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TITLE

Multidimensional Deprivation in Contemporary Switzerland across Social Groups and Time

Research Paper

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Abstract

We have investigated the phenomenon of deprivation in contemporary Switzerland through the adoption of a multidimensional, dynamic approach. By applying Self Organizing Maps (SOM) to a set of 33 non-monetary indicators from the 2009 wave of the Swiss Household Panel (SHP), we identified 13 prototypical forms (or clusters) of well-being and deprivation within a topological, two-dimensional space. Then new data from the previous waves (2003 to 2008) were classified by the SOM model trained with the data of wave 2009, making it possible to estimate the weight of the different clusters in time and reconstruct the dynamics of stability and mobility of individuals within the two-dimensional output space. During the period from 2003 to 2009, the size of the clusters remained basically unchanged. Looking at the transition matrices between year t and year t+1, we observed a high mobility among the adjacent multidimensional forms compared to those which are more distant, a sign that well-being and deprivation in contemporary Switzerland show certain stability over time.

Keywords

Multidimensional deprivation, Self-Organizing Maps, Swiss Household Panel, Transition probabilities.

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1. Limits of previous approaches of well-being and deprivation

There is full agreement in academic research and in policy-oriented debate in considering well-being and poverty as multi-faceted phenomena, hardly captured with a single monetary indicator. As widely discussed in the literature, measuring the well-being of individuals and families implies the adoption of a wider array of items that describe the different aspects of a person's life (Atkinson 2002, 2003). Several studies have documented that there is only a partial overlap between the condition of the lack of income and the experience of deprivation as it is subjectively perceived by individuals (Whelan and Maître 2005, 2007).

In the wake of the popularity of the 'capability approach' of Sen (1985), social scientists and international organizations have shown a strong interest in the comparison of constructs with a high degree of generality and semantic ambivalence, such as social exclusion, vulnerability, precariousness and psychophysical fragility (cf. World Bank 2001; UNDP 2005; European Commission 1992). These concepts should intercept substantial aspects of the life conditions of individuals and families, such as the difficulties encountered in safeguarding health, in realizing achievements in education, in enjoying adequate living conditions, in protecting oneself against risks in the surrounding environment, in being integrated into a network of friends and family, in taking an active part in social life, in being able to achieve freely chosen aims and in experiencing a feeling of self-esteem (cf. Atkinson et al. 2002; Atkinson 2002; Brandolini 2008).

In general, multidimensional measures are obtained by selecting a certain number of dimensions and indicators which characterize the condition of exclusion from ordinary living patterns, the relevance of which is decided by the researcher in accordance with the current literature. The selected indicators are subsequently combined into synthetic indices according to criteria which are affected by a certain degree of subjectivity and arbitrariness (cf. Callan et al., 1993; Hallerod 1996; Ringen 1987, 1988; Mack and Lansley 1985).

Examples of measures of synthetic macro-level indices are the Human Development Index (HDI) and the Human Poverty Index (HPI), obtained by combining the information related to per capita income, life expectancy and literacy for each country (Bourguignon and Chakravarty 2003). A limitation of these indices is that, being based on national averages, they do not allow us to investigate the distribution of the phenomenon at the individual level. In other words, the macro indices are not able to detect groups which experience increased risks of deprivation and which may require supportive intervention by institutions.

In order to take into account heterogeneity at the individual level, several measures of deprivation were developed which take the individual, rather than the country, as the unit of analysis. After having chosen a valid and reliable set of dimensions and indicators for each dimension, the researcher adopts a certain strategy of aggregation of the indicators in order to obtain a synthetic

index. Various strategies may be adopted in order to identify individuals who are poor in multidimensional terms: the simplest is to combine the different indicators of deprivation within a synthetic index, in reference to which a threshold has been fixed for identifying the multidimensionally deprived subjects. As may be seen, this approach has an obvious weakness in that the multidimensionality is collapsed within a one-dimensional vector. Another way to build synthetic indices is to select a certain number of relevant dimensions which are initially kept separate. For each of the selected dimensions, a synthetic index is constructed, along which is fixed a specific cutoff which distinguishes between those who are deprived and those who are not. The number of dimensions in reference to which each individual is deprived is then counted ('counting approach').

At this point, one of two different procedures may be taken in order to assess who is poor in multidimensional terms: the 'union approach', which considers as poor those who are deprived in at least a single dimension, and the 'intersection approach', which considers as deprived those who are placed either above or below the cutoff point in all of the selected dimensions (Brandolini 2008). Recently, both the union and intersection approaches have been criticized because the former tends to overestimate the proportion of deprived individuals, while the second underestimates it (cf. Whelan et al.2012).

In order to improve the methods just described, Alkire and Foster (2007, 2011a, 2011b) propose to set a second cutoff on the minimum number of dimensions in reference to which an individual is considered as being multidimensionally deprived. The Alkire and Foster methodology therefore represents a middle way between the union and intersection approaches.

The choice of dimensions and indicators, as well as the strategy of aggregation of indicators and dimensions, are particularly delicate aspects and are not free from subjectivity and arbitrariness. The synthetic index, despite being easily understandable for policy makers and media, is ultimately rooted in a counting of dimensions rather than in the way in which the dimensions combine with each other, thereby generating distinctive forms of multidimensional deprivation. In other words, the synthetic index ends up sacrificing the multidimensionality within a scalar which, by definition, fails to account for the different prototypical forms of well-being and deprivation which characterize the multidimensional space of the data. Expressing multidimensional forms of deprivation requires something more than a scalar quantity. A better strategy is to compress the multidimensional space of data within vectors of elements which express specific combinations of the attributes selected for the values of the chosen indicators.

2. Towards a dynamic multidimensional mapping approach

As an alternative to synthetic indices based on some method of aggregation arbitrarily chosen, we present a non-parametric and clustering approach – the Self Organizing Maps (SOM) – capable of

preserving the multidimensionality contained in the empirical data. The SOM have already been applied in previous work on multidimensional deprivation in order to identify homogeneous clusters of subjects (cf. Lucchini et al. 2007; Pisati et al. 2010; Whelan et al. 2010; Lucchini and Assi 2012). However, in these studies a single wave was taken into consideration, which prevents us from capturing the dynamic aspects involved in the concepts of well-being and deprivation. The originality of this contribution is therefore that for the first time, we propose an application of SOM to data of the Swiss Household Panel. Working with repeated measurements has permitted us to describe how the weight of the clusters varies within the temporal window 2003-2009, as well as to identify factors which increase or decrease the risk of transition from one group to another.

Such an approach establishes a robust framework for monitoring the weight of several prototypical forms of well-being and deprivation, each of which expresses a different combination of dimensions which matter most in people's lives over time and within different social groups. Furthermore, we believe that this analytical tool can contribute to designing more effective policies against poverty as an alternative to other, more widely-used, multidimensional measures.

This paper is organized as follows: section 3 describes the data and the non-monetary indicators of deprivation on which the analyses will be performed. Section 4 provides a description of the Self Organizing Map, which is the topological technique which we have adopted in order to preserve multidimensionality. Section 5 presents the main results of the topological mapping: after having identified 400 microclusters, we propose a reduction of the output space to 13 macro-clusters. In section 6 we study the extent to which some important heterogeneity factors (such as age, level of education, economic poverty, region of residence, family typology, community typology) exert an effect on the probability of belonging to the prototypical forms identified. In section 7 we investigate how the weight of each cluster changes over time and how individuals maintain or change position from a year to the next. Concluding remarks are given in section 8.

