Feedback Form

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Student ID: **200818341**	Assessment Name (e.g. Essay 2, Group Project etc): Assignment #2: Administrative Data characterisation
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A Residential Classification of Bristol Urban Area using Administrative Data

INTRODUCTION

Household multivariate statistical ('geodemographic') classifications are most commonly used for business marketing, though they are increasingly used in the public sector (Singleton, 2004, p4). In the UK there are several well-established commercial classification systems: CAMEO (Callcredit, 2014), MOSAIC (Experian, 2014) and Acorn (CACI, 2014), as well as the freely available ONS (2008) 2001 Area Classifications. Most of these systems use 10-yearly census data as the core of their model. With the future of the UK census uncertain, the question of whether similar classifications can be generated based solely on administrative data is an important one. This report describes the generation and results of a simpler classification for the year 2005 (approximately mid-way between censuses) using only administrative data at Lower Super Output Area (LSOA) granularity. The classification intent is to describe residential property types, life states of typical occupants (pensioners, families, childless working adults, unemployed) and level of affluence. Geographical scope is limited to the Bristol Urban Area.

After introducing data sources used, the methodology is described in several sections (urban area definition, variable selection, data preparation, classification). A results section is followed by an analysis including comparison with existing classifications.

DATA SOURCES

In recent years, large amount of UK government administrative data have been made publicly available. For this classification, although a wide range of data was used (see table 1), much of it could be obtained from a small number of websites:

Table 1: Data sources and sets used

Source	Data Set	Description	Use
UK Data Service Census Support (EDINA, 2014) [academic access only]	English Urban Areas, 2001	Multiple unconnected polygons of "areas of urban land use of 20 hectares or more with 1,500 or more residents." (source: included metadata).	Bristol-specific polygons selected to define which LSOAs included in the classification.
	CAS Ward boundaries, 2001	Hierarchical census boundaries [also publicly available via Open Geography Portal (ONS Geography, 2014)]. Subsets selected that intersected with Bristol Urban Area.	Used only for map labelling.
	Lower Super Output Area boundaries (LSOA), 2001		Defining location of classification data.
Neighbourhood Statistics (ONS, 2014a) [public access]	Dwelling Stock by Council Tax Band, 2005	Count of households in each tax band.	Proxy for values of properties. Also gives a total household count.
	Land Use Statistics (Generalised Land Use Database), 2005	Percentage of each land type, based on Ordnance Survey (OS) MasterMap® data.	Determining land area for residential property and residential gardens.
	2001 Area Classifications (Super Output Areas).	Detailed hierarchical classification based on 2001 census data	(Using top hierarchy 'Supergroups' only for comparison with final classification).
	Indices of Deprivation 2007 Underlying Indicators	Index of Multiple Deprivation (IMD) components (based on 2005 data): Employment; Living Environment; Barriers To Housing and Services	(Used only for comparison with final classification results).
	Benefits Data: Working Age Client Group, May 2005	Quarterly benefit payment snapshot made by Department of Work and Pensions (DWP).	Proxies for unemployment or partial employment (Job Seekers Allowance, Incapacity Benefit)
NOMIS Official Labour Market Statistics (ONS, 2014b) [public access]	Income Support Claimants, May 2005	Benefit payments made by DWP for those working part-time or unavailable for work.	Proxy for poorly paid part-time employment.
	Resident Population Estimates by Broad Age Band, Mid 2005	Annual population estimates broken down by age group.	Indication of proportions of working age population, children and pensioners.

METHODOLOGY: DEFINING BRISTOL URBAN AREA

To only analyse the area defined by the Bristol Unitary Authority could give a misleading impression as a large section of the city resides in the South Gloucestershire Unitary Authority. Thus the Bristol 'Urban Area' polygons as defined by the ONS have been used. Using LSOAs as the unit of area provides a good compromise between detail and lack of clutter when mapping an area the size of a city. It also avoids (some of) the problems of smaller areas due to data rounding done to preserve anonymity. Unfortunately, LSOAs on the urban boundary are usually designed to include non-urban areas, so LSOA population density measures may not give a representation of housing density at street level in such areas.

As a working method, LSOAs were only included if they were covered by more than 20% by the 'urban area' polygons. Although the Bristol polygons just overlap the Unitary Authorities of 'North Somerset' and 'Bath and Northeast Somerset', this 20% threshold excluded LSOAs in those. The ONS 'urban area' definition includes areas of industry and commerce which must be taken into account as this aims to be a ***residential*** classification. It was considered whether these areas should be rejected by using the 'residential building' area information from the Land Use Statistics dataset. However, this risked rejecting shopping areas which often include high-rise residential blocks. The area of the (360) selected LSOAs is illustrated in figure 1.

