	0.0409 (.0264)	-0.0717*** (.0207)	0.0287 (.0575)		
Δ inc	0.0014** (.0005)	-0.4349*** (.0149)	-0.0004 (.0019)	-0.0007 (.0017)	0.207*** (.0053)	0.0016** (.0005)	-0.2398*** (.0131)	0.0013 (.002)	-0.0046* (.0019)	0.0212*** (.0056)		
Δ hl	0.0103*** (.0012)	-0.0426** (.0131)	-0.5463*** (.0066)	0.0051 (.0041)	0.0078 (.0117)	0.0085*** (.0013)	-0.047*** (.0133)	-0.3457*** (.0067)	0.0092* (.0044)	-0.0151 (.0119)		
Δ food	0.0033** (.0013)	0.0372* (.0156)	-0.0043 (.0053)	-0.4213*** (.0056)	0.1291*** (.0138)	0.0018 (.0014)	0.0494** (.0153)	-0.0007 (.0056)	-0.2276*** (.0054)	0.0786*** (.0142)		
Δ mobi	0.0039* (.0017)	0.1046*** (.0194)	0.0144* (.007)	0.0431*** (.006)	-1.0899*** (.0191)	0.0038* (.0018)	0.0729*** (.0207)	0.0124 (.0074)	0.0477*** (.0066)	-0.6696*** (.0191)		
	β_{t-3}						(pseudo-) R^2					
Δ hap	-0.1915*** (.0067)	-0.1188* (.0579)	-0.0471* (.0233)	-0.0505** (.019)	-0.0367 (.0534)	0.2799						
Δ inc	0.0006 (.0005)	-0.1007*** (.013)	0.0034 (.0018)	-0.0034* (.0017)	0.004 (.0049)	0.1711						
Δ hl	0.0044*** (.0012)	-0.0124 (.012)	-0.1819*** (.0058)	0.0102* (.004)	-0.0107 (.0112)	0.2364						
Δ food	0.0016 (.0013)	0.0389** (.0136)	-0.0072 (.0051)	-0.1009*** (.0048)	0.0547*** (.0126)	0.0654						
Δ mobi	0.0018 (.0016)	0.0387* (.0194)	0.0118 (.0067)	0.0121* (.0059)	-0.3378*** (.0181)	0.1063						

Table 10: Regression results of a two-lag vector autoregression, full sample period, males, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***). The equations where changes in “being nourished” and “moving about freely” are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). Control variables are included in the regressions but not reported here. For each regression we have 27,913 observations.

	β_{t-1}										β_{t-2}										(pseudo-) R^2
	$l-\Delta$ hap	$l-\Delta$ inc	$l-\Delta$ hl	$l-\Delta$ food	$l-\Delta$ mobi	$l2-\Delta$ hap	$l2-\Delta$ inc	$l2-\Delta$ hl	$l2-\Delta$ food	$l2-\Delta$ mobi	$l2-\Delta$ hap	$l2-\Delta$ inc	$l2-\Delta$ hl	$l2-\Delta$ food	$l2-\Delta$ mobi						
Δ hap	-.5514*** (.009)	-.0498 (.0693)	.0498 (.0288)	-.0484* (.0215)	.0807 (.0616)	-.2774*** (.0086)	-.1362* (.0648)	-.0147 (.0281)	-.0376 (.0206)	-.0222 (.0575)							0.2460				
Δ inc	.0023*** (.0006)	-.4012*** (.023)	-.0028 (.0024)	-.0015 (.0023)	.011 (.0065)	.0017*** (.0006)	-.1779*** (.0166)	-.0019 (.0026)	-.0055** (.0021)	.0095 (.0067)							0.1544				
Δ hl	.0104*** (.0015)	-.0102 (.0143)	-.486*** (.0083)	-.0016 (.0046)	.0035 (.0132)	.0067*** (.0015)	-.0232 (.0146)	-.2507*** (.0078)	-.0039 (.0046)	-.0164 (.0128)							0.2012				
Δ food	.0026 (.0016)	.0256 (.0176)	-.0061 (.0064)	-.3881*** (.0064)	.0885*** (.0157)	.0002 (.0015)	.0178 (.0164)	-.0005 (.0064)	-.1778*** (.0057)	.056*** (.0152)							0.0607				
Δ mobi	.0047* (.002)	.0519* (.0225)	.0081 (.0082)	.0408*** (.0069)	-1.0264*** (.0213)	.0016 (.002)	.0475* (.021)	.0193* (.0083)	.0358*** (.0067)	-.5151*** (.0203)							0.1013				