3. Data and Variables

The data used in the analysis comes from wave 2009 of the Swiss Household Panel (SHP), a longitudinal survey conducted annually since 1999 that aims at exploring the dynamics of changing living conditions in Switzerland. Our analysis makes use of 5956 respondents in reference to which we have selected 33 non-monetary indicators accounting for 9 different dimensions: emotional capital, health, relational support, trust and satisfaction in people and institutions, satisfaction with free time, housing conditions, neighbourhood environment, and material and financial deprivation.

The choice of the dimensions and of the indicators has been made taking into account previous empirical studies on the dimensional structure of deprivation (cf. Layte, Maître, Nolan and Whelan 2001; Whelan, Layte, Maître and Nolan 2001; Guio 2005a, 2005b). In particular, Whelan and Maître (2012) have identified six dimensions of deprivation: basic deprivation, consumption

deprivation, health, neighbourhood environment, housing, and access to facilities through the application of factor analysis to a broad range of deprivation items available in the EU-SILC 2009. The focus of our analysis roughly follows the above-mentioned dimensions, with the addition of other dimensions which we consider interesting and which recur extensively in the literature on subjective well-being (Kahneman 2007; Frey and Stutzer 2002; Easterlin 2001), social capital (Coleman 1990; Putnam 1993; Fukuyama 1995) and quality of life (Cantril 1965; Allardt 1976; Andrews and Withey 1976). We refer in particular to dimensions of emotional capital, health, relational support, trust and satisfaction in people and institutions, satisfaction with free time and leisure time, housing conditions, neighborhood, environment, material and financial deprivation. It goes without saying that the selection of indicators has, to a large extent, been conditioned by the information contained in the SHP within the time frame of 2003-2009.

The indicators have been rescaled so that they have the same direction. In Table 1 we have reported the individual indicators, their respective means and standard deviations, and finally the Cronbach's Alpha reliability coefficients relating to each specific dimension.[i] The indicators are measured either at the individual level or at the household level. Since the analysis is performed at the individual level, the properties measured at the household level are associated with each family member.

Table 1. List of indicators of well-being and deprivation

	Code	**Mean**	**Std dev.**	**Alpha**
Happiness / Emotional Capital				*0.671*
1) In general, how satisfied are you with your life? Scale: 0 (not at all satisfied) - 10 (completely satisfied)	Happy	2.04	1.48	
2) Do you often have negative feelings such as having the blues, being desperate, suffering from anxiety or depression? Scale: 0 (never) - 10 (always)	Blues	2.18	2.14	
3) Are you often full of strength, energy and optimism? Scale: 0 (never) - 10 (always)	Energy	2.82	1.74	
Health				*0.5933*
4) How satisfied are you with your state of health? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Health	2.22	1.82	
5) Since last year, has your health improved or worsened? Scale: 0 (greatly worsened) - 10 (greatly improved)	Improv_health	4.82	1.26	
6) Please indicate to what extent, generally, your health is an impediment in your everyday activities, in your housework, your work or leisure activities. Scale: 0 (not at all) - 10 (a great deal)	Impediment	2.03	2.60	

Relational Support				*0.6678*
7) If necessary, in your opinion, to what extent can your relatives provide you with practical help, that is, concrete help or useful advice? Scale: 0 (not at all) - 10 (a great deal)	Practical_help	2.81	2.43	
8) To what extent can your relatives be available in case of need and show understanding, for example by talking with you? Scale: 0 (not at all) - 10 (a great deal)	Relatives_available	2.16	2.00	
9) How satisfied are you with your personal relationships? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Sat_relationship	1.91	1.54	
Trust and Satisfaction in People and Institutions				*0.6445*
10) Would you say that most people can be trusted, or that you can't be too careful in dealing with people? Scale: 0 (most people can be trusted) - 10 (can't be too careful)	Trust_people	3.98	2.29	
11) Overall, how satisfied are you with the way in which democracy works in our country? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Sat_democracy	3.88	1.95	
12) How much confidence do you have in the Federal Government ? Scale: 0 (full confidence) - 10 (no confidence)	Conf_government	4.58	2.18	
Satisfaction with Free Time and Leisure Time Activities				*0.6462*
13) How satisfied are you with the amount of free time you have? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Free_time	2.76	2.44	
14) How satisfied are you with your leisure time activities? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Leisure_time	2.26	2.02	
Housing Conditions				*0.1459*
15) Are you faced with accommodation which is too small? Dummy: 1 (yes), 0 (no)	Too_small	0.08	0.28	
16) Are you faced with poorly heated accommodation? Dummy: 1 (yes), 0 (no)	Heat	0.07	0.26	
Neighbourhood Environment				*0.4629*
17) Are you faced with a noisy external environment? Dummy; 1 (yes), 0 (no)	Noisy	0.23	0.42	
18) Are you faced with traffic and industrial pollution? Dummy: 1 (yes), 0 (no)	Pollution	0.11	0.33	
19) Are you faced with crime, violence or vandalism in the area? Dummy: 1 (yes), 0 (no)	Crime	0.11	0.32	
Material Deprivation				*0.5985*
20) Can't afford one week holiday away from home per year? Dummy; 1	Holiday	0.08	0.27	

(yes), 0 (no)				
21) Can't afford to invite friends at least once a month? Dummy: 1 (yes), 0 (no)	Invite_friends	0.03	0.18	
22) Can't afford to go to a restaurant at least once a month? Dummy: 1 (yes), 0 (no)	Restaurant	0.14	0.35	
23) Can't afford a private car? Dummy: 1 (yes), 0 (no)	Car	0.03	0.18	
24) Can't afford a colour TV? Dummy: 1 (yes), 0 (no)	TV	0.002	0.04	
25) Can't afford a home computer? Dummy: 1 (yes), 0 (no)	Computer	0,01	0.11	
26) Can't afford a washing machine? Dummy: 1 (yes), 0 (no)	Washing_machine	0.01	0.09	
27) Can't afford a dishwasher? Dummy: 1 (yes), 0 (no)	Dishwasher	0.01	0.12	
28) Can't afford to go to the dentist if necessary? Dummy: 1 (yes), 0 (no)	Dentist	0.02	0.15	
Financial Pressure and Savings Deprivation				*0.7538*
29) How satisfied are you with the financial situation of your household? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Fin_household	2.74	1.98	
30) Overall, how satisfied are you with your financial situation? Scale: 0 (completely satisfied) - 10 (not at all satisfied)	Fin_individual	2.98	2.13	
31) How do you manage on your household's current income? Scale: 0 (very easily) - 10 (with great difficulty)	Manage_house_inc	2.73	2.19	
32) Can't you afford savings into the 3rd pillar? Dummy: 1 (yes), 0 (no)	3rd_pillar	0.10	0.30	
33) Assessment of household's income and expenses: Scale: 1 (your household can save money); 2 (your household spends what it earns); 3 (your household eats into its assets and savings); 4 (your household gets into debt)	Assess_income	1.58	0.70	

The level of reliability of the items selected, measured by using Cronbach's Alpha, range from 0.14 for housing conditions to 0.75 for financial deprivation. We can clearly see how the items which have less discriminating power, are those which refer to material deprivation. This finding is not surprising, as Switzerland is one of the most affluent countries in the world. However, we believe it is important to use these items in the analysis, as they allow us to identify those individuals who, despite being a small minority, are in a state of severe material deprivation in relation to the Swiss standard.

