Operationalization of the capability approach, from theory to practice: 
a review of techniques and empirical applications

Enrica Chiappero- Martinetti 
(University of Pavia)

José Manuel Roche 
(University of Sussex)

Acknowledgements

Keywords

Introduction

The operationalization of the capability approach is undeniably a complex issue to deal with and thus not surprisingly some researchers (Srinivasan 1994; Sugden 1993; Ysander 1993) raised serious doubts during the early 90’s about the concrete possibility to make an effective use of such a theoretical framework for empirical purposes. As Comim (2008: 159) synthesizes when reviewing some common critique addressed to this approach, “the multidimensional-context-dependent-counterfactual-normative nature of the capability approach might prevent it from having practical and operational significance”.

As a matter of fact, what exactly “operationalization” means is nonetheless questionable. Does it denote the process that allows the transformation of concepts or a theoretical foundation into a well-defined metric or algorithm that can be mechanically applied to any circumstance, or are alternative procedures and methods reasonably admitted? Should an operationalization process be able to produce an accurate description and application of each single constitutive element of a theory, or should it provide criteria for identifying key elements of the theory itself? Or might it simply be inspired by the theory itself?

Different positions can be found at this regard within the capability literature. Comim, for instance, defines the operationalization as “the diverse sequence of transforming
a theory into an object of practical value” (2001, p.1) and argues that this procedure should not be restricted to the mere “quantification” of a theory but should be seen in the broader sense of “using" a theory for different purposes. From this broad perspective, measurement would generally entail many steps from the preliminary one related to the clarification of abstract concepts into measurable entities, till the final phase of a coherent organization of results.

Alkire (2001, p. 11) spells out that “to “operationalize” a hypothesis is to add enough particularities that it can be tried out, put to work in time and space, in an informative if not entirely conclusive manner”. In a number of papers, including her contribution to the present book (see Alkire 2008), she gives a substantial contribution on how to put the capability approach into practice.

Other scholars (Brandolini, D’Alessio, 2008; Kuklys, 2005), considering the underlying substantial incompleteness of this approach and its underspecified nature, discuss the operationalizational issue mainly in terms of methods and procedures that might be used for allowing a concrete use of this approach. And as Atkinson and Bourguignon write: “the challenge which this raises is to translate this concept into one which can be implemented in empirical analysis of distributional issues. There is a scope for a great deal of future research” (2000; 49).

Moving in this direction Robeyns (2003), identifies three additional specifications required for applying this approach - namely, the identification of a list of valuable capabilities, the decision to focus on the broader space of opportunities to achieve or on the narrow achievements set (that is between capability or functionings space) and the selection of a weight system to be assigned to the evaluative elements - i.e. functionings or capabilities; in that paper she also proposes a methodology to select relevant capabilities for analyzing gender inequality. Zimmerman (2006) discusses how the question of freedom and social opportunities raised by the capability approach can be methodologically completed and transposed for sociological analysis and social policy purposes (see also Fukuda Parr, 2003).

Even when the discussion is confined to the relatively narrow meaning of operationalization, basically restricted to empirical, mainly quantitative, analysis of the capability approach, the number of open matters is nonetheless negligible and as remarked by Bourguignon (2006, p. 101) “the challenge of making alternative concepts to the income poverty paradigm truly operational remain great”. How intangible elements such as capability or agency can be estimated, how the demanding need of statistical data can be met, what are the most appropriate
methods or techniques for managing such multidimensionality, are some of the recurrent questions a researcher interested in the empirical application of the capability approach has to cope with.

If till the end of the '90s, the empirical applications of the capability approach were rather scarce, during the last years this literature is growing considerably fast and the range of disciplines in which this research has been developed is widening, as well as the variety of aims, the multiplicity of data and techniques used. This evolution produces undeniable advantages but does not make it easy at all to find one's way, particularly for a PhD student or a researcher who approaches this kind of literature for the first time.

For these reasons, a couple of years ago, the initiative to collect experiences and empirical evidence related to the capability approach started up and an ad-hoc section on the website of the Human Development and Capability Association (HDCA) (www.capabilityapproach.org) was created for spreading and sharing this information and for stimulating new empirical research with the aim to improve quantity and quality of the empirical work in this field. This chapter complements and extends the database posted on the HDCA website and discusses more in-depth some methodological requirements any researcher aimed to make empirical studies based on the capability approach will have to deal with. It does not aim to be an exhaustive survey of the empirical literature nor to provide a blueprint for operationalizing the capability approach. It is simply aimed to discuss some basic principles and to review how the most consolidated applied literature dealt with these kind of issues. For space reason, the attention will be largely confined to quantitative methods and quantitative applications even if some brief remarks and some references on qualitative analysis will also be mentioned. For evident reasons this chapter is and will remain a work in progress that can be updated and complemented with the contribution of all scholars invited to help us to integrate, extend and update this database.

The chapter is structured as follows. First, we will discuss the main challenges and problems a researcher can meet in the shift from the conceptual level to the practical transposition of the capability approach (section 2). In the subsequent section we will compare the main data requirements and datasets more frequently used or potentially helpful for implementing empirical analysis based on the capability

---

1 People who want to signal further references on empirical studies conducted in this field of research can use the form available on the HDCA website and/or send an email to the authors (J.M.Roche@sussex.ac.uk or enrica.chiappero@unipv.it).
approach (section 3). Following, we will present an overview of the main statistical techniques used in empirical applications in the capability approach (section 4). In the last section we will review some of the most recent or well-known empirical application in the capability approach (section 5). Some final conclusions are presented at the end.

2. From concepts to measurement: some preliminary issues a researcher should consider for operationalizing the capability approach

Most empirical literature on the capability approach narrows the meaning of “operationalization” to the empirical methods used for measuring capabilities or more frequently functionings. In these cases, the richness of the approach and the consequential difficulty in its implementation is usually acknowledged in the preface and a pragmatic solution for its operationalization is generally drawn from the existing data or conventional methods used in well-being assessments. As Brandolini and D’Alessio writes in the chapter xx of this book (p. xxx) “much of what one can do [in deriving operational measures of functionings and capabilities] depends on the available data” but as we will see in the second part of this chapter, the range of available datasets is large and various enough to give room to different strategies and methods to be applied for.

In his Tanner Lectures, Sen also argues that an appropriate approach to the evaluation of well-being should be able not only to capture the inherent complexities and richness that lays behind the idea of well-being (relevance criterion) but also to be usable for empirical assessments (usability criterion) and “this imposes restrictions on the kinds of information that can be required and the techniques of evaluation that may be used” (Sen, 1987:20).

However, as we know, Sen does not provide any specific guidelines on how his approach can concretely be implemented for policy analysis or social evaluation, and it cannot but be different taking into consideration the broad and context dependent nature of the approach itself and the different scopes that the analysis can have.

Moreover some interesting efforts for conducting sample surveys specifically based on the capability approach and aimed to collect *ad hoc* data have been recently done, as we will see you later on this paper.
Some constitutive elements of this normative framework (e.g. agency, freedom, well-being, functionings, capabilities) may be extremely important in a given context and not in others; the possibility to make interpersonal comparisons is essential in distributive analysis but not required, for instance, for measuring absolute capabilities deprivation for which the living condition of each individual is compared with a common (absolute) standard or threshold. Number and type of internal and external factors that can affect the conversion process of resources into well-being can vary according to the level of disaggregation we want to reach, and so on.³

Thus, even if the spectrum in terms of aims and focal points can vary in a considerable way, nonetheless a researcher interested in the empirical application of this approach will generally face a common cluster of statistical requirements referring to⁴:

i) a plurality of evaluative spaces ranging from agency-autonomy-empowerment and capabilities to material standard of living and achieved functionings;

ii) a plurality of dimensions and a multiplicity of indicators and scales, of quantitative or qualitative nature, and objectively or subjectively measured;

iii) a plurality of units of analysis (individuals, households, subgroups of population) and personal heterogeneities that can affect the conversion process of resources into capabilities, such as gender, age, or racial and religious differences;

iv) a plurality of environmental contexts, including socio-economics, geographical, cultural and institutional variations.

