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Exploring the Impact of Public Services on Quality of Life Indicators

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Abstract

The fundamental aim of public services is to improve the quality of life of citizens. The main objective of this study was to investigate the influence of public service organisations (PSOs) on aspects of quality of life (very broadly defined) at a local level. In doing so we addressed three main issues: we considered the degree to which different PSOs can influence a range of aspects of the quality of life of citizens both within and outside their usual domains of influence; we examined the degree to which factors outside the control of PSOs (e.g. socio-demographic population characteristics) influence quality of life outcomes; and we investigated at which hierarchical level in the public sector service area there appears to be most scope to influence quality of life of citizens. We assembled a database of quality of life measures proposed by the Audit Commission covering areas such as safety, housing, health, education, and transport, measured at "small area" level. We added data on indicators of deprivation (to measure "needs" of the local population) and on the performance of PSOs. We used a range of advanced statistical methods to analyse the relationships between PSOs and quality of life measures at different hierarchical levels. Our findings illustrate the level at which variation in quality of life indicators is most apparent. It suggests that where those variations are large, there may be scope to influence outcomes at that level to a greater extent than where the variations are small. PSOs at higher levels may therefore have an important role in influencing quality of life. However, the large variation found in many quality of life indicators at small area level is also important. Whilst there are no PSOs with responsibility for quality of life at this level, it indicates the importance of policies that operate at neighbourhood and community level.

Background

The fundamental aim of public services is to improve the quality of life of citizens. The success of public service organisations (PSOs) is often judged in terms of the degree to which they are able to improve aspects of the quality of life of citizens in their jurisdiction. The main objective of this study was to investigate the influence of PSOs on aspects of quality of life (very broadly defined) at a local level.

Little is known about the degree to which PSOs can influence specific local quality of life measures, especially those outside their main domain of influence. For instance, how much variation in health outcomes is under the influence of local authorities responsible for education, housing and community safety, compared with the health service? To what extent are the actions of different authorities coterminous in improving health outcomes? Indeed, is there a correlation across different quality of life measures or does achievement on one measure come at the expense of attainment on another? How much of this variation is attributable to socio-economic circumstances of the population rather than to the actions of PSOs? And finally, at what level in the organisational hierarchy can most of the variation in quality of life measures be explained – for instance, in the case of health outcomes, is it at the level of Primary Care Trust or at the higher level of the Strategic Health Authority? This project sets out to examine some of these questions empirically and hence offer policymakers useful information on the role of organisations operating within a hierarchical structure and within a system where attribution of performance may be multi-faceted.

We first undertook a literature review tailored to the main themes of our project. The review focused on three main areas relevant to our analysis: quality of life; social capital; and the policy context. The full review is available in a comprehensive report from the Centre for Health Economics, as well as the Public Services Programme website: http://www.york.ac.uk/inst/che/publications/publicationsbyyear.htm (RP 46) or http://www.publicservices.ac.uk/category/library/papers/.

A definition for quality of life is as follows:

> *"Quality of life requires that people's basic and social needs are met and that they have the autonomy to choose to enjoy life, to flourish and to participate as citizens in a society with high levels of civic integration, social connectivity, trust and other integrative norms including at least fairness and equity, all within a physically and socially sustainable global environment"* (Phillips, 2006, page 242).

First, we noted that quality of life can be interpreted very broadly at both the individual and the community level and we explored the way in which it is linked to concepts of happiness and subjective well-being. In exploring the determinants of happiness or well-being it was clear that many aspects of the broader social and environmental context in which people live, are key factors in their well-being.

Second, we considered the concept of social capital which broadly concerns *"networks together with shared norms, values and understandings that facilitate co-operation within or among groups"* (OECD, 2001). Social capital highlights the importance of many aspects of the social associations that people encounter in their everyday life that may contribute to their well-being and quality of life. Public policy has a current emphasis on the role of social capital and the responsibility of organisations and agencies to work together to address the needs of local communities in terms of creating the conditions that enhance social capital.