The dimension of emotional capital is represented by three indicators: satisfaction with life in general, the frequency of negative feelings and the frequency of optimism. The dimension of health is expressed by three items: satisfaction with one's state of health, the improvement or worsening of one's health as compared to the previous year and the presence of obstacles in everyday activities. The dimension of relational support is represented by three indicators which refer to practical help, emotional support, and satisfaction with personal relationships. Three items were

selected to represent trust and satisfaction: trust in people in general, satisfaction with democracy and confidence in the federal government. The dimension of free time is described by two items which express satisfaction with the amount of one's free time and satisfaction with the activities carried out in one's free time. To represent the dimension of the housing situation, two items have been selected: having an accommodation which is too small and having an accommodation which is poorly heated. A noisy neighborhood, traffic and industrial pollution, and crime, violence and vandalism in the surrounding area are the three items used to represent the dimension of deprivation in the neighborhood environment. Material deprivation is described by nine items relating to the possibility of going on holiday, of inviting friends to one's home, of going to the restaurant, of seeing a dentist when needed and of being able to afford a private car, a color TV, a home computer, a washing machine, and a dishwasher. These indicators should capture what is labeled in the literature as 'basic and consumption deprivation'.

4. The SOM tool

The Self-Organizing Map (SOM) is a type of unsupervised neural network by which it is possible to visualize high dimensional data on a low dimensional display. The SOM algorithm therefore reduces, through clustering, the size of the data and then projects it on a regular, planar grid. Besides reducing the dimensionality, the algorithm also preserves the topology of the data which means that observations that are close in the input space tend to be close also in the output space. Therefore the SOM is a powerful visualization tool that displays similarities between the identified clusters.

Since its introduction by Teuvo Kohonen in 1982, the SOM tool has been applied in fields ranging from engineering to environmental studies, medicine and finance, that is in those fields when a data reduction technique was needed.

The input data manifold consist of p real vectors **x** of length n. They represent a matrix of n observations on p variables and are called "training vectors". A SOM consists of neural units (or nodes) organized on a regular two-dimensional grid that is called output space or lattice.

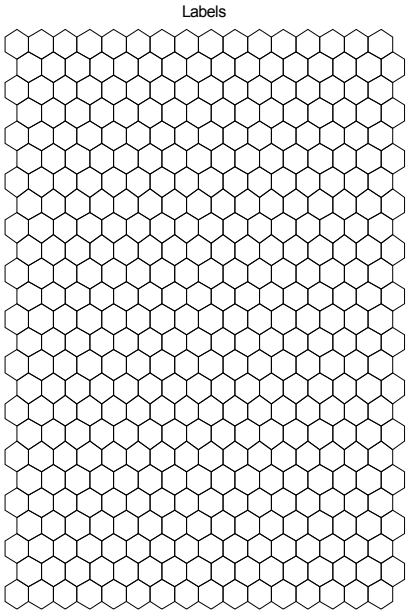

Figure 1. Example of a two-dimensional SOM made of 48 units arranged in a 25x16 hexagonal lattice

Each node is associated with a weight vector **m** of length n that is called prototype vector or reference vector. The updating of the weight vector is carried out by a learning process which finds the best matching unit $\mathbf{m}_c$ (BMU) for a given data sample **x**, such that:

$$\|\mathbf{x} - \mathbf{m}_c\| = min_i\{\|\mathbf{x} - \mathbf{m}_i\|\}$$

The Euclidean distance is the most commonly used distance measure.

Through the learning process, the weight vectors are updated iteratively according to the adaptation rule:

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + h_{ci}(t)[\mathbf{x}(t) - \mathbf{m}_i(t)]$$

where $\mathbf{x}_t$ is the input vector randomly drawn at time t, $h_{ci}(t)$ is the neighborhood function around the winner unit c. The neighborhood function is a smoothing kernel that tends to zero when time tends to infinity. It is a function of the distance between: (a) the location vector of the node that corresponds to the BMU ($r_c \in R^2$) and: (b) the location vector of the node i ($r_i \in R^2$).

The starting values of $m_i(0)$ can be chosen at random.

The function $h_{ci}(t)$ can be chosen in different ways such as:

- $h_{ci}(t) = \alpha(t)$ if $i \in N_c$ and zero otherwise. N_c is a neighborhood set of points around node c. The value of $\alpha(t)$ is the learning-rate factor at time t ($0 < \alpha(t) < 1$) that decreases

monotonically with time along with the radius of N_c. If the map is not large, that is up to a few hundred nodes, the choice of $\alpha(t)$ is not crucial. However, if the map is large it is convenient to choose $\alpha(t)$ as a function that is inversely proportional to t.

- $h_{ci}(t) = \alpha(t) \cdot exp\left(\frac{\|r_c - r_i\|}{2\sigma^2(t)}\right)$ where the value of $\alpha(t)$ is, again, the learning-rate factor at time t and $\sigma(t)$ corresponds to the width of the kernel.

The training is performed in two phases. The first is characterized by a wide neighborhood radius (close to half the diameter of the network) and by a large learning rate (close to 1). The second phase is characterized by a progressive decreasing of both the learning rate and the neighbourhood radius. The number of iterations necessary to reach convergence depends on the number of neural units rather than on the dimension of the input matrix.

After training the SOM network, its quality must be evaluated. Usually two errors (quantization and topographic) are calculated. The quantization error E_{qe} takes values in the interval [0,1] and it measures the average distance between each data vector and its best matching unit (BMU).

$$E_{qe} = \frac{1}{n}\sum \|\mathbf{x} - \mathbf{m}_c\|$$

Through the topographic error it is possible to assess the map's degree of topology preservation. It is calculated as the proportion of all data vectors for which first and second BMUs are adjacent.

$$E_{te} = \frac{1}{n}\sum u(\mathbf{x})$$

In fact the function u(**x**) is 1 if the data first and second BMUs are adjacent and 0 otherwise.

5. Results

The analyses were carried out using the SOM Toolbox for Matlab 5 (Vesanto, Himberg, Alhoiemi and Parhankangas 2000). We reduced a multidimensional space (1.31072E+22) into a two-dimensional rectangular array (25 x 16) made up of 400 micro-clusters. At the end of the training process, each observation is allocated to its final BMU and the quality of the SOM is evaluated by using the 'quantization error' and the 'topographic error' (Kohonen 1982, 2001). Our SOM exhibits a normalized quantization error equal to 0.038, meaning that, on average, each element of the input vector differs from its corresponding best-matching-unit weight by 3.8 percentage points and a topographic error equal to 0.142%, meaning that only about nine observations are affected by some degree of 'topological misplacement'.

Weight vectors were initialised using the linear method and the SOM training was carried out in two phases: a 20-epoch ordering phase, based on a large initial value and a fast decrease of both

the neighbourhood radius and the learning rate, and a 100-epoch fine-tuning phase, based on a slow adjustment of both the neighbourhood radius and the learning rate. In both training phases, a Gaussian neighbourhood kernel was used (Kohonen, 2001).

To understand the configuration of the trained SOM, we visually inspect its component planes shown in Figure 2. Component planes are a type of graph which illustrates the value taken by a given element of the weight vector in each SOM unit. Looking at the component planes, we may observe that the units take on a different shade of color: black units are specialized in recognizing disadvantaged people in reference to a given item, while white units capture the advantaged ones. The units between the maximum advantage and the maximum disadvantage are represented by different shades of gray. The values of components are denormalised so that the values shown on the colour bar are in the original value range.