With reference to these issues a set of questions follows related to: the concrete possibility to operationalize the capability approach for empirical purposes; the adequacy of the most common available datasets to capture the multidimensionality nature of the capability approach or, alternatively, the necessity to implement ad-hoc surveys for satisfying the demanding statistical requirements; and the general criteria, if any, that can be followed in the choice among different kinds of data

³ During a discussion session with the participants to the Cortona Colloquia, Sen outlined that the operationalization matter is first of all a matter of being clear what we are looking for and then, depending on the context, why we are looking for it in that particular case. Then, depending on that, depending on the data we have, how we want to use it, it will be possible to arrive in some way to some measurement.
⁴ On the layers of complexity that characterize the capability approach see also Chiappero-Martinetti 2007.
sources that can be used in this field of investigation. The next session is devoted to discuss these aspects.

3. Data availability: what the available data sources potentially offer

One of the first dilemma you would probably deal with if you decide to measure poverty or well-being according to the capability approach, is what kind of data source you might refer to. In particular, the preliminary decision which needs to be taken is whether to use a dataset already available even if originally collected for other purposes, what we could define as secondary analysis, or if you prefer or need to collect primary data generating a new, ad hoc dataset, that is conducing a primary research or analysis. It could be misleading to consider these two options as two alternatives. Sometimes the boundary between these two approaches is quite blurred and in most cases, an appropriate combination of both approaches could prove to be very helpful, and sometimes necessary, especially for supplementing the set of information we can draw from each of them and organize it in a cohesive manner. Nevertheless, taking into account time and cost constraints as well as our predilection and past research experience, we would usually opt only for one of these options. Let us first briefly discuss in the next sections what potentially could be the advantages and disadvantages associated to these two choices. We will come back on the possibility to integrate different data and methodological strategies later on this chapter.

3.1 Primary analysis

Generally speaking, primary analysis refers to any type of research that requires some fieldwork and a direct collection of data in order to address a specific research question; in our field of interest it could be measuring capabilities or achieved functioning, or to build up agency or empowerment indexes. Primary analysis are typically conducted through interviews (carried out face-to-face or by phone, they allow to collect specific information from a small number of people), surveys (based on questionnaires and usually involving a larger group of people), observations

5 On this point see the very interesting and intensive research activity conducted by the “Q-Square research group” (Combining Qualitative and Quantitative Approaches in Poverty Analysis) based at the Centre for International Studies at the University of Toronto. Some preliminary results of a workshop on this topic are in Kanbur (2003).

6 Distinctive features and differences between primary and secondary analysis are usually discussed in the vast literature on social research methodology. For a concise but effective discussion see, for instance, Sapsford and Jupp (2006) or Bryman (2001).
(detailed and organized notes about specific people, occurrences or events) or ethnographic research (qualitative description of aspects related to social life or cultural phenomena for a small number of cases). Moreover, according to the research purposes, the unit of observation can be individuals or households, as well as focus groups, decision makers, stakeholders or experts. Finally, they are often implemented for collecting qualitative information more than quantitative data. Broad in terms of goals, tools as well as techniques, are the community approaches and the participatory methods that have been extensively used in the last years in development studies, for learning about people's conditions, preferences, perceptions or priorities in an iterative manner.7

Independently of the kind of technique chosen, what can be considered as a distinctive feature of a primary analysis is that collected data or information are tailored on the specific research question you want to investigate, instead of tailoring your research question to the statistical information available as it usually happens when you refer to secondary datasets.

Primary analysis offers some undeniable merits. First of all, it could be the proper (sometimes the sole) solution if you are working on a very specific, relatively new or original topic that might not have been addressed before or for which little empirical research is available thus requiring an exploratory research. Secondly, it allows to investigate more in-depth specific topics, contexts, situations or people and to gather not only quantitative data but also, and particularly, qualitative, subjective information and open-ended questions. Thirdly, it is generally acknowledged that through these approaches respondents can play a more active role and express their opinions, values and priorities. It is rather evident that all these aspects are not extraneous to the capability perspective and thus a primary analysis can be fruitfully applied, and is sometimes the only chance for addressing matters such as how to know what people has reason to value, how to select a list of functionings or assigning weights not in a arbitrary manner, how to estimate capabilities or measure agency indexes.8

7 (Alkire 2002; Apsan-Frediani 2006 2007; Clark 2002; Ferrero y de Loma-Osorio and Zepeda 2007; Manu V. 2003)
8 The impossibility of measuring capabilities due to the lack of information in standard representative surveys on freedom of choice and alternative options among which people can freely choose, is the main motivation that can push a researcher to implement a primary analysis. Not surprising some interesting primary analysis of the capability approach that will be reviewed in the next section, were precisely aimed by this kind of motivation.
Evidently, there are also some not negligible disadvantages associated to it, first and foremost that primary analysis are generally quite expensive, time-consuming and require a good expertise with respect to the research methods that need to be entailed for dealing with this type of investigation. Secondly, the validity and reliability of the analysis is generally difficult to verify or replicate, and as the analysis is generally conducted on a relatively small number of observations sample, the sampling design as well as the response rates can strongly affect the statistical significance of the sample and thus reduce the possibility to make any disaggregate analysis. Thirdly and directly related to the previous points, any possibility to make comparisons over time or across countries is very limited. Finally, as it will be remarked also in the next sessions, the set of statistical techniques to be used for analyzing data collected by primary analysis are substantially affected by the sample size and the nature of the data.

### 3.2 Secondary analysis

Secondary analysis traditionally involves the utilization of existing, generally large datasets for addressing a research question (e.g. measuring “proxies” for functionings or capabilities) that is distinct from that for which the dataset was originally collected (e.g. multipurpose household surveys on the quality of life in urban contexts) and it largely entails quantitative analysis.

As long as the nature and quality of the used dataset fits sufficiently well with the purpose of the analysis, the secondary analysis shows some obvious advantages. First, it generally makes use of large-scale, random sample surveys that are statistically representative of the whole population. Second, the availability of multiple data sources can permit comparison of trends over time and allow complementary data analysis (e.g. pooling of data-sources for creating a larger dataset, or test and replicate the same hypothesis on different datasets). Third, the same dataset can be analyzed from different disciplinary perspectives contributing to a broader multidisciplinary understanding. Fourth, the number, size and reliability of data archives have grown substantially in the last two decades and many datasets,

---

9 This is particularly the case with ad hoc surveys aimed to collect quantitative data while qualitative research is not necessarily expensive in terms of resources or time while it equally requires good skills with respect the specific techniques adopted.
already cleaned and stored in electronic format and thus ready-to-use, are now freely available on the web.\textsuperscript{10}

From a broader point of view it has also been argued (see Hakim, 1982, p. 16) that secondary analysis, in some way, “helps the researcher to overcome the narrow focus on individuals and their characteristics (prevalent in primary analysis) in favour of a broader concern “ forcing the researcher herself to focus more on the theoretical aims of the study rather than the practical problems of collecting new data.

It should be underlined that secondary analysis does not necessarily represent an alternative to primary methods but can complement as long as it is used as a preliminary investigation (having a first view on size and main characteristics of a specific problem or a particular social group) before implementing a primary analysis.

The potential disadvantages associated to secondary analysis are nothing more than the mirror of the advantages discussed with reference to primary analysis. The decision to use secondary data imposes, in a certain measure, to adapt or to force the research question to the data available. Information you would like to find in your dataset may not have been collected or not in the year or for the country you need; variables may have been defined or categorized differently than you would have chosen, and so on and so forth.

Moreover, secondary datasets largely differ in term of size, depth of interviewing, coverage, degree of geographical detail, time-specificity, and this array in terms of quantity and quality of information can affect both the level of specificity of the analysis as well as the possibility to make any serious comparison. Finally, large datasets can require a considerable amount of statistical analysis, adequate computers and statistical-packages determining a not negligible cost in terms of both resources and knowledge.\textsuperscript{11}

Until now we referred to secondary analysis as a unique entity, while in fact different sources of secondary analysis in social sciences can be used. A major distinction needs to be made between macro or aggregate data and micro-data that will be briefly clarified below.

\textsuperscript{10} It is sufficient to browse the web to realize the number of data-providers and data-sources available. An illustration it can be mentioned: the Social Science Info Gateway (www.intute.ac.uk/socialsciences), the UK data archives at the University of Essex (www.data-archive.ac.uk), the Economic and Social Data Service (www.esds.ac.uk), the European Community Statistical database (http://epp.eurostat.ec.europa.eu/portal/page?_pageid=1090,30070682,1090_330765766&_dad=portal&_schema=PORTAL), and the Living Standard Measurement Surveys of World Bank (www.worldbank.org/LSMS).

