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Understanding the Socio-Economic Distribution and Consequences of Patterns of Multiple Deprivation: An Application of Self-Organising Maps

Christopher T, Whelan*, Mario Lucchini**, Maurizio Pisati* * and Bertrand Maître***
School of Sociology & Geary Institute, **Universitá degli Studi di Milano-Bicocca (Unimib) Milan University College Dublin, *** Economic and Social Research Institute*,

Abstract

In this paper we apply self organising maps (SOM) to a detailed set of material deprivation indicators from the Irish component of European Union Community Statistics on Income and Living Conditions (EU-SILC). The first stage of our analysis involves the identification and description of sixteen clusters of multiple deprivation that allow us to provide a detailed account of such deprivation in contemporary Ireland. In going beyond this mapping stage, we consider both patterns of socio-economic differentiation in relation to cluster membership and the extent to which such membership contributes to our understanding of the manner in which individuals experience their economic circumstances. Our analysis makes clear the continuing importance of traditional forms of stratification relating to factors such as income, social class and housing tenure in accounting for patterns of multiple deprivation. However, it also confirms the role of acute life events and life cycle and location influences. It suggests that debates relating to the extent to which poverty and social exclusion have become individualized should take particular care to distinguish between different kinds of outcomes. Further analysis demonstrates that the SOM approach is considerably more successful than a comparable latent class analysis in identifying those exposed to subjective economic stress. This finding, combined with those relating to the role of socio-economic factors in accounting for cluster membership, confirms that a focus on a set of eight SOM macro clusters seems most appropriate if our interest lies in broad patterns stratification,. For other purposes differentiation within clusters, which clearly takes a systematic form, may prove to be crucial.

Introduction

As knowledge of the increasing limitations of relying solely on income to measure poverty and social exclusion has become more widespread, attention has been increasingly focused on multi-dimensional approaches. Associated with this development, non-monetary indicators are increasingly used in individual European countries as well as at European Union level in measuring poverty and exclusion. [1]Particular attention has been devoted to the fact that low income may in fact be unreliable as an indicator of poverty or social exclusion, failing in practice to identify those experiencing deprivation and exclusion (Nolan and Whelan, 2007). However, our attention here will be focused on the somewhat different concern that low income may miss an important part of the picture, namely the multidimensional nature of poverty and social exclusion.

Kakwani and Silber (2007: xv) identify the most important recent development in poverty research as the shift from a uni-dimensional to a mult-dimensional approach. Developments in this area can be viewed against the background of attempts to implement Townsend's (1979) understanding of poverty as exclusion from ordinary living patterns, customs and activities because of resources that are substantially below non-monetary indicators of deprivation have by now been used in various ways in measuring poverty in many European countries.[2]

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[1] Various measures of material deprivation have been also employed in studying poverty in the USA, e.g. Mayer and Jencks (1988, 1993) and Mayer (1997).
[2] Pantazis *et al*, (2006) in the UK, Nolan and Whelan (1996) for Ireland, Muffels and Dirven (1998) with Dutch data, Halleröd (1996) for Sweden, Kangas and Ritakallio (1998) for Finland, Bohnke and Delhey (1999) for Germany, and Tsakloglou and Papadopoulos (1998) for Greece.

A major contribution to comparability in measuring deprivation at the European level was provided by the inclusion of a substantial number of non-monetary indicators covering a wide range of areas in the European Community Household Panel Survey (ECHP) 1994-2001.[3] The European Union Statistics on Income and Living Conditions (EU-SILC) instrument includes a more limited but still substantial number of non-monetary indicators. In this paper we make use of the Irish component of EU-SILC which includes a wider range of material deprivation items than the common European module.

At the level of conceptualisation, the case for a multi-dimensional approach to understanding what it means to be socially excluded is compelling. However, as Nolan and Whelan (2007) argue, the value of a multidimensional approach needs to be empirically established rather than being something that can be read off the multidimensional nature of the concept. Approaches that produce higher rather than lower dimensional profiles are not intrinsically superior. At this point, it seems to be generally agreed that many unresolved conceptual and measurement issues remain in the path of seriously implementing multidimensional measures in any truly operational sense (Thorbecke, 2007). Grusky and Weeden (2007:33) set out the need as to develop “a methodological platform” for analysing the shape and form of social exclusion. In this paper we seek to contribute to this enterprise specifically in relation to forms of material deprivation.

Comparing Approaches to Analysing Multiple Deprivation

In this paper our primary focus is on providing an assessment of the extent to which an approach known as Self Organising Maps (SOM), utilizing an artificial neural

[3] See for example 2000, 2003; Whelan et al 2001.

network algorithm developed by Kohonen in the early 1980s to extract meaningful patterns from complex data and display them in an orderly fashion (Kohonen, 1982, 2001), can contribute to our understanding of the socio-economic distribution and consequences of patterns of multiple deprivation. In order to achieve this objective, we will make some key comparison between the outcomes of the SOM approach and those deriving from the application of a latent class approach to the same set of deprivation items.

Having provided a relatively non-technical account of the approach and the pattern of differentiation it reveals in relation to multiple deprivation when applied to Irish data, we will seek to assess the validity of the SOM typology and the implications of decisions relating to levels of aggregation for our capacity to address substantive sociological issues. Our particular focus will be on the contribution the SOM approach can make to enhancing our understanding of the role of socio-economic influences in shaping patterns of deprivation and the manner in which individuals experience their economic circumstances.

Our analysis will proceed as follows. In the section that follows we will provide details of our data and the specific measures we employ. We then go on to provide an overview of the SOM approach and a brief comparison with the latent class approach. Having done so, we provide a brief description of the clustering outcomes deriving form the application of this approach to the detailed set of deprivation items available in the Irish EU-SILC instrument. Our analysis will then address issues relating to levels of aggregation and the implications for understanding socio-economic differentiation. It will be extended to provide an assessment of the impact of different forms of multiple deprivation on subjective economic stress.

Data and variables

The data used in this paper are drawn from the 2004 wave of the Irish EU-SILC survey, a voluntary annual survey of private households conducted by the Central Statistics Office (CSO). In 2004, the total completed sample size was 5,477 households and 14,272 individuals (CSO, 2005). The analysis reported here refers to all persons in the EU-SILC. Where household characteristics are involved these have been allocated to each individual. The HRP is the one responsible for the household accommodation and their characteristics have been attributed to all individuals in the household.

Our analysis makes use of forty-two dichotomous indicators of life-style deprivation. A confirmatory factor analysis of these forty-two items by Maître *et al*. (2006) revealed the following relatively distinct deprivation dimensions:

1. *Basic deprivation*: eleven items relating to food, clothing, furniture, debt, and minimal participation in social life.
2. *Consumption deprivation*: nineteen items relating to various forms of consumption.
3. *Housing facilities*: four items regarding basic facilities such as bath, toilet etc.
4. *Neighbourhood environment*: five items concerning pollution, crime/vandalism, noise, and deteriorating housing conditions.
5. *Health status of the HRP*: three items relating to overall evaluation of health status, having a chronic illness or disability and restricted mobility.