From the component planes, it can be seen that the emotional capital items are very closely related. The units which take on the darker shades and which therefore recognize those individuals who are the unhappiest, are concentrated in the portion at the bottom right of the map. The component planes for indicators of poor health also reveal a concentration of black units in the same region of the map: a sign that the dimensions of health and happiness correlate to some extent. The indicators of relational support instead show distributions of black units at different points of the map, with an emphasis in the bottom right and top right corners. The black units referring to the indicators of trust in others and institutions assume a random configuration. The same applies to the housing and neighborhood environmental items, which are distinguished by the fact that black units form small, spatially dispersed clusters. Dissatisfaction with leisure time is well represented by the units which make up the center-right area of the map and the region in the lower right. A small group placed at the bottom left represents individuals who live in conditions of severe material deprivation. The items regarding financial deprivation, instead, generate a large cluster of black units positioned in the lower left of the map. As has already emerged from the descriptive statistics, indicators of financial deprivation show a higher discriminative power than indicators of material deprivation.

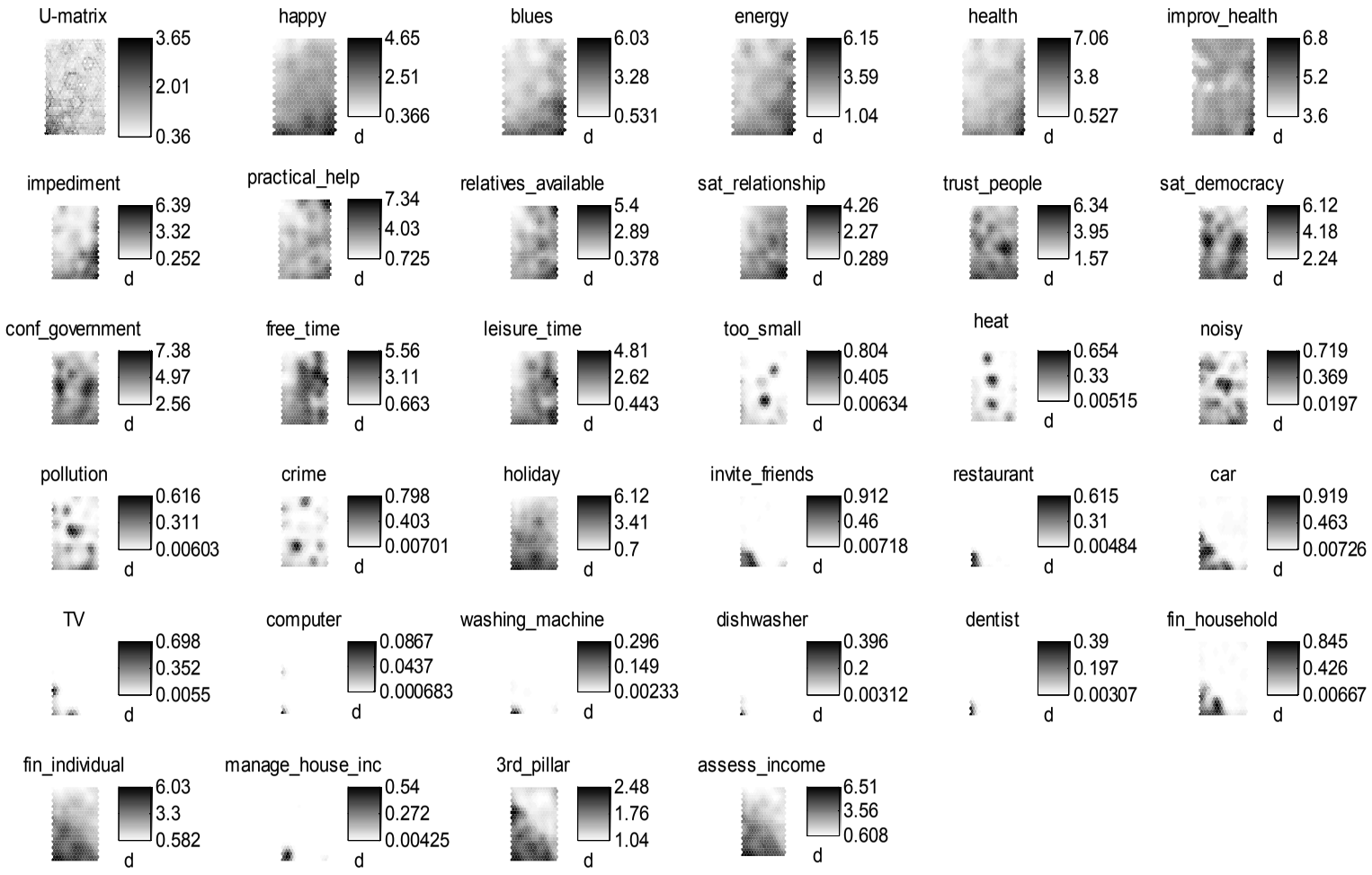

Figure 2. Component planes for some representative indicators of deprivation (the variable labels are the same as in table 1).

Since the description of the four hundred microclusters which make up the map would be too detailed and unusable for policy makers, we propose a reaggregation of the units into macro-clusters by using an agglomerative clustering technique based on the average linkage method. Figure 3 displays the results of this operation. We opt for 13 macro-clusters which are highly homogenous internally, as this solution appears to offer a reasonable balance between parsimony and precision. The partition of the output space into a smaller set of macro-clusters can easily be achieved thanks to the topological properties of the map.

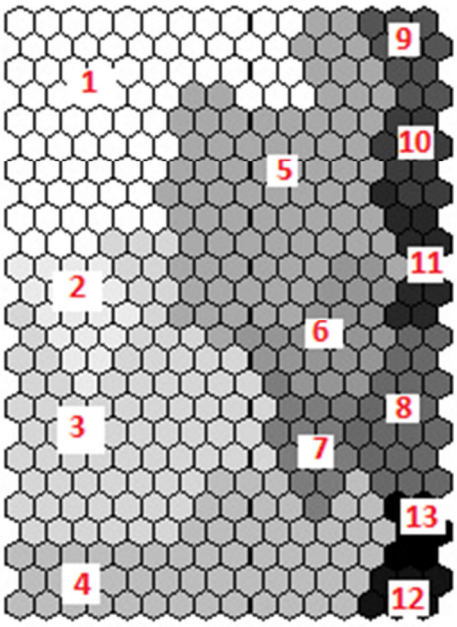

Figure 3. Reaggregation of the 400 units into 13 clusters.

The next step is to interpret the macro clusters by examining the component mean deviations. In order to better understand the cluster's profiles, we have pursued a strategy that is a variation of a procedure developed by Pisati et al. (2010) (see appendix 1). We transformed the component mean deviations into an alphanumeric code consisting of symbols "+" and "-" as can be seen in Table 2. In the table, the number of symbols in the alphanumeric code expresses the intensity of deprivation. The higher the number of plus symbols, the more deprived are the people belonging to a specific cluster; the higher the number of minus symbols, the better are the well-being conditions of people belonging to a specific cluster.

Below is a brief description of the profile of each cluster.