Third, we considered the policy agenda which has placed a heavy emphasis on the responsibility of PSOs, working together, for the well-being of citizens, especially focusing on the community and neighbourhood level where social capital may have a major role to play. Over the last decade there has been increasing emphasis on the need for partnerships between organisations and for policy to be developed and implemented across traditional sector boundaries. In particular, local authorities have been charged with promoting the well-being of their area and this explicitly entails working with other agencies - even where boundaries are not coterminous - in order to develop sustainable community strategies that address the full range of quality of life issues. The increasing emphasis on notions of "community" and "neighbourhood" as levels at which well-being, community cohesion and social capital are fostered, implies that is useful to look beyond the usual regional, local authority or health area level to smaller geographical areas (Robinson, 2005; Green and Pinto, 2005).

The main contribution of this study was to undertake a series of quantitative analyses of quality of life data in England, collected at small area level, as explained in the next section. A number of themes emerged from the literature review which helped inform the analysis:

- The quality of life indicators we included in our analysis attempt to reflect broad aspects of the quality of life of citizens.
- The models we used were structured to capture the degree to which PSOs may influence aspects of quality of life outside their main domain of influence.
- The analysis included consideration of the level at which influence on quality of life and well-being of citizens may occur. In particular it goes beyond the traditional organisational boundaries to consider the importance of lower levels which may more closely reflect communities or neighbourhoods.

Objectives

The objectives of the study were to develop statistical models to explain the link between PSOs and quality of life indicators in order to:

1) examine the degree of variation in quality of life indicators associated with different PSOs;
2) explore the extent to which factors beyond the control of PSOs influence the quality of life of citizens;
3) explore the correlation in quality of life indicators across PSOs; and
4) examine the level in the organisational hierarchy which exerts the most influence on quality of life measures.

Data

In order to address the above research questions, we created an extensive dataset based on: quality of life indicators, measures of deprivation, and additional performance indicators of PSOs. The database had a hierarchical structure enabling us to explore the levels at which variation in quality of life indicators occurs.

Quality of life indicators

It was beyond the remit and capacity of this study to develop our own indicators of quality of life. Instead, we assembled a dataset based on indicators developed by the Audit Commission, Department for Environment, Food and Rural Affairs and the Office of the Deputy Prime Minister and published at Local Authority level to "paint a picture" of the quality of life in a local area (Audit Commission, 2005a; 2005b). Whilst we recognise the indicators are not perfect, they were developed with the aim of offering operational measures that capture diverse elements of quality of life and therefore are appropriate for our study.

The Audit Commission suggested 45 quality of life measures covering ten themes, such as health and social well-being, transport and access, community safety, housing, and education and life-long learning.

For each theme, we looked for quality of life indicators similar to those published by the Audit Commission, but defined at small area level (the most disaggregated level possible) rather than Local Authority level. This produced 20 quality of life indicators, with their descriptive statistics given in Table 1.