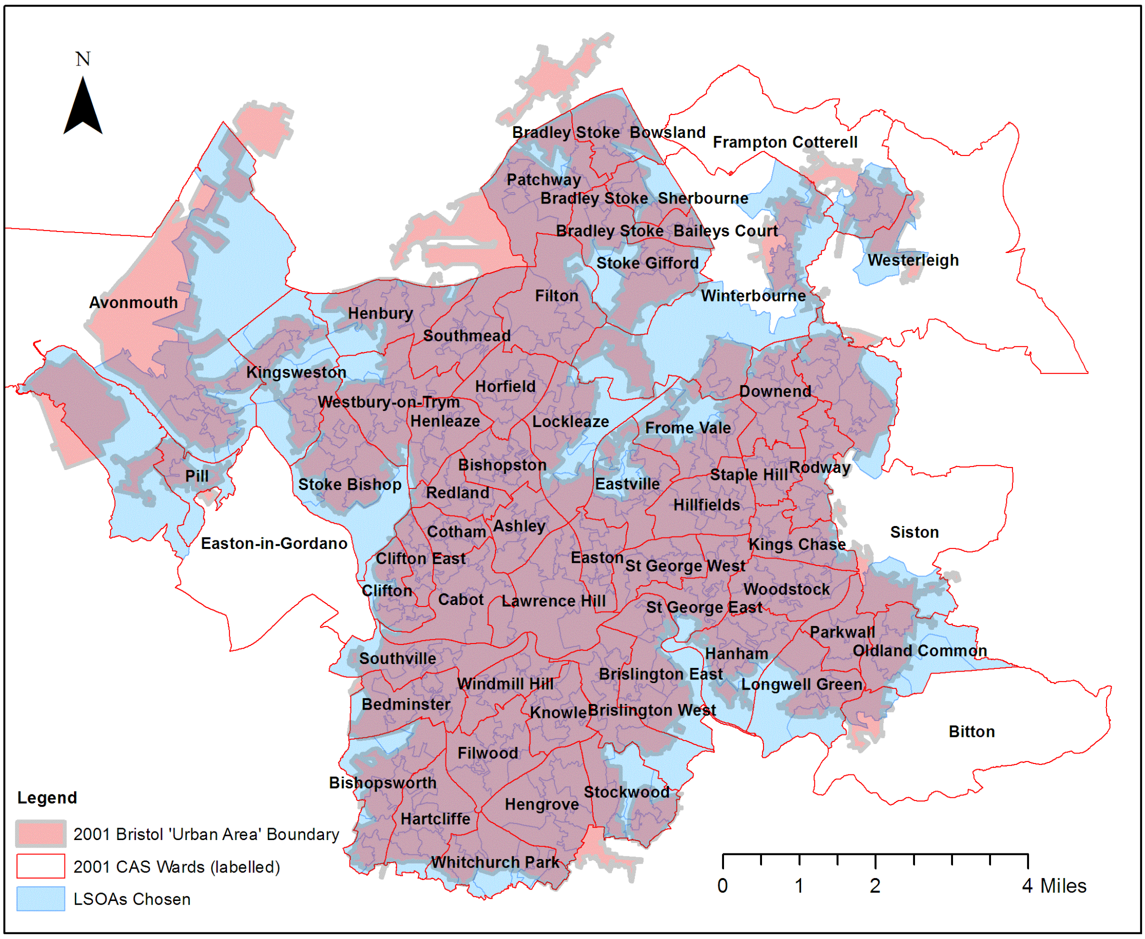

Figure 1: Bristol Urban Area (LSOAs selected)

METHODOLOGY: SELECTING COMPONENT VARIABLES

It is difficult to find (zero cost) small area demographic data other than on census and ONS websites as most administrative and survey data is only available aggregated into larger areas. However, much ONS data is unusable due to rounding to the nearest 5 to preserve anonymity. Component variables from as many relevant (and reliable) data sets as possible were selected (table 2).

Variables were examined with box plots (to explore general distribution and outliers) and Pearson Correlations (to identify potential redundancy). Including all Council Tax Band variables would introduce significant redundancy so an attempt was made to select bands/groups with low correlation between them, but which had usable distributions without extreme outliers – which can produce poor classifications (Debenham, 2002, p1). Even grouping together the three highest bands FGH still produced a problematic distribution, but it was decided to keep this as the only available strong indicator for affluence. It should be noted that most middle bands can indicate very diverse circumstances: a 'Band B' property could be a big house in a bad condition/area or a very desirably-located one bedroom flat.

Appendix 1 gives the full correlation matrix for the remaining candidate variables. '% Low Income' was consequently rejected as having too high a Pearson Correlation (0.943) with '% Incapacity'. Although '% Incapacity' and '% Job Seek' are moderately correlated, both were kept as they potentially tell different stories. Vickers et al (2005, p11) recommend that sometimes keeping apparently correlated variables can be useful in itself in providing evidence for such a relationship. Also, although '% Job Seek' is more relevant for this classification, numbers are much smaller, so including '% Incapacity' may reduce errors.

Table 2: Potential classification component variables

Component Variable	Calculation [Source]	Indicator value
Pop Density	Population[Resident Pop Est] / Area in hectares [EDINA LSOA Boundary Polygons]	Good general housing density indicator, though low values can indicate area dominance by shops, businesses, industry.
Persons per HH	Population[Resident Pop Est] / Households [Dwelling Stock]	Differentiate presence of small flats or large family homes.
% Children	Age 0-15 [Resident Pop Est] / Population[Resident Pop Est] *100	Indicates family housing.
% Pensioner	Age 65+ (Male) / 60+ (Female) [Resident Pop Est] / Population[Resident Pop Est] *100	Over the state retirement age (though may still be working).
% Job Seek	Job Seekers Allowance Claimant [Benefits Data] / Working Age Population [Resident Pop Est] *100	Unemployed, but considered economically active
% Incapacity	Incapacity Benefit Claimant [Benefits Data] / Working Age Population [Resident Pop Est] *100	Unemployed/under-employed due to illness/disability.
% Low Income	Total Claimants [Income Support Benefits] / Working Age Population [Resident Pop Est] *100	Poorly paid part-time employment
% No	Residential Building Area [Land Use] / (Residential Building Area + Domestic Garden	Area ratio of house to garden. A low value indicates large

Garden	Area [Land Use]) *100	gardens.
% Tax A	Council Tax Band A [Dwelling Stock] / Households [Dwelling Stock] *100	Lowest household values
% Tax B	Council Tax Band B [Dwelling Stock] / Households [Dwelling Stock] *100	Largest household value grouping
% Tax C	Council Tax Band C [Dwelling Stock] / Households [Dwelling Stock] *100	Less interesting, but not strongly correlated with A or B
% Tax FGH	Council Tax Bands F+G+H [Dwelling Stock] / Households [Dwelling Stock] *100	Highest household value grouping

METHODOLOGY: DATA PREPARATION

Data with non-normal skewed distribution can cause problems for classification algorithms (Vickers and Rees, 2006, p16). The 'Boxplot', 'Histogram' and 'Descriptives' functions of the SPSS software were used to examine dataset skew and for the presence of extreme outliers. Very different transformations were required to make appropriate corrections for the different data sets. Many of these had large positive skews as well as large counts of zero value data for which square/cube root transformations were more effective than log transformations.