Table 2. Profile of SOM clusters in terms of deprivation dimensions

Cluster	Happiness	Health	Relationships	Trust	Free time	Housing	Environment	Material dep.	Financial dep.
1	---	--	---	--	---	--	.	---	---
2	---	---	---	+++	---	--	--	---	+
3	.	-	.	.	.	+	.	-	++
4	+++	++	++	+++	++	+	.	+++	+++
5	-	--	-	-	++	.	-	---	---
6	.	-	++	+++	+	---	--	---	-
7	+++	++	+	++	--	---	--	---	+
8	+++	+++	+	.	-	---	.	---	--
9	--	.	++	---	---	---	-	---	--
10	+	+++	.	--	--	---	---	---	---
11	+	++	++	.	+++	---	---	---	---
12	+++	+++	+++	+++	++	++	+	--	++
13	+++	+++	+++	++	+++	+	.	---	-

- Cluster 1 brings together the largest number of sample observations (20.0%) and expresses a state of multidimensional well-being. The individuals within this cluster show strong negative deviations from the average with respect to most of the dimensions discussed.
- Cluster 2, with 3.9% of the cases, shows a similar profile to cluster 1, at least regarding the dimensions of happiness, health, relationships, leisure, housing conditions and material well-being. It differs, however, in relation to the dimensions of trust and financial deprivation. The members of this cluster show levels of trust in other people and institutions which are significantly lower than average, as well as a slightly lower level of financial deprivation.
- In cluster 3, comprising 20.9% of the observations, there are individuals with a level of health and material well-being that is slightly higher than average. In the remaining dimensions, these individuals roughly follow the average profile. Another distinguishing feature of this group is a

certain degree of housing and financial vulnerability. The latter appears to be more intense than in the previous cluster.

- 13.0% of the cases compose cluster 4, which we have classified as a group of cumulative deprivation. The members of this cluster show a strong deprivation with respect to the dimensions of emotional capital, financial and material deprivation and trust in people and institutions. Other noteworthy differences concern health, relational support, leisure time and housing conditions. The dimension of neighborhood environment roughly corresponds to the average profile of the sample.
- In cluster 5, which brings together 17.8% of the records, we observe negative deviations in almost all of the dimensions (that is a condition of cumulative well-being). Dissatisfaction with free time represents the only problematic dimension. It follows that this cluster can be classified in the region of multidimensional well-being and, not coincidentally, is spatially adjacent to cluster 1.
- Cluster 6, which represents 5.0% of the sample, includes individuals with a lower level of relational support and a lower degree of trust in other people and institutions. Furthermore, there is a slight dissatisfaction with free time and leisure time. In the other dimensions – health, housing, neighbourhood environment, material and financial deprivation – the deviations are all negative, indicating that those who belong to this group enjoy a state of relative well-being.
- Cluster 7 brings together a small percentage of observations (2.3%). Here we find relatively well-off individuals in the areas of leisure time, housing, neighborhood environment and material resources, but who show some vulnerability in relation to happiness, health, finance, trust in people and institutions.
- Cluster 8 consists of 5.0% of the observations, and may be labeled as a group with psychophysical fragility. Those within this group show deprivation in the dimensions of emotional capital, health and relational support, while they are satisfied with housing, free time, material and financial resources.
- In cluster 9, which constitutes 3.7% of the sample, we find subjects who experience a condition of multidimensional well-being, that is, they show negative deviations with reference to all of the dimensions examined. The only exceptions are the condition of health, which roughly follows the average profile, and the relational aspect, which shows a marked positive deviation.[ii]
- Cluster 10, which contains 3.3% of the observations, expresses a strong deprivation on indicators of health and emotional capital, while the remaining dimensions show opposite signs. Similarly to cluster 8, this cluster may also be labeled as a group with psychophysical fragility which is accompanied by a state of economic well-being.
- In cluster 11, which comprises 2.4% of the sample, we find individuals with a profile of psychophysical fragility similar to the previous cluster, with positive differences in the

dimensions of happiness, health, relationships and leisure time. With regard to housing, neighbourhood environment, and material and financial property, a state of relative well-being emerges.

- Cluster 12, equal to 1.3% of the sample, is similar to cluster 4 and therefore may be labeled as a cluster of multiple deprivation. In this cluster there are individuals who show strong positive deviations in the dimensions of happiness, health, relational support and trust with the exception of material deprivation. Also, seemingly of note are the positive deviations in the dimensions of free time, housing and financial situation.
- Finally, cluster 13, which includes 1.3% of the sample, combines subjects in conditions of relative material and financial comfort which nevertheless show marked signs of deprivation with reference to the dimensions of happiness, health, relational support and free time. Within the dimensions of trust and housing, a certain degree of deprivation may also be observed.

6. Bivariate Analyses

This paragraph illustrates the bivariate analyses that should clarify whether traditional heterogeneity factors play a role in accounting for patterns of multiple deprivation and well-being.

Table 3. Probability of cluster membership conditional on age

Pr(C|age)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
Up to 25	12,83	5,34	26,33	17,78	18	6,97	1,33	1,79	2,31	3,49	2,22	0,71	0,91
26-45	15,44	3,84	23,26	12,16	25,8	5,13	1,26	3,63	0,9	2,82	3,45	0,78	1,53
46-65	22,97	3,18	18,29	11,65	16,51	5,55	2,38	5,41	5,28	3,4	2,35	1,75	1,28
Older than 65	27,61	3,01	17,3	11,59	3,47	2,2	5,02	10,67	8,01	5,92	0,89	2,49	1,83
Total	19,38	3,73	21,18	12,78	18,1	5,12	2,21	5	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,1807

Membership in clusters 1 and 9 of multidimensional well-being appears to be positively associated with old age. On the other hand, the probability of belonging to clusters 5 and 6, which also represent clusters of well-being, is markedly lower for those over 65 years old. As expected, the probability of belonging to clusters 8 and 10 of psychophysical fragility is relatively higher for people aged 65 or more. The clusters of financial vulnerability show a different pattern of associations with age. While clusters 2 and 3 seem to better characterize the segment of young people, the probability of belonging to cluster 7 is relatively higher for people aged 65 or more. It is also important to note how membership in cluster 4 is associated with younger age.

Table 4. Probability of cluster membership conditional on economic poverty[iii]

Pr(C|poverty)	*c1*	*c2*	*c3*	*c4*	*c5*	*C6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
No poverty	19,75	3,41	20,74	11,23	19,28	5,49	1,98	5,28	3,78	3,76	2,68	1,25	1,38

Poverty	12,9	3,27	27,29	27,72	11,2	2,4	3,01	2,52	2,55	1,96	1,6	2,71	0,85
Total	18,94	3,4	21,52	13,18	18,32	5,12	2,11	4,95	3,63	3,54	2,55	1,42	1,32

Cramér's V = 0,0944

As might be expected, the membership in cluster 4, that represents the cumulative deprivation, is highly dependent on economic poverty: among the subjects under the poverty threshold, 27.7% belong to cluster 4, while only 11.2% of subjects positioned above the threshold belong to the same cluster. It should also be noted that economic poverty is a good predictor of cumulative well-being (c1, c5), financial deprivation (c3, c7) and of psychophysical fragility (c8, c10).