\textsuperscript{11} It has also been remarked that secondary data can have a large margins of error despite of the fact that economists tend to consider this source more accurate and reliable (see Thorbecke, 2003)
3.2.1 Macro data

The category of macro-data includes population census, large continuous, regular and official surveys and datasets derived from administrative records, such as marriage registers or tax records. These data, even if are collected at individual or household level, are generally available only in aggregate format on published reports that describe methods used and summarize main results. Statistics or tables are also provided at different levels of disaggregation such as sectors, groups, areas or categories. At international level, United Nations, OECD or EUROSTAT are among the major data-producers and data-providers of harmonized time-series and cross-section datasets while, at a national level, population censuses as well as administrative records and national account statistics are the most typical data provided by National Statistical Offices or Institutions such as Central Banks.

Unfortunately, aggregate analysis can hide deep inequalities and internal disparities among subgroups of population and individuals, and even if statistics and tables generally offer disaggregated figures by individual characteristics and by socio-economic or geographical features, these levels of disaggregation are not necessarily coherent with the purposes of your analysis12.

3.2.2 Micro data

On the contrary, a direct access to the raw data that contains the recorded information on individual respondents (generally, individuals and/or households) to a specific inquiry, allow you to choose the disaggregated level of analysis you need, compatibly to the width and depth of data collected. The broad spectrum of micro-datasets includes, among others: multipurpose surveys, that usually collect both quantitative and qualitative data on a wide range of topics of broad interest; longitudinal analysis, that provide information for the same respondents (individuals or households) along time and are generally used for dynamic analysis; ad-hoc surveys with a fairly specific focus, for instance on labour force, education, elderly, income or wealth.

---

12 This problem is partially overcome since the National Statistical Offices are increasingly making census data available for research purposes. See, among others, the US Bureau of Census (www.census.gov) or the Integrated Public Use of Microdata Series Project (http://usa.ipums.org/usa/)
As already remarked data gathered through sample surveys are generally more informative and allow making more refined analysis but they are more complex and “time-expensive” at the computational level.

What can we conclude from this brief review on primary and secondary analysis? Not too much. Actually, the set of options open to a researcher in terms of available data is sufficiently wide and rich to potentially allow making adequate choices. However as Alkire writes (2006, p. xx) “a straightforward way for choosing how to choose” unfortunately is not yet available. An accurate and honest analysis on the issue to what extent the aims of our investigation match reasonably well with the alternative options we have in terms of statistical data, still remains a crucial aspect of the research activity, and the experience we have can give support to this choice. Moreover, the opportunity to learn from other experiences is also a “golden rule” and luckily, as we will see in the next sections, the applied capability literature is rapidly increasing in quantity and improving in quality during the most recent years.

4. Briefing on applied statistical techniques

The theoretical shift from an income based approach to the capability approach has also other important challenge at a methodological level. The techniques and instruments traditionally used in income based research are not suitable to deal with some of the complexity of the capability approach. It is in this sense that Bourguignon (2006: 79) highlights that ‘the challenge is to create those instruments, rather than trying to make the initial paradigm artificially fit a different conceptual basis’. The capability approach operationalization demands the development of new techniques and research strategies.

Indeed, a range of alternative statistical techniques has been used in the empirical applications based on the capability approach. They have been used separately or jointly in order to deal with different technical and statistical issues related to the capability approach operationalization. Some of these issues have to do with dealing with qualitative variables, finding a common unit of measurement, defining a weight structure for their aggregation, dealing with measurement error, and modelling
complex causal relations. The solutions given to these matters are diverse and not only based on practical reasons but in analytical considerations as well. The range of statistical techniques that deal with these issues can be roughly classify in four groups: Scaling and Ranking Solutions, Fuzzy Set Theory, Multivariate Data Reduction Technique, and Regression Approach.

This section presents an overview of these four groups of techniques. We briefly summarized their main features and assess their strengths and weakness. This assessment aims to be a support to be used when choosing the most appropriate technique for each particular research. The comparison that is expanded in along the section is summarized in Table 1. The table implies certain degree of generalization and simplification and it should be taken only as a snapshot. It illustrates how some techniques are more suitable for certain contexts than others, or how they can be used jointly.

[Table 1 approximately here]

### 4.1 Scaling and ranking solutions

Scaling techniques are statistical solutions for the aggregation of indicators with different units of measurement, generally at a macro level. They have normally been used in order to obtain a single multidimensional measure for countries and regional ranking comparisons. The most emblematic example is the Human Development Index (HDI) published by UNDP in the Human Development Reports since 1990 (HDRs). Similar techniques are used in the whole range of UNDP’s indices: Gender-related Development Index (GDI), Gender Empowerment Measure (GEM), and Human Poverty Index for developing countries (HPI-1) or industrialized countries (HPI-2). The scaling solution can be applied with many variants. As a didactic

---

13 This section concentrates on quantitative methods (for qualitative methods used in the Capability Approach see: Alkire 2002; Apsan-Frediani 2006-2007; Clark 2002; Ferrero y de Loma-Osorio and Zepeda 2007; Manu V. 2003).
14 New methodologies for the measurement of multidimensional poverty and inequality have been developed by recent literature (c.f. Alkire and Foster 2007; Bourguignon and Chakravarty 2003).
15 The first publication for the HDI: UNDP (1990).
16 The first publication for GDI and GEM: UNDP (1995), and for HPI-1 and HPI-2: UNDP (1997).
illustration, we opt to describe the methodology followed by the range of UNDP's indices\textsuperscript{17}.

These indices are generally based on secondary data at a macro level, provided by the UN Statistics Division. Each dimension is measured with indicators that are provided by different UN agencies, obtained from a variety of sources (e.g. Census, Household Surveys, and Administrative Records). The result is a list of indicators per dimension at a macro level that have different units of measurement, lacking a natural aggregator. For instance, in the HDI, income is measured with purchasing power parity (PPP), life expectancy in terms of years of age, and the literacy rate or enrolment rate as percentages. The scaling solution consists in a standardization procedure. Each indicator $x_i^k$ is standardized following a lineal function by defining a maximum and a minimum value as follows:

\begin{equation}
\tilde{x}_i^k = \frac{x_i - M_i}{M_i - m_i}
\end{equation}

The maximum and minimum limits, $M_i$ and $m_i$ respectively, are considered goalposts for each dimension $i$. The standardized indicators $\tilde{x}_i^k$, are a linear projection of the original indicator in a scale between 0 and 1. This becomes a common unit of measurement suitable for aggregation. While solving the problem of having a common unit of measurement, the final measure also has a straightforward interpretation. The final measure refers to the level of attainment in each particular dimension expressed as a proportion of the goalpost. At a technical level, the definition of a maximum and minimum goalpost is, nevertheless, a matter of discussion (Anand and Sen 1994; Chakravarty 2003; Kabur 1990; Kuklys 2005; McGillivray and White 1993). In addition, the scaling solution requires continuous variables which are not always the variables’ level of measurement. Ordinal or categorical variables are common in multidimensional analysis, particularly at a micro level. As a result, these techniques are not completely suitable for interpersonal or interhousehold comparisons.

The aggregation of the standardized indicators in a single measure is finally solved with averaging procedures. A variety of average can be implemented. The HDI is

\textsuperscript{17} For a full technical reference: UNDP (2007b).
calculated by a simple unweighted arithmetic average of the standardized indicators. This solution avoids allocating arbitrary weights, but allows substitutability between dimensions (Kuklys 2005: 36) and certain redundancy between components (Berenger and Verdier-Chouchane 2007; Ivanova et al. 1999; McGillivray and White 1993). GDI and GEM are unweighted harmonic averages, which take into account a moderate aversion to inequality between genders, but still assume substitutability (particularly relevant to mention the conceptual and empirical critics of the Gender-related Measures, see: Klasen 2006). HPI-1 and HPI-2 are weighted averages, where greater weights are given to the dimension in which there is most deprivation. The main difficulty remains in defining the weighting structure for the aggregation, and the arbitrariness this might imply (Chowdhury and Squire 2006; Stapleton and Garrod 2007; Qizilbash 2004). The final indices should be treated as ordinal measures for ranking comparison (Anand and Sen 1994: 8). Country performance can be assessed, but the indices are not completely suitable for multivariate modelling techniques that require continuous variables.