Before classification, variables must be standardised to ensure they have equal weighting on the clustering algorithm. Due to the large number of outliers in many data sets giving distribution curves rather 'ragged' tails, a conventional 'range standardisation' method [$=(x_i - x_{min})/(x_{max} - x_{min})$] transforming the variable to a range (0..1) was more appropriate than a Z-score method (Vickers et al, 2005, p28).

However, where there are extreme outliers (see figure 2), range standardisation would result in the range of data in most cases being highly compressed. To handle such outliers, one systematic method would be to simply rank the data. However, this would risk losing information about clustering within the data. Given that the small number of extreme outlier cases could be considered on an individual basis, data was capped to values just beyond the range of the rest of the data to maintain order, whilst preventing generation of classes with few members. Table 3 summarises the outliers, capping and transforms performed.

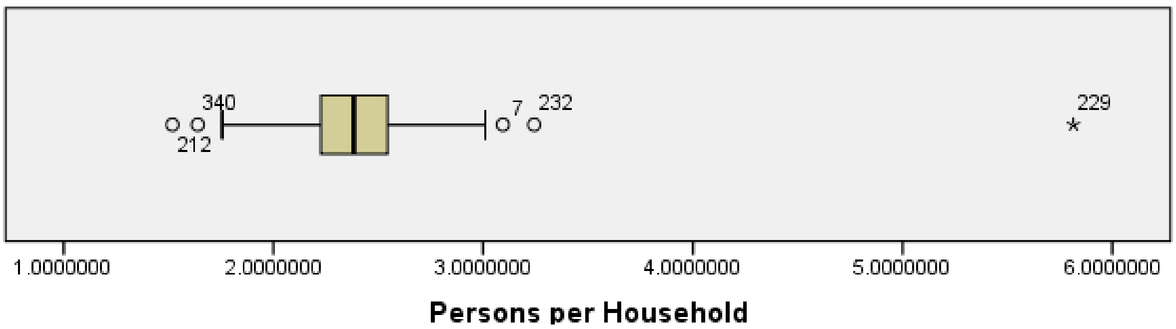

Figure 2: Extreme outlier in 'Persons per Household' component variable

Table 3: Component variable outlier capping and transforms

Component Variable	LSOA: Capped value (original value)	Cause of Extreme Outliers	Transform
Pop Density	E01014562: 150.0 (174.3)	Very densely packed Victorian terraces and 4-storey houses converted to flats.	Sqrt(x)
Persons per Household	E01014714: 3.30 (5.81)	Several large student halls of residence	(None required)
% Children	-		(None required)
% Pensioner	-		(None required)
% Job Seek	-		Log(x + 0.5)
% Incapacity	-		Log(x + 0.5)
% No Garden	E01014540: 57.0 (76.9)	Heart of city centre shopping area;	Cubrt(x)
	E01014656: 56.0 (68.7)	Light industrial area just east of city centre	
% Tax A	-		Cubrt(x)
% Tax B	-		Sqrt(x)
% Tax C	-		Sqrt(x)
% Tax FGH	-		Cubrt(x)

METHODOLOGY: PERFORMING CLASSIFICATION

Various 'clustering' algorithms exist for generating classifications (SPSS software directly implements TwoStep, Hierarchical and K-Means methods). ONS (2004) reports "Ward's Method" as being commonly used as it can build up clusters from single cases through an agglomerative approach resulting in clusters of similar size (Ward, 1963). These are often used as initial clusters for refinement by K-Means classification. Vickers et al (2005, p34) highlight two criteria for choosing numbers of classes:

1. Minimum variation in cluster size between clusters,
2. Minimum distance of each case from its cluster centre, averaged across all cases.

An initial classification was made using the hierarchical Ward's method based on squared Euclidean distance as number of classes does not need to be specified at the start (4-12 classes anticipated). On the basis of the first criterion above, Ward's method showed promise for a 6-class solution (see figure 3). Comparing K-Means classification for each of these class-counts, Ward's method was apparently poor for small numbers of classes of 4/5 (due to only being able to agglomerate already large classes), but gave apparently better results for larger class numbers.

However, by the second criterion (see figure 4), a marked step down in cluster size is seen going from the K-means 7-class to the 8-class solution, favouring the latter. It was decided that a decision on the optimum method and number of classes required looking in more detail at the usefulness of the classes produced.