Table 5. Probability of cluster membership conditional on education

Pr(C|education)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
Less than sec. education	13,79	4,89	25,09	22,18	12,25	5,42	2,83	4,08	2,66	2,44	1,74	2,05	0,58
Secondary education	20,71	3,73	21,93	12,62	15,84	5,25	2,45	5,42	3,53	3,73	2,17	1,29	1,34
Tertiary education	20,4	3,03	16,88	7,36	26,15	4,72	1,4	4,8	4,54	4,05	3,62	1,04	2,02
Total	19,41	3,73	21,05	12,81	18,13	5,13	2,22	5,01	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,1397

As one might expect, the probability of belonging to clusters of multiple deprivation (clusters 4 and 12) appears significantly lower for those with high qualifications. Only 7.4% of those in possession of a tertiary degree fall into cluster 4, as compared with 12.6% of those with a secondary education and 22.2% of those with less than a secondary education. Moreover education performs as an important protective action against forms of financial vulnerability (c2, c3 and c7).

Table 6. Probability of cluster membership conditional on region

Pr(C|region)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
Lake Geneva	14,65	3,28	26,31	20,62	12,57	3,46	2,83	6,54	2,22	2,63	1,86	1,68	1,34
Middleland	18,28	5,37	21,27	13,84	15,39	5,47	2,98	4,71	3,62	3,35	3,08	1,83	0,81
N-W Switzerland	20,38	3,13	21,48	7,84	19,07	6,52	1,84	4,54	6,31	3,73	3,53	0,38	1,25
Zurich	19,22	2,62	18,96	12,54	23,5	3,92	1,32	4,14	4,01	4,53	2,15	0,53	2,57
East Switzerland	24,62	2,94	21,97	7,43	19,74	5,04	1,2	4,81	3,07	3,45	1,92	2,47	1,33
Central Switzerland	20,92	4,28	16,84	9,48	23,07	5,79	1,95	3,78	4,11	4,33	2,88	1,26	1,31
Ticino	23,23	4,46	14,17	14,96	13,73	10,08	4,32	8,82	0,89	3,22	1,12	0,36	0,66
Total	19,38	3,73	21,18	12,78	18,1	5,12	2,21	5	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,0927

From Table 6, the existence of a geographical gradient in the distribution of the forms of well-being and deprivation may be inferred. The most striking feature regards the Lake Geneva region, whose

inhabitants show a probability of belonging to cluster 4 (multiple deprivation) equal to 20.6% (when the sample mean amounts to 12.8%) while the probability of belonging to cluster 3 of financial vulnerability is equal to 26.3% (when the sample mean is 21.2%).

Table 7. Probability of cluster membership conditional on nationality

Pr(C|nationality)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
Swiss nat.	21,58	4,08	20,21	10,16	17,99	5,03	2,4	5,43	3,85	3,91	2,44	1,5	1,41
Foreign nat.	10,76	2,34	25	23,08	18,53	5,44	1,48	3,3	2,91	2,32	2,72	0,78	1,33
Total	19,38	3,73	21,18	12,78	18,1	5,12	2,21	5	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,1246

Nationality is also a good predictor of belonging to clusters of well-being and deprivation. Among the subjects of Swiss nationality, the probability of belonging to cluster of cumulative well-being (c1) stands at 21.6%, while among foreigners that probability drops to 10.8%. In contrast, the probability of belonging to the cluster of multiple deprivation (cluster 4) reaches 23.1% among foreigners, while for Swiss citizens it does not exceed 10.2%.

Table 8. Probability of cluster membership conditional on family typology

Pr(c|family typology)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
One person aged 65 years or more	23,13	2,84	16,55	15,41	2,67	2,69	6,62	12,74	5,9	4,79	0,36	3,02	3,26
One person aged 30-64 years	16,14	3,05	17,33	19,23	19,69	4,31	1,54	6,68	3,25	3,14	2,39	1,56	1,69
One person aged less than 30 ys	21,29	13,23	25	13,06	22,57	0,95	0	1,29	0	1,25	1,37	0	0
Lone parent with one or more children aged 16 or younger	4,67	2,22	25,29	32,84	13,22	1,8	1,86	6,13	1,32	5,13	0	3,29	2,23
Lone parent with at least one child older than 16 years	13,3	5,62	28,67	18,62	14,63	5,5	0,6	1,57	3,75	0,98	4,11	1,42	1,24
Couple with at least one person aged 65 or over, no children	30,23	2,81	16,08	10,83	4,18	2,41	4,16	8,78	9,19	6,67	1,35	2,22	1,08
Couple under 65, no children	23,43	3,72	16,81	7,46	21,26	6,29	2,33	4,9	3,5	3,39	3,97	1,12	1,82
Couple with one child	13,68	3,85	20,11	14,16	28,91	4,21	2,46	2,74	1,79	3,58	2,88	0,73	0,89
Couple with two children	15,47	2,86	25,37	12,78	24,95	7,56	1,18	2,98	1,71	1,26	2,16	0,18	1,53
Couple with three + children	16,12	2,04	36,23	11,8	20,44	2,14	0,61	1,12	0,41	3,09	4,59	1,11	0,31
Couple with at least one child over 16	17,8	4,3	23,56	11,87	18,8	6,75	1,58	4,17	2,72	4,22	1,8	1,17	1,26
Other households with all members related	9,79	4,91	21,31	18,39	27,28	3,53	2,18	2,85	3,74	0,23	3,4	2,39	0
Total	19,38	3,73	21,18	12,78	18,1	5,12	2,21	5	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,1064

The category of lone parents with at least one child older than 16 shows a probability of belonging to cluster 4 equal to 18.6% while the category of lone parents with one or more children aged 16 or younger shows a probability equal to 32.9%. The class of a single person aged 30-64 years or under the age of 30 reveals a high risk of belonging to the same cluster (about 18%).

The probability of falling in cluster 3 of financial vulnerability appears to be particularly high for the category of lone parent with at least one child older than 16 (28.7%) and of couple with three children or more (36.2%).

The category of one person aged 65 years or more and of the couples without children with at least one aged 65 or over show the highest probability of belonging to cluster 8 of psychophysical fragility.

On the other hand, the class of couples without children with at least one individual aged 65 or over and of couples under 65 without children displays a higher probability than average of belonging to cluster 1 of multidimensional well-being. Finally, couples with one or two children show the highest probability (28.9% and 24.9% respectively) of belonging to cluster 5.

Table 9. Probability of cluster membership conditional on community typology

Pr(C|community typology)	*c1*	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*	*c8*	*c9*	*c10*	*c11*	*c12*	*c13*
Centres	17,12	2,32	23,68	15,5	19,05	3,35	1,68	5,19	3,68	3,37	1,94	2,08	1,05
Suburban	19,97	4,48	19,62	12,2	18,28	5,63	2,32	4,53	3,67	4,12	2,16	1,02	2,01
Wealthy	23,06	2,75	16,83	11,34	15,62	7,29	2,1	7,83	3,02	4,05	4,1	0	2,02
Peripheral Urban	22,26	3,03	21,52	7,2	18,75	6,13	1,78	5,86	4,43	3,91	3,48	0,38	1,27
Tourist	20,87	4,42	18,92	9,88	19,89	5,1	0	6,65	3,65	1,05	5,74	2,05	1,78
Industrial and Tertiary Sector	20,64	6,86	23,02	13,62	13,95	6,03	4,1	3,92	2,05	2,54	1,98	0,97	0,32
Rural Commuter	20,23	3,44	16,23	12,28	17,87	5,39	2,13	5,89	5,96	3,88	3,41	2,09	1,2
Mixed Agricultural	16,76	3,28	22,9	14,37	18,93	5,35	3,06	3,72	2,23	3,64	2,78	1,53	1,44
Peripheral Agricultural	18,66	6,23	21,03	9,05	18,51	9,18	2,06	3,01	4,86	1,93	2,14	1,42	1,91
	19,38	3,73	21,18	12,78	18,1	5,12	2,21	5	3,66	3,59	2,5	1,35	1,4

Cramér's V = 0,0588

If we look at the type of community, centers and mixed agricultural communities show the highest probability of belonging to cluster 4 of multiple deprivation (around 14%-15%) while wealthy and tourist communities show the highest probability of belonging to cluster 8 of psychophysical fragility (around 7%-8%).