Important disagreements exist in relation to the chosen indicators and the way in which the technique deals with issues of measurement error. The technique works under the assumption that the best indicators for measuring each dimension have been chosen. The indicators are provided by different UN’s agencies in an effort to obtain a reliable and comparable data. If a single indicator is considered insufficient for capturing the whole dimension appropriately, a number of indicators are combined in order to reduce the measurement error (Kuklys 2005: 35). Although choosing a large list of indicators could be seen as a way of reducing the measurement error, this would be difficult to do owing to the lack of internationally comparable data. In addition, a large list of indicators would imply additional problems when defining the weighting structure for their aggregation. As a result, the construct validity of the final index depends substantially on the choice of indicators for each dimension.

The scaling solution is an important step toward the operationalization of the Capability Approach. Despite its limitations, it is a relatively successful way of

---

18 A well documented example is the dimension “knowledge” in the HDI. Although this dimension was initially measured with literacy rate only, other indicators were incorporated later in order to obtain a more appropriate measure. In 1991, the mean year of schooling was incorporated. Finally, in 1995, this last one was replaced with the combined enrolment rate (primary, secondary and tertiary enrolment). Multiple indicators are also used in the dimension “Economic participation and decision-making power” in the GEM or “Economic deprivation” in HPI-1.
aggregating indicators with different units of measurement at a macro level. As a result, countries can be ranked and their performance assessed in accordance to each dimension or to a multidimensional measure. The indices can also be calculated for population subgroups providing the data is available at this level (Anand and Sen 1994: 10). The technique is, nevertheless, limited in its capacity to deal with the complexity and richness of the capability approach in its own. In particular, there is extensive literature, including the HDRs, which emphasizes that the HDI is far from being a comprehensive measure of Human Development (Fukuda-Parr 2003; Stewart et al. 2006). Other literature focuses on more technical issues some of which have been briefly mentioned in this section (see also: Raworth 1997; Sagar and Najam 1998). Interestingly, its simplicity and its capacity to raise public awareness and to stimulate public debate, remains an important strength of these measures. In Streeten (1994: 235) words, these indices “caught the public's eye” and “contribute to an intellectual muscle therapy that helps us to avoid analytical cramps”. Despite modest, this is perhaps one of the most significant contributions of the HDI.

4.2 Fuzzy Set Theory

Fuzzy set theory is a technique that handles continuous and ordinal variables simultaneously, and is generally used in the capability approach for micro level analysis. Initially introduced by Zadeh (1965), fuzzy set theory has been applied in diverse fields, including an extensive use in the social sciences19. In well-being analysis, it has been widely used for the measurement of multidimensional poverty and inequality since the pioneer works of Cerioli and Zani (1990)20. Its application to the Capability Approach was initiated by Chiappero Martinetti (1994; 1996; 2000; 2006), followed by several other empirical researches most frequently at a micro level (Addabbo et al. 2004; Balamoune 2004; Berenger and Verdier-Chouchane 2007; Qizilbash 2002; Qizilbash and Clark 2005; Lelli 2001; Roche 2007; Vero 2006).

Fuzzy Set Theory is considered an extension of classical sets theory, providing a mathematical framework for handling categories that permits partial membership (Smithson and Verkuilen 2006). Instead of considering categories in a binary form (member/non-member of a category), it conceives variables in terms of a degree of

---

19 For a didactic review see Smithson and Verkuilen (2006).
20 For a review in other research in multidimensional poverty measurement see Lemmi and Betti (2006).
membership. This is necessary when there is not a clear cut-off point between those cases that belong to a category and those that do not, for instance poor and non-poor. The achievement of functionings is considered to belong to this group of concepts. There are some clear situations where functionings have been totally achieved or clearly not achieved, but, more commonly, there are intermediate positions with a partial degree of achievement (Chiappero Martinetti 2000). In this case, defining the cut-off point is not just a technical problem, but the consequence of the concept being intrinsically complex and vague (Qizilbash 2006). Fuzzy Set Theory preserves this quality in the measurement and aggregation of functionings by treating variables in terms of a degree of membership, and later generalizing the procedure of union and intersection, or using averaging procedure for their aggregation.

The degree of membership is captured by a membership function that takes values between 0 and 1, where 1 represents total membership to the particular set and 0 total non-membership. Any value between 0 and 1 represents partial membership. Different membership functions can be chosen, allowing a variety of projections such as linear, trapezoidal, or sigmoid (logistic) functions. The justification of a particular membership function is normally theoretically grounded, so the analyst requires a broad knowledge about the indicators and the context, in order to choose the appropriate function. Alternatively, the membership function can be derived directly from the distribution, following the membership function proposed by Cheli and Lemmi (1995). This procedure can be applied to continuous or ordinal variables, while dichotomy variables would simply take values 0 or 1. The modalities in an ordinal variable would just need to be arranged and assessed in order to apply the appropriate membership function. The process reaches a common unit of measurement, while handling vagueness systematically. In micro level analysis, functionings that are measured with continuous or ordinal variables can later be expressed in terms of degree of achievement for their aggregation.

There are many different aggregation operators, the most common being the fuzzy union, the fuzzy intersection, and average procedures. They satisfy different axioms.

---

21 The intrinsically complex and vague nature of the Capability Approach have been extensively examined by Chiappero Martinetti (1994; 1996; 2000; 2006; forthcoming) and Qizilbash (2003; 2006).
22 Kuklys (2005) sustains that, to a certain extent, this procedure can be considered an extension of the scaling solution.
23 Ragin (2000) has extensively referred to this requirement in the more particular context of political science, which might also apply to some extent to the measurement of well-being.
and emphasize specific aspects. For instance, in their standard form, fuzzy union and fuzzy intersection capture the maximum or minimum achievement among the sets, which implies non-substitutability between functionings. Alternatively, weak intersection represents an algebraic product, emphasizing deprived situations. Average aggregators can be used to calculate an arithmetic, harmonic or geometric mean, similarly as in the scaling solution. Finally, a weight structure can be incorporated, providing more flexible substitution patterns between functionings (Kuklys 2005). The selection of the appropriate weighting structure is a matter of discussion, and it is commonly solved based on value judgment. Some attempts to define a weight structure based on more empirical basis have also been considered (Cerioli and Zani 1990; Chakravarty 2006; Cheli and Lemmi 1995; Vero 2006). As a result of the aggregation, an overall measure expressed in fuzzy set terms is obtained. This measure allows interpersonal or interhousehold comparisons, and it is suitable for most multivariate statistical techniques for inferences and models testing. Fuzzy Set Theory is seen as a technique that deals with complexity and vagueness systematically, having at the same time more theoretical fidelity (construct validity).

4.3. Multivariate data reduction techniques

A group of statistical techniques can be referred to as multivariate data reduction techniques. These statistical techniques are suitable when dealing with large amounts of data as they have a high power of data reduction and facilitate the design of aggregated variables. They analyze the interrelation between a large list of indicators in order to understand their underlying structure making it possible to reduce them to a small number of aggregated variables. These techniques include Factor Analysis, Principal Component Analysis, Multiple Correspondences Analysis and Cluster Analysis. Despite an early development, these techniques have experienced a more extensive use after the computational progress in the last decades. Currently, their use is common in diverse disciplines in social science. In the capability approach these statistical techniques were introduced by Schokkaert and Van Ootegem (1990), and followed by Maasoumi and Nickelsburg (1988), Klasen (2000), Balestrino and Sciclone (2000), Hirschberg et al. (2001), Lelli (2001), Neff (2006), and Roche (2007).

24 It is called HOMALS in SPSS.
25 They have been used extensively in psychology for scale construction in psychometric, attitudinal and subjective well-being scales (e.g. Ryff (1989), Williamson et al. (2002)). They have also been used in sociology for data reduction in social inequality (e.g. Arias and Devos (1996), Fiadzo et al. (2001))
Factor Analysis is the most common of these techniques (applied in: Balestrino and Sciclone 2000; Lelli 2001; Schokkaert and Van Ootegem 1990). When used in the capability approach, well-being, or the set of functionings, is conceptualised as a latent variable or as a factor underlying a large list of indicators. The factors are obtained based on the analysis of the correlation matrix. Factors are linear combinations of the indicators, clustering those highly correlated. In their compute, each indicator is explicitly considered to contain certain degree of measurement error, contributing just partially to each factor (for a detailed explanation see: Kuklys 2005; Krishnakumar and Nagar 2007). The factors, as aggregated measures, can be used for ranking comparison, or as variables in further analysis.

