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Mapping Patterns of Multiple Deprivation Using Self-Organising Maps: An Application to EU-SILC Data for Ireland

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Abstract: The development of conceptual frameworks for the analysis of social exclusion has somewhat out-stripped related methodological developments. This paper seeks to contribute to this process through the application of *self-organising maps* (SOMs) to the analysis of a detailed set of material deprivation indicators relating to the Irish case. The SOM approach allows us to offer a differentiated and interpretable picture of the structure of multiple deprivation in contemporary Ireland. Employing this approach, we identify 16 clusters characterised by distinct profiles across 42 deprivation indicators. Exploratory analyses demonstrate that position in the income distribution varies systematically by cluster membership. Moreover, in comparison with an analogous latent class approach, the SOM analysis offers considerable additional discriminatory power in relation to individuals' experience of their economic circumstances. The results suggest that the SOM approach could prove a valuable addition to a 'methodological platform' for analysing the shape and form of social exclusion.

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1. Introduction

The widespread adoption of the terminology of social exclusion/inclusion in Europe reflects *inter alia* an emerging consensus regarding the limitations of poverty research that focuses solely on income. Kakwani and Silber (2007, p. xv) identify the most important recent development in poverty research as the shift from a uni-dimensional to a multi-dimensional approach. Progress 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 average levels and Sen's (2000) broader 'capabilities' and 'functionings' framework.

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 such a perspective 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).

In this paper we seek to contribute to developing what Grusky and Weeden (2007, p. 33) describe as "a methodological platform" for analysing the shape and form of social exclusion. We do so specifically in relation to forms of material deprivation. A number of earlier efforts have employed latent class analysis to map patterns of material deprivation.[1] The basic idea underlying such analysis is that the associations

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

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. Where this assumption is justified, considerable gains can be achieved in terms of parsimony and understanding of underlying processes.

When the number of indicators of the latent typology of interest is large, several analytic difficulties arise from data sparseness, making it necessary to resort to a number of simplifying assumptions and procedures. One such approach consists in conducting latent class analysis in two stages, where dichotomised dimensions from the first stage are used as input at the second stage (Dewilde, 2004). An alternative approach has involved first conducting confirmatory factor analysis to identify a range of deprivation dimensions, and then entering categorical versions of the extracted factors into a latent class analysis (Whelan and Maitre, 2007). Such approaches have tended to start with the objective of moving fairly rapidly from highly detailed description of multiple outcomes to identification of a small number of underlying classes or clusters. An analytic strategy of this kind can clearly be justified in terms of the value of such simplifying assumptions in enabling us to identify underlying patterns relating to the detailed matrices constituted by large numbers of deprivation items and respondents. However, the question remains as to what extent these assumptions may influence our conclusions and, in particular, conceal important within-cluster heterogeneity.

In this paper we seek to explore the potential for analysing multiple deprivation of an approach that, in contrast to latent class analysis, involves minimal assumptions. The objective is to produce a segmentation of individuals in terms of a wide range of indicators without the need for weighting these indicators and without resorting to synthetic measures or other forms of reduction of the complexity of input to the clustering procedure. The analytical tool for implementing this approach, *self-organising maps* (SOMs henceforth), is presented in the next paragraph.

2. Self-organising maps

Usually the groups into which researchers classify their observations are known in advance and correspond to the values taken on by particular variables or combination of variables. In some cases, however, the groups of interest are not known a priori and must then be discovered using suitable classification techniques. Self-organising maps is one such technique that combines the best properties of both classical clustering algorithms and projection methods, providing them with considerable potential value in analysing complex multi-dimensional data.

SOMs are an artificial neural 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). Essentially, what the SOM algorithm does is to project a high-dimensional dataset **X** onto a lower dimensional output space so as to represent **X** in a compact form and easily identify its underlying structure. To clarify how this projection works and the outcomes it generates, we proceed as follows: first, we define the basic ingredients of any SOM, i.e., the input data **X** and the corresponding output space; then, we offer a basic description of the SOM algorithm.

The starting point of a standard SOM analysis is a case-by-variable dataset, formally defined as a $n \times d$ matrix **X** whose rows represent observations and whose columns represent their attributes of interest. The d elements that make up each row i of **X** ($i = 1,...,n$) correspond to the values taken by each attribute j ($j = 1,...,d$) on observation *i*; together, they are referred to as the *input vector* $\mathbf{x}_i$ and represent the coordinates of observation *i* in the *d*-dimensional *input space* $\Re^d$.

A SOM can be seen as an analytical procedure that helps to reduce the complexity of **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,[2] i.e., a rectangular array of *m* cells arranged in a square or hexagonal lattice (see Figure 1 for an illustration). 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 **X** onto the SOM, then, amounts to allocating each observation *i* to the unit that attracts it most. More precisely, each SOM unit *k* ($k = 1,...,m$) is characterised by a unique $1 \times d$ *weight vector* $\mathbf{w}_k$ that belongs to the same coordinate space as the input vectors $\mathbf{x}_i$ – i.e., $\mathbf{w}_k \in \Re^d$; this means that the input vectors can be systematically compared with the weight vectors and each observation *i* can be properly allocated to its *best matching unit* – i.e., to the SOM unit whose weight vector is closest (most similar) to the input vector $\mathbf{x}_i$. 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 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.

[FIGURE 1 ABOUT HERE]

[2] Although in principle the output space can be of any dimension lower than the dimension of **X**, in practice most SOM analyses rely on a two-dimensional output space.

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* – also known as *training process* – that incrementally adjusts the weight vectors according to a set of rules aimed at maximizing both the discriminatory power of the map (i.e., the *map resolution*) and its degree of topology preservation. The learning process begins by assigning proper starting values to each weight vector $\mathbf{w}_k$ and develops over T iterations called *learning epochs*. For every learning epoch t, each input vector $\mathbf{x}_i$, in turn, is "learnt" by the SOM; therefore, the whole learning process is made of $L = n \times T$ *learning steps*. At each learning step ℓ, weight vectors are adjusted as follows:[3]

Compute the distance D_{ik} between the input vector $\mathbf{x}_i$ and each weight vector $\mathbf{w}_k(\ell-1)$.[4] Typically, D_{ik} is the Euclidean distance $\|\mathbf{x}_i - \mathbf{w}_k(\ell-1)\|$.

Identify the best matching unit of $\mathbf{x}_i$ – i.e., the SOM unit corresponding to the minimum value of D_{ik} – and denote it by index b.

Adjust the weight vector of each SOM unit k as follows:

$$\mathbf{w}_k(\ell) = \mathbf{w}_k(\ell-1) + \alpha(t)\nu_{kb}(t)[\mathbf{x}_i - \mathbf{w}_k(\ell-1)]$$

This formula shows that the weight vector $\mathbf{w}_k$ at learning step ℓ is equal to the weight vector $\mathbf{w}_k$ at learning step $\ell-1$ plus an adjustment factor $\alpha(t)\nu_{kb}(t)[\mathbf{x}_i - \mathbf{w}_k(\ell-1)]$. Here, the term $[\mathbf{x}_i - \mathbf{w}_k(\ell-1)]$ indicates that the adjustment of the weight vector $\mathbf{w}_k$ adds up to making it incrementally closer to the input vector under consideration – and, therefore, to making the corresponding SOM unit incrementally more 'attractive' for that input vector. The extent to which this 'approaching' takes place depends on the value taken on by the *neighbourhood kernel* $\nu_{kb}(t)$, which is a decreasing function of the spatial distance between each unit k and

[3] For more details on the SOM algorithm, its practical implementation and its variants, see Oja and Kaski (1999), Allinson et al. (2001), Kohonen (2001), Obermayer and Sejnowski (2001), Samarasinghe (2007).