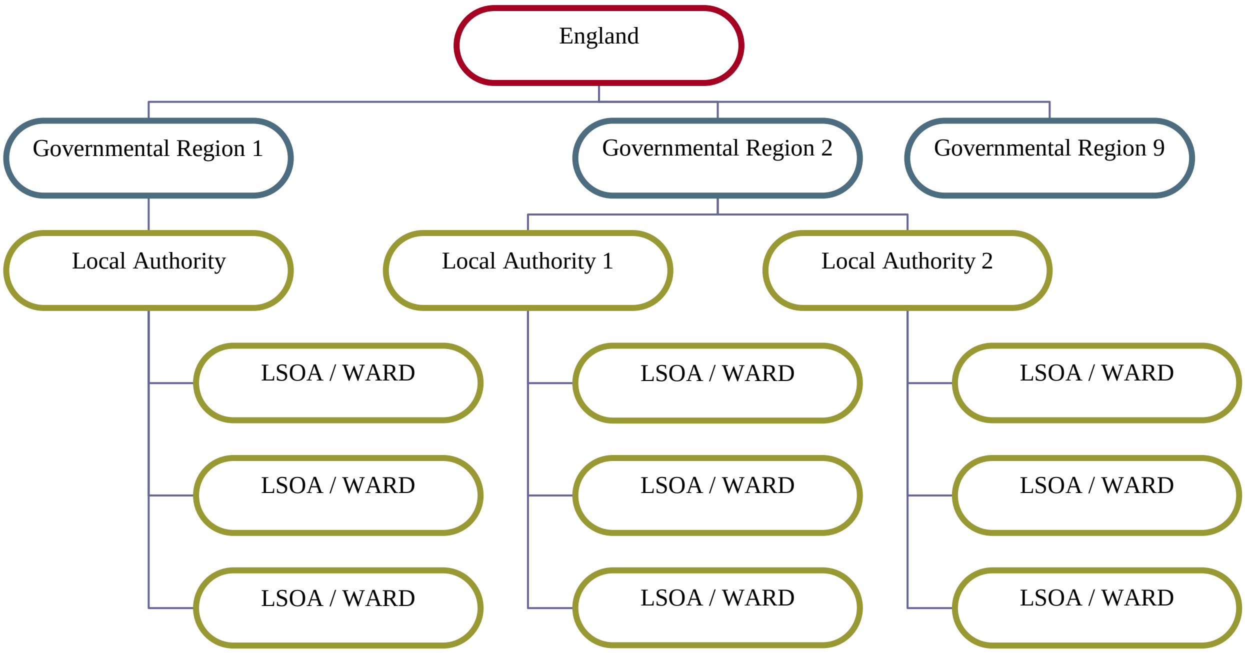
Data sources included: 2001 Census, Index of Multiple Deprivation (IMD), British Local Elections Database, Neighbourhood Statistics and the Public Health Observatory. Seventeen of our quality of life measures are defined at lower super output area (LSOA) and three at ward level, either electoral ward or 2001 Census Standard table ward.

LSOAs have been developed by the Office for National Statistics, have an average population of 1,500 and are created by "taking into account measures of population size, mutual proximity and social homogeneity" (ONS, 2008). There are 32,482 LSOAs in England.

Electoral wards are the spatial units used to elect local government and there are 8797 electoral wards in England. 2001 Census Standard table wards are a subset of statistical wards and there are 7932 standard wards in England.

Small areas (both LSOAs and wards) are nested into 150 Local Authorities, which are in turn nested into nine Governmental Regions, as shown in Figure 1. In the health sector, small areas are nested within 304 Primary Care Trusts (PCTs), which in turn are nested within 28 Strategic Health Authorities (SHAs).

Figure 1: Hierarchy of database and nesting



Socio-economic factors

In order to take account of the broad range of socio-economic factors which may impact on the ability of PSOs to influence the quality of life of citizens we used the Index of Multiple Deprivation (ODPM, 2004). The overall IMD is a weighted area level aggregation of seven underlying domain indices of multiple deprivation. The

IMD is measured at LSOA level and we used both the overall index and individual domain indices.

Other data

In order to capture organisational influences on quality of life, we added data on the performance of LAs and PCTs as assessed by national regulators. Data for LAs used in the Comprehensive Performance Assessment (CPA) and for PCTs used in their annual assessment include an overall composite performance score (star rating), and an underlying measure of financial management / use of resources which goes into the composite score. As indicators of resource availability we used Council Tax (Band D) tax rates for Local Authority areas and distance from target for PCTs. Both these metrics offer indications of the extent to which the local organisation’s spending varied from national assessments of budgetary needs.