Table 11: Regression results of a two-lag vector autoregression, full sample period, females, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***) . The equations where changes in “being nourished” and “moving about freely” are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). Control variables are included in the regressions but not reported here. For each regression we have 32,014 observations.

	β_{t-1}										β_{t-2}										(pseudo-) R^2
	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi	Δ hap	Δ inc	Δ hl	Δ food	Δ mobi						
Δ hap	-.573*** (.0078)	-.2507*** (.0741)	.034 (.0269)	-.0298 (.0231)	-.0441 (.0703)	-.2795*** (.0075)	-.1025 (.0718)	-.0276 (.0266)	-.0705** (.0229)	.0014 (.0709)	-.2795*** (.0075)	-.1025 (.0718)	-.0276 (.0266)	-.0705** (.0229)	.0014 (.0709)						
Δ inc	.0006 (.0005)	-.4195*** (.0143)	-.0015 (.002)	-.0003 (.002)	.0043 (.0066)	.001 (.0005)	-.2118*** (.0138)	.0015 (.002)	-.0006 (.0019)	.0122* (.0061)	.001 (.0005)	-.2118*** (.0138)	.0015 (.002)	-.0006 (.0019)	.0122* (.0061)						
Δ hl	.0096*** (.0013)	-.0502*** (.0149)	-.5074*** (.007)	.0146** (.0049)	.0032 (.014)	.006*** (.0013)	-.039** (.0138)	-.2559*** (.0065)	.0127** (.0048)	-.0316* (.0137)	.006*** (.0013)	-.039** (.0138)	-.2559*** (.0065)	.0127** (.0048)	-.0316* (.0137)						
Δ food	.0041** (.0013)	.0533** (.0168)	-.0111* (.0055)	-.397*** (.0061)	.1234*** (.0153)	.0033* (.0013)	.024 (.0163)	-.0028 (.0054)	-.1752*** (.0054)	.0695*** (.0148)	.0033* (.0013)	.024 (.0163)	-.0028 (.0054)	-.1752*** (.0054)	.0695*** (.0148)						
Δ mobi	.0035* (.0017)	.1206*** (.0212)	.0099 (.0073)	.0354*** (.0067)	-1.0217*** (.0214)	.0023 (.0017)	.0879*** (.0213)	.009 (.0072)	.0349*** (.0068)	-.5106*** (.0206)	.0023 (.0017)	.0879*** (.0213)	.009 (.0072)	.0349*** (.0068)	-.5106*** (.0206)						

Table 12: Regression results of a two-lag vector autoregression, full sample period, disabled subsample, estimated via OLS (the reported results are OLS coefficients and *t*-statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***) and 99.9%(***) and 99.9%(***) are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and *z*-statistics). Control variables are included in the regressions but not reported here. For each regression we have 4,994 observations.