Principal Component Analysis is commonly referred to as a generalization of Factor Analysis and it is, to an extent, interchangeable (applied in: Klasen 2000; Maasoumi and Nickelsburg 1988; Roche 2007). However, Factor Analysis is considered more theoretically grounded, and more appropriate for understanding the factor structure. In contrast, Principal Component Analysis is seen as a more appropriate solution for data reduction (Krishnakumar and Nagar 2007). This is partly because the latter uses the total variance, while the former just the common or share variance between the indicators. However, both techniques leads to very similar results under certain circumstances such as large list, or highly correlated indicators (this is still a controversial issue: Velicer and Jackson 1990; Widaman 1993; Gorsuch 1990). In both techniques the weighting structure is directly derived from the data (see: Berenger and Verdier-Chouchane 2007: 1268; Klasen 2000: 39; Maasoumi and Nickelsburg 1988). This is an advantage when the list of indicators is considerably large and there is not a strong criterion for defining the weight structure. It also has the advantage of reducing the chance of double counting. This is, nevertheless, an ad hoc solution, since the aggregation and weights will vary every time a new data is considered, making comparison difficult. Similarly, these techniques require, at least, an ordinal level of measurement, but even in this case, variables are interpreted in a cardinal form. Processes of standardization, such as transforming the indicators into Fuzzy Sets, can make ordinal scales more suitable for these types of analysis (an illustration in: Roche 2007).
Multiple Correspondences Analysis also reduces a large set of variables into factors but it does not assume cardinality in the initial indicators (applied in: Neff 2006; Berenger and Verdier-Chouchane 2007). Instead of using the correlation matrix, this technique bases the analysis on simultaneous correspondence analysis between categorical data. Although this technique can be used as an aggregation solution, it seems more appropriate for exploratory analysis as a way to understand the underlying structure of the data. Finally, cluster analysis, in its general form, can be used to cluster similar cases or variables based on a proximity matrix of entropy distance. Hirschberg et al (2001) applied cluster analysis in order to group indicators with similar distribution, from a time series of eighty years of macro level indicators in the US. In this way, it also contributes to the understanding of interrelationships between indicators.

Multivariate data reduction techniques are, to some degree, good ad hoc and empirically based aggregation solutions, but perhaps their main strength is their exploratory potential. They facilitate the understanding of complex interrelationships between variables, by identifying relevant groups of interrelated variables (applied in: Hirschberg et al. 2001; Lelli 2001; Neff 2006; Roche 2007; Schokkaert and Van Ootegem 1990). This information is in itself valuable, while it can also be used as a way to reduce redundancy and double counting attributes when generating aggregated measures. Similarly, these techniques facilitate the selection of the most relevant indicators from a large list, reducing measurement error and increasing the construct validity of the final aggregated measure (frequently used in scale design in psychology, partially applied in: Klasen 2000: 39). Finally, they provide valuable insights that are useful when defining a weighting structure scheme, or aggregating the indicators with other techniques (Klasen 2000; Maasoumi and Nickelsburg 1988; Roche 2007).

4.4 Regression Approach

The Regression Approach has been used for modelling functioning achievement, subjective well-being, or perception of capability. The intention is to predict the multidimensional aggregated measure, usually a functioning or set of functionings, by income, contextual variables, or a range of socio-demographic characteristics. A broad range of techniques has been used in empirical research based on the
Capability Approach including OLS Regression Analysis, Probit Models, Ordered Logit, and Structural Equation Modelling. The selection of the appropriate technique depends roughly on the level of measurement of the variable involved, and the complexity of the relations to be included in the model.

OLS Regression analysis has been used by Schokkaert and Van Ootegem (1990), Klasen (2000) and Anand et al. (2005). This type of model is appropriate when the output or dependent variables have a continuous level of measurement. A multidimensional measure is normally regressed by income and some contextual and demographic variables. This multidimensional measure can be a variable generated in a previous step, using any aggregate solution. For instance, Schokkaert and Van Ootegem (1990) use the factor loadings generated in a previous Factor Analysis.

If the dependent variable is an ordinal measure, a generalized regression model is more appropriate. In this context, ordered logit models have been applied by Burchardt (2005), and Anand and Van Hees (2006), while ordered probit models have been applied by Kuklys (2005). Despite being mathematically different, these models operate in a roughly similar ways, often generating similar results. The ordered logit model allows different categories in the dependent variable, while providing a single coefficient for each independent variable (Burchardt 2005: 67). In the probit model, an unobserved continuous variable is considered to be underlying the dependent variable. This model measures the probability that an observed event occurs, affected by the independent variables. These techniques have been applied to models’ adaptive preferences in income satisfaction, (Burchardt 2005), capability satisfaction (Anand and Van Hees 2006) and functioning conversion factors and economy of scales (Kuklys 2005).

Structural equation modelling has been used by Addabbo et al. (2004), Di Tommaso (2007), Kulkys (2005), and Krishnakumar (2007). In essence, structural equation modelling is a technique that combines regression analysis and confirmatory factor analysis, simultaneously. The technique allows the researcher to employ several indicators to measure a single independent or dependent variable. Similarly to factor analysis, a set of indicators can be used in order to measure a broader concept as a latent variable, taking into account measurement error (Kuklys, 2005). In the capability approach, well-being or a set of functionings are measured as a latent
variable of a group of observed variables, as in Factor Analysis. Simultaneously, this latent variable is regressed by a range of independent variables, generally demographic and contextual variables. In this case there is a simultaneous use of Factor Analysis and Regression analysis (see: Krishnakumar and Nagar 2007).

Among its advantages, structural equation modelling allows assessing the overall fit of the model simultaneously with the factor analysis, while dealing explicitly with measurement error26. It has, nevertheless, similar problems to those associated with Factor Analysis. Interestingly, structural equation modelling has the potential for dealing with more complex causal relations than other techniques. It can consider multiple equations simultaneously or take into account reverse causality, which is common in the capability approach. This would be a better way of dealing with the complexity of causal relations in the Capability Approach. However, it is theoretically and statistically demanding. As a result, the applications in the capability approach have focused on more manageable models (MIMIC models)27.

5. Review of empirical analysis in the capability approach

Despite the important challenge that operationalizing the capability approach represents, there is a large range of empirical research in the field. Several applications have been produced particularly in the last decade. Table 2 presents a review of some of these empirical applications. The table focus on a comparison mainly between applications based on quantitative methods, and even though, it does not by far include an exhaustive list. Instead, it focuses on some of the most recent or well-known of these empirical applications, as a way of illustrating its diversity. They vary in many aspects: the type of data, the level of analysis, the number of dimensions and indicators, the statistical technique, among other aspects. In this section we give an overview of the large diversity of these empirical applications.

[Table 2 approximately here]

26 Kuklys (2005: 42) highlights that structural equation modelling includes a procedure for taking into account ordinal measurement of variables.
27 MIMIC: Multiple Indicator Multiple Cause model.
Some of the differences between the empirical applications can be explained by the variety of purposes among the applications. The most general aim has to do with valuation purpose for country or regional comparison, such as the case of the UNDP's range of indices. Another group of applications focuses on analyzing the differences between standard of living and functionings achievements, or just on understanding the interrelation between different functionings (e.g. Hirschberg et al. 2001; Krishnakumar 2007; Schokkaert and Van Ootegem 1990; Sen 1985; Drèze and Sen 2002). Several applications have been oriented towards measuring and explaining differences in well-being or deprivation at a household or individual level (e.g. Chiappero Martinetti 2000; Klasen 2000; Lelli 2001; Qizilbash and Clark 2005). Some other concentrate in specific sub-groups of population (such as children in: Addabbo et al. 2004; Biggeri et al. 2006; Di Tommaso 2007; or gender differences: Robeyns 2006). Another group of applications focuses on a specific aspect related to the capability approach operationalization, such as subjective perception of capability (e.g. Anand et al. 2005; Anand and Van Hees 2006), adaptive preferences (Burchardt 2005), or differences in functioning conversion factors (Kuklys 2005). The variety of orientations is considerable. Similarly, the context of the applications is diverse. Some studies focus on developing countries (e.g. India, South Africa, Venezuela) while others are oriented to more developed ones (e.g. Belgium, UK, USA).