Table 1: Descriptive statistics for 20 quality of life variables in 8 domains

Variable name	Variable label	level	mean	median	N	min	max	sd	variance	skewness	kurtosis	coeff. variation
Community cohesion												
turnout	Election turnout	ward*	33.4188	32	29152	10.4900	76.4100	9.3093	86.6636	0.6764	3.2855	0.2786
Community safety												
imd_score_crime	IMD score on crime	lsoa	0.0000	0.0000	32482	-3.4600	3.1300	0.8387	0.7034	0.0328	2.7158	-
Economic well-being												
imd_score_kids	Children IMD score	lsoa	0.1992	0.1429	32482	0.0032	0.9931	0.1695	0.0287	1.1725	3.9235	-
imd_score_elderly	Older people IMD score	lsoa	0.1614	0.1344	32482	0.0084	0.9209	0.1064	0.0113	1.3437	5.3625	-
wa_tot_ben	All people of working age claiming a key benefit: percentage	lsoa	14.3793	12.000	32482	0.0000	68.0000	9.1784	84.2439	1.2926	4.6495	0.6383
wa_jsa	All people of working age claiming job seekers allowance: percentage	lsoa	2.1817	2.000	32482	0.0000	19.0000	1.7932	3.2156	1.9540	8.6842	0.8219
Education												
sec_school_absence	Secondary school absence indicator: rate	lsoa	8.1035	8.0000	32262	2.0000	20.0000	1.8562	3.4453	0.7485	4.9240	0.2291
ks4_mean_points_score	Nat. curri assessments: average points score Key Stage 4 indicator	lsoa	34.5914	34.9600	32415	0.0000	64.0000	7.5501	57.0039	-0.1964	2.8782	0.2183
Environment												
combi_air_qual_ind	Combined air quality indicator: 26/10/2007	lsoa	1.1634	1.1500	32482	0.4000	2.3500	0.2911	0.0847	0.1694	2.9988	0.2502
area_green	Area of green space per head: m2(thsnds)	lsoa	2.2824	0.1018	32480	0.0000	402.9088	8.1526	66.4651	11.5308	302.6789	3.5720
Health												
le_all	Life expectancy at birth (years): all people	ward*	78.4785	78.6000	32477	65.4000	93.4000	2.5636	6.5719	-0.0871	3.3034	0.0327
concept_teen	Conceptions teenagers: 2002 and 2004 figures combined	ward*	27.7464	21.0000	27416	5.0000	168.0000	22.3346	498.8333	1.7077	6.7827	0.8050
smr_lsoa_01	Standardised mortality ratio at lsoa level: 2001	lsoa	1.1217	1.0499	32482	0.0000	7.4606	0.4736	0.2243	1.6194	11.0776	0.4222
pphhlds_limlong_ill	Percentage of households with 1 or more limiting longstanding illnesses	lsoa	33.4493	32.9100	32482	5.6400	70.4400	8.3675	70.0150	0.2553	3.0184	0.2502
Housing												
perc_rough	Percentage of people living rough	lsoa	0.0016	0.0000	32482	0.0000	1.4867	0.0278	0.0008	28.5482	1144.4580	17.0029
phhlds_noheating	Percentage of all occupied households without central heating	lsoa	8.4209	5.9968	32482	0.0000	82.6498	8.1894	67.0657	2.4683	11.4508	0.9725
Transport												
perc_commute_wrk	Percentage of population travelling over 20km to work	lsoa	5.7258	4.6512	32482	0.1886	44.1308	3.9106	15.2927	1.2235	4.8627	0.6830
perc_privtrans_wrk	Percentage of population travelling to work by private vehicle	lsoa	25.6133	26.3574	32482	2.2551	54.5161	8.8557	78.4234	-0.2053	2.4753	0.3457
perc_pubtrans_wrk	Percentage of population travelling to work by public transport	lsoa	6.8371	4.7850	32482	0.0000	54.7890	6.5118	42.4037	2.2076	8.7670	0.9524
perc_footbike_wrk	Percentage of population travelling to work by bike or on foot	lsoa	5.8431	4.9225	32482	0.1924	66.0511	3.6854	13.5820	2.3425	14.1693	0.6307

* Election turnout and teenage conception data are available at electoral ward, whereas life expectancy is available at 2001 Census Standard table ward

Data linkage

Our intention was to model all variables as close as possible to the study base year 2001. In some cases an exact match was not feasible. As variables became available at small area level through the course of the project, we added these to our database. At the outset, we spent considerable time constructing an education database at school level. However, in the course of the study, indicators of educational attainment were made available at LSOA level. We abandoned the school database in favour of the smaller area level data as we believed this was more aligned with the objectives of our study. The biggest data constraint was in the area of crime, where the only data available at small area level related to the IMD Crime domain. No other crime data of adequate quality was made available during the course of the project, despite extensive searches.