Details of the indicators comprising each of the dimensions are set out in Table 1

Table 1: Indicators of life-style deprivation used in the analysis (N = ?)

Indicator	Description	Prevalence (%)
	Basic deprivation	
4	Having friends or family for a drink or meal at least once a month	11.5
6	Eating meat chicken or fish (or vegetarian equivalent) every second day	3.7
7	Having a roast joint (or equivalent) once a week	4.8
8	Buying new rather than second-hand clothes	5.9
9	A warm waterproof overcoat for each household member	2.6
10	Two pairs of strong shoes for each household member	3.8
11	Replacing worn-out furniture	13.7
12	Keeping home adequately warm	3.1
13	Buying presents for family/friends at least once a year	4.5
32	A morning, afternoon, or evening out in the last fortnight for entertainment	9.9
33	Going without heating during the last 12 months	5.5
	Consumption deprivation	
5	Paying for a week's annual holiday away from home in the last 12 months	23.4
14	A satellite dish	13.7
15	A video recorder	4
16	A stereo	4.5
17	A CD player	4.7
18	A camcorder	16
19	A personal computer	12.8
20	A washing machine	1.2
21	A clothes dryer	10.1
22	A dish washer	14.2
23	A vacuum cleaner	1.6
24	A fridge	2.3
25	A deep freeze	6.1
26	A microwave	2.4
27	A deep fat fryer	3.5
28	A liquidiser	6.7
29	A food processor	7.3
30	A telephone (fixed line)	5.9
31	A car	13.5
	Housing deprivation	
34	Bath or shower	1.1
35	Internal toilet	0.8
36	Central heating	9.4
37	Hot water	1.8
	Neighbourhood environment deprivation	
38	Leaking roof, damp walls/ceilings/floors/foundations, rot in doors, window frames	13.6
39	Rooms too dark, light problems	6
40	Noise from neighbours or from the street	12.2
41	Pollution, crime or other environmental problems	8.9
42	Crime, violence or vandalism in the area	14.8
	Health status of the HRP:	
1	General health problems	20.6
2	Chronic illness or condition	26.5
3	Limitation in usual activities for at least the last 6 months because of a health problem	23.2

Self-organising maps and latent class analysis

A number of earlier efforts have employed latent class analysis to map patterns of multi-dimensional material deprivation.[4] The basic idea underlying such analysis is that the associations between a set of categorical variables, regarded as indicators of an unobserved typology, are accounted for by membership of a small number of underlying classes. Latent class analysis assumes that each individual is a member of one and only one of *C* latent classes and that, conditional on latent class membership, the manifest variables are mutually independent of each other. The question arises as to the extent to which such simplifying assumptions may influence our conclusions and, in particular, conceal important within-cluster heterogeneity.

In contrast, the SOM approach involves minimal assumptions. The objective is to produce a segmentation of individuals in terms of a wide range of indicators without reducing the complexity of input to the clustering procedure. Essentially, what the SOM algorithm does is to project a high-dimensional dataset $\mathbf{X}$ onto a lower dimensional output space so as to represent $\mathbf{X}$ in a compact form and facilitate identify its underlying structure. A SOM can be seen as a mathematical model that helps to reduce the complexity of $\mathbf{X}$ by projecting it onto a lower dimensional *output space*. This space corresponds to the SOM itself and, typically, takes the form of a two-dimensional grid. Each grid cell is called a *unit*, or *node*, and can be regarded as a pole specialized in attracting observations that possess certain combinations of attributes; projecting $\mathbf{X}$ onto the SOM, then, amounts to allocating each observation i to the unit that attracts it most. Formally, we say that the SOM partitions the input space $\Re^d$ into m Voronoi regions, each of which corresponds to a specific SOM unit k and attracts all the input vectors that are closer to its generating point $\mathbf{w}_k$ than to

[4] See Dewilde (2004, 2008), Moisio (2004), and Whelan and Maître (2005, 2007).

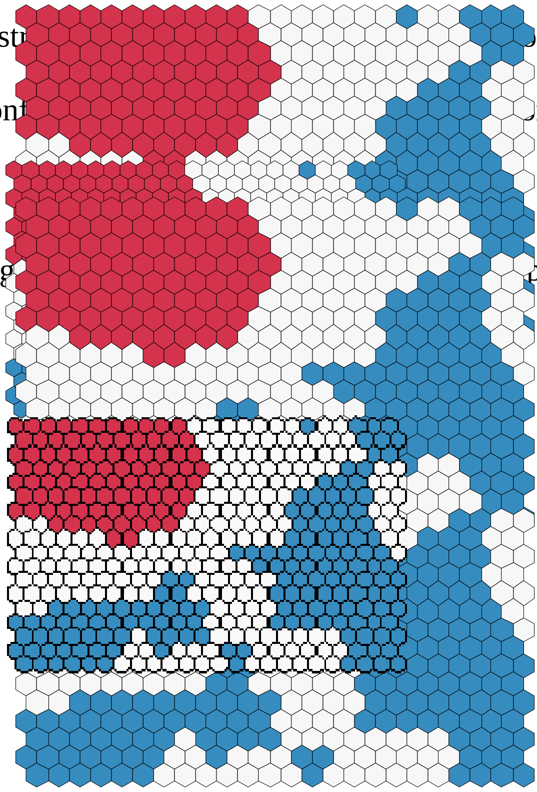
any other generating point. If properly realized, this partition is such that the Voronoi regions that are close in the input space are also close in the output space, i.e., their corresponding SOM units are spatially contiguous on the two-dimensional grid. This property is called *topology preservation* and is one of the most appealing features of SOMs, since it makes for a clearer and more accurate representation of the structure of the input data.

To sum up, projecting a d-dimensional dataset $\mathbf{X}$ onto a two-dimensional SOM amounts to (a) computing the weight vectors $\mathbf{w}_k$ associated with the m SOM units; and (b) on the basis of these weights, allocating each observation i to its best matching unit. To achieve this result, the SOM goes through a *competitive learning process* that incrementally adjusts the weight vectors according to a set of rules aimed at maximizing both the discriminatory power of the map and its degree of topology preservation.

The starting point of our analysis[5] is a $14{,}219 \times 42$ matrix which we project onto a two-dimensional SOM made of 432 units arranged in a 18×24 hexagonal lattice. To analyse the configuration of the trained SOM, we visually inspect its *component planes*, a kind of specialized graph that illustrates the value taken by a given element of the weight vector $\mathbf{w}_k$ on each SOM unit. This is illustrated in relation to the item relating to a personal computer in Figure 1. SOM units are classified into up to three distinct groups: (a) black units ‘specialise’ in attracting ‘disadvantaged respondents’, i.e., observations that take value 1 on the corresponding indicator; (b) grey units

[5] All the analyses reported in this paper, including SOM training and visualization, have been carried out using routines written in Stata programming language (StataCorp, 2007).