Most frequently, applications are based on Secondary Data. At the macro level, applications make use of the United Nations statistics for intercountry comparison (Baliamoune 2004; Berenger and Verdier-Chouchane 2007; Krishnakumar 2007; Sen 1985; UNDP 2007a), or national macro data for interregional comparison (Balestrino and Sciclone 2000; Drèze and Sen 2002; Qizilbash 2002). Micro level analysis have been carried out principally using household surveys (Anand et al. 2005; Chiappero Martinetti 2000; Di Tommaso 2007; Klasen 2000), but, occasionally, with census data when the microdata is available (Roche 2007). Some other empirical applications have been carried out with primary data analysis (Anand and Van Hees 2006; Biggeri et al. 2006; Qizilbash and Clark 2005).

As a result of the limitations for measuring capabilities directly, most research focuses on functionings achievement or refined functionings (e.g. Chiappero
Martinetti 2000; Drèze and Sen 2002; Kuklys 2005; Sen 1985). This is not surprising, considering that most analyses are based on secondary data. There have been, nevertheless, some attempts to measure capabilities. An interesting effort has been carried out by Anand et al. (2005) and Anand and Van Hees (2006), initially with secondary data, and later with the design of ad-hoc surveys. This group of research focuses on the subjective perception of capabilities which is extremely linked with subjective well-being. Although there have not been any empirical applications yet, there is some interesting literature on the measurement of agency and subjective well-being by Alkire (2005) and Samman (2007). Finally, Krishnakumar (2007) and Di Tommaso (2007) have attempted to measure capabilities as latent variables with Multiple Structural Equation. However, Kuklys (2005), using similar techniques opts for conceptualizing the latent variables as sets of functionings (similar approach is followed in factor analysis, e.g. Schokkaert and Van Ootegem 1990). Most application of the capability approach remains in the functioning space, but interesting efforts have been done to incorporate other illustrative aspects.

There is also a great diversity concerning the selection of dimensions and indicators. Some empirical analysis might focus on a small selection of dimensions, such as the three dimensions in the illustration carried out by Sen (1985). Alternatively, other empirical applications include a large list of dimensions (Anand et al. 2005; Chiappero Martinetti 2000; Klasen 2000; Robeyns 2006). Dimensions can be captured by a single indicator or, most frequently, by a range of indicators. A good illustration is Drèze and Sen (2002) that focuses on three dimensions but includes a list of more than 30 indicators. Most empirical applications make some link between dimensions and normally generate an aggregated multidimensional measure. Other applications opt for avoiding any aggregation attempt concentrating on analyzes by dimensions or indicators (Robeyns 2006).

Finally, different applications in the capability approach make use of a variety of statistical techniques, mostly depending on the purpose of the analysis. The most common aggregation techniques and the regression approach were summarized earlier. Additionally, empirical applications use partial scaling or stochastic dominance when they opt for a non-aggregation solution (e.g. Brandolini and D’Alessio 1998; Robeyns 2006). The supervaluationist approach has been applied by Qizilbash (2002) and Qizilbash and Clark (2005) as a procedure for defining the appropriate limits of
fuzzy set membership functionings. Empirical applications show the complementarities between different statistical techniques.

6 Conclusions

The theoretical richness of the capability approach certainly implies important challenges at an empirical level. We have presented in this chapter a guideline for young scholars who aim to carry out empirical research based on the capability approach. We have briefly explained the main data requirements, and reviewed the available datasets and most common statistical techniques used in empirical application in the field. Indeed, the efforts to operationalize the capability approach have been undertaken by many researchers resulting in a growing production of empirical applications and methodological alternatives. This abundance of production should dissipate the concerns regarding the possibility of operationalizing the capability approach, and instead encourage further and innovative research.

After our exposition, it should be clear that there is not a standard and exclusive procedure to translate the capability approach’s theoretical level into empirical counterparts. Instead, there is a rich variety of alternatives that can be implemented depending on the research’s objectives and available resources. In terms of statistical requirements, researches on the capability approach need information regarding a plurality of evaluative spaces, a plurality of dimensions which are measured with multiple indicators and scales, a plurality of units of analysis including the possibility to capture personal heterogeneities, and also regarding to a plurality of environmental contexts. We have deliberated on the advantages and disadvantages of primary analysis and secondary analysis, and the benefits and limitations of macro and micro data to meet these data requirements. As we have seen, the set of option open to researches is sufficiently wide and rich to allow making adequate choices. There is also a range of statistical techniques suitable for dealing with the statistical requirements of the capability approach. We have presented a briefing on the most common ones, and highlighted their strengths and weaknesses in order to facilitate choice.

Despite these progresses, the challenges still remain great. The empirical applications in the capability approach have only explored a segment of a much
larger research agenda. Other alternative and innovative tools are still required in order to deal with the range of research questions within the capability approach. This new paths would surely imply new interdisciplinary joint efforts. The ad-hoc section on the Human Development and Capability Association website is intended to contribute in this process. It remains a space in which to spread and share the new developments.
# Table 1. Comparison between main applied statistic techniques

<table>
<thead>
<tr>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scaling and ranking solutions</strong></td>
<td></td>
</tr>
<tr>
<td>✓ Aggregation solution at a macro level for indicators with different units of measures</td>
<td>✓ Requires continuous variables (not handling categorical variables)</td>
</tr>
<tr>
<td>✓ The final indices have straightforward interpretations as levels of achievement in relation to a goalpost</td>
<td>✓ Non-satisfactory solution for micro level analysis (interpersonal or interhousehold comparisons, where categorical variables are frequent)</td>
</tr>
<tr>
<td>✓ Facilitates ranking comparison and performance assessment in accordance to each dimension or to the synthetic index</td>
<td>✓ The final indices should be treated as ordinal scales which makes them not suitable for most modelling techniques</td>
</tr>
<tr>
<td>✓ The indices can be calculated by population subgroups provided the data is available</td>
<td>✓ Based on many previous analytical considerations (e.g. selecting best indicators in each dimension, defining bottom and top limits, weighting structure)</td>
</tr>
<tr>
<td>✓ A weight structure can be incorporated into the formula</td>
<td>✓ Implied assumptions (e.g. HDI assumes substitutability between dimensions)</td>
</tr>
<tr>
<td><strong>Fuzzy set theory</strong></td>
<td></td>
</tr>
<tr>
<td>✓ Aggregation solution at a micro level, that can handle continuous variables with different units of measurements simultaneously with categorical variables</td>
<td>✓ The “fuzzy measures” are theoretically accurate, but are difficult to interpret intuitively</td>
</tr>
<tr>
<td>✓ Combines set-wise thinking and continuous variables in a rigorous way</td>
<td>✓ Involves significant analytical considerations (e.g. defining membership functions, weighting structure)</td>
</tr>
<tr>
<td>✓ The cut-off levels, in poverty analysis, are defined as fuzzy measures</td>
<td>✓ Normally requires a broad knowledge about the indicators and context in order to define the appropriate membership functions (alternatively: distribution function)</td>
</tr>
<tr>
<td>✓ Deals with complexity and vagueness systematically having more theoretical accuracy</td>
<td>✓ Does not directly deal with issues of redundancy or excess of data/indicators, or with issues concerning measurement error</td>
</tr>
<tr>
<td>✓ Different weighting schemes provide more flexible substitution</td>
<td>✓ In confirmatory analysis, the construct validity of the final factors depends on the theoretical relevance of the chosen initial indicators</td>
</tr>
<tr>
<td>✓ Suitable to be used with other statistical techniques for inferences and models testing</td>
<td>✓ In most techniques, ordinal scale variables need to be interpreted in cardinal sense (alternatively: nominal variables in Multiple Correspondence Analysis, or latent continuous variables in Structural Equation Modelling)</td>
</tr>
<tr>
<td><strong>Multivariate Data Reduction techniques</strong></td>
<td></td>
</tr>
<tr>
<td>✓ Aggregation solution with high power of data reduction</td>
<td>✓ The final factors score tends to be difficult to interpret</td>
</tr>
<tr>
<td>✓ Weights are derived directly from the data, instead of the researcher’ decisions</td>
<td>✓ Aggregation and weights would vary every time new data is considered, making comparison difficult (e.g. comparison between years or countries)</td>
</tr>
<tr>
<td>✓ Suitable for exploratory analysis or confirmatory analysis in the identification of relevant underlying dimensions</td>
<td>✓ Not a single solution depending on the choice of extraction and rotation method</td>
</tr>
<tr>
<td>✓ Reduces the chance of double counting highly similar attributes and deals with issues concerning measurement error</td>
<td>✓ In confirmatory analysis, the construct validity of the final factors depends on the theoretical relevance of the chosen initial indicators</td>
</tr>
<tr>
<td>✓ The factors loadings or component score can be saved and used in further analysis for inferences and model testing (alternatively incorporated directly in the model as in Structural Equation Modelling)</td>
<td>✓ In most techniques, ordinal scale variables need to be interpreted in cardinal sense (alternatively: nominal variables in Multiple Correspondence Analysis, or latent continuous variables in Structural Equation Modelling)</td>
</tr>
<tr>
<td><strong>The Regression Approach</strong></td>
<td></td>
</tr>
<tr>
<td>✓ Allows modelling multidimensional aggregate variables (e.g. capabilities, functionings, subjective well-being), as a function of resources, contextual or demographic variables.</td>
<td>✓ The models have to deals with the complex interrelationship between the variables in the capability approach</td>
</tr>
<tr>
<td>✓ Indicators or synthetic indices calculated with previous techniques can be incorporated as dependent or independent variables in the models</td>
<td>✓ The more the technique deals with the complexity of the capability approach the more the models loose in parsimony</td>
</tr>
<tr>
<td>✓ There is a large range of regression techniques depending on the unit of measurement of the dependent and independent variables</td>
<td>✓ The outcomes of some techniques are difficult to interpret, non-intuitive, and to some extent inaccessible to policy makers</td>
</tr>
<tr>
<td>✓ SEM combines factor analysis and regression analysis in one single step, and allows running simultaneous equations for complex causation modelling</td>
<td>✓ Some techniques does not deal with measurement error (except for SEM)</td>
</tr>
</tbody>
</table>
Table 2 - Review of empirical analyses based on the capability approach