The creation of the linked dataset was a major undertaking. Substantial effort went into tracking down, linking, collating and cleaning the data and ensuring the correct geographical and contractual boundaries of the PSOs. We did thorough quality checks on the data to ensure its robustness and consistency.

Methods

We first undertook exploratory data analysis. The bivariate correlations between different quality of life indicators and performance indicators were examined. We used factor analysis to draw out the key dimensions in the quality of life indicators. We used Analysis of Variance (ANOVA) to examine the variation in the quality of life indicators. All these methods gave us an important descriptive view of the dataset.

We then used three further statistical methods to address the study's research objectives: (a) multilevel (or hierarchical) models (ML); (b) models of multiple outcomes or seemingly unrelated regression (SUR) models, and (c) an integration of both these approaches, namely the multivariate multilevel model (MVML model).

a) ML models are variations on the familiar regression-based theme. However, the error term is decomposed into parts attributable to each level of the hierarchy. The analysis of the residual variances in ML models provides information on the extent of variability in quality of life measures at different hierarchical levels. ML models offer useful information on relative performance of organisations operating within a hierarchy when a single quality of life indicator is under scrutiny.

b) When important relationships exist between individual quality of life measures, these will be lost if piecemeal univariate regression models are developed. In many circumstances individual regression models, or more precisely the error terms from each regression, will be linked. SUR models seek to model explicitly the covariance between indicators and allow one to explore the correlation across quality of life indicators.

c) The multivariate multilevel model (MVML model) is a SUR model in a ML context. By considering the quality of life indicators as the lowest tier in the data hierarchy, the possibility of within-small area and within-higher organisational level correlation among indicators can be assessed. Thus the MVML model is conceptualised as a multilevel model, in which, say quality of life indicators (level 1) are clustered within small areas (level 2), which are themselves clustered within higher organisational levels (level 3), say Strategic Health Authorities (SHAs). The correlation between the various quality of life indicators can then be explored.

In our models we included deprivation measures (the IMD overall index and the domain indices) to capture the role of exogenous factors (beyond the immediate managerial control of PSOs) on quality of life. There is some overlap between the deprivation indices and quality of life indicators, so we set up our models to exclude any potential for endogeneity bias. We also included performance indicators at the PSO level as control variables to pick up organisational effects.

We ran the ML models for all 20 quality of life variables, using 4 overall models with different combinations of hierarchical structures, with a number of specifications for each. For example, in addition to the basic model with just the levels, we control for only 1 need variable (the overall IMD score) = variant A, then the domain specific

IMD scores = variant B, then the domain specific IMD scores plus performance indicators (where applicable) = variant C, and then the performance indicators only with the basic model = variant D. Models 1 to 3 are a 2-tier structure with the top hierarchical level (Governmental Regions) included as nine dummy variables with the reference dummy being the region London. Regions were included as dummy variables rather than as an additional tier in the ML models because there were so few regions relative to the lower levels.

For the basic model alone, we therefore ran 20 x 4 models, for variant A another 80 models, for variant B another 80 models, and so on. These specifications are summarised in Table 2.