	β_{t-1}						β_{t-2}						(pseudo-) R^2
	l- Δ hap	l- Δ inc	l- Δ hl	l- Δ food	l- Δ mobi	l2- Δ hap	l2- Δ inc	l2- Δ hl	l2- Δ food	l2- Δ mobi			
Δ hap	-.5234*** (.0195)	-.18 (.2073)	.1017 (.0584)	-.1522* (.0631)	.1119 (.2247)	-.2541*** (.0185)	-.5526* (.2151)	.0383 (.0571)	-.0816 (.0603)	.136 (.2099)			0.2234
Δ inc	.0001 (.0012)	-.5532*** (.0286)	-.0053 (.0036)	.0031 (.0043)	.0158 (.0157)	.0021 (.0013)	-.2473*** (.0232)	-.0084* (.0041)	.0047 (.0041)	.0118 (.0151)			0.2494
Δ hl	.0181*** (.0039)	.0014 (.0504)	-.4721*** (.0168)	.0091 (.0158)	-.0342 (.0565)	.0113** (.004)	-.0405 (.0526)	-.2428*** (.0161)	.0017 (.016)	-.053 (.0524)			0.1892
Δ food	.007* (.003)	-.0257 (.0415)	-.0059 (.0113)	-.4431*** (.0159)	.1015* (.0487)	.0041 (.0031)	.0027 (.0393)	.0065 (.0115)	-.2196*** (.0146)	.0787 (.0434)			0.0737
Δ mobi	.0079 (.0046)	.1846*** (.0559)	.0078 (.0156)	.0543** (.021)	-1.1732*** (.0694)	-.0004 (.0046)	.0492 (.0628)	.0275 (.0169)	.0733*** (.0194)	-.6522*** (.069)			0.1155

Table 13: Regression results of a two-lag vector autoregression, full sample period, separated/divorced/widowed subsample, estimated via OLS (the reported results are OLS coefficients and t -statistics). Asterisks denote significance levels 95%(*), 99%(**) and 99.9%(***) . The equations where changes in “being nourished” and “moving about freely” are the dependent variables are estimated via ordered probit estimator (reported are ordered probit coefficients and z -statistics). Control variables are included in the regressions but not reported here. For each regression we have 10,976 observations.

	β_{t-1}						β_{t-2}						(pseudo-) R^2
	l- Δ hap	l- Δ inc	l- Δ hl	l- Δ food	l- Δ mobi	l2- Δ hap	l2- Δ inc	l2- Δ hl	l2- Δ food	l2- Δ mobi			
Δ hap	-.5595*** (.0133)	-.1882 (.107)	.0709 (.0454)	-.1496*** (.0414)	-.3765** (.1366)	-.2636*** (.0127)	.0148 (.1177)	-.0341 (.0449)	-.1778*** (.0413)	-.3053* (.1406)	0.2622		
Δ inc	.0007 (.001)	-.4664*** (.0329)	-.0036 (.0037)	-.0014 (.0034)	-.0181 (.0132)	.0012 (.001)	-.2317*** (.0231)	-.0008 (.004)	.0022 (.0035)	.0138 (.0141)	0.2061		
Δ hl	.0082*** (.0023)	-.0397 (.0235)	-.4798*** (.0122)	.0074 (.0088)	-.0186 (.0284)	.0061** (.0023)	-.006 (.025)	-.2561*** (.0119)	-.0004 (.0087)	-.06* (.0272)	0.2022		
Δ food	.0107*** (.0021)	.031 (.0216)	-.0163 (.0089)	-.3818*** (.0101)	.1235*** (.0293)	.0092*** (.0022)	.0346 (.022)	-.0011 (.009)	-.171*** (.0092)	.0819** (.0299)	0.0571		
Δ mobi	.017*** (.0031)	.0344 (.0328)	.0128 (.0126)	.0505*** (.0125)	-1.1203*** (.0425)	.0132*** (.0031)	.0587 (.0326)	.0096 (.0125)	.0302* (.0125)	-.5213*** (.0441)	0.1013		