[4] When $\ell = 1$, $\mathbf{w}_k(\ell-1) \equiv \mathbf{w}_k(0)$ denotes the starting values of the weight vector.

the best matching unit *b* on the two-dimensional grid. In general, this means that the closer a given SOM unit *k* is to the best matching unit *b*, the greater is the degree to which its weight vector $\mathbf{w}_k$ is adjusted toward the input vector $\mathbf{x}_i$; for example, if unit 22 in Figure 1 is the best matching unit, then the adjustment will be maximum for unit 22 itself, somewhat smaller for the units in its immediate surroundings (16, 21, 27, 28, 29, 23), even smaller for its second-order neighbouring units (15, 14, 20, 26, 33, …), and so on.[5] The value of the neighbourhood kernel is regulated the *neighbourhood radius* $\sigma(t)$ parameter, which defines the width of the kernel itself and is a strictly decreasing function of *t*.[6] Finally, the overall degree of weight vector adjustment is controlled by the *learning rate* parameter – denoted by $\alpha(t)$; this parameter is a multiplier in the interval $[0,1]$ that regulates the velocity of weight vector adjustment and is a strictly decreasing function of *t*.[7]

When the training is concluded, each observation *i* can be allocated to its final best matching unit, i.e., to the SOM unit that minimizes the distance D_{ik} between $\mathbf{x}_i$ and $\mathbf{w}_k(L)$. The end result of this allocation is the classification of the *n* observations of interest into $g \leq m$ exhaustive and mutually exclusive groups.[8]

SOMs have found wide application in such diverse fields as image analysis, speech recognition, engineering, chemistry, physics, mathematics, linguistics, medicine, biology, ecology, geography, marketing and finance (Kaski et al., 1998; Oja et al., 2003), but much less so in sociology. Recently, attempts have been made to extend SOM analysis to the study of multiple deprivation in Italy (Lucchini and Sarti, 2005;

[5] It is true that this example applies only when the neighbourhood kernel is a strictly decreasing function of the distance between units *k* and *b*.
[6] This implies that, when setting up the SOM, it is necessary to specify the initial value of the neighbourhood radius $\sigma(1)$, the final value of the neighbourhood radius $\sigma(T)$, and the radius decay function.
[7] As with the neighbourhood radius, the dependence of $\alpha(t)$ on *t* requires that, when setting up the SOM, the initial value of the learning rate $\alpha(1)$, the final value of the learning rate $\alpha(T)$, and the rate decay function be specified.
[8] The number of actual groups *g* can be smaller than the number of SOM units *m* because it is possible that one or more units do not attract any of the observations at hand and, therefore, remain empty.

Lucchini et al., 2007). In this paper we take advantage of the availability of detailed data relating to material deprivation for a large representative sample in the Irish component of the European Union Community Statistics on Income and Living Conditions (EU-SILC) instrument to extend such efforts.

3. Overview of the analysis

Below we describe the data on which our analysis is based and the key variables. We then provide an account of the technical details relating to the application of SOM procedures to the Irish data, including weighting of vectors and choice of 'training' parameters. We proceed to analyse the configuration of the trained SOM by examining some representative examples of a type of specialized graphs known as *component planes*. Focusing on a number of key indicators, we illustrate the discriminatory power of the SOM by distinguishing three groups of nodes in the two-dimensional grid, characterised in terms of their relative 'specialisation' in attracting disadvantaged, average and advantaged individuals. We go on to partition the output space of the SOM units into a smaller set of homogeneous regions which we consider to offer a reasonable balance between detail and parsimony and map this outcome. To aid in the interpretation of this clustering outcome, we employ a multidimensional scaling algorithm to project the clusters onto a two-dimensional space illustrating their relative size and location.

A detailed description of the resulting structure requires an account of the distribution of the forty-two deprivation indicators across the emerging clusters. In order to provide a summary of this large volume of information, we develop profiles for each cluster relating to levels of deprivation across the five dimensions underlying the forty-two indicators on which our analysis is based. We go on to provide a graphical summary of these profiles that facilitates interpretation of the structure of the clusters.

Finally, we provide an exploratory analysis of the validity of the SOM typology. We do so initially by showing the extent to which cluster membership is differentiated in terms of household income. We proceed to compare the clustering outcome deriving from SOM analysis to that resulting from the application of latent class procedures to the same set of indicators. Lastly, we provide an assessment of the extent to which the clusters identified utilising the SOM procedure offer additional discriminatory capacity in relation to the manner in which economic circumstances are experienced.

4. 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, with a declared response rate equal to 48% (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 deprivation.[9] 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.

[9] Full details of the question format relating to these items are provided in Whelan and Maître (2007).

3. *Household facilities deprivation*: four items regarding basic facilities such as bath, toilet etc.
4. *Neighbourhood environment deprivation*: five items concerning pollution, crime/vandalism, noise, and deteriorating housing conditions.
5. *Health deprivation*: three items relating to overall evaluation of health status of the HRP, 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 ABOUT HERE]

5. Results

5.1. SOM training and interpretation

The starting point of our analysis[10] is a $14{,}219 \times 42$ matrix[11] which we project onto a two-dimensional SOM made of 432 units arranged in a 18×24 hexagonal lattice[12]. Weight vectors were initialised using the linear method (Kohonen, 2001), and the SOM training was carried out in two phases:

1. An 8-epoch *ordering phase*, based on a large initial value and a fast decrease of both the neighbourhood radius ($\sigma(1) = 20, \sigma(8) = 10$, linear decay function) and the learning rate ($\alpha(1) = 1, \alpha(8) = 0.1$, linear decay function).

[10] All the analyses reported in this paper, including SOM training and visualization, have been carried out using routines written in the Stata programming language (StataCorp, 2007).
[11] 53 observations have been eliminated from the analysis because they were missing on one or more of the forty-two indicators.
[12] The hexagonal lattice was chosen because, contrary to the square lattice, it offers uniform adjacency – i.e., each hexagonal cell has six adjacent neighbours in symmetrically equivalent positions – which makes for better SOM training and visualization (Kohonen, 2001). The number of SOM units was chosen because it offered a good compromise between training complexity and detail (432 equals about one fifth of the number of distinct combinations of attributes found in our data matrix). Finally, a non-square rectangular shape was chosen for the two-dimensional grid because it roughly corresponds to the two major dimensions of the data matrix (Kohonen, 2001).

2. A 50-epoch *fine-tuning phase*, based on a minute and slow adjustment of both the neighbourhood radius ($\sigma(1) = 10$, $\sigma(50) = 1$, linear decay function) and the learning rate ($\alpha(1) = 0.1$, $\alpha(50) = 0$, linear decay function).[13]

At the end of the training process, each observation was allocated to its final best matching unit and the quality of the SOM was assessed by means of two measures: the quantization error and the topographic error (Kohonen, 2001). The *quantization error* – normalized so as to take values in the interval [0,1] – is a measure of the SOM resolution and corresponds to the average distance between each input vector $\mathbf{x}_i$ and its best matching unit; our SOM exhibits a normalized quantization error equal to 0.124, meaning that – on average – each element of the input vector differs from its corresponding best-matching-unit weight by 12.4 percentage points. In turn, the *topographic error* is a measure of the SOM's degree of topology preservation and corresponds to the proportion of all input vectors for which the best matching unit and the second-best matching unit are not adjacent on the two-dimensional grid; our SOM exhibits a topographic error equal to 0.009, meaning that only 128 observations are affected by some degree of 'topological misplacement'.

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. Some representative component planes, each corresponding to a distinct element of $\mathbf{w}_k$ – and, therefore, to a specific indicator of deprivation – are shown in Figure 2. As we can see, in each graph 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 '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

[13] In both training phases, a Gaussian neighbourhood kernel was used (Kohonen, 2001).

both types.[14] The spatial distribution of these three types of units on the two-dimensional grid describes the configuration of the SOM in terms of the corresponding indicator.[15]

In order to clarify what is involved, we first consider the component plane representing 'inability to afford a video recorder' (Figure 2, panel *a*). As we can see, in this case the vast majority of SOM units belong to the 'neutral' (white) category, i.e., attract a quota of disadvantaged respondents that is not substantially different from that observed in the working dataset (4%, see Table 1). There is also a small cluster of 'hot' (black) units, i.e., units that attract a disproportionate share of disadvantaged. In contrast, there are no 'cold' (grey) units, i.e., units that attract a number of disadvantaged respondents substantially lower than the average.[16] It is worth noting that a similar pattern holds for the inability to afford a range of other durables, including a vacuum cleaner, a fridge, a freezer, a micro wave, a deep fat fryer, a liquidiser, a video, a stereo, and a washing machine. For this set of items, therefore, we observe a weak pattern of discrimination combined with a sharp pattern of spatial differentiation between the small number of 'hot' units and all the others.

[FIGURE 2 ABOUT HERE]

For more expensive consumer durables, a more typical pattern is that represented by the component plane shown in Figure 2, panel *b* (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,

[14] It is important to note that 'specialisation' here, should be understood in relative terms.

[15] Typically, component planes represent the distribution of SOM weights in more detail, i.e., by means of a larger number of ordered classes. For illustrative purposes, however, the threefold repartition described above has the merit of conveying a sufficient amount of information in a compact way.