7. Evolution of the prototypical forms across time and mobility of subjects across the topological space

In order to understand in depth the phenomenon of deprivation and well-being, it is necessary to reconstruct the individual trajectories of life by taking a series of 'snapshots' and connecting them within a 'film'. The adoption of a longitudinal approach is justified by the fact that well-being, vulnerability, psychophysical fragility and deprivation are states that are prone to change over time.[iv] The increased availability of longitudinal data allows us to focus our attention on the individual dynamics of transition from a given state to a different one across life courses (see Walker and Ashworth 1994; Jenkins and Rigg 2001; Fourage and Layte 2005; Layte and Whelan 2002). With longitudinal data it is possible to describe the evolution of the prototypical forms of well-being and deprivation and the paths of permanence and mobility of subjects along topological space.

Table 10. Distribution of the prototypical forms of well-being and deprivation across waves.

	2003	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*
c1	19,51	21,5	20,36	20,22	21,37	20,66	19,97
c2	3,28	3,45	2,94	3,02	3,43	2,98	3,87
c3	21,71	21,47	21,1	21,9	20,74	20,75	20,89
c4	12	12,77	13,91	12,85	12,32	12,27	13,04
c5	17,94	16,19	17,95	17,75	18,28	18,31	17,76
c6	4,48	4,05	4,58	4,65	4,04	4,58	5
c7	1,77	2,17	1,94	1,98	2,4	2,43	2,25
c8	5,31	5,31	5,11	5,86	5,17	5,43	5,05
c9	6,16	4,94	4,62	4,37	4,34	4,02	3,73
c10	3,49	3,3	2,99	3,22	2,99	3,38	3,35
c11	2,08	2,26	1,9	1,87	2,43	2,45	2,41
c12	1,23	1,32	1,41	1,17	1,42	1,43	1,33
c13	1,03	1,27	1,18	1,14	1,06	1,33	1,34
quantization error	3,9176	3,9517	3,9216	3,9053	3,863	3,8722	3,814
topographic error	0,1838	0,1627	0,1715	0,1659	0,1693	0,1684	0,142

In Table 10 we report the distribution of the prototypical forms of well-being and deprivation across time. The classification of individuals prior to 2009 has been obtained by projecting data of previous waves onto the Self Organizing Map already trained. The main result of the projection is that the distributions of the prototypical forms within the time span 2003-2009 appear to be

stable. The quantization error and the topographical error remain low. A slight increase in these errors is noted as we move away from wave 2009. These results show that the estimated topological space adequately reproduces the information contained in waves prior to 2009.

The study of the trajectories of persistence and mobility of the subjects is carried out on a balanced subsample of 1272 subjects repeated for seven consecutive waves. The subjects that have missing values have been excluded from the analysis.

Table 11 reports the transition probabilities among the 13 prototypical forms from time t-1 to time t. The rows of the table indicate the previous well-being and deprivation state while the columns show the current state.[v]

Table 11. Transition probabilities from time t-1 to time t

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	59.13	1.51	9.03	0.73	14.84	1.56	0.54	2.78	4.88	4.20	0.68	0	0.10
2	17.74	20.43	23.66	7.53	10.22	8.60	4.84	1.61	2.15	0.54	1.08	1.08	0.54
3	9.80	2.48	47.04	12.38	14.37	2.96	1.99	2.91	1.51	1.78	1.78	0.65	0.38
4	1.55	1.42	29.51	44.59	6.06	2.19	3.22	4.90	0.52	0.64	1.80	2.32	1.29
5	16.88	1.17	12.78	2.56	47.02	3.67	0.91	3.25	2.88	3.57	4.42	0.27	0.64
6	12.85	4.39	13.48	5.02	20.06	23.51	4.08	5.64	1.57	1.57	6.58	0	1.25
7	11.96	5.43	16.85	11.41	7.61	2.72	22.83	10.87	2.17	3.80	1.09	2.72	0.54
8	12.72	0.99	10.14	5.96	11.33	6.16	3.58	33.6	2.78	5.17	2.39	2.78	2.39
9	27.45	0.82	9.78	1.09	16.30	2.45	2.17	2.17	26.09	7.07	3.80	0.27	0.54
10	23.35	0.60	8.98	1.20	14.97	2.69	2.69	12.57	5.39	21.86	5.09	0	0.60
11	3.53	1.41	7.77	5.65	30.04	4.59	1.06	7.07	3.18	5.65	26.5	0.71	2.83
12	1.18	0	8.24	34.12	1.18	1.18	2.35	12.94	0	0	1.18	31.76	5.88
13	2.44	0	4.88	14.63	7.32	6.10	2.44	17.07	3.66	1.22	7.32	4.88	28.05
Total	23.29	2.09	20.17	8.82	20.86	3.78	2.20	5.78	3.81	3.89	3.30	1.01	1.00

Years 2003-2009. Number of person-year observations 8904. Source: SHP 2003-2009

The discretization of the topological plane in 13 clusters allows us to detect a high degree of mobility, represented by the observations which are concentrated in the cells outside of the main diagonal, although, on closer inspection, most transitions are of short-range or very short-range. In other words, the channels of maximum mobility are those which link topologically adjacent forms.

On average, 56% of the subjects change cluster from year to year, while 44% remain in the same cluster[vi]. The highest stability is observed in cluster 1 (59.13%), followed by cluster 3 (47.04%) and by cluster 5 (44.59%).

In order to keep the presentation of the results readable, we will comment the flows that concern the larger clusters (c1, c3, c4, c5 and c8). The subjects belonging to the area of cumulative well-being generally move to clusters that have a similar semantic connotation and, less frequently, toward regions of financial vulnerability and psychophysical fragility. Only few subjects of the well-being region fall in the cluster of cumulative deprivation. More precisely, 21% of the subjects in cluster 1 in a given year move to clusters topologically adjacent and semantically similar (c5, c6, c9) the following year, while 11% fall in the area of financial vulnerability (c2, c3, c7), 8% in the area of psychophysical fragility (c8, c10, c11, c13) and only 1% slip into the region of cumulative deprivation (c4, c12). Turning to cluster 5, we observe the same dynamics: a relatively high proportion of observations (23%) moves to the adjacent well-being clusters c1, c9 and c6; 15% move to region of financial vulnerability (c2, c3, c7); 12% move to the area of fragility (c8, c10, c11, c13) and less than 3% fall into the region of multiple deprivation (c4, c12).