References

- Alkire, S. (2002a). Dimensions of human development. *World Development*, 30(2):181–205.
- Alkire, S. (2002b). *Valuing Freedoms - Sen's Capability Approach and Poverty Reduction*. Oxford University Press, Oxford.
- Anand, P. and Hees, M. v. (2006). Capabilities and achievements: An empirical study. *Journal of Socio-Economics*, 35:268–284.
- Anand, P., Hunter, G., and Smith, R. (2005). Capabilities and well-being: Evidence based on the Sen-Nussbaum approach to welfare. *Social Indicators Research*, 74:9–55.
- Arrow, J. (1996). Estimating the influence of health as a risk factor on unemployment: A survival analysis of employment durations for workers surveyed in the German Socio-economic Panel (1984-1990). *Social Science & Medicine*, 42(12):1651–1659.
- Becchetti, L., Pelloni, A., and Rossetti, F. (2008). Relational goods, sociability, and happiness. *Kyklos*, 61(3):343–363.
- Becker, G. S. (1964). *Human Capital - A Theoretical and Empirical Analysis, with Special Reference to Education*. Columbia University Press, New York/London.
- BHPS (2009). British Household Panel Survey. <http://www.iser.essex.ac.uk/ulsc/bhps/>.
- Binder, M. and Broekel, T. (2008). Applying a robust non-parametric efficiency analysis to measure conversion efficiency in Great Britain. SSRN Working Paper No. 1104430. Accepted for publication in: *Journal of Human Development and Capabilities*.
- Binder, M. and Coad, A. (2009). An examination of the dynamics of happiness using vector autoregressions. *Papers on Economics & Evolution* #0904.
- Buhmann, B., Rainwater, L., Schmaus, G., and Smeeding, T. M. (1988). Equivalence scales, well-being, inequality, and poverty: Sensitivity estimates across ten countries using the Luxembourg Income Study (LIS) database. *Review of Income and Wealth*, 34(2):115–142.
- Burchardt, T. (2005). Are one man's rags another man's riches? Identifying adaptive expectations using panel data. *Social Indicators Research*, 74:57–102.
- Chiappero-Martinetti, E. and Salardi, P. (2007). Well-being process and conversion factors: An estimation of the micro-side of the well-being process. Mimeo.
- Clark, A. E., Frijters, P., and Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, 46(1):95–144.
- Clark, A. E. and Oswald, A. J. (2002). A simple statistical method for measuring how life events affect happiness. *International Journal of Epidemiology*, 31:1139–1144.
- Coad, A. (2010). Exploring the processes of firm growth: Evidence from a vector autoregression. *Industrial and Corporate Change*, forthcoming, doi:10.1093/icc/dtq018.

- Deutsch, J., Ramos, X., and Silber, J. (2003). Poverty and inequality of standard of living and quality of life in Great Britain. In Sirgy, M. J., Rahtz, D., and Samli, A. C., editors, *Advances in Quality-of-Life Theory and Research*, chapter 7, pages 99–128. Kluwer Academic Publishers, Dordrecht.
- Diener, E., Suh, E., Lucas, R. E., and Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, 125(2):276–302.
- Easterlin, R. A. (2003). Explaining happiness. *Proceedings of the National Academy of Sciences*, 100(19):11176–11183.
- Ferrer-i Carbonell, A. and Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, 114:641–659.
- Frederick, S. and Loewenstein, G. F. (1999). Hedonic adaptation. In Kahneman et al. (1999), pages 302–329.
- Gardner, J. and Oswald, A. (2004). How is mortality affected by money, marriage, and stress? *Journal of Health Economics*, 23:1181–1207.
- Gardner, J. and Oswald, A. J. (2007). Money and mental wellbeing: A longitudinal study of medium-sized lottery wins. *Journal of Health Economics*, 26:49–60.
- Graham, C., Eggers, A., and Sukhtankar, S. (2004). Does happiness pay? An exploration based on panel data from Russia. *Journal of Economic Behavior & Organization*, 55:319–342.
- Grossman, M. (2005). Education and nonmarket outcomes. NBER Working Paper, No. 11582, <http://www.nber.org/papers/w11582>.
- Johnston, D. W., Propper, C., and Shields, M. A. (2007). Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient. CMP Working Paper Series, No.07/171, University of Bristol.
- Kahneman, D., Diener, E., and Schwarz, N., editors (1999). *Well-Being: The Foundations of Hedonic Psychology*. Russell Sage Foundation, New York.
- Klasen, S. (2000). Measuring poverty and deprivation in South Africa. *Review of Income and Wealth*, 46(1):33–58.
- Kolenikov, S. and Angeles, G. (2009). Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer? *Review of Income and Wealth*, 55(1):128–165.
- Kuklys, W. (2005). *Amartya Sen's Capability Approach - Theoretical Insights and Empirical Applications*. Springer, Berlin et al.
- Lancaster, K. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