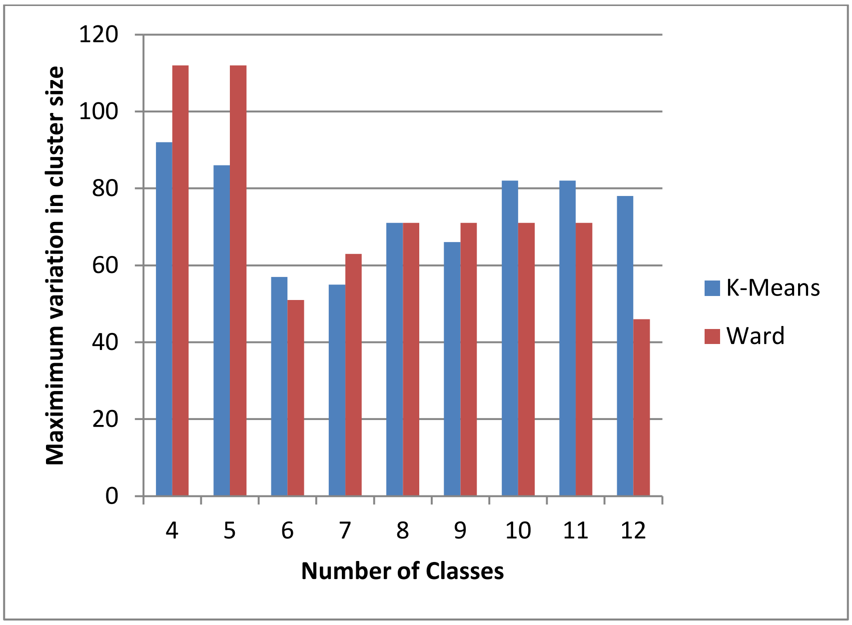

Figure 3: Comparing class count by similarity in number of members in each class

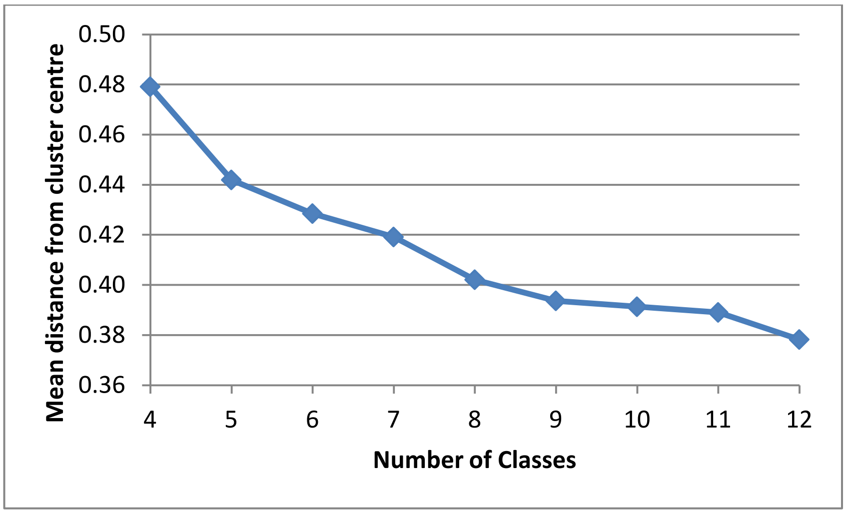

Figure 4: K-Means classification: comparing mean distance from cluster centres

RESULTS

The most useful classifications are those for which most classes have distinct characteristics (component variables which diverge markedly from the mean). From radar charts made for each candidate classification, notes were made of what made each class distinctive. For the most promising classifications (K-means), classes were mapped and compared with the author's knowledge of Bristol, allowing initial class descriptions to be checked (and refined) against the nature of the actual areas. Although (for brevity) radar charts are not shown for all candidate classifications, table 4 gives a brief assessment of each.

A 7-class version might seem more directly comparable with the 7 classes of the 2001 ONS LSOA 'Supergroups'. However, ONS Supergroups alone are sometimes not very informative - a large area of Bristol is simply classed "Miscellaneous Built Up Areas" (though of course it is possible to drill down to ONS 'Group' level).

The 9-class result was thus chosen and illustrated by radar charts (figures 5-6) and a map (figure 7). For each class component variable the mean standardized value (across all LSOAs) has been subtracted, so that distance from the middle red ring (labelled 0.0) indicates how variables vary above/below the mean. Table 5 outlines what makes each class distinct - highlighting key variables more than +/-0.1 from standardised mean. Variables are listed in order of distance from standardised mean (those more than 0.2 from mean are marked '++' or '- -').

Table 4: Comparison of K-Means classifications produced

Number of Classes	Strengths & Weaknesses of Candidate Classifications
6	Smallest variation in cluster size, but too few classes to usefully distinguish between areas.
7	Unclear differentiation between classes 1 & 2 (in terms of variable values and the associated groups of LSOAs viewed on the map). Class 3 had no strong indicator variables, though being the only class to do so it reasonably represents the 'typical' case.
8	Distinct improvement in distance from cluster centre over 7-class version. However, both classes 5 & 7 in this classification had no strong indicator variables. Also fails to include the useful "High income families" grouping seen in both 7- and 9-class versions.
9	Class 5 had no strong indicator variables, but was only class to be so. Other classes all implied descriptions that seemed plausible against knowledge of the areas mapped.