Table 2: Summary of all ML models for 20 quality of life variables

<table>
<tr><th></th><th></th><th>Basic model</th><th>A:
1 Need variable</th><th>B:
7 Domain specific need variables</th><th>C & D:
Performance indicators</th></tr>
<tr><td rowspan="3">2-tier structure</td><td>Model 1</td><td>LA
LSOA / Ward</td><td rowspan="4">Overall IMD score</td><td rowspan="4">• Income deprivation,
• Employment deprivation,
• Health deprivation and disability,
• Education, skills and training deprivation,
• Barriers to housing and services,
• Living environment deprivation,
• Crime</td><td>• LA - star rating
• LA - use of resources
• LA - Band D council tax</td></tr>
<tr><td>Model 2</td><td>SHA
LSOA / Ward</td><td>• No indicators</td></tr>
<tr><td>Model 3</td><td>PCT
LSOA / Ward</td><td rowspan="2">• PCT - star rating
• PCT - financial management
• PCT - distance from target</td></tr>
<tr><td>3-tier structure</td><td>Model 4</td><td>SHA
PCT
LSOA / Ward</td></tr>
</table>

Given the size and complexity of the datasets, running some of the more computationally complex models presented a considerable challenge. Since we have over 32000 LSOAs, the MVML could not run with all 17 quality of life variables at LSOA level simultaneously. The model ran for nearly five days on one of the University's most powerful computers and did not reach complete iterations. We therefore took subsamples of the quality of life variables to estimate our models. This challenge did not however prevent us from investigating the main questions posed in our project.

Results

We can show only a small subset of our results here. A full set of results is published in the comprehensive report available on the CHE and PSP website.

Our descriptive analyses (bivariate correlations, factor analysis and ANOVA) suggested overall some significant correlations between some of the quality of life variables. As expected, variables measuring various domains of income deprivation were highly correlated. Similarly variables picking up measures of environmental deprivation were highly correlated. However, these naïve correlations are not especially helpful in drawing policy inferences. The SUR model results (not shown here) showed a significant Breusch-Pagan result which suggests, as expected, that the quality of life indicators are correlated, and therefore that we should ideally look at these measures in a joint modelling approach such as MVML, as envisaged in the study objectives.

The coefficient estimates on the performance indicators and needs variables are too numerous to discuss here, but in short, had the expected signs, though negligible influence. The regional dummy variables all moved in a consistent direction, as expected, although London was sometimes an exception.

We report here mainly the ML results for Model 4C: the 3-tier model with LSOAs and wards nested within PCTs, nested within SHAs, where we control for domain specific need variables and PCT performance.

Table 3 shows the estimates of the residual variance for all 20 quality of life variables. They are all significant at the 5 percent level, except for secondary school absence rate (sec_school_absence) and percentage of people living rough (perc_rough). The total level of variance explained by each of the quality of life models also differs. This is shown in column four where we see that the majority of quality of life indicators show comparable coefficients of variation (a measure which allows us to compare the total residual variance across different quality of life indicator models). An exception is the percentage of people living rough (perc_rough) and to a lesser extent the area of green space per head (area_green) which have high levels of total variance, compared to life expectancy (le_all) which has a very small total variance.

Table 3: Three-level random-intercept model of the proportion of variance in quality of life indicators attributable to SHAs, PCTs and small areas (Model 4C controlling for domain specific need variables and PCT performance indicators)