The subjects belonging to the clusters of financial vulnerability undertake mobility paths towards similar clusters (4%) and, to a lesser extent, to the area of cumulative well-being as well as that of multiple deprivations. Of great interest is the flow of downward mobility connecting cluster 3 (financial vulnerability) to region of multiple deprivation (c4, c12) intercepting 13% of the observations. It should be stressed that 29% of the members of cluster 3 experience upward mobility in the direction of the area of cumulative well-being (c1, c5, c6, c9). The percentage of cases that flows from cluster 3 into the area of fragility is about 7%. Of the subjects in cluster 4 of cumulative deprivation, 34% move the following year into clusters of the financial deprivation (c2, c3, c7), while 10% reach the area of cumulative well-being (c1, c5, c6, c9) and 9% end up in the area of psychophysical fragility. 9.95% of the members of cluster 8 move within the same fragility area (c10, c11, and c13), 32.99% move to the region of cumulative well-being (c1, c5, c6, c9), 14.71% to the vulnerability region (c2, c3, c7) and 8.84% to the cumulative deprivation area (c4, c12). In conclusion, what emerges from the analysis of the transition matrix is that the paths of mobility which catalyse the largest number of observations are those which connect to the adjacent clusters or those which are placed in the immediate vicinity.

8. Conclusions

In the last thirty years, the notion of economic poverty has been integrated into abstract constructs that rely on a wide range of indicators across different domains: health, housing conditions, social network, trust in people and institutions, satisfaction with life, material and financial resources.

In order to overcome the limitations of standard approaches that are based on synthetic indices we have proposed a data reduction technique that is able to compress the multidimensional space into vectors that characterize a specific profile of well-being and deprivation states. The profiles that we

have identified express with greater precision than standard approaches the different configurations of life conditions experienced by individuals.

The results of the analysis are, in a nutshell, that about one of two Swiss enjoys a state of multidimensional well-being (those belonging to clusters c1, c5, c6, c9), one in four shows signs of financial vulnerability (clusters c2, c3, c7), one in seventh falls into conditions of multiple deprivation (clusters c4 and c12), and finally about one in eight is in a condition of psychophysical fragility (clusters c8, c10, c11, c13).

On the whole, it might be noted that the chances to belong to well-being or deprivation clusters are strongly associated with some important factors of individual heterogeneity such as level of education, income, age, nationality, type of household, type of community and geographical area. These results seem to support the thesis of social stratification and of 'social risks' (Erikson and Goldthorpe 2002, Whelan et al. 2003) rather than the thesis of individualization (Beck 1992, Leisering and Leibfried 1999).

The originality of our study lies in the fact that, for the first time, a Self Organizing Map has been applied to the study of prototypical well-being and deprivation forms on a time span of seven years, in order to reconstruct the individual paths of mobility.

To summarize, the transition probabilities show that about 74% of the subjects belonging to the area of cumulative well-being (clusters c1, c5, c6, c9) in a certain year remain in the same area the following year, 13% of them pass in the area of vulnerability (clusters c2, c3, c7), 10% in the area of fragility (clusters c8, c10, c11, c13) and the remaining 2% in the area of cumulative deprivation (clusters c4, c12). If we consider the members of the area of vulnerability, 29% of them move to the area of multidimensional well-being, 7% move to the area of vulnerability and 13% to the area of multiple deprivation. 38% of those belonging to the area of psychophysical fragility move to the area of well-being, 12% to the area of vulnerability and 7% to the area of cumulative deprivation. Finally, of those that belong to the area of cumulative deprivation in a given year, 49% remain in the same area for the following year, 10% move up to the area of cumulative well-being, 31% pass in the area of vulnerability and the remaining 10% enter the area of psychophysical fragility.

In conclusion what emerges from the dynamic analysis is that the most frequent paths of mobility are those which connect adjacent clusters and that the chances of mobility decrease gradually when moving farther away on the topological map.

Notes

[i] The data have been weighted using individual cross-sectional weights (not calibrated).

[ii] Since the indicators used to represent the relational dimension do not allow us to rigorously map the quality and quantity of support received, it would be risky to conclude that these individuals are in a state of relational isolation.

[iii] Following the practice of Eurostat, the poverty line used in the current thesis is set at 60% of the National median equivalised household income, as it has been calculated using the modified OECD scale which assigns 1 to the first adult, 0.5 to the next adults and 0.3 to children

[iv] In literature, vulnerability to poverty is measured as the risk that a household or community will fall into deprivation at least once in the next few years (see Silber 2004).

[v] Data reported in table 11 can be considered as transition probabilities in a Markov sense.

[vi] The global mobility has been calculated as the percentage of observations out of the main diagonal.

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Appendix.

Formula for transforming the component mean deviations into an alphanumeric code.

For each indicator X_j ($j = 1,\ldots,33$), we have calculated the sample mean $\bar{x}_j$ and variance $V(X_j)$[vi];

1. For each indicator X_j, we have calculated three threshold values:

$$t_{1j} = \left| \ln\left(\frac{\bar{x}_j + V(X_j)\cdot 0.75}{\bar{x}_j} \right) \right|$$

$$t_{2j} = \left| \ln\left(\frac{\bar{x}_j + V(X_j)\cdot 1.5}{\bar{x}_j} \right) \right|$$

$$t_{3j} = \left| \ln\left(\frac{\bar{x}_j + V(X_j)\cdot 2.25}{\bar{x}_j} \right) \right|$$

2. For each indicator X_j, we have calculated the mean within each cluster C_g ($g = 1,\ldots,13$): $\bar{x}_{j|g}$
3. For each indicator X_j and each cluster C_g, we have calculated the 'deviation' of the cluster-specific mean from the overall mean: $\delta_{jg} = \ln(\bar{x}_{j|g} / \bar{x}_j)$.
4. We have transformed the deviation values δ_{jg} into a corresponding set of discrete scores s_{jg} in accordance with the following rules:

$$s_{jg} = \begin{cases} 3 & \text{if } \delta_{jg} \geq t_{3j} \\ 2 & \text{if } t_{2j} \leq \delta_{jg} < t_{3j} \\ 1 & \text{if } t_{1j} \leq \delta_{jg} < t_{2j} \\ 0 & \text{if } -t_{1j} \leq \delta_{jg} < t_{1j} \\ -1 & \text{if } -t_{2j} \leq \delta_{jg} < -t_{1j} \\ -2 & \text{if } -t_{3j} \leq \delta_{jg} < -t_{2j} \\ -3 & \text{if } \delta_{jg} < -t_{3j} \end{cases} .$$

5. For each cluster C_g and each deprivation dimension D_q ($q = 1,\ldots,13$), we have calculated the mean of the scores s_{jg} pertaining to the relevant indicators:

$$\mu_{gq} = \frac{\sum_{j \in D_q} s_{jg}}{\sum_{j=1}^{d} (j \in D_q)}.$$

6. Finally, we have transformed the mean values μ_{gq} into a corresponding set of symbols in accordance with the following rules:

$\mu_{gq} \leq -2,5 \quad \rightarrow \quad "---"$

$-2.5 < \mu_{gq} \leq -1,5 \quad \rightarrow \quad "--"$

$-1,5 < \mu_{gq} \leq -0,5 \quad \rightarrow \quad "-"$

$-0,5 < \mu_{gq} \leq 0,5 \quad \rightarrow \quad "."$

$0,5 < \mu_{gq} \leq 1,5 \quad \rightarrow \quad "+"$

$1,5 < \mu_{gq} \leq 2,5 \quad \rightarrow \quad "++"$

$\mu_{gq} > 2,5 \quad \rightarrow \quad "+++"$.