[16] In this case, the absence of blue units reflects on the fact that the overall proportion of disadvantaged respondents (4%) is too low for any significant number of observations to emerge fitting the description "substantially lower than the average".

the remaining units are more widely distributed. This pattern also applies to the inability to afford a clothes dryer, a dish washer, and a satellite dish. Moreover, a similar pattern is observed for the inability to afford a car, a camcorder, and new furniture; in these cases, however, the number of neutral units is a good deal lower.

For all the indicators of health deprivation, the component plane is close to that shown in Figure 2, panel *c*, with a significant majority of cold units, a significant minority of hot units, and a much smaller minority of neutral units. The item regarding the inability to afford a holiday exhibits a similar pattern. Thus, for these items we observe a pattern of differentiation which involves a very modest intermediate ground.

As regards the absence of basic household facilities, both hot and cold units are more widely dispersed in the two-dimensional space. This is illustrated in Figure 2, panel *d*, for the item indicating rooms being too dark or without light. In this case we have a very substantial quota of neutral units from whom the remaining units are distinguished in a bipolar fashion.

Finally, the neighbourhood environmental items are distinguished by the fact that hot units form two spatially separate clusters, suggesting that multiple and distinct influences may underlie this form of deprivation. The component plane representing crime, violence or vandalism in the area of residence typifies this pattern (see Figure 2, panel *e*).

The foregoing analysis illustrates the discriminatory capacity of the SOM in relation to the individual deprivation items. Moreover, the joint analysis of the whole set of component planes also suggests that the 432 units making up the SOM can be grouped into a smaller number of homogeneous clusters. We explore this possibility in the next section.

5.2. Clustering the SOM units

As illustrated in the previous section, the visual inspection of the forty-two component planes associated with our 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. Figure 3 displays the result of this operation. It is worth noting that, without imposing any constraint to the clustering algorithm, each cluster turns out to be entirely made of spatially contiguous SOM units.

[FIGURE 3 ABOUT HERE]

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 result of this projection is shown in Figure 4, 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, offering a differentiated picture of the structure of multiple deprivation in contemporary Ireland.

[FIGURE 4 ABOUT HERE]

A detailed description of the resulting structure is provided in Figure A1, where we display the prevalence of the forty-two indicators of deprivation within each of the sixteen clusters. In order to provide a summary of this large mass of information, we develop the profile for each cluster relating to deviations around the mean levels of the five dimensions as described earlier, comprising basic, consumption, household facilities, neighbourhood environment, and health.

In developing these profiles, we have pursued a strategy seeking to synthesize the information given by each single indicator in a way that takes into account the strongly skewed distribution of almost all the indicators. Namely:

1. For each indicator X_j ($j = 1,\ldots,42$), we have computed its sample variance $V(X_j) = p_j(1 - p_j)$, where $p_j = \Pr(X_j = 1)$.
2. For each indicator X_j, we have computed two threshold values:

$$t_{1j} = \left| \ln\left(\frac{p_j + V(X_j) \times 0.75}{p_j} \right) \right|$$

$$t_{2j} = \left| \ln\left(\frac{p_j + V(X_j) \times 1.5}{p_j} \right) \right|.$$

3. For each indicator X_j, we have computed its mean within each cluster C_g ($g = 1,\ldots,16$): $p_{j|g} = \Pr(X_j = 1 \mid C_g)$.
4. For each indicator X_j and each cluster C_g, we have computed the 'deviation' of the cluster-specific mean from the overall mean: $\delta_{jg} = \ln(p_{j|g} / p_j)$.

5. We have transformed the deviation values δ_{jg} into a corresponding set of discrete scores s_{jg} according to the following rules:

$$s_{jg} = \begin{cases} -1 & \text{if} \quad \delta_{jg} < -t_{1j} \\ 0 & \text{if} \quad -t_{1j} \le \delta_{jg} \le t_{1j} \\ 1 & \text{if} \quad t_{1j} < \delta_{jg} \le t_{2j} \\ 2 & \text{if} \quad \delta_{jg} > t_{2j} \end{cases} .$$

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

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

7. Finally, we have transformed the mean values μ_{gq} into a corresponding set of symbols according to the following rules:

$$\mu_{gq} < 0 \quad \rightarrow \quad \text{"–"}$$

$$\mu_{gq} = 0 \quad \rightarrow \quad \text{"="}$$

$$0 < \mu_{gq} \le 1 \quad \rightarrow \quad \text{"+"}$$

$$\mu_{gq} > 1 \quad \rightarrow \quad \text{"++"} .$$

The end result of this procedure is shown in Table 2.

[TABLE 2 ABOUT HERE]

Informed by the analysis relating to both the deprivation dimensions and the full set of indicators, 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 characterised by above average deprivation in relation to all dimensions other than health but with the scale being somewhat weaker for neighbourhood environment than for the remaining dimensions. This group comprises 1.1 per cent of the population.

Cluster 4 (*Multiple deprivation least pronounced on neighbourhood environment)* is distinctive primarily in relation to health, basic, consumption and household facilities. It involves 1 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 most pronounced*) is made up of individuals displaying above average deprivation on all dimensions other than health, especially in relation to the dimension of basic deprivation. In terms of consumption, enforced absence of a car is particularly prevalent. It involves 2.3 per cent of the sample.

Cluster 6 (*Consumption deprivation with a high-tech appliances emphasis)* is characterised by basic and, above all, consumption deprivation, the latter particularly pronounced in relation to high-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 11 (*Health deprivation with consumption secondar*y) 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 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 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 *(Minimal deprivation other than for 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.

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 5 provides 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 the small grey region comprising clusters 8 and 11. Dark grey clusters are also characterised by a substantial degree of deprivation in terms of household facilities. Finally, clusters with a thick black outline exhibit a relatively high degree of deprivation also in terms of neighbourhood environment.

[FIGURE 5 ABOUT HERE]

5.3. Validating the SOM clusters

We have identified a set of clusters that can be interpreted in meaningful substantive terms. Our results fulfil the criterion of face validity. Clearly, the next step is to undertake a systematic analysis relating to the construct validity of the typology of deprivation that we have identified. Such an analysis would require a range of multivariate analysis that cannot be accommodated within the constraints of the current paper. Instead what we provide is a simpler illustrative analysis relating to the manner to which the clusters are differentiated in socio-economic differentiation, the relationship between the SOM typology and the outcome of a latent class analysis of the same data, and the extent to which the former offers additional discriminatory capacity in relation to outcomes such as subjective economic stress.

Our first step in pursuit of these objectives is to set out in Table 3 the composition of the SOM clusters in terms of equivalent income quintiles. A systematic pattern of variation is observed. For the forms of deprivation represented by clusters 1 and 2, with basic and consumption deprivation being dominant in the former case and health and basic in the latter, the numbers in the bottom quintile exceed 60 per cent. Taking the two bottom quintiles into account this figure rises to 90 per cent. Correspondingly, the respective figures for the top two quintiles are respectively 2 per cent and zero.

The pattern of differentiation is only marginally less striking for clusters 3 and 4, representing respectively patterns of deprivation where consumption and consumption and health are the dominant elements. The number in the bottom quintile falls to the mid-50s with relatively proportionate increases across the remaining quintiles. For cluster 5, involving a pattern of health and basic deprivation, and cluster 15 involving the latter combined with enforced deprivation of a car, the figure in the bottom quintile falls to the mid-40s. In none of the six cases we have considered so far does the figure in the two bottom quintiles fall much below three-quarters and in no case does the number found in the top two quintiles rise above 2 per cent.

The foregoing categories can be clearly distinguished from clusters 6, 7 and 11 in terms of their tendency to be concentrated at the lower end of the income distribution. For these groups the number in the bottom quintile ranges between 33 and 37 per cent, and the corresponding figures for the top two quintiles run from 14 to 20 per cent.

For clusters 8, involving health and neighbourhood deprivation, the pattern is rather different with the members of this group being slightly underrepresented in the bottom quintile. In contrast, they are over-represented in the second and third clusters with 60 per cent of their members being located in these categories. For cluster 9, relating to general health, the pattern is somewhat different with one in five located in the bottom quintile and three in five being found in the first and second quintile combined. However, the distribution of individuals across the remaining quintiles is similar to that observed in cluster 8. Finally, for cluster 10 relating to chronic illness, individuals are distributed across quintiles in a somewhat more uniform fashion, with the range running from 27 (bottom quintile) to 13 per cent (top quintile).