'specialise' in attracting 'advantaged respondents', i.e., observations that take value 0 on the corresponding indicator; (c) white units have no clear-cut 'specialisation', i.e., attract a more or less balanced mix of observations of both types. The spatial dist n the two-dimensional grid describes the con rrespo



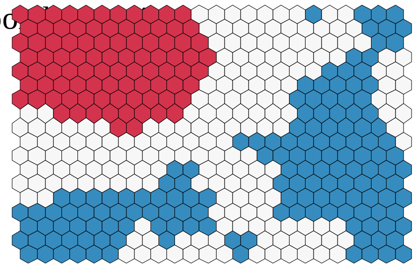


Fig puter

For relatively expensive consumer durables such as a PC, a typical pattern is that represented by the component plane shown in Figure 1 (inability to afford a personal computer). A tripartite division emerges with half or more of the SOM units being neutral. Of the remaining units, the grey ones are slightly more frequent than the black ones. While the latter tend to be clustered in the upper left-hand corner of the SOM, the remaining units are more widely distributed. Other items, such as for example, holidays are characterised by a more polarised pattern with a very modest intermediate space. In contrast cheaper consumption items, such as a video recorder exhibit a pattern whereby vast majority of SOM units belong to the 'neutral' (white) category with is also a small cluster of 'hot' (black) units, i.e., units that attract a disproportionate share of disadvantaged and no 'cold' (grey) units, i.e., units that attract a number of disadvantaged respondents substantially lower than the average.

Visual inspection of the forty-two component planes associated with the SOM reveals the fine structure of the underlying input space. Treating each SOM unit individually would require dealing with an overwhelming level of detail. To address this issue, we partition the output space (i.e., the 432 SOM units) into a smaller set of sufficiently homogeneous regions (i.e., clusters of SOM units), using weight vectors as the clustering variables (Vesanto and Alhoniemi, 2000; Wu and Chow, 2004) and the hierarchical agglomerative average linkage method as the clustering algorithm (Kaufman and Rousseeuw 1990). Based on careful inspection of the component planes, experimentation and past experience (Lucchini et al., 2007), we opt for a 16-cluster solution that offers a reasonable balance between detail and parsimony.

To aid interpretation, we project the sixteen clusters of SOM units onto a two-dimensional space so as to maximize the correlation between the location of the clusters in the data space and the location of the clusters in the plane; to this aim, we use a classical metric multidimensional scaling algorithm (Torgerson, 1952) adjusted *ex post* via a genetic algorithm (Mitchell, 1996). The results of this projection are shown in Figure 2 where the size of each cluster is proportional to its prevalence, and the Euclidean distance between clusters on the plane closely mirrors their Euclidean distance in the data space. As we can see, clusters vary substantially in terms of both size and location.

Informed by consideration of the profile of the clusters on both the 42 deprivation indicators and the synthetic deprivation dimensions distinguished earlier our substantive interpretation of the sixteen clusters identified is set out below:

- Cluster 1 (*Multiple deprivation least pronounced on health)* is characterised by a fairly uniform pattern of deprivation which is least severe in relation to health. It comprises 1.8 per cent of the sample.

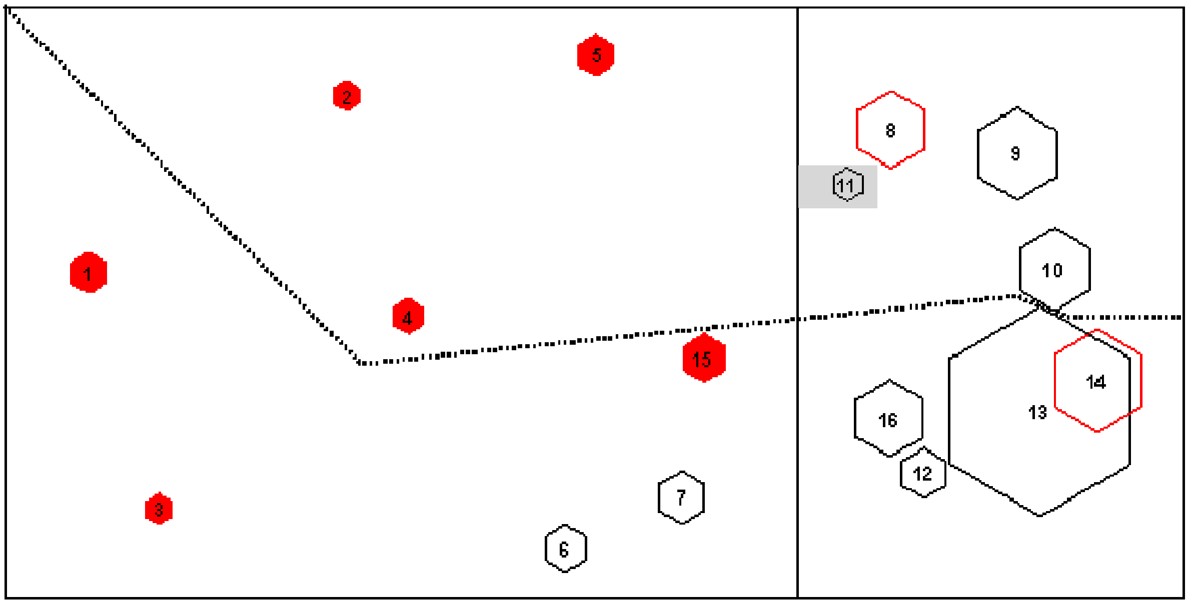
- Cluster 2 (*Multiple deprivation least pronounced on household facilities)* also involves a relatively uniform pattern of deprivation that is more pronounced than for cluster 1 in relation to health but somewhat less so with regard to household facilities. It makes up 1.1 per cent of the sample.
- Cluster 3 (*Multiple deprivation other than on health)* is characterized by above average deprivation in relation to all dimensions other than health but with the scale being somewhat weaker for neighbourhood facilities than for the remaining dimensions. This group comprises 1.1 per cent of the population.
- Cluster 4 (*Multiple deprivation least pronounced on basic and neighbourhood environment)* is distinctive primarily in relation to health, consumption and housing facilities. It involves 1.0 per cent of the sample.
- Cluster 5 (*Multiple deprivation least pronounced on consumption)* is distinguished from the foregoing clusters by a lower level of consumption deprivation. It makes up 1.7 per cent of the sample.
- Cluster 15 (*Multiple deprivation other than health with basic and household facilities most pronounced*) is made up of individuals displaying above average deprivation in relation to basic and household facilities. In terms of consumption enforced absence of a car is particularly prevalent. It involves 2.7 per cent of the sample
- Cluster 6 (*Consumption deprivation with a high tech appliances emphasis)* is characterised by consumption deprivation which is particularly pronounced in relation to hi-tech consumer durables and holidays. It comprises 2.4 per cent of the sample.
- Cluster 7 (*Consumption with basic and neighbourhood environment secondary*) is also differentiated from others in relation to consumer durables, but high-tech items play less of a role. Neighbourhood environment joins basic deprivation as a secondary element. It involves 2.7 per cent of the sample.
- Cluster 8 (*Health and neighbourhood environmen*t) exhibits a profile of deprivation in relation to health and neighbourhood environment with

consumption and household facilities playing a secondary role. It is the largest group up this point, involving 5.3 per cent of the sample.