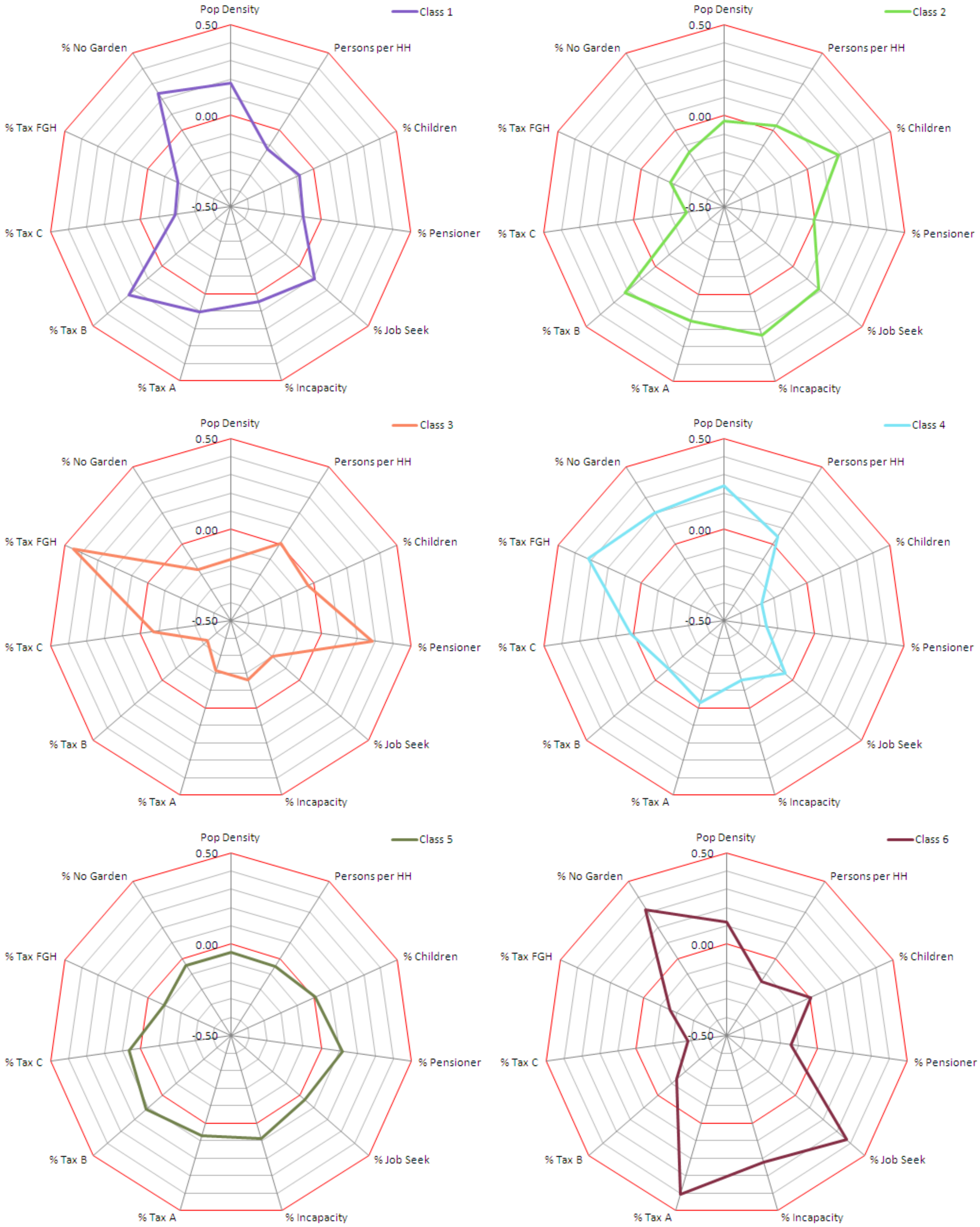

Figure 5: K-Means 9-class classification radar charts (classes 1-6)

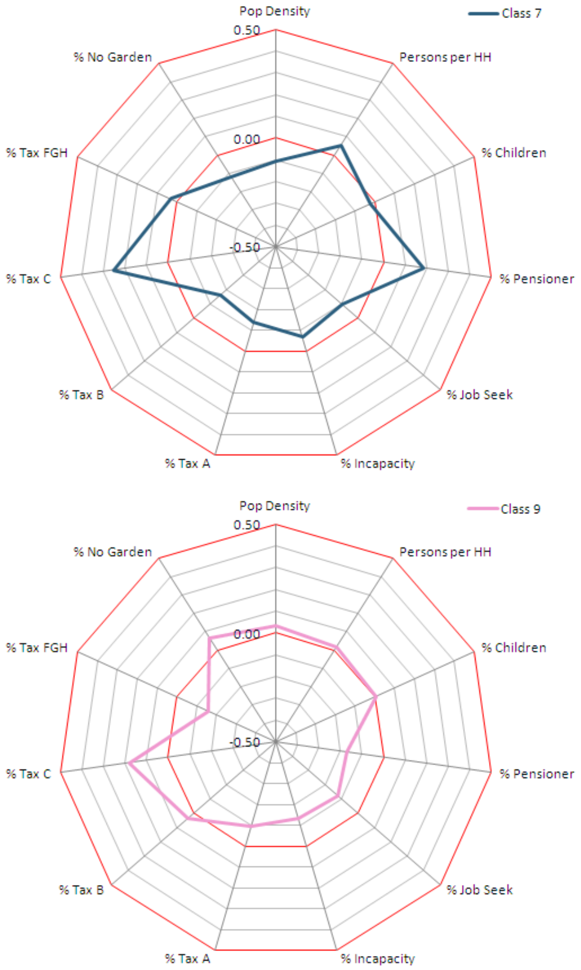

Figure 6: K-Means 9-class classification radar charts (classes 7-9)

Table 5: K-Means 9-class classification description

Class		Member Count	Variables Notably Above Mean	Variables Notably Below Mean	Description
1		24	++ Tax B ++ No Garden + Pop Density + Job Seek + Tax A	- Pensioner - Persons per HH - Tax FGH - Tax C	“Early Career Steps” Moderately priced dense housing, no gardens. Fewer families. Typically inner suburban terraces and flats close to arterial road shops.
2		49	++ Incapacity ++ Tax B + Children + Job Seek + Tax A	- No Garden - Tax FGH - - Tax C	“Unhealthy Striving Families” Health problems and lower incomes. Families in houses with gardens. Typically poorer housing estates in outer-suburbia.
3		26	++ Tax FGH ++ Pensioner	- Incapacity - Pop Density - No Garden - - Job Seek - - Tax A - - Tax B	“Affluent Older Suburbanites” Very affluent, older. Typically houses with gardens in the more desirable suburban areas and outer fringe communities.
4		34	++ Tax FGH ++ Pop Density ++ No Garden	- Tax B - Incapacity - - Pensioner - - Children	“Wealthy Independent Professionals” Affluent and child-free. Dense urban areas with no gardens. Typically desirable urban flats.
5		86	+ Tax B + Pensioner	- Tax FGH	“Established in Suburbia” Middle-aged & older, some families. Moderate income. Typically pleasant housing in the heart of suburbia.
6		20	++ Tax A ++ Job Seek ++ No Garden ++ Incapacity + Pop Density	- Tax B - Pensioner - Persons per HH - Tax FGH - - Tax C	“Struggling Inner-city” Deprivation: Poor, health problems. Few gardens. Mix of families and child-free. Typically tower blocks and small terraced houses in run-down inner suburbs.
7		48	++ Tax C + Pensioner	- Job Seek - Pop Density - No Garden - Tax A - Tax B	“Prospering Outer Suburbia” Moderately affluent, slightly older. Typically outer suburban fringes.
8		25	++ Tax FGH + Persons per HH + Children	- Pensioner - Job Seek - - Tax B - - Incapacity - - Tax A	“High Income Families” Expensive family houses. Typically desirable suburban areas and greener fringes of the larger urban area.
9		48	+ Tax C	- Job Seek - Incapacity - Tax FGH - Pensioner	“Healthy Middle Age” Moderately expensive housing. Few health problems. Mid-career. Some families. Typically houses in pleasant lower density suburban areas.