[TABLE 3 ABOUT HERE]

When we turn to the clusters involving minimal deprivation, a further pronounced shift is observed. Cluster 14 is characterised by a uniform distribution of its members across the five quintiles (18-23 per cent of respondents in each quintile). In turn, clusters 16, 12 and 13 are characterised by a low probability of being located in the bottom quintile, with approximately 11 per cent being found there in each case. The total in the bottom two quintiles is uniform across the three clusters, with 25 per cent being so located. A divergence is observed in the numbers in the third quintile, with members of cluster 16 being a good deal more likely to be found there. The relevant figure declines from 32 per cent for cluster 16, involving deprivation on certain high tech consumer items, to 22 and 17 per cent respectively for clusters 12 and 13. Corresponding differences are observed in the number in the top quintile. This rises to from 19 per cent for cluster 16 to approximately 30 per cent for the other two clusters.

The patterns of economic differentiation are very much as we would have expected on the basis of our substantive interpretation of the clusters. The most pronounced variation is observed for the patterns of multiple deprivation characterising clusters 1 and 2, where basic and consumption deprivation and health and basic, respectively, dominate. Basic deprivation appears to be a particularly powerful discriminatory factor. Next in line are clusters 3 and 4 involving multiple deprivation, where respectively consumption and health and consumption are the primary factors. Forms of multiple deprivation involving consumption deprivation are the next most powerful. The next level of differentiation relates to clusters 5 and 15 involving, in turn, the combination of health and consumption and basic deprivation and the enforced absence of a car. While there is evident variation between these six clusters, they are clearly differentiated from the remaining groups.

In the hierarchy of income differentiation, the next position is occupied by clusters 6, 7 and 11 which are characterised by relatively specific forms of consumption deprivation. Cluster 8, which is characterised by health deprivation accompanied by significantly more modest neighbourhood environment deprivation, displays a similar profile. The previous three clusters differ from the remaining health clusters 9 and 10, which are associated with substantially less skewed distribution of income.

In turn, the consumption and health clusters are clearly differentiated from the four remaining clusters involving minimal deprivation. The fact that the cluster involving solely neighbourhood environment (cluster 14) forms part of the group is likely to be a consequence of the fact that relatively affluent individuals may choose to endure such deprivation in return for the compensatory advantages conferred by particular urban locations.

The set of deprivation indicators on which we have focused have been previously subjected to latent class analysis by Whelan and Maître (2007). They found that the best fitting solution involved four latent classes which they labeled as follows:

1. *Minimally Deprived* comprising 82.6 per cent of the sample.
2. *Health and Housing Deprived* making up 4.5 per cent of the sample.
3. *Deprived in terms of current living standards (CLSD)* involving 6.2 per cent of the sample.
4. *Maximally Deprived* incorporating 6.8 per cent of the sample.

In order to further assess the value of the SOM typology, in Table 4 we consider the relationship between it and the corresponding 4-cluster latent class typology. From Table 4, we can see that almost 75 per cent of the latent class minimally deprived cluster are located in the SOM clusters 14, 16, 12, and 13 involving minimum deprivation, while none are located in cluster 1-4 and only 3 per cent in clusters 1-5 and 15 characterised by multiple deprivation. The major differentiation within the latent class minimal deprivation group involves the allocation of 3 per cent of its membership to SOM consumption clusters 6 and 7, and 20 per cent to the health clusters 8-11.

[TABLE 4 ABOUT HERE]

Focusing on the latent class health and housing cluster, we find that over 90 per cent of this group have been allocated to SOM categories that have strong elements of deprivation relating to health, housing and neighbourhood environment. Focusing on the latent class CLSD cluster, we find that almost 50 per cent are found in the SOM consumption clusters 6 and 7 and in the multiply deprived clusters 3 and 4 which involve significant consumption elements. A further 35 per cent are found in the remaining multiply deprived clusters 1, 2, 5, and 15.

Finally, focusing on the latent class maximal deprivation cluster, we find that two thirds of its members are located in the SOM multiple deprivation clusters 1-5 and 15. A further 10 per cent are found in the clusters 6, 7 and 1, which involve significant consumption elements, while 11 per cent are located in cluster 8 characterised by health and neighbourhood environment deprivation. Contrary to expectation, about 9 per cent are found in the minimal deprivation and neighbourhood environment SOM clusters.

Overall, allowing for aggregation of SOM clusters, we observe a broad correspondence between the two typologies that is reassuring. However, the earlier results relating to income distribution suggest that the latent class approach loses out on important patterns of differentiation. In Table 5 we explore this issue further by considering the extent to which levels of subjective economic stress are affected by SOM cluster membership within the latent class minimal deprivation cluster. We have chosen the latter cluster in order to have sufficient numbers to make reliable estimates. Even so we have had to exclude clusters 1 to 5 of the SOM typology. The economic stress indicator is derived from a question answered by the Household Reference Person relating to the extent to which, in comparison with other households, the household has ‘difficulty in making ends meet’. The dichotomous dependent variable on which we focus contrasts those individuals in households reporting “great difficulty” or “difficulty” with all others. From Table 5 we can see that, within the latent class minimal deprivation cluster, considerable variation in level of subjective economic stress is observed conditional on SOM cluster membership.

[TABLE 5 ABOUT HERE]

The lowest level of subjective economic stress of 11 per cent is observed for the SOM minimal deprivation cluster 13. A modest rise to 14 per cent is observed for neighbourhood environment (cluster 14) and general health (cluster 9). A further increase to approximately 20 per cent occurs for deprivation solely in relation to specific high-tech consumer durables and the chronic illness cluster. The figure increases to 33 and 37 for the remaining health groups, where consumption and neighbourhood environment respectively are accompanying aspects. For the consumption categories we observe a rise to 40 per cent where the secondary aspect relates to neighbourhood environment, and to 49 per cent for the broader consumption deprivation dimension incorporating high-tech consumer durables. The holiday cluster (cluster 16) occupies an intermediate position (44 per cent). Finally, cluster 15, which is characterised by basic deprivation and the enforced absence of a car, is quite distinctive and is associated with a level of economic stress of 85 per cent.

Overall the results confirm that the SOM typology offers considerable additional discriminatory power. The pattern of differentiation is very much in line with our expectations. Levels of economic stress tend to decline as we move from SOM clusters dominated by basic deprivation to those where consumption deprivation is the key factor, to those where health combines with other forms of deprivation, to more purely health clusters, and finally to clusters characterised by minimal deprivation. Taken together with the evidence on income differentiation, it provides strong support for the validity of the SOM typology in terms of its capacity to identify meaningful forms of multiple deprivation that can be accounted for by key socio-economic variables and have a significant influence on the manner in which individuals experience their economic circumstances. A more comprehensive demonstration that is the case will require undertaking an appropriate set of multivariate analyses.

6. Conclusion

The development of conceptual frameworks for the analysis of social exclusion and the pervasive use of related terminology in both academic and policy debates has somewhat out-stripped related methodological developments. This paper constitutes an effort to contribute to "a methodological platform" for analysing the shape and form of social exclusion (Grusky and Weeden, 2007, p. 31).

We have done so by applying the *self-organising maps* approach to a detailed set of deprivation indicators that span a number of underlying dimensions of deprivation. The SOM approach allows for a segmentation of individuals in relation to a wide range of indicators with a minimum of prior assumptions. Employing this approach, we were able initially to illustrate the discriminatory capacity of the two-dimensional SOM in relation to representative set of items. Extending the analysis we identified sixteen spatially contiguous clusters. The clusters are characterised by distinct profiles across the forty-two deprivation indicators. In order to facilitate the interpretation of these results, we developed profiles for each cluster relating to deviations around the mean levels of deprivation across the five underlying dimensions. As illustrated in Figure 5, a number of clear principles of differentiation emerge. Clusters 1 to 5 and 15 are contrasted with the rest in terms of basic deprivation, while these clusters, together with clusters 6 and 7, are also distinctive in terms of their levels of consumption. Cluster 8 and 11 occupy an intermediate position with regard to consumption. High levels of health deprivation distinguish clusters 1, 2, 4, 5 and 8 to 11. On the other hand, clusters 7 and 14 are distinctive in terms of neighbourhood environment.

Taken together, cluster 1 to 5 and 15 capture 9 per cent of the population who experience forms of multiple deprivation with varying emphasis on basic deprivation, health and neighbourhood environment. Clusters 6 and 7, comprising 5 per cent of the sample, are characterised by different forms of consumption deprivation with the distinction between high and low tech consumer durables playing an important role. Clusters 8 to 11, which are primarily differentiated in terms of health, make up 18 per cent of the sample. Clusters 9 and 10 are distinguished pretty well entirely by the health indicators while 8 and 11 combine significant elements of consumption and, in the case of cluster 8, neighbourhood deprivation. Clusters 14 and 16, involving respectively 11 and 6 per cent of the sample, are located towards the minimum deprivation end of the continuum and are distinguished, in turn, solely by deprivation relating to neighbourhood environment and inability to afford a holiday. Finally, clusters 12 and 13 represent relatively uniform patterns of minimal deprivation and comprise just less than one half of the sample.