- Cluster 11 (*Health deprivation with consumption secondary*) it involves a combination of health and consumption deprivation. It is somewhat smaller than the two previous clusters, making up 1.1 per cent of the sample.
- Cluster 9 (*General health*) is distinguished from the other groups almost exclusively in terms of deprivation in relation to health. It comprises 7.8 per cent of the sample.
- Cluster 10 (*Chronic illness*) is also characterised almost entirely by deprivation in relation to health. In this case differentiation is less sharp and is largely in relation to chronic illness. It includes 6.2 per cent of the sample.
- Cluster 14 (*Neighbourhood environment)* involves a pattern of minimal deprivation, with the crucial exception being in relation to neighbourhood environment. It is a relatively large group making up 10.7 per cent of the sample.
- Cluster 16 *(Consumption deprivation involving holidays*) is also characterised by a pattern of minimal deprivation other than with regard to enforced absence of a holiday. It includes 5.9 per cent of the sample. [6]
- Cluster 12 (*Minimal deprivation other than for specific high-tech consumption items*) is distinguished from cluster 13 almost entirely by deprivation in relation to high-tech items and, most particularly, in relation to a CD player and a satellite dish. It involves 2.7 per cent of the sample.
- Cluster 13 (*Minimal deprivation*) displays a uniformly low pattern of deprivation. It is the largest group by far, comprising 46.2 per cent of the sample.

Figure 2: Basic features of the SOM clusters

[6] For further discussion of the profiles of these clusters in terms of both deprivation indicators and dimensions see Pisati *et al* (2008)



The vertical and horizontal lines in Figure 2 contribute to providing a graphical summary of the above description. The dotted line separates the clusters characterised by a substantial level of health deprivation (above the line) from the “healthy” clusters (below the line). In turn, the solid (vertical) line separates the clusters exhibiting a significant level of basic deprivation (left) from those that do not experience this form of deprivation (right). The area of consumption deprivation coincides with that of basic deprivation, with the addition of two small grey regions comprising clusters 8 and 11. Finally, black clusters are also characterised by a substantial degree of deprivation in terms of both household facilities and neighbourhood environment; when only the cluster outline is black, deprivation is limited to neighbourhood environment. The SOM analysis thus provides a differentiated picture of the structure of multiple deprivation in contemporary Ireland.

As we have seen, the SOM procedure produces a set of 16 clusters to which we can attribute substantive meaning without great difficulty. However, many clusters involve relatively small fractions of the sample. These relatively small Ns create some difficulties in estimating multivariate multinomial models. In addition, the nature of the distinctions between clusters varies considerably in their substantive significance. In some cases clusters are defined by deprivation in relation to one or two highly specific consumer durables while in other case they identify relatively broad and distinct spheres of deprivation. Based on our understanding of the nature of the substantive differences distinguishing clusters, we might expect that rather different types of factors may prove to be effective in explaining some rather than other forms of cluster differentiation. In particular, we might hypothesise that variables capturing command over economic resources, such as income, social class and housing tenure may play a very different role from those which influence preferences relating to different forms of consumption and exposure to different types of deprivation such as life-cycle stage and urban-rural location.

This distinction seems particularly important in light of the fact that increased emphasis on de-standardisation or individualisation of the life cycle and a related stress on life-events, together with increasing flexibility and precariousness in the labour market and the changing role of the welfare state, has led some to suggest that the impact of factors such as social class and indeed education on poverty and inequality are declining (Beck, 1992).

With these distinctions in mind and guided by the results of the SOM analysis set out in Figure 2, we proceed to aggregate the initial set of 16 categories into the following 8 *macro* clusters. We give priority given to combining clusters that are closest in terms of that basic deprivation and consumption deprivation that earlier research has shown to be most highly associated with resource variables such as income.

1. The first macro cluster combines micro clusters 1 and 3 involving uniform *multiple deprivation that is least pronounced on health*. It comprises 2.9 per cent of the sample.

2. The second aggregated cluster combines the original groups 2 and 4 and involves *multiple deprivation that is less pronounced on housing facilities and neighbourhood environment*. It involves 5.0 per cent of the sample
3. Micro clusters 5 and 15 are aggregated to produce the next macro cluster. It involves *multiple deprivation most pronounced for basic deprivation and household facilities* and accounts for 8.9 cent of the sample.
4. The next aggregation combines clusters 6, 7 and 16 and captures a variety of forms of *consumption deprivation*. It captures 11.1 per cent of the sample.
5. Micro clusters 8 and 11 are collapsed in order to produce an aggregated cluster that combines *pronounced deprivation in relation to health aspect of deprivation other than basic.* It accounts for 6.4 per cent of the sample
6. In contrast, the macro cluster resulting from the original clusters 9 and 10 is defined entirely in terms of *health deprivation*. It makes up 14.0 per cent of the sample
7. The next cluster is made up entirely of the original *neighbourhood deprivation* group comprising 10.7 per cent of the sample
8. The final macro cluster, which we characterise as *minimally deprived*, combines the original clusters 12 and 13 and accounts for 48.9 per cent of the sample.

Socio-economic Differentiation within and between Macro Clusters

The overall hypothesis, guiding our subsequent analysis, is that the factors associated with membership of the micro clusters within the macro clusters will be somewhat different from those that discriminate between members of the latter clusters. A good number of the measures of basic and consumption deprivation that we have employed involve enforced deprivation of items that respondents wish to possess. Thus, reported deprivation on a particular item will be influenced not only by resources but also tastes. Absence of an item will not be counted as a deprivation unless the respondent expresses a desire to possess the item or engage in the activity.

Authors, such as McKay (2004) and Dominy and Kempson (2006), have raised the issue of the extent to which such responses are influenced by preferences or tastes as opposed to adaptation to economic circumstances. The issue is not a simple one to resolve. There clearly are differences across age groups and by factors such as urban-rural location in the extent to which particular items are seen as necessary or desirable and ideally we wish to take these into account. If older people place less value on having a holiday it is reasonable to take this into account. On the other hand, even where it is clear that they cannot afford certain activities, older people may be less likely to indicate this if factors such as ill health make it more difficult for them to engage in them. The evidence does suggest that simply focusing on absence leads us to observe stronger relationships with income with the situation of older people contributing to disproportionately to this outcome. However, given the potential limitation of income in relation to older people, it is less obvious that conclusions regarding the relationship between command over economic resources and enforced deprivation are substantially affected by such considerations.

For reasons of both tastes and constraints/opportunities, we anticipate that deprivation in relation to specific items is likely to be particularly influenced by factors such as life-cycle stage and urban–rural location. For other items, relating to health, housing and neighbourhood and environment, we may again expect that the specific form of such deprivations that are experienced will once again be influenced by life cycle and location factors. At the same time, we would continue to expect that aggregate levels of deprivation would be significantly related to factors tapping primarily command over economic resources; as taste and need type factors average out across items.