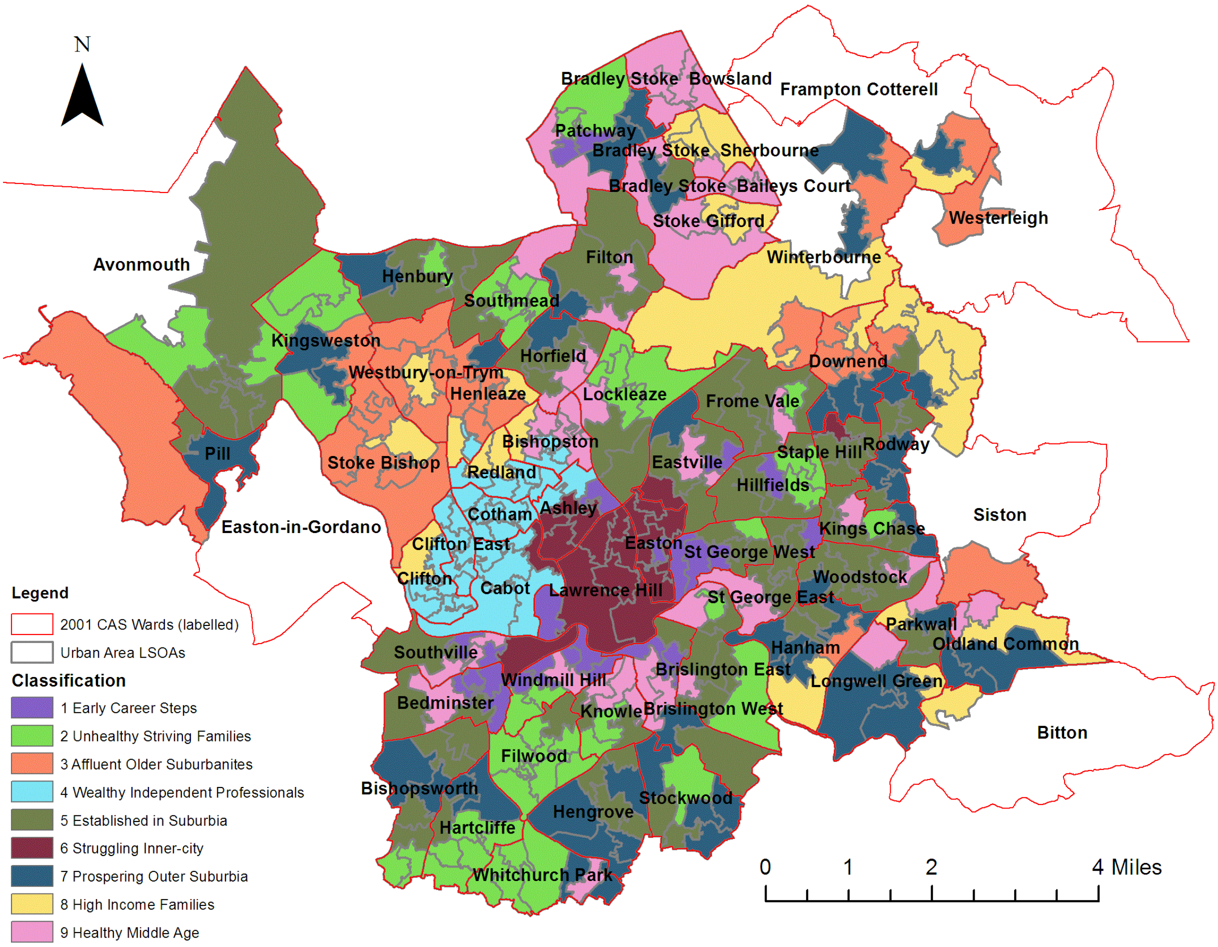

Figure 7: Bristol mapping of K-Means 9-class classification

ANALYSIS

Comparison with ONS 'Supergroups'

7-class 'Supergroup' data for the ONS 2001 LSOA census-based classification (ONS, 2008) is mapped in figure 8 (only six classes are present as the "Countryside" class is not relevant). Although based on a much broader range of component variables, many quite similar LSOA groupings are apparent – table 6 lists some of the new classes that are near-equivalents to ONS Supergroups. Note that new classes '1 Early Career Steps' and '9 Healthy Middle Age' do not map to any particular Supergroups.

Compared to census data used in the ONS classification, descriptive variables distinctly missing from the new administrative variable-based classification include ethnicity, education and occupation. Being able to isolate students in a classification would be helpful as this group has a very strong localized and seasonal impact on residential properties and neighbourhood demographics.