The following is a non-exhaustive list of some of the most recent or well-known empirical analyses based on the capability approach.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Aim of the Study</th>
<th>Focus</th>
<th>Data</th>
<th>Level</th>
<th>Source</th>
<th>Dimensions</th>
<th>Indicators</th>
<th>Diversity</th>
<th>Context</th>
<th>Link between dimensions or levels</th>
<th>Technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sen (1985)</td>
<td>Illustrating the difference between living standards rankings and functioning or capability rankings</td>
<td>F</td>
<td>SD</td>
<td>Macro</td>
<td>UN</td>
<td>Income, the ability to live longer and avoid mortality during infancy and childhood, the ability to read and write and to benefit from sustained schooling</td>
<td>3</td>
<td>No</td>
<td>Selected countries</td>
<td>No</td>
<td>Descriptive Statistics, Partial ranking</td>
</tr>
<tr>
<td>Schockkoert &amp; van Ootogem (1990)</td>
<td>Measurement of living standard of unemployed according to the capability approach and its relation with some demographic variables.</td>
<td>F</td>
<td>SD</td>
<td>Micro</td>
<td>A survey set up by RVA</td>
<td>Social, Psychological, Physical Microsocial contact, Activities, Financial</td>
<td>46</td>
<td>Yes (ex-ante)</td>
<td>Belgium</td>
<td>Yes</td>
<td>Factor Analysis, Regression Analysis</td>
</tr>
<tr>
<td>UNDP (1990)28</td>
<td>Measuring and monitoring progress in Human Development for comparisons across countries</td>
<td>F</td>
<td>SD</td>
<td>Macro</td>
<td>UN</td>
<td>Longevity, Knowledge, Decent living standards</td>
<td>4</td>
<td>No</td>
<td>Almost all countries</td>
<td>No</td>
<td>Scaling Normalization (linear function), Complete Ranking</td>
</tr>
<tr>
<td>UNDP (1995)29</td>
<td>A measure of Human Development that is sensitive to gender inequality for cross-country comparison.</td>
<td>F</td>
<td>SD</td>
<td>Macro</td>
<td>UN</td>
<td>Longevity, Knowledge, Decent living standards</td>
<td>4</td>
<td>Yes (ex-ante)</td>
<td>Almost all countries</td>
<td>No</td>
<td>Scaling Normalization (weighting formula with aversion to inequality), Complete Ranking</td>
</tr>
<tr>
<td>UNDP (1995)30</td>
<td>Measuring the relative empowerment of men and women in political and economic spheres for cross-country comparison</td>
<td>F</td>
<td>SD</td>
<td>Macro</td>
<td>UN</td>
<td>Economic participation and decision-making power, Political participation and decision-making power, Power over economic resources</td>
<td>4</td>
<td>Yes (ex-ante)</td>
<td>Almost all countries</td>
<td>No</td>
<td>Scaling Normalization (weighting formula with aversion to inequality), Complete Ranking</td>
</tr>
</tbody>
</table>

28 Date of first publication. Since 1990 the HDI has experienced a number of improvements and modification.
29 Date of first publication.
30 Date of first publication.
<table>
<thead>
<tr>
<th>Study Source</th>
<th>Measurement and Monitoring Progress</th>
<th>Scales/Indices Used</th>
<th>Scores</th>
<th>Data Type</th>
<th>Methodology and Analysis Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UNDP (1997)</strong>&lt;sup&gt;31&lt;/sup&gt; Human Poverty Index (HPI -1)</td>
<td>Measuring and monitoring progress in decreasing Human Poverty for comparisons across developing countries and over time.</td>
<td>F SD Macro UN Deprivation related to survival, Deprivation related to knowledge, Deprivation in a decent living standard in terms of overall economic provisioning</td>
<td>5</td>
<td>No</td>
<td>Scaling Normalization, Generalized weighted mean with $\alpha=3$, Complete ranking</td>
</tr>
<tr>
<td><strong>UNDP (1997)</strong>&lt;sup&gt;32&lt;/sup&gt; Human Poverty Index (HPI -2)</td>
<td>Measuring and monitoring progress in decreasing Human Poverty for comparisons across industrialized countries and over time.</td>
<td>F SD Macro UN Deprivation related to survival, Deprivation related to knowledge, Deprivation in a decent living standard in terms of overall economic provisioning</td>
<td>4</td>
<td>No</td>
<td>Scaling Normalization, Generalized weighted mean with $\alpha=3$, Complete ranking</td>
</tr>
<tr>
<td><strong>Brandolini &amp; D’Alessio (1998)</strong></td>
<td>Assessment of multidimensional measure of deprivation, and capability approach’s methodological applications</td>
<td>F SD Micro SHIW Deprivation related to survival, Deprivation related to knowledge, Deprivation in a decent living standard in terms of overall economic provisioning</td>
<td>16</td>
<td>Yes (ex-post)</td>
<td>Sequential stochastic dominance, deprivation index, Partial and complete ranking</td>
</tr>
<tr>
<td><strong>Chiappero-Martinetti (2000)</strong></td>
<td>Dealing with some methodological issues related to the multidimensional analysis of well-being from the capability approach’s theoretical perspective.</td>
<td>F SD Micro ISTAT Health, Education, Social relations, Labour market, Housing, Household’s economic resources</td>
<td>34</td>
<td>Yes</td>
<td>Fuzzy Sets Theory Complete ranking</td>
</tr>
<tr>
<td><strong>Balestrino &amp; Sciclone (2000)</strong></td>
<td>Comparison between ranking with empirical measures of functioning achievements and ranking with standard income-based measures</td>
<td>F SD Macro ISTAT Health, Education, Employment, Housing, Safety, Environment, Income, Social Infrastructure</td>
<td>26</td>
<td>No</td>
<td>Factor analysis, Complete ranking</td>
</tr>
<tr>
<td><strong>Hirschberg et al. (2001)</strong></td>
<td>Identifying distinct dimensions in multidimensional analysis of welfare and quality of life.</td>
<td>F SD Macro Various The dimensions are not specified a priory but later as a result of the cluster analysis.</td>
<td>15</td>
<td>No</td>
<td>ARIMA Models and entropy measures, Cluster analysis</td>
</tr>
</tbody>
</table>

<sup>31</sup> Date of first publication.