- Lelli, S. (2001). Factor analysis vs. fuzzy sets theory: Assessing the influence of different techniques on Sen's functioning approach. Center for Economic Studies Discussion Paper Series 01.21.
- Lelli, S. (2005). Using functionings to estimate equivalence scales. *Review of Income and Wealth*, 51(2):255–284.
- Levy, H. and Jenkins, S. P. (2008). Documentation for derived current and annual net household income variables, BHPS waves 1-16. Institute for Social and Economic Research, University of Essex, Colchester.
- Lykken, D. and Tellegen, A. (1996). Happiness is a stochastic phenomenon. *Psychological Science*, 7(3):186–189.
- Lyubomirsky, S., King, L., and Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin*, 131(6):803–855.
- McClements, L. D. (1977). Equivalence scales for children. *Journal of Public Economics*, 8(2):191 – 210.
- Myers, D. G. (1999). Close relationships and quality of life. In Kahneman et al. (1999), pages 374–391.
- Nussbaum, M. C. (2000). *Women And Human Development*. Cambridge University Press, Cambridge.
- Oswald, A. J. (1997). Happiness and economic performance. *The Economic Journal*, 107(445):1815–1831.
- Praag, B. S. v. (1991). Ordinal and cardinal utility: An integration of the two dimensions of the welfare concept. *Journal of Econometrics*, 50(1-2):69–89.
- Qizilbash, M. (2002). Development, common foes and shared values. *Review of Political Economy*, 14(4):463–480.
- Ramos, X. (2008). Using efficiency analysis to measure individual well-being with an illustration for Catalonia. In Kakwani, N. and Silber, J., editors, *Quantitative Approaches to Multidimensional Poverty Measurement*, chapter 9, pages 155–175. Palgrave Macmillan, Basingstoke.
- Ramos, X. and Silber, J. (2005). On the application of efficiency analysis to the study of the dimensions of human development. *Review of Income and Wealth*, 51(2):285–309.
- Robeyns, I. (2006). Gender inequality in functionings and capabilities: Findings from the British Household Panel Survey. In Bharati, P. and Pal, M., editors, *Gender Disparity: Its Manifestations, Causes and Implications*, chapter 13, pages 236–277. Anmol, Delhi.
- Roche, J. M. (2008). Monitoring inequality among social groups: A methodology combining fuzzy set theory and principal component analysis. *Journal of Human Development and Capabilities*, 9(3):427–452.

- Sen, A. K. (1984). Rights and capabilities. In *Resources, Values and Development*, pages 307–324. Harvard University Press, Cambridge/Mass.
- Sen, A. K. (1985a). *Commodities and Capabilities*. North-Holland, Amsterdam.
- Sen, A. K. (1985b). Well-being, agency and freedom: The Dewey lectures 1984. *The Journal of Philosophy*, 82(4):169–221.
- Sen, A. K. (1992). *Inequality Reexamined*. Clarendon Press, Oxford.
- Shields, M. A. and Wheatley Price, S. (2005). Exploring the economic and social determinants of psychological well-being and perceived social support in England. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 168(3):513–537.
- Smeeding, T. M., Saunders, P., Coder, J., Jenkins, S. P., Fritzell, J., Hagenaars, A. J. M., Hauser, R., and Wolfson, M. (1993). Poverty, inequality, and family living standards impacts across seven nations: The effect of noncash subsidies for health, education and housing. *Review of Income and Wealth*, 39(3):229–256.
- Smith, J. P. (1999). Healthy bodies and thick wallets: The dual relation between health and economic status. *Journal of Economic Perspectives*, 13(2):145–166.
- Stevenson, B. and Wolfers, J. (2008). Economic growth and subjective well-being: Reassessing the Easterlin paradox. NBER Working Paper No. 14282.
- Taylor, M. F. E. (2009). British Household Panel Survey user manual volume a: Introduction, technical report and appendices. edited with John Brice, Nick Buck and Elaine Prentice-Lane. Colchester: University of Essex.
- UNDP (2006). Human development report. <http://hdr.undp.org/hdr2006/report.cfm>.
- Zaidi, A. and Burchardt, T. (2005). Comparing incomes when needs differ: Equivalization for the extra costs of disability in the U.K. *Review of Income and Wealth*, 51(1):89–114.