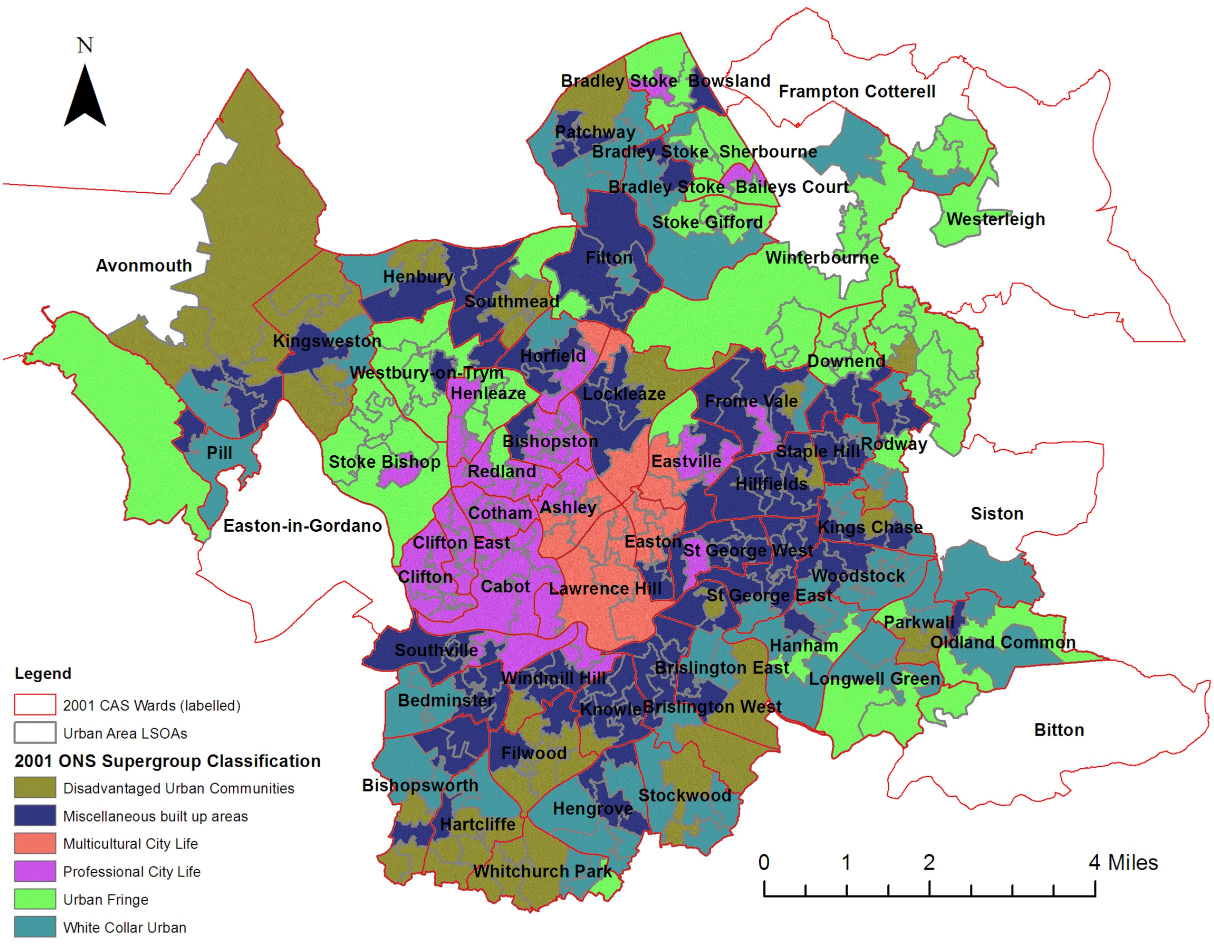

Figure 8: Bristol mapping of 2001 ONS Supergroup LSOA Classification

Table 6: Relating the new LSOA classification to ONS 2001 Supergroup classifications

ONS 2001 LSOA Supergroup class (43 variables)	New LSOA Classification (11 variables)
Disadvantaged Urban Communities	2 Unhealthy Striving Families (5 Established in Suburbia)
Miscellaneous built up areas	(5 Established in Suburbia)
Multicultural City Life	6 Struggling Inner-city
Professional City Life	4 Wealthy Independent Professionals
Urban Fringe	3 Affluent Older Suburbanites 8 High Income Families
White Collar Urban	7 Prospering Outer Suburbs

Comparison with Index of Multiple Deprivation (IMD)

The 3-yearly IMD is a composite index based on administrative data and as one of the government's preferred indicators (Norman, 2010, p5) it should be a good alternative comparison for the new classification. The following 'underlying indicators' seemed most appropriate to compare against:

- Living Environment -> Housing in Poor Condition
- Barriers to Housing and Services -> Difficulty of Access to Owner-Occupation
- Employment -> Combined Indicator

Unfortunately, closer inspection of 2007 LSOA data revealed that many of the underlying variables have the same numbers across large numbers of LSOAs and the first two indicators exhibit step changes in value on crossing the Bristol/South Gloucestershire Unitary Authority boundary. Mapping the housing indicator suggests more an indication of property age than quality, with many high value period property areas marked as low quality. However, the employment indicator is better and is mapped in figure 9. Indicated areas of highest employment deprivation largely coincide with the new '(6) Struggling Inner-city' class, with the next most deprived areas often matching the '(2) Unhealthy Striving Families' class.