<sup>32</sup> Date of first publication.
<table>
<thead>
<tr>
<th>Lelli (2001)</th>
<th>Comparing the use of Factor Analysis with Fussy Sets Theory for the operationalization of the capability approach</th>
<th>FSD</th>
<th>SGM</th>
<th>PSHIB</th>
<th>Social interactions, Cultural activities, Economic conditions, Health, Psychological distress, Working conditions, Shelter</th>
<th>Yes</th>
<th>Belgian</th>
<th>No</th>
<th>Factor Analysis Fuzzy Set Theory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qizilbash (2002)</td>
<td>Examining vulnerability and 'definitive poverty' and producing an inter-provincial ranking of provinces in various dimensions of the quality of life.</td>
<td>FSD</td>
<td>SGM</td>
<td>National Census</td>
<td>Seven indicators are selected, but no dimensions are specified. Implicitly the dimensions are: consumption, education, employment and housing.</td>
<td>7</td>
<td>No</td>
<td>No</td>
<td>Fuzzy sets theory and supervaluationist approach</td>
</tr>
<tr>
<td>Baliamoune (2004)</td>
<td>Proposing a framework that uses fuzzy-set theory to measure human well-being according to the capability approach.</td>
<td>FSD</td>
<td>SGM</td>
<td>UN</td>
<td>Health, Knowledge, and freedom to communicate, Income, Freedom dimension</td>
<td>10</td>
<td>No</td>
<td>No</td>
<td>Fuzzy sets theory Complete ranking</td>
</tr>
<tr>
<td>Anand et al. (2005)</td>
<td>Showing that secondary data source provides some information about capabilities and that this can be incorporated into models of subjective well-being.</td>
<td>FSD</td>
<td>SGM</td>
<td>BHPS</td>
<td>Bodily Health, Bodily Integrity, Sense, Imagination, and Thought, Emotions, Practical reason, Affiliation, Play, Satisfaction</td>
<td>25</td>
<td>No</td>
<td>No</td>
<td>OLS Regression analysis</td>
</tr>
<tr>
<td>Burchardt (2005)</td>
<td>Studying process of adaptive expectation, with an empirical application to changes in income and satisfaction with income.</td>
<td>FSD</td>
<td>SGM</td>
<td>BHPS</td>
<td>One dimension (satisfaction with income), predicted by income and some socio-demographic variables.</td>
<td>1</td>
<td>Yes</td>
<td>No</td>
<td>Ordered logit regression</td>
</tr>
<tr>
<td>Kuklys (2005)</td>
<td>Examining alternative econometric techniques to put into practice the capability approach for poverty and inequality measurement. Three empirical applications.</td>
<td>FSD</td>
<td>SGM</td>
<td>BHPS</td>
<td>First two empirical applications: Health, Housing, Income Third empirical application: Satisfaction with household income, Household Income, Needs, Preference shifters</td>
<td>15</td>
<td>Yes</td>
<td>No</td>
<td>Structural Equation Model (MIMIC), Axiomatic inequality measures for the general entropy class, Equivalence scale method, Ordered probit model</td>
</tr>
<tr>
<td>Qizilbash &amp; Clark (2005)</td>
<td>Defining a new approach to specifying the cut-off levels that define the boundaries of fuzzy poverty measures.</td>
<td>FSD</td>
<td>SGM</td>
<td>Ad-hoc quest.</td>
<td>Education, Housing, Water, Sanitation, Energy, Jobs, Health-Health care, Perceived well-being</td>
<td>9</td>
<td>Yes</td>
<td>No</td>
<td>Fuzzy set theory and supervaluationist approach</td>
</tr>
<tr>
<td>Reference</td>
<td>Title</td>
<td>Identification of a list of relevant capabilities for children through a participatory bottom-up approach</td>
<td>Capability Assessment</td>
<td>Life and physical health, love and care, mental wb, bodily integrity and safety, social relations, participation, education, freedom from economic and non-economic exploitation, shelter and environment, leisure activities, respect, religion and identity, time autonomy, mobility</td>
<td>Yes (ex-ante)</td>
<td>Yes (ex-post)</td>
<td>Yes (income/functioning)</td>
<td>Yes (ex-ante)</td>
<td>Yes (ex-post)</td>
</tr>
<tr>
<td>-----------</td>
<td>-------</td>
<td>--------------------------------------------------</td>
<td>-----------------------</td>
<td>-------------------------------------------------</td>
<td>----------------</td>
<td>----------------</td>
<td>--------------------------</td>
<td>----------------</td>
<td>----------------</td>
</tr>
<tr>
<td>Biggeri et al. (2006)</td>
<td>Identification of a list of relevant capabilities for children through a participatory bottom-up approach</td>
<td>C &amp; A</td>
<td>Micro</td>
<td>Ad-hoc quest</td>
<td>Life and physical health, love and care, mental wb, bodily integrity and safety, social relations, participation, education, freedom from economic and non-economic exploitation, shelter and environment, leisure activities, respect, religion and identity, time autonomy, mobility</td>
<td>Yes (ex-ante)</td>
<td>Yes (ex-post)</td>
<td>Yes (income/functioning)</td>
<td>Yes (ex-ante)</td>
</tr>
<tr>
<td>Robeyns (2006)</td>
<td>Measuring gender inequality in Functioning and Capabilities using the British Household Panel Study</td>
<td>B &amp; C</td>
<td>Micro</td>
<td>BHPS</td>
<td>Life and physical health, Mental well-being, Bodily integrity and safety, Social relations, Education and knowledge, Domestic work and nonmarket care, Paid work and other projects, Shelter and environment, Mobility, Leisure activities, Religion</td>
<td>Yes (income)</td>
<td>Yes (gender)</td>
<td>Yes (income)</td>
<td>Yes (gender)</td>
</tr>
<tr>
<td>Krishnakumar (2007)</td>
<td>Proposing a structural equation econometric model to measure capabilities as latent factors, and their interrelation with other observed endogenous factors.</td>
<td>F &amp; C</td>
<td>Micro</td>
<td>UN</td>
<td>Health, Knowledge, Political freedom</td>
<td>Yes</td>
<td>No</td>
<td>Countries</td>
<td>No</td>
</tr>
<tr>
<td>Roche (2007)</td>
<td>Methodological proposal for the design of sets of indicators for monitoring inequality between social groups based on large datasets.</td>
<td>F &amp; C</td>
<td>Micro</td>
<td>VenHHS</td>
<td>Three dimension of Housing Adequacy: Services, Structure, and Space and Density</td>
<td>Yes (ex-ante)</td>
<td>Yes (ex-post)</td>
<td>Countries</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Focus: (C) Capabilities (F) Functionings (SWB) Subjective Well-Being (A) Agency
Data: (SD) Secondary Data Analysis (PD) Primary Data Analysis
Level: (Macro) Macro Level (Micro) Micro Level
Technique: (MIMIC) Multiple Indicator Multiple Causes model


Contribution to “Debating Global Society: reach and limits of the CA”, Fondazione Feltrinelli Part II – Ch. 1 – Enrica Chiappero-Martinetti, José Manuel Roche 07/10/2008, 2.55


Contribution to “Debating Global Society: reach and limits of the CA”, Fondazione Feltrinelli
Part II - Ch. 1 – Enrica Chiappero-Martinetti, José Manuel Roche 07/10/2008, 2.55
SCHOKKAERT, E. and L. VAN OOTEGEM (1990) 'Sen's Concept of the Living Standard
Applied to the Belgian Unemployment'. Research Economiques de Louvain, 56, 429-450.
SRINIVASAN, T. N. (1994) 'Human development: A new paradigm or reinvention of the wheel?'
American Economic Review, 84 (2), 238.
Index should not diverge from its equal weights assumption'. Social Indicators Research, 84
(2), 179-188.
STEWART, F., G. RANIS and E. SAMMAN (2006) "Human Development: Beyond the Human
Development Index". Journal of Human Development, 7 (3), 323-358.
84 (2), 232-237.
Macmillan.
VELICER, W. F. and D. N. JACKSON (1990) 'Component Analysis Versus Common Factor-
Analysis - Some Issues in Selecting an Appropriate Procedure'. Multivariate Behavioral
VERO, J. (2006) 'A Comparison of Poverty According to Primary Goods, Capabilities and
WIDAMAN, K. F. (1993) 'Common Factor Analysis Versus Principal Component Analysis:
Differential Bias in Representing Model Parameters?' Multivariate Behavioral Research, 28
(3), 263.
WILLIAMSON, D., L. WOMBLE, M. SMEETS, R. NETEMEYER, J. THAW, V. KUTLESIC and
D. GLEAVES (2002) 'Latent structure of eating disorder symptoms: A factor analytic and
ZIMMERMANN, B. "Pragmatism and the Capability Approach: Challenges in Social Theory and
Empirical Research". European Journal of Social Theory, 2006; 9; 467