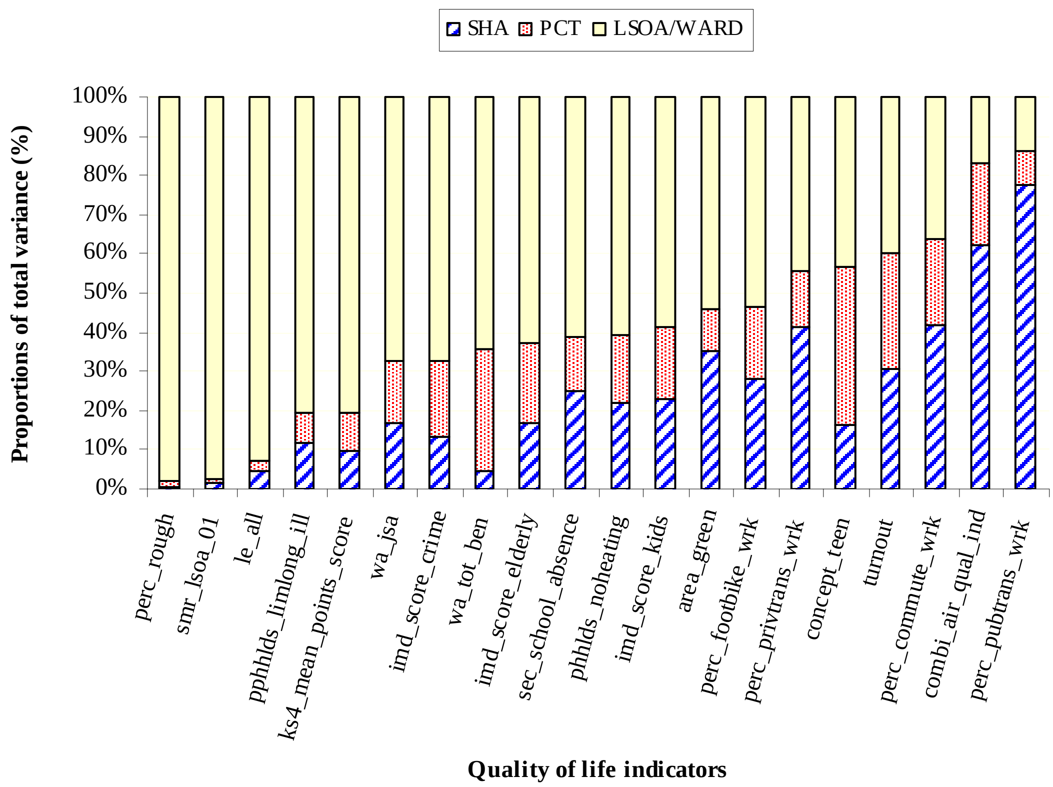
Quality of life indicators	ρ_v	ρ_u	ρ_e	Coefficient of variation
imd_score_crime	0.1595	0.1841	0.6564	-
imd_score_kids	0.3224	0.1013	0.5763	-
imd_score_elderly	0.1597	0.2079	0.6324	-
wa_tot_ben	0.1608	0.1905	0.6487	0.2811
wa_jsa	0.1611	0.1292	0.7097	0.5450
sec_school_absence	0.0647	0.3160	0.6193	0.2083
ks4_mean_points_score	0.1607	0.0742	0.7651	0.1629
combi_air_qual_ind	0.6358	0.1799	0.1843	0.2274
area_green	0.2361	0.1915	0.5724	3.1573
smr_lsoa_01	0.0106	0.0108	0.9786	0.3910
pphhlds_limlong_ill	0.0725	0.0879	0.8396	0.1519
perc_rough	0.0031	0.0016	0.9953	18.7308
phhlds_noheating	0.1713	0.2408	0.5878	0.7848
perc_commute_wrk	0.3964	0.2086	0.3950	0.6066
perc_privtrans_wrk	0.3122	0.1548	0.5330	0.2168
perc_pubtrans_wrk	0.7356	0.0897	0.1748	0.8437
perc_footbike_wrk	0.2973	0.1697	0.5330	0.6465
turnout	0.0000	0.5330	0.4670	0.2726
le_all	0.0398	0.0190	0.9411	0.0252
concept_teen	0.2934	0.2204	0.4862	0.5366

ρ_v, proportion of variance attributable to strategic health authorities; ρ_u, proportion of variance attributable to primary care trust s and ρ_e, proportion of variance attributable to small areas. The coefficient of variation can only be calculated for data on a ratio scale and not an interval scale such as the IMD indicators.

We plot these estimates of the proportion of variance (called the intra-class correlation coefficient) at each level to show graphically (in Figure 2) at which level in the hierarchy the most variance can be explained. We see that the majority of the variation is at the small area level although a significant proportion of the variance is also attributable to the two higher level organisations. For the health variables - life expectancy (le_all), standardised mortality ratio (smr_lsoa_01), and households with limiting long-standing illnesses (phhlds_limlong_ill) - 98%, 94%, and 84% of the variation (respectively) is at small area level, whereas for teenage conceptions (concept_teen) it is only 49%. This suggests that PCTs and SHAs may be able to exert more influence over the latter variable than the former.