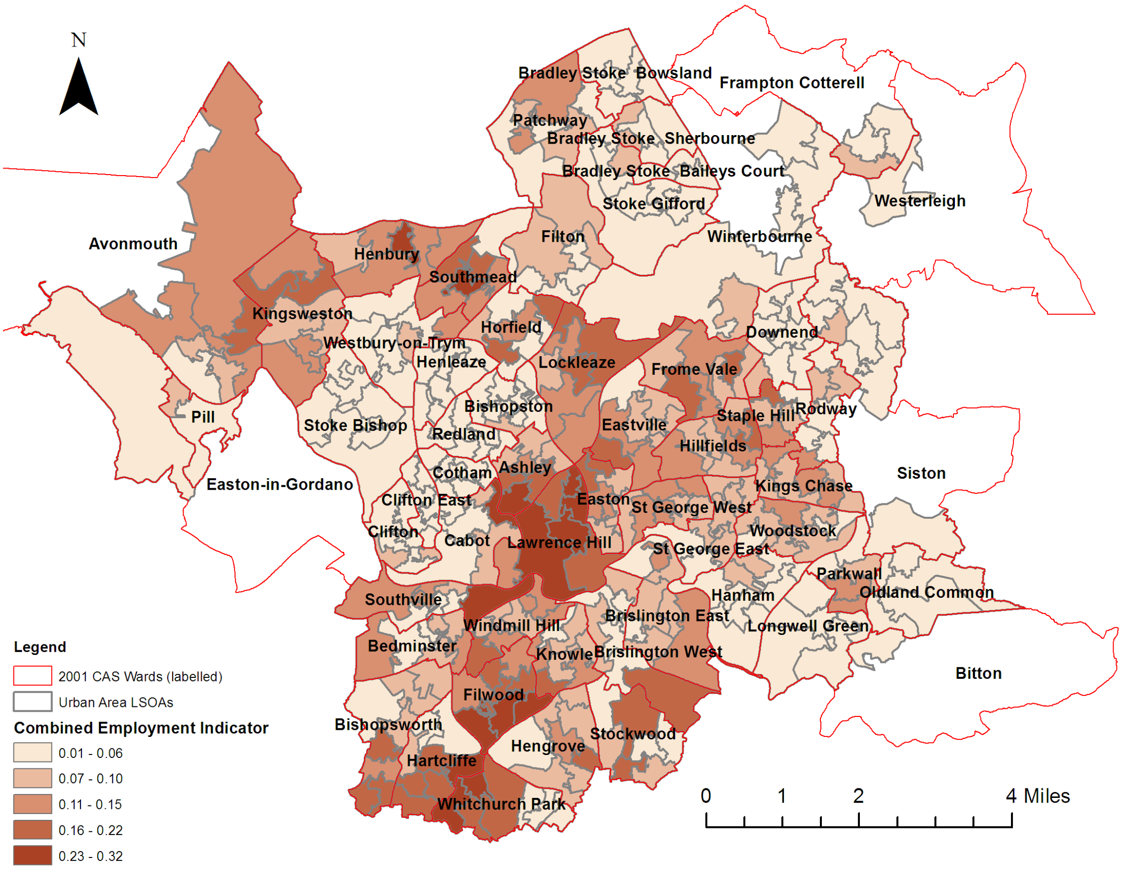

Figure 9: Bristol mapping of 2007 Index of Deprivation 'Combined Employment Indicator'

Methodology Analysis

Limiting analysis to only urban areas complicated data preparation, but helped ensure classification would not be confused by the low household/population densities of more rural or coastal areas. The far-from-normal distributions of data proved problematic; finding suitable transformations was time-consuming and always risks distorting the source data influence. However, the reasonable outcome of this classification suggests that the methodology was satisfactory, though there is scope to investigate alternative clustering algorithms (Jain, 2009) and consider classification method sensitivities

CONCLUSIONS

The ONS websites provide structured ways to access available administrative data. However, much of this data is only available for larger geographies or is rendered unreliable due to disclosure-prevention rounding. Although helpful guides to other administrative data sets exist (Jones and Elias, 2006), it can be laborious to access details of such data sets to assess their suitability. Despite the limitations of the administrative variables available, the new classification achieved reasonably similar groupings to many of the census-based ONS Supergroup classes, which is good. However, the limited range of the variables makes it more difficult to determine meaningful descriptions of these groupings. This particular classification does suffer from a high dependence on council tax banding, which associated metadata indicates is based on a 1991 valuation of property value. A more suitable classification might use a hybrid compromise of recent administrative data (where available), plus older census data; census-based component variables could also be adjusted if suitable proxy variables can be found to track them (Haynes et al, 1996).

ACKNOWLEDGEMENTS

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Appendix I: Pearson Correlations of potential classification component variables

		% Tax A	% Tax B	% Tax C	% Tax FGH	% Job Seek	% Incapacity	% Low Income	% Children	% Pensioner	Pop Density	Persons per HH	% No Garden
% Tax A	Correlation	1	-.017	-.445	-.299	.737	.706	.733	.155	-.064	.077	-.360	.366
	Sig. (2-tailed)		.744	.000	.000	.000	.000	.000	.003	.227	.147	.000	.000
% Tax B	Correlation	-.017	1	-.341	-.456	.190	.346	.323	.217	-.111	.137	-.095	-.071
	Sig. (2-tailed)	.744		.000	.000	.000	.000	.000	.000	.035	.009	.071	.178
% Tax C	Correlation	-.445	-.341	1	-.132	-.418	-.440	-.488	-.207	.133	-.104	.106	-.133
	Sig. (2-tailed)	.000	.000		.012	.000	.000	.000	.000	.012	.048	.044	.011
% Tax FGH	Correlation	-.299	-.456	-.132	1	-.306	-.385	-.341	-.230	.057	-.057	.291	-.078
	Sig. (2-tailed)	.000	.000	.012		.000	.000	.000	.000	.280	.280	.000	.140
% Job Seek	Correlation	.737	.190	-.418	-.306	1	.752	.788	.217	-.128	.166	-.278	.349
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.015	.002	.000	.000
% Incapacity	Correlation	.706	.346	-.440	-.385	.752	1	.943	.325	.117	-.078	-.309	.043
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000	.027	.138	.000	.418
% Low Income	Correlation	.733	.323	-.488	-.341	.788	.943	1	.423	-.009	-.027	-.237	.053
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.870	.611	.000	.317
% Children	Correlation	.155	.217	-.207	-.230	.217	.325	.423	1	.001	-.281	.152	-.423
	Sig. (2-tailed)	.003	.000	.000	.000	.000	.000	.000		.986	.000	.004	.000
% Pensioner	Correlation	-.064	-.111	.133	.057	-.128	.117	-.009	.001	1	-.494	-.174	-.477
	Sig. (2-tailed)	.227	.035	.012	.280	.015	.027	.870	.986		.000	.001	.000
Pop Density	Correlation	.077	.137	-.104	-.057	.166	-.078	-.027	-.281	-.494	1	.014	.496
	Sig. (2-tailed)	.147	.009	.048	.280	.002	.138	.611	.000	.000		.789	.000
Persons per HH	Correlation	-.360	-.095	.106	.291	-.278	-.309	-.237	.152	-.174	.014	1	-.241
	Sig. (2-tailed)	.000	.071	.044	.000	.000	.000	.000	.004	.001	.789		.000
% No Garden	Correlation	.366	-.071	-.133	-.078	.349	.043	.053	-.423	-.477	.496	-.241	1
	Sig. (2-tailed)	.000	.178	.011	.140	.000	.418	.317	.000	.000	.000	.000	