The SOM approach allows us to offer a differentiated and interpretable picture of structure of multiple deprivation in contemporary Ireland. At the same time, the spatially contiguous nature of the clusters affords the possibility of constructing a set of nested forms of the typology. This offers possibilities that we intend to exploit in future work focusing on the role of socio-economic factors in differentiating within and between ‘micro’ and ‘macro’ clusters and the relative influence of these different forms of variation on the manner in which individuals experience their economic circumstances.

While addressing such issues will require in-depth or multivariate analysis, in this paper we have presented some exploratory analyses aimed at assessing the construct validity of the SOM typology. Our findings demonstrate that an individual's position in the income distribution is associated with cluster membership very much as we would expect on *a priori* grounds. The SOM typology also differentiates with clusters derived from latent class analysis of the same data in the hypothesised manner. Finally, our initial analysis suggests that, in comparison with the corresponding latent class clusters, it offers considerable additional discriminatory power. Further detailed analysis is required to provide a comprehensive analysis of the value of the SOM approach in relation to multiple deprivation. However, the results we have reported here suggest that it could prove a valuable addition to 'a methodological platform' for analysing the shape and form of social exclusion.

Appendix

Figure A1

Prevalence (%) of the indicators of deprivation within each SOM cluster. Empty bars represent the prevalence (%) of indicators in the whole sample.

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Table 1

Indicators of deprivation used in the analysis (N = 14,219)

Indicator	Description	Prevalence (%)
	Basic deprivation	
4	Having friends or family for a drink or meal at least once a month	11.3
6	Eating meat chicken or fish (or vegetarian equivalent) every second day	3.7
7	Having a roast joint (or equivalent) once a week	4.5
8	Buying new rather than second-hand clothes	5.8
9	A warm waterproof overcoat for each household member	2.7
10	Two pairs of strong shoes for each household member	3.8
11	Replacing worn-out furniture	13.5
12	Keeping home adequately warm	3.3
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	10.1
33	Going without heating during the last 12 months	5.6
	Consumption deprivation	
5	Paying for a week's annual holiday away from home in the last 12 months	22.7
14	A satellite dish	13.2
15	A video recorder	3.5
16	A stereo	4.2
17	A CD player	4.5
18	A camcorder	16.6
19	A personal computer	12.6
21	A clothes dryer	9.4
22	A dish washer	14.4
23	A vacuum cleaner	1.4
24	A fridge	2.2

25	A deep freeze	6.0
26	A microwave	2.3
27	A deep fat fryer	3.6
28	A liquidiser	6.9
29	A food processor	7.7
30	A telephone (fixed line)	5.5
31	A car	13.6
	Household facilities deprivation	
20	A washing machine	0.9
34	Bath or shower	1.1
35	Internal toilet	0.7
36	Central heating	8.5
37	Hot water	1.7
	Neighbourhood environment deprivation	
38	Leaking roof, damp walls/ceilings/floors/foundations, rot in doors, window frames	13.5
39	Rooms too dark, light problems	6.1
40	Noise from neighbours or from the street	12.3
41	Pollution, crime or other environmental problems	9.4
42	Crime, violence or vandalism in the area	14.6
	Health deprivation	
1	General health problems	19.6
2	Chronic illness or condition	24.4
3	Limitation in usual activities for at least the last 6 months because of a health problem	21.6

Table 2

Profile of SOM clusters in terms of deprivation dimensions

Cluster	Basic	Consumption	Household facilities	Neighbourhood environment	Health
1. Multiple deprivation least pronounced on health	++	++	++	++	+
2. Multiple deprivation least pronounced on household facilities	++	++	+	++	++
3. Multiple deprivation other than on health	++	++	++	+	=
4. Multiple deprivation least pronounced on neighbourhood environment	++	++	++	+	++
5. Multiple deprivation least pronounced on consumption	++	+	++	++	++
15. Multiple deprivation other than health with basic most pronounced	++	+	+	+	–
6. Consumption deprivation with a high-tech appliances emphasis	+	++	–	–	–
7. Consumption with basic and neighbourhood environment secondary	+	++	=	+	–
11. Health deprivation with consumption secondary	–	+	–	–	++
8. Health and neighbourhood environment	–	+	+	++	++
9. General health	–	–	=	–	++
10. Chronic illness	–	–	–	–	+
14. Neighbourhood environment	–	–	–	++	–
16. Minimal deprivation other than for holidays	–	–	–	–	–
12. Minimal deprivation other than for specific high-tech consumption items	–	–	–	–	–
13. Minimal deprivation	–	–	–	–	–

Table 3

Composition of SOM clusters by equivalent income quintile (row percentages)

Cluster	Income quintile						
	1	2	3	4	5	Total	N
1. Multiple deprivation least pronounced on health	64.8	24.5	8.7	2.0	0.0	100.0	253
2. Multiple deprivation least pronounced on household facilities	62.1	28.1	9.8	0.0	0.0	100.0	153
3. Multiple deprivation other than on health	53.5	40.6	1.9	3.2	0.6	100.0	155
4. Multiple deprivation least pronounced on neighbourhood environment	54.5	28.7	14.7	1.4	0.7	100.0	143
5. Multiple deprivation least pronounced on consumption	45.7	27.4	24.8	1.3	0.9	100.0	234
15. Multiple deprivation other than health with basic most pronounced	46.3	38.0	5.9	6.5	3.4	100.0	324
6. Consumption deprivation with a high-tech appliances emphasis	34.0	31.7	20.1	11.1	3.1	100.0	388
7. Consumption with basic and neighbourhood environment secondary	32.9	28.0	20.2	15.6	3.2	100.0	346
11. Health deprivation with consumption secondary	37.1	28.5	14.0	12.7	7.7	100.0	757
8. Health and neighbourhood environment	25.4	35.2	24.5	11.5	3.3	100.0	841
9. General health	18.6	39.1	27.3	10.6	4.3	100.0	161
10. Chronic illness	26.7	26.2	17.9	15.9	13.2	100.0	1,111
14. Neighbourhood environment	19.8	19.2	20.2	17.9	22.9	100.0	887
16. Minimal deprivation other than for holidays	11.5	14.1	31.5	24.0	19.0	100.0	384
12. Minimal deprivation other than for specific high-tech consumption items	10.8	14.1	22.0	25,2	27.9	100.0	6,573
13. Minimal deprivation	11.1	14.3	17.0	27.6	30.1	100.0	1,524

Table 4

Distribution of SOM cluster location within latent class clusters (column percentages)

Cluster	Minimal Deprivation	Health & Housing	Current Life Style	Maximal
1. Multiple deprivation least pronounced on health	0.0	0.0	12.0	19.2
2. Multiple deprivation least pronounced on household facilities	0.0	1.1	3.2	15.9
3. Multiple deprivation other than on health	0.0	1.6	14.7	3.0
4. Multiple deprivation least pronounced on neighbourhood environment	0.0	0.5	8.1	3.5
5. Multiple deprivation least pronounced on consumption	0.7	0.5	8.0	17.3
15. Multiple deprivation other than health with basic most pronounced	1.3	0.5	12.0	7.6
6. Consumption deprivation with a high-tech appliances emphasis	1.7	0.5	14.1	1.7
7. Consumption with basic and neighbourhood environment secondary	1.6	9.5	11.5	6.7
11. Health deprivation with consumption secondary	1.1	2.1	0.4	2.0
8. Health and neighbourhood environment	4.4	19.4	7.3	10.5
9. General health	7.0	8.5	0.1	0.0
10. Chronic illness	7.8	38.2	0.0	1.8
14. Neighbourhood environment	11.9	10.6	0.0	4.4
16. Minimal deprivation other than for holidays	6.4	0.3	4.7	2.8
12. Minimal deprivation other than for specific high-tech consumption items	3.1	0.3	0.6	0.0
13. Minimal deprivation	53.3	6.9	3.2	1.5
Total	100.0	100.0	100.0	100.0
N	12,218	377	849	787

Table 5

Probability (%) of experiencing difficulty in making ends meet, by SOM cluster (only members of the latent class minimal deprivation cluster)