Also, the results suggest that much of the variation at small area level for variables such as percentage of people living rough (perc_rough) may be very localised and area specific; whereas for variables such as air quality (combi_air_qual_ind), election turnout (turnout) and transport (perc_commute_wrk; perc_pubtrans_wrk), the majority of the variation is attributable to the higher levels suggesting that PSOs at these levels may have a greater role to play in influencing outcomes on such variables.

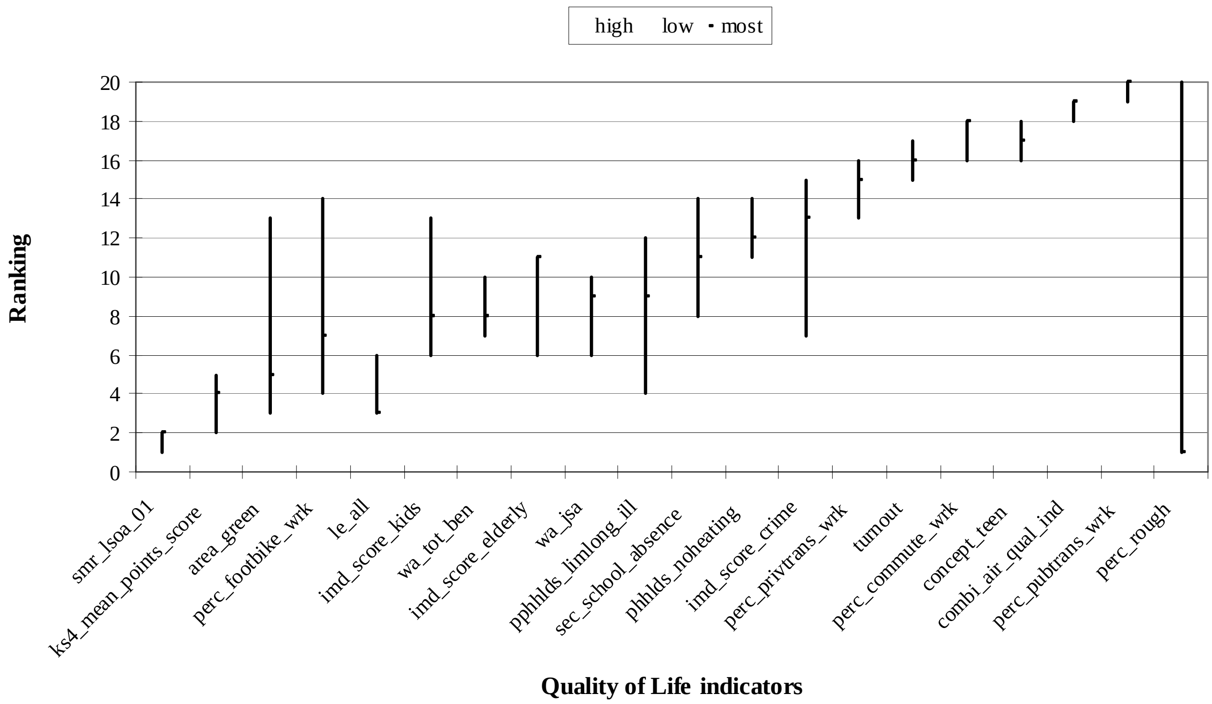
Figure 2: The proportion of variance in quality of life indicators attributable to SHAs, PCTs and small areas (intra-class correlation coefficients) (Model 4C controlling for domain specific need variables and PCT performance indicators)



As a summary measure of the stability of the quality of life indicators within the various permutations of Model 4, we show the ranking of the indicators in terms of the proportion of variation explained at the higher PSO levels, ranking the indicators from left to right: those with the least variation explained at higher levels to those with the most variation explained at higher levels (Figure 3). The bars around each point estimate show how far their rankings change in the different permutations of Model 4 when adjusting for different needs variables and performance indicators.