Thus we anticipate that variation in location within macro cluster membership will tend to be significantly influenced by life cycle stage and geographical location. On the other hand, we expect that membership of macro clusters will be substantially influenced by factors significantly associated with resources such as income social class, housing circumstances and life events such as lone parenthood and marital disruption. Life cycle and geographical location may also be expected to play a significant, although lesser and somewhat more variable, role.

In Table 2 we set out the results of a multinomial regression showing the relationship between membership of the 8 macro clusters and the range of socio-economic variables comprising household and household reference person characteristics.[7] These include equivalent income quintile, an aggregated version of the ESeC class schema, marital status, lone parenthood. urban-rural location, housing tenure and age group. Other potential influences were shown to have significant gross effects but contributed little once the variables currently included in the equation were taken into account.[8] Given the cross-sectional nature of the data, the patterns of socio-economic economic differentiation will involve reciprocal influences, as between income and health. However, we have chosen our independent variables so as to ensure, as far as

[7] In all subsequent multivariate analysis standard errors have been calculated to allow for clustering of individuals in households.
[8] We have avoided using variables such as principal economic status because of the crucial role of health status in constructing such variables.

possible, that the direction of influence is predominantly from socio-economic attributes to forms of multiple deprivation

Table 2 : Multinomial 8-Cluster SOM by Socio-Demographic Characteristics (Reference Group Clusters 12 &13)

	Clusters 1 & 2		Clusters 3 & 4		Clusters 5 & 15		Clusters 6 & 7 & 16		Clusters 8 & 11		Clusters 9 & 10		Cluster 14	
	Odds Ratio	Sig												
Income														
Bottom Quintile	519.021	***	67.213	***	26.665	***	11.830	***	7.942	***	2.403	***	1.258	
Quintile 2	245.432	***	46.277	***	21.120	***	12.548	***	5.261	***	1.781	***	1.068	
Quintile 3	45.130	***	15.980	***	6.148	***	6.271	***	2.298	***	1.151		0.772	
Quintile 4	18.311	**	1.221		1.883		3.739	***	1.792		1.026		1.091	
Social Class														
Farmers	0.419		0.148	**	0.510		1.536		0.252	***	0.904		0.721	
Petit Bourgeoisie	1.319		1.976		1.527		1.166		0.786		1.108		1.041	
Higher non-manual	2.189		2.440	*	2.044		1.237		1.506		1.469	**	1.048	
Lower grade non-manual	1.697		3.061	**	1.527		2.243	***	1.372		1.286		0.946	
Semi-non skilled	2.672	*	2.608		1.839		2.167	***	2.322	***	1.153		0.938	
Marital Status														
Single	3.527	***	1.689		2.156	**	1.539	**	1.248		1.451	**	0.569	
Widowed	1.786		3.048	***	1.160		1.721		1.631		1.570	**	0.039	
Separated/divorced	2.218	*	1.849		3.199	***	1.326		1.372		1.245		0.268	
Lone parent	1.318		5.014	***	1.221		2.140	***	1.645		0.772		0.438	
Tenure														
Public sector owner	1.722		2.128		2.942	*	1.281		1.156		0.877		0.889	
Private tenant	3.145	**	3.858	***	2.532	**	2.011	***	0.990		0.798		0.647	*
Public sector tenant	5.683	*	2.673		6.426	**	5.448	***	8.116	***	3.141	**	1.235	
Urban	0.697		0.608		1.340		0.669	**	1.152		0.862		2.400	***
Public sector tenant*Urban	1.653		5.541	*	1.066		0.811		0.343		0.506		2.158	
<29	1.757		0.118	***	1.852		2.905	***	0.081	***	0.122	***	1.591	
30-49	4.006	***	0.403	**	1.705		2.540	***	0.230	***	0.200	***	1.571	**
50-64	5.072		1.309		2.532	***	2.283	***	0.638	***	0.515	***	1.845	***
Nagelkerke R^2	0.373													
Reduction in Log Likelihood Ratio	5.806.3													
Df	147													
N	12, 992													

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From Table 2 we can see that membership of the macro clusters is most sharply differentiated by equivalent income quintile. Taking cluster 8 as the reference category, we find that the odds on being in cluster 1 - characterised by multiple deprivation that is least pronounced on health - is over 500 times higher for those in the bottom rather than the top cluster. This declines to 245 for the second quintile to 45 for the third and 18 for the fourth. Thus membership of this cluster is profoundly influenced by position in the income distribution. Other factors play a significant but considerable more modest role. In comparison with the professional and managerial class, farmers are only half as likely to be found in this cluster. All other classes are more likely to be found here with the odds ratio ranging from 1.3 for the petit bourgeoisie to 2.7 for the semi-no skilled manual class.[9] Odds are also higher for those who are not married - ranging from 1.8 for widowed to 3.5 for single. A modest effect is also observed for lone parents. In relation to housing tenure, private home owners enjoy a significant advantage. The odds of being in cluster 1 are 1.7 times higher for public sector owners, 3.1 times for private tenants. For each of these groups a rural location reduces the odds by 0.7. For public sector tenants, on the other hand, it is necessary to take into account of the manner in which location and tenure interact. If private home owners in rural areas are taken as the benchmark, public sector tenants are 5.7 times more likely to be found in cluster 1. For urban public sector tenants this rises to 6.5 and they are 9.4 times more likely to be located there in comparison with urban owners.[10] Finally, a curvilinear relationship with age is observed. The lowest risk is observed where the HRP is 65 or over. It increases by a factor of 1.8 for those under 30 before rising to 4.0 and 5.1 respectively for those 30-49 and 50-64.

[9] The gross effects are substantially higher with the odds ratio for the comparison of the professional and managerial classes reaching 7.3
[10] The gross effect reaches 126

Overall those found in cluster 1 are particularly likely to be in low income households. They are also more likely to be drawn from households in which the reference person is middle aged non-married and not in the professional-managerial or farming classes. They are less likely to be private home owners or live in rural areas. Being a public sector tenant, particularly when combined with being in an urban area, is associated with a sharp increase in risk level.

Turning to cluster 2 - involving multiple deprivation that is least pronounced on housing facilities - we again observed a substantial impact for income with the odds gradually declining from 67.2 to 1.2 as we move from the bottom to the fourth quintile. Farmers are even less likely to be found in this cluster than in cluster 1 with an odds ratio of 0.14. Class differentials are also greater for the remaining classes with the odds ratios ranging from 2 for the petit bourgeois to 3 for the lower grade non-manual. Not being married again raises the risk but in this case the strongest effect is for being widowed with an odds ratio of 3. The impact of lone parenthood is considerably greater than in the previous case with the odds ratio reaching 5.0. Rural residents and home owners enjoy comparable advantages to those prevailing for cluster 2. However, the pattern of interaction between public sector tenure and urban location is rather stronger. On this occasion the gap between tenants and private home owners is less in rural areas with an odds ratio of 2.7 while in urban areas it is wider with the corresponding value being 15. In contrast with cluster 1, where the HRP is aged less than 30, individuals are least likely to be found in this cluster as reflected in an odds ratio of 0.12. This figure rises to 0.4 for the 30-39 category and to 50-64 to 1.3. Overall, this cluster shows more moderate but still substantial differentiation in relation to income and stronger effects in relation to lone parenthood and urban public sector tenure.

Macro cluster 3 is characterized by multiple deprivation that is most pronounced in relation to basic deprivation and household facilities. Income is once again the most important differentiating factor but its discriminatory power is significantly less than in case of cluster 2 with the odds ratios declining from 26.7 for the bottom quintile to 1.9 for the fourth. The impact of social class and marital status is broadly similar to cluster 1 as are the effects of being a public sector home owner or private tenant. However, on this occasion urban respondents have slightly higher risk level and the odds ratio of 6.4 relating to public sector tenure applies uniformly across urban and rural locations. As with cluster 1, those in households where the HRP is 65 or over are least likely to be found here but the effect is more modest with the odds ratios going from 1.7 to 2.5.

Macro cluster 4 is characterized by consumption deprivation. Income remains important but the pattern of differentiation is a good deal more modest. Little difference is observed between the bottom and second deciles and the odds ratio goes from 12.5 for the latter to 3.7 for the bottom quartile. On this occasion farmers have a slightly higher risk level than the professional and managerial class and the impact for the petit bourgeoisie and the higher non-manual class are weaker then heretofore. Non-married groups and lone parents suffer modest disadvantages. Rural respondents are generally slightly less likely to be found in this category. However, the pattern of interaction between public sector tenure and location is rather different than in the earlier cases with the impact of the former being greater in rural locations on this occasion. Such tenants have risk levels that are 5.4 times higher than comparable home owners while the comparable urban figure is 4.41. Comparing public sector tenants in rural and urban areas, the latter are 1.8 times more likely to be found in cluster 4. The major age contrast relates to the 65 versus all other with the odd ratio for the remaining groups declining from 2.9 to 2.2 with increasing age.

Focusing on cluster 5 which involves health deprivation in combination with forms of deprivation other than basic, we observe a further weakening of the impact of income with the odds ratio going from 7.9 to 1.8. The effects for class are broadly similar to those observed earlier with farmers being even less likely to be found in this cluster. Effects for marital status and lone parenthood are rather modest. The pattern in relation the combined effects for tenure and location is quite different to those observed thus far. With regard to the former, the only significant contrast is between public sector tenants and all others. For the latter, urban-rural location has little impact. In contrast for public sector tenants location makes a considerable difference on this occasion. The risk level for the rural group is 8.1 times higher than for comparable home owners and 2.5 times higher than for their urban counterparts. The impact of HRP age is substantially sharper than for the earlier cluster. The risk level for the youngest age group is 12.3 times lower than for the oldest. For the remaining groups the respective odds ratios are 4.3 and 1.6. Overall those in households with older HRPs, in rural public sector rented accommodation with lower incomes are most likely to be found in macro cluster.

Macro cluster 6 is distinguished by deprivation in relation to health. Income effects are rather weak with the odds ratios going from 2.4 for the bottom quintile to 1.0 for the fourth. Class effects are extremely modest and marital status risk levels are similar to those observed earlier. Lone parents are marginally less likely to be found in this group. Tenure and location have little impact with the exception of rural public sector tenants whose relative risk level is three times higher than for home owners. For urban public sector tenants this falls to 1.6. The most powerful differentiating factor is once again the age of the HRP. The relative risk level for the youngest age group is 8.2 times lower than for the oldest. For the intermediate groups it declines to 5.0 and 1.9. Cluster 6 is distinguished from Cluster 5 by the weaker role of income, social class, lone parenthood and public sector tenancy particularly in its rural form.

For macro cluster 7, which is distinguished solely by deprivation in relation to neighbourhood environment, income and class have little effect. In contrast with all of the earlier clusters, individuals in households where the HRP is married are significantly more likely to be found in this cluster. Their relative risk is 1.8 times higher than for the single group, 3.7 times that for the divorced/separated and 25 times greater than for the widowed. In interpreting these results, it is necessary to keep in mind the distinctively insulated form of deprivation involved here. Membership of this cluster is also slightly higher for private home owners than for their public sector counterparts and private tenants. For those other than public sector tenants, an urban location raises the odds of group membership by 2.4. For public sector tenants this rises to 5.2. Finally, those in households where the HRP is 65 and over are somewhat less likely to be found in this cluster. The members of this group seem to comprise public sector tenants who are not sharply differentiated in terms of income and married private urban home owners who have probably made choices that involve off setting the experience of this particular form of disadvantage against other attractions of the particular urban environments in which they are located.

As we have seen, there is a clear hierarchy in terms of the impact of income on cluster membership in relation to the macro clusters. The extent to which it distinguishes members of a cluster from those in the minimally deprived cluster declines as one moves from cluster 2 to cluster 7. The impact of factors such as class, marital status and lone parenthood operate somewhat more uniformly across the forms of multiple deprivation captured in cluster 1 to 3. Public sector tenancy is consistently related to forms of multiple deprivation and consumption deprivation but the manner in which it interacts with urban location varies across clusters. Similarly, while there is a significant tendency for those in middle aged households to be more exposed to multiple deprivation and consumption deprivation, this expectation is reversed in cluster 2 where health plays a prominent role and lone parenthood has its most substantial impact. For cluster 5, combing health with housing facilities and neighbourhood environment, income is still as significant factor but rather less so than life cycle stage and rural public sector tenancy. The latter factors also play a distinctive role in relation to membership of cluster 6 relating solely to health deprivation. Finally, neigbourhood environment deprivation, detached from other forms, is influenced by a distinct set of influences.

Shifting our focus to differentiation within macro clusters, in Tables 3 and 4 we show the impact of age group and urban-rural location. The findings show that in terms of micro cluster membership urban location is associated with greater likelihood of being located in 1 v 3, 2 v 4, 5 v 15, 6 v 7, 6 v 16. The odds ratios vary from 2.3 to

3.7. In contrast for 8 v11 the odds ratio is 0.32 and for 9 v 10 and 12 v 13 it plays no significant role. In terms of life cycle effects, for 1 v 3 the major contrast is between the case where the HRP is 65 or over and all others. In contrast for 2 v 4 a positive age gradient is observed and for 8 v 11 and 9 v 10 similar but less pronounced relationships are found. In contrast, for the comparison involving 5 v 15 the age effect is in the opposite direction. While we do not intend to operate detailed interpretations of these effects they do appear to entirely consistent with the impact of both tastes and the opportunities and constraints associated with particular locations and life cycle stages.