Cluster	%	N
15. Multiple deprivation other than health with basic most pronounced	85.1	137
6. Consumption deprivation with a high-tech appliances emphasis	49.1	211
7. Consumption with basic and neighbourhood environment secondary	39.5	200
11. Health deprivation with consumption secondary	33.1	133
8. Health and neighbourhood environment	36.9	539
9. General health	13.5	853
10. Chronic illness	19.0	953
14. Neighbourhood environment	14.3	1,449
16. Minimal deprivation other than for holidays	44.2	778
12. Minimal deprivation other than for specific high-tech consumption items	19.8	378
13. Minimal deprivation	10.9	710

Figure 1

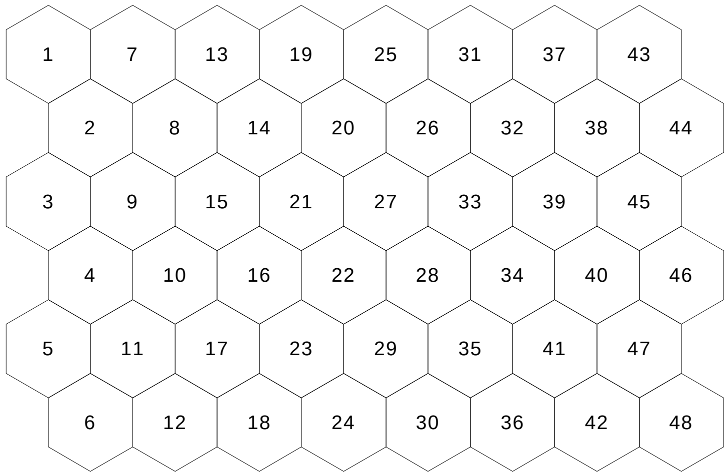
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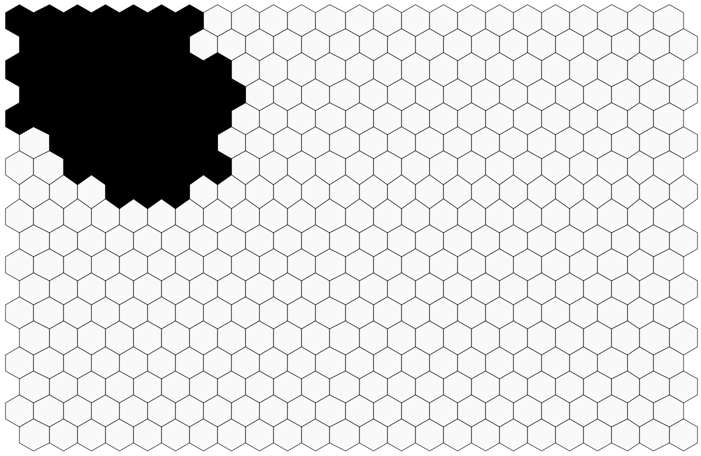
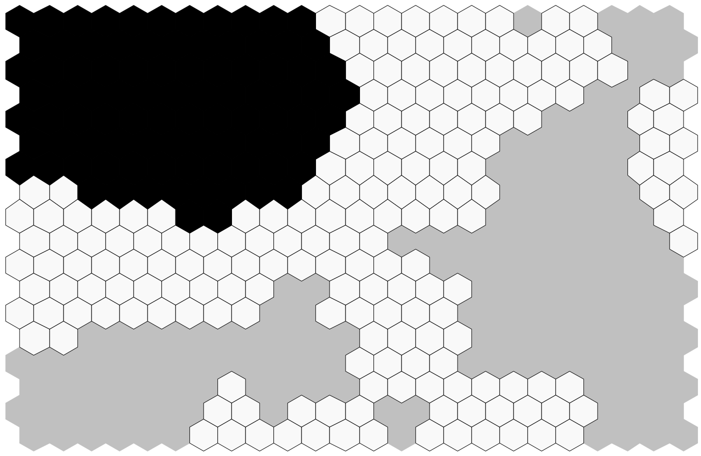
Figure 2

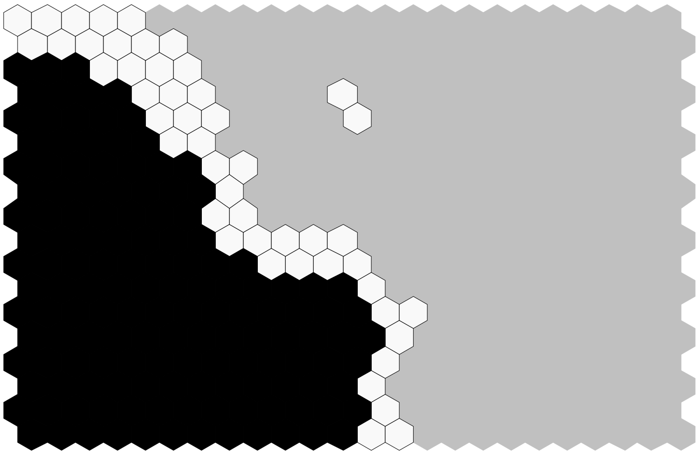
a) Inability to afford a video recorder



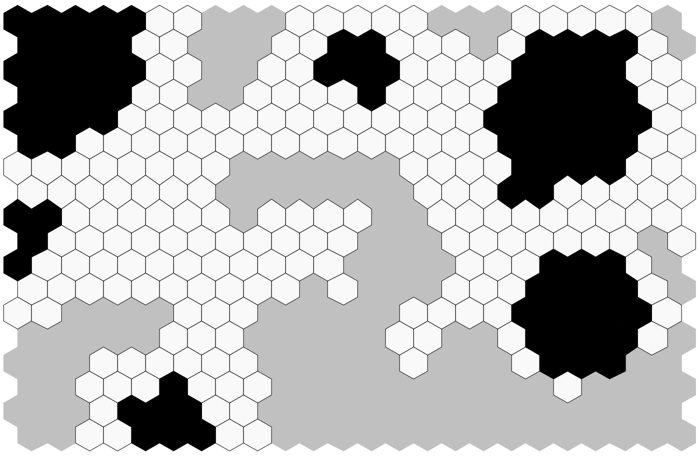
b) Inability to afford a personal computer



c) Chronic illness or condition



d) Dwelling with too dark rooms and light problems



e) Crime, violence or vandalism in the area of residence

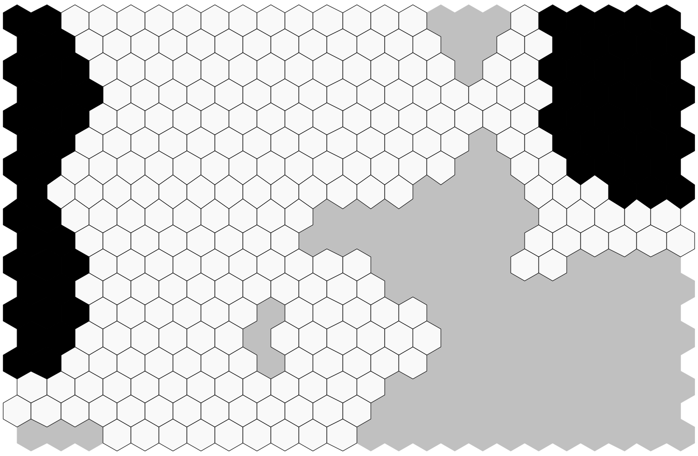


Figure 3

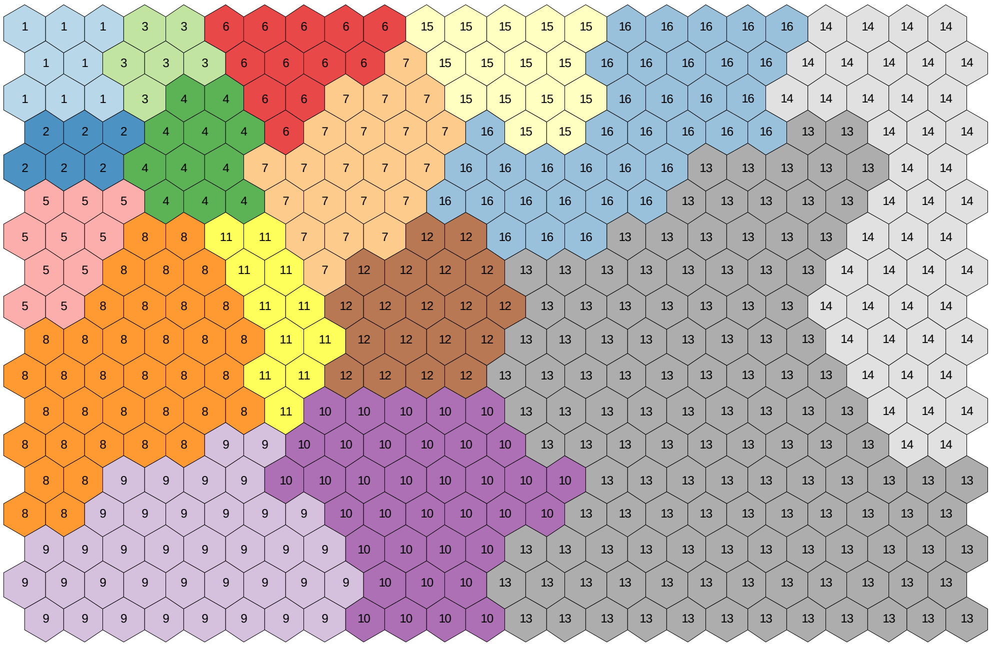


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Figure 4

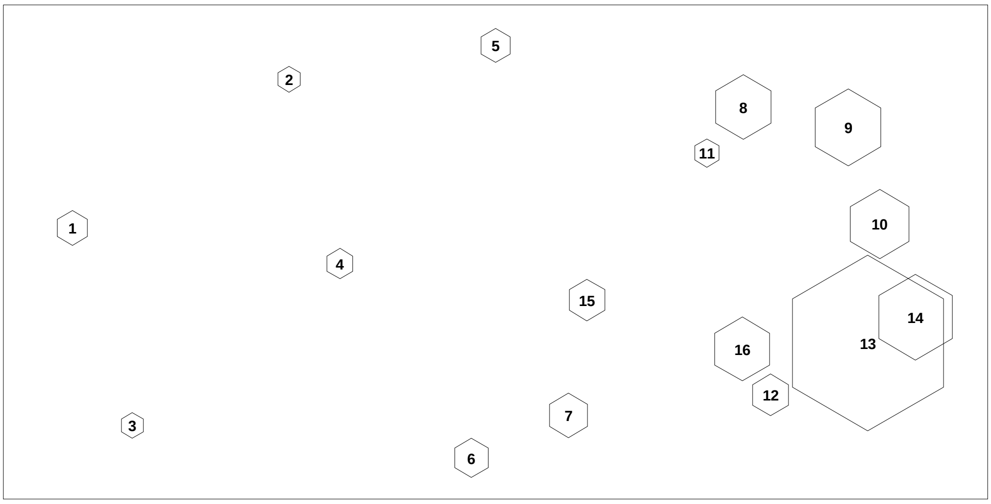


Figure 5

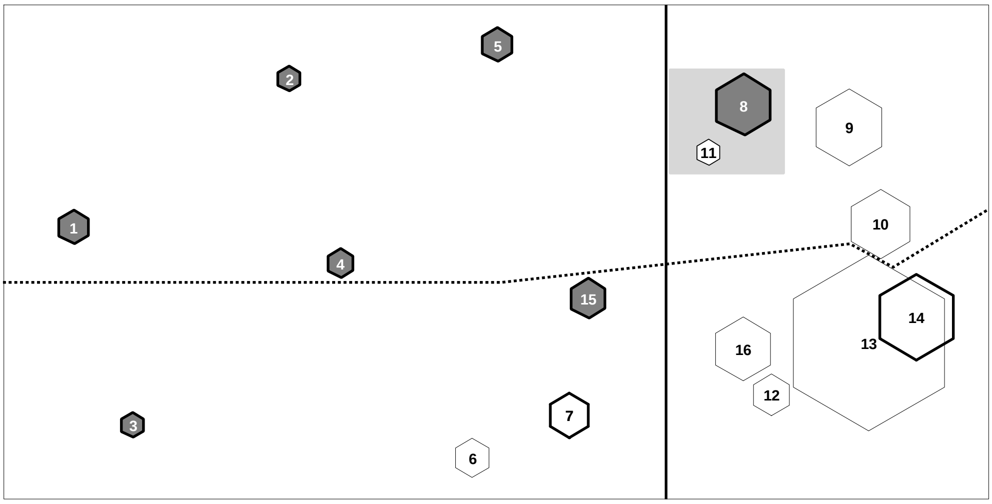
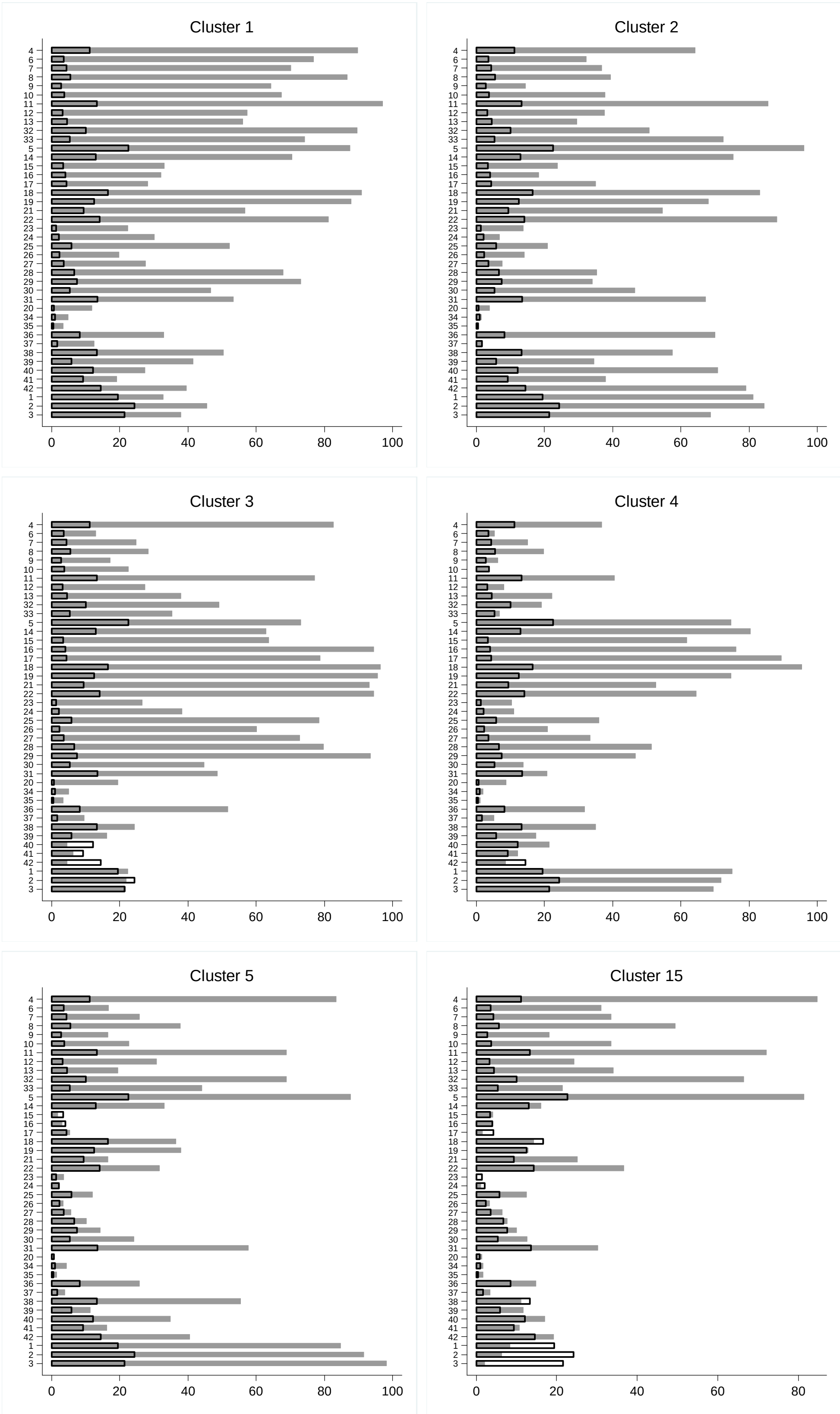