Table 3: Logistic Regression within Macro SOM Clusters (Other than Consumption) by Urban-Rural Location and HRP Age Group												
	Cluster 1 v 3		Cluster 2 v 4		Cluster 5 v 15		Cluster 8 v 11		Cluster 9 v 10		Cluster 12 v 13	
	Odds ratio	Sig>	Odds ratio	Sig>	Odds ratio	Sig>	Odds ratio	Sig>	Odds ratio	Sig>	Odds ratio	Sig>
Urban	3.711	**	3.187	**	2.327		0.320	***	1.279		1.027	
<29	3.854		66.928	***	1.132		13.058	**	7.513	***	0.569	
30-49	3.643	*	36.183	***	2.658		1.957		2.151	***	1.914	*
50-64	2.947		7.444	***	10.870		1.307		1.439	*	1.418	
Nagelkerke R^2	0.151		0.482		0.191		0.099		0.048		.011	
Reduction in Log Likelihood Ratio	48.2		132.9		113.4		56.8		73.0		25.8	
Df	4		4		4		4		4		4	
N	384		326		719		1,026		2,172		6,670	

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Multinomial Regression within Macro SOM Consumption Cluster (6,7,16) by Urban-Rural Location and HRP Age Group				
	Cluster 16 v 6		Cluster 7 v 6	
	Odds ratio	Sig.	Odds ratio	Sig.
Urban	2.284		1.033	
<29	2.854		2.351	
30-49	2.649		0.971	
50-64	5.966		0.545	
Nagelkerke R^2				
Reduction in Log Likelihood Ratio	0.150.6			
Df	8			
N	1,575			

*** p<0.01, ** p<0.05, * p<0.1

Multiple Deprivation and Economic Stress

In order to further develop our understanding of the patterns of multiple deprivation revealed by the SOM analysis, in this section we examine the extent to which individuals' experience of economic stress is affected by their cluster membership. In pursuing this issue we make use of two subjective indicators. The first item captures whether an individual is located in a household that is "experiencing difficulty in making ends meet" where we distinguish individuals in households experiencing "great difficulty" or "difficulty". The second item identifies individuals living in households that are unable to cope with unanticipated expenses. We have combined these items to form a scale of economic stress that runs from 0 where none of these problems is experienced to 2 where both apply.

In assessing the extent to which the SOM typology discriminates in relation to such experiences, we need to take into account both absolute and relative stress levels. In Table 5 we show the breakdown of levels of multiple economic stress across the detailed SOM clusters. The number experiencing both forms of stress goes from 92.9 per cent in the cluster 1 characterised by multiple deprivation that is least pronounced on health to 2.3 per cent for cluster 13 involving minimal deprivation. Conversely, the number experiencing neither form of stress goes from 1.2 to 84.7 per cent for the same clusters. For the six clusters identifying forms of multiple deprivation a substantial majority report multiple economic stress with the figure ranging from 92.9 to 59.1 per cent. Within this group, the ranking is broadly in line with our earlier findings regarding the relationship between income and clusters membership. Within such clusters, a pattern of differentiation emerges whereby economic stress levels are somewhat lower for clusters where health plays a more prominent role.

Outside the multiple deprivation clusters, the highest level of economic stress is found for cluster 7 involving consumption deprivation with a high tech emphasis where the figure is 50.3 per cent. For the other forms of consumption deprivation associated with clusters 7 and 16, the relevant figure falls to 28.0 and 23.5 per cent respectively. For clusters 8 and 11, which combine health deprivation with neighbourhood environment deprivation and consumption, multiple stress level falls to 20.2 and 16 per cent respectively. Finally, for the remaining five clusters the levels decline substantially with the figure ranging between 2.3 and 5.4 per cent.

Table 5: Multiple Economic Stress by SOM Multiple Deprivation Clusters (per cent by row)

		Multiple Economic Stress				
		0	1	2	Total	N
	SOM Clusters					
1	Multiple deprivation least pronounced on health	1.2	6.0	92.9	100	252
3	Multiple deprivation least pronounced on household facilities	2.3	34.1	63.6	100	132
2	Multiple deprivation other than on health	0.7	23.2	76.1	100	138
4	Multiple deprivation least pronounced on basic and neighbourhood environment	28.2	.30.9	41.0	100	188
5	Multiple deprivation least pronounced on consumption	5.5	26.8	67.7	100	235
15.	Multiple deprivation other than health with basic and household facilities most pronounced	11.2	29.7	59.1	100	205
6	Consumption deprivation with a high-tech appliances emphasis	23.4	26.3	50.3	100	159
7	Consumption with basic and neighbourhood environment secondary	30.5	41.4	28.0	100	403
16	Minimal deprivation other than for holidays	41.1	35.4	23.5	100	834
8.	Health and neighbourhood environment	45.3	34.5	20.2	100	863
11.	Health deprivation with consumption secondary	52.1	31.9	16.0	100	163
9	General health	78.1	17.1	4.8	100	1,201
10	Chronic illness	80.9	15.8	3.3	100	971
14	Neighbourhood environment	77.0	18.0	5.1	100	1,504
12	Minimal deprivation other than for	71.0	23.6	5.4	100	352

	specific high-tech consumption items					
13	Minimal deprivation	84.7	13.0	2.3	100	347

At this point we shift our focus to relativities in relation to economic stress and in Table 6 we present the results deriving from a set of ordered logistic regressions. Equation (i) looks at the impact of SOM cluster membership. The full set of dummies produces a Nagelkerke R^2 0.380 and leads to a reduction in the log likelihood ratio of 5,284.2 for 15 degrees of freedom. By far the largest odds ratio of 393 is observed for cluster involving multiple deprivation that is least pronounced on health. It is followed by cluster 2 involving multiple deprivation other than health with a value of 93. For multiple deprivation clusters 3, 5 and 15 it ranges between 53 and 63 while for cluster 4 it falls to 22. For the consumption clusters it declines from 25 to 8 as one goes from cluster 6 to clusters 7 and 16. For cluster 8 and 11, involving health and secondary deprivation on other dimensions, the odds ratio declines to 7 and 5 respectively. Finally for the remaining clusters it does not rise above 2.

The SOM typology of multiple deprivation succeeds in distinguishing groups a substantial majority of whom are experiencing multiple economic stress and in providing a differentiated pattern in relation to relative risk of such stress. Further analysis shows that the vast bulk of such differentiation relates to variation between the eight macro SOM clusters identified earlier. Moving from the 8 to the 16 category classification increases the Nagelkerke R^2 by 0.015 and reduces the log likelihood ratio by 236.4 for 8 degrees of freedom. Further differentiation within these macro clusters may be related to between group differentiation in terms of income, age and urban-rural location. However, the general pattern remains even when controlling for these factors. It appears that different patterns of deprivation have somewhat different consequences for economic stress and that in, particular, forms of health deprivation that are relatively isolated from other forms of deprivation have modest effects on economic stress.

As a final test of the discriminatory power of the SOM typology we proceed to compare its ability to identify those experiencing economic stress in comparison with the latent class typology referred to earlier. Whelan and Maître (2007) found that for the 42 items utilized in our SOM analysis the best fitting latent class solution involved 4 latent classes which they labeled as follows.

1. *Maximally Deprived* incorporating 6.8 per cent of the sample.
2. *Deprived in terms of current living standards* involving 6.2 per cent of the sample.
3. *Health and Housing Deprived*. This group makes up 4.5 per cent of the sample.
4. *Minimally Deprived* on all 5 dimensions. This comprises 82.6 per cent of the sample.

From equation (ii) in Table 6, we can see that the set of dummies defining this variable produces a Nagelkerke R^2 of 0.268 and reduces the log likelihood ratio by 3,525.8 for 3 degrees of freedom. The highest odds ratio of 24 relates to the consumption and the maximal deprivation clusters.. The value then falls sharply to 2 for the health and housing clusters. In equation (iii) we enter both the SOM and latent class variables and this produces a Nagelkerke R^2 of 0.395 and reduces the log likelihood ratio by 5,557.5 for 18 degrees of freedom.

Table 6: Ordered Logit of Economic Stress with SOM Macro Clusters and Latent Class Clusters							
		Odds Ratio	Sig	Odds Ratio	Sig	Odds Ratio	Sig
	SOM Clusters						
1	Multiple deprivation least pronounced on health	392.977	***			115.024	***
3	Multiple deprivation least pronounced on household facilities	63.198	***			18.061	***
2	Multiple deprivation other than on health	93.511	***			28.156	***
4	Multiple deprivation least pronounced on basic and neighbourhood environment	22.444	***			8.047	***
5	Multiple deprivation least pronounced on consumption	79.315	***			28.239	***
15.	Multiple deprivation other than health with basic and household facilities most pronounced	52.915	***			30.838	***
6	Consumption deprivation with a high-tech appliances emphasis	25.423	***			15.630	***
7	Consumption with basic and neighbourhood environment secondary	13.627	***			7.982	***
16	Minimal deprivation other than for holidays	7.846	***			7.305	***
8.	Health and neighbourhood environment	6.817	***			5.190	***
11.	Health deprivation with consumption secondary	4.530	***			3.784	***
9	General health	1.808	***			1.724	**
10	Chronic illness	1.523	***			1.525	**
14	Neighbourhood environment	1.940	***			1.890	***
12	Minimal deprivation other than for specific high-tech consumption items	2.464	***			2.436	***
	Latent Class Clusters						
1	Maximal			23.905	***	3.438	***
2	Current Lifestyle			24.422	***	4.009	***
3	Health & Housing			2.044	***	1.347	
	Ref: Maximal						
	Nagelkerke R^2	0.380		0.268		0.395	
	Reduction in Log Likelihood Ratio	5,284.261		3,525.84		5,557.504	
	Df	15		3		18	
	N	14,230					

*** p<0.01, ** p<0.05, * p<0.1

Entering the latent class variable after the SOM typology increases the Nagelkerke R^2 of 0.015 and reduces the log likelihood ratio by for 273.2 degrees of freedom. In contrast, reversing the order of entry increases the R^2 by 0.127 and reduces the log likelihood ratio by 2,031.7 for 15 degrees of freedom. The SOM typology clearly offers substantial additional discriminatory capacity. This conclusion is confirmed by an examination of the net coefficient. The odds ration for SOM cluster 1 is 115 and four of the six multiple deprivation clusters have values above 20. For the latent class maximal and current living conditions clusters the net coefficients fall to 3 and 4 respectively.

Conclusions

In this paper we have sought to contribute to recent efforts to develop and apply appropriate methodological tools for the multidimensional analysis of poverty and social exclusion. As we have argued, despite the compelling conceptual case for a multidimensional approach its value needs to be empirically established. Our particular focus has been on multi-dimensional deprivation and the extent to which the SOM approach, by allowing us to extract meaningful patterns from complex data and display them in an orderly fashion, can advance our understanding of such deprivation. Our analysis has involved a number of stages. The first has involved the identification and description of sixteen clusters or profiles of multiple deprivation that allow us to provide a detailed account of such deprivation in contemporary Ireland.

In seeking to go beyond this mapping stage we have considered both patterns of socio-economic differentiation in relation to cluster membership and the extent to which such membership contributes to our understanding of the manner in which individuals experience their economic circumstances. In pursuing these goals, it has been necessary to take into account both the advantages and limitations of the SOM approach. As we have seen, while minimising the need for *a priori* assumptions, the SOM approach allows us to identify and visualise complex patterns of differentiation and capture important distinctions that may be concealed within more aggregated typologies such as those that have typically emerged from latent class analysis of deprivation patterns. However, while the SOM approach achieves an enormously parsimonious reduction of the complexity of the original input relating to complex deprivation profiles relating to large numbers of individuals, it presents us with formidable *post hoc* problems of interpretation. Informed by an understanding of contemporary research on poverty and social exclusion, it is apparent that distinctions between clusters have varying substantive significance and likely to be accounted for by somewhat different socio-economic influences.

Pursuing this logic we distinguished between influences such as income, social class, acute life events and housing tenure that are likely to capture command over economic resources and factors such as life cycle stage and urban-location that may reflect both tastes and preferences and non-economic restrictions or facilitation of particular forms of consumption or activities. Of course any such distinction is an over simplification and the distinction is a relative rather than an absolute one. However, guided by it we proceeded to aggregate the original 16 SOM micro clusters into a set of 8 macro clusters. An analysis of the factors discriminating between these clusters, revealed a striking reduction in the importance of resource related variables as one moves from the more to the less extreme forms of multiple deprivation, to consumption deprivation, forms of health deprivation accompanied by secondary aspects of other dimensions, relatively pure forms of health deprivation, neighbourhood environment deprivation and finally minimal deprivation. Other factors such as lone parenthood, marital status, housing tenure and its interaction with urban-rural location impact on some forms of multiple deprivation than on others. Similarly, while there is a clear tendency for older people to be relatively insulated from multiple deprivation, specific forms of such deprivation are associated with different distributions across the life cycle. The extent to which health deprivation is an important element in defining a cluster is obviously a crucial element and for the health cluster life cycle stage takes on a crucial significance.

Focusing on the macro clusters, while highly revealing in terms of resource related variation in patterns of multiple deprivation, obscures within cluster variation that may prove extremely significant from other perspectives. A consideration of differentiation within macro clusters reveals the important role of life cycle factors and urban-rural location. The role of health elements is important once again but so too it appears are tastes/preferences and constraints/opportunities in relation to specific forms of consumption and activities.

Our analysis make clear the continuing importance of traditional forms of stratification relating to factors such as income, social class and housing tenure in accounting for patterns of multiple deprivation. However, it also confirms the role of acute life events and life cycle and location influences. It suggests that debates relating to the extent to which poverty and social exclusion have become individualized should take particular care to distinguish between different kinds of outcomes.

Switching our attention to the consequences of forms of multiple deprivation, our analysis showed that while differentiation was evident across the 16 cluster SOM typology in levels of economic stress, the vast bulk of such variation was accounted for by membership of the 8 macro clusters. Finally a comparison of results deriving from the SOM approach with those resulting from a comparable latent class analysis revealed that the former was considerably more efficient in identifying those exposed to multiple economic stress. This finding, combined with the earlier evidence relating to the role of socio-economic factors in accounting for cluster membership, confirms that if our interest lies in broad patterns stratification a focus on the SOM macro clusters seems most appropriate. For other purposes differentiation within clusters which clearly takes a systematic form may prove to be crucial.

Our analysis provides considerable evidence that a theoretically informed application of the SOM approach has considerable potential in advancing our understanding of patterns of multiple deprivation, their socio economic distribution and the manner in which they are experienced.

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