Figure A1


Cluster 1
0 20 40 60 80 100
Cluster 2
0 20 40 60 80 100
Cluster 3
0 20 40 60 80 100
Cluster 4
0 20 40 60 80 100
Cluster 5
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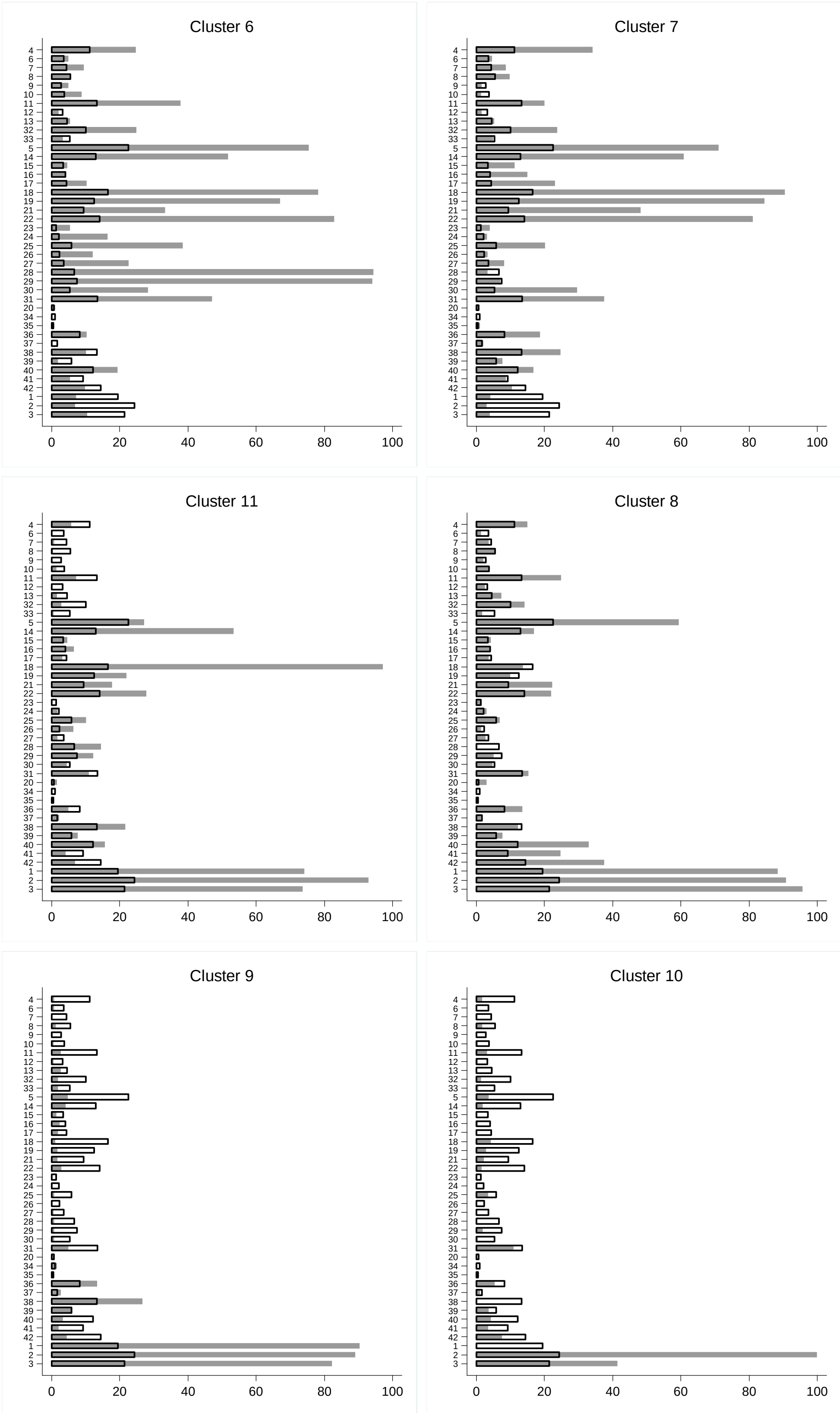
Cluster 15
0 20 40 60 80


Cluster 6
4 6 7 8 9 10 11 12 13 32 33 5 14 15 16 17 18 19 21 22 23 24 25 26 27 28 29 30 31 20 34 35 36 37 38 39 40 41 42 1 2 3
0 20 40 60 80 100
Cluster 7
4 6 7 8 9 10 11 12 13 32 33 5 14 15 16 17 18 19 21 22 23 24 25 26 27 28 29 30 31 20 34 35 36 37 38 39 40 41 42 1 2 3
0 20 40 60 80 100
Cluster 11
4 6 7 8 9 10 11 12 13 32 33 5 14 15 16 17 18 19 21 22 23 24 25 26 27 28 29 30 31 20 34 35 36 37 38 39 40 41 42 1 2 3
0 20 40 60 80 100
Cluster 8
4 6 7 8 9 10 11 12 13 32 33 5 14 15 16 17 18 19 21 22 23 24 25 26 27 28 29 30 31 20 34 35 36 37 38 39 40 41 42 1 2 3
0 20 40 60 80 100
Cluster 9
4 6 7 8 9 10 11 12 13 32 33 5 14 15 16 17 18 19 21 22 23 24 25 26 27 28 29 30 31 20 34 35 36 37 38 39 40 41 42 1 2 3
0 20 40 60 80 100
Cluster 10
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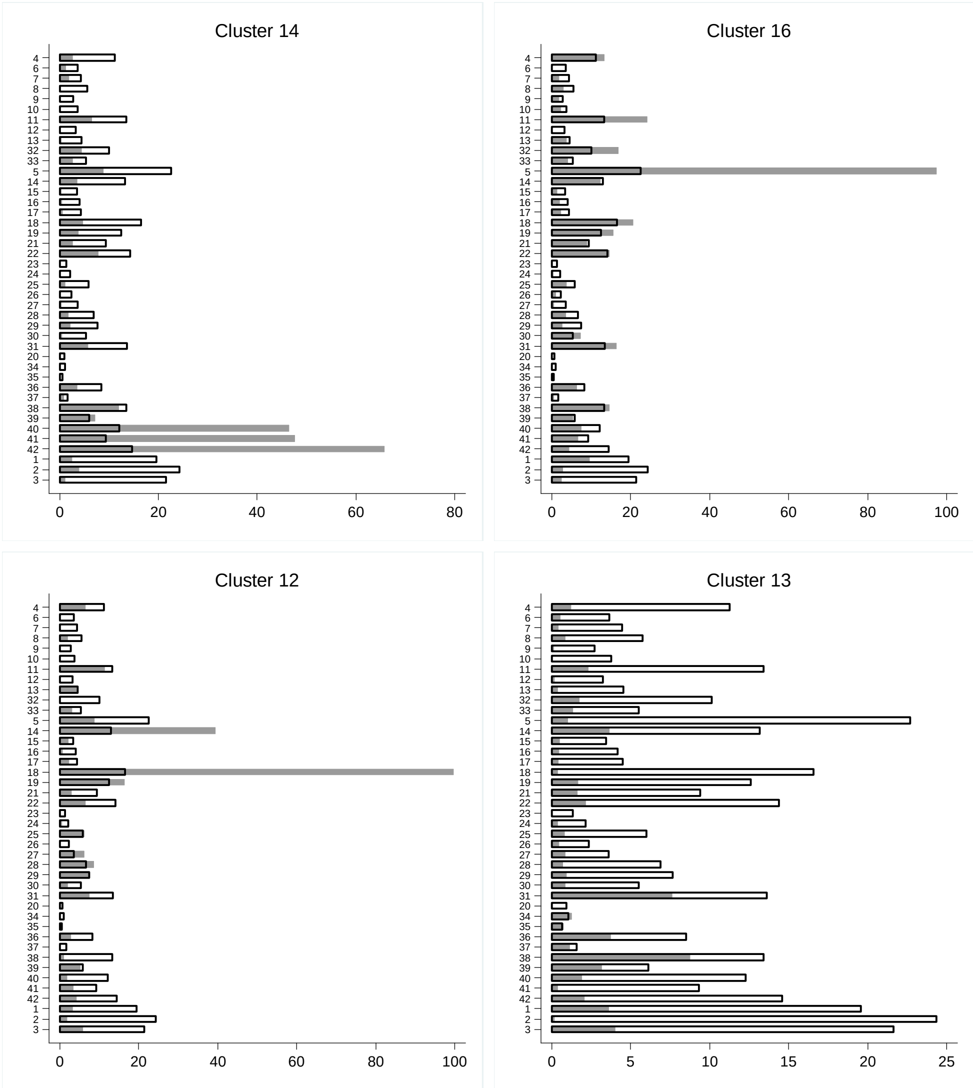
0 20 40 60 80 100


Cluster 14
0 20 40 60 80
Cluster 16
0 20 40 60 80 100
Cluster 12
0 20 40 60 80 100
Cluster 13
0 5 10 15 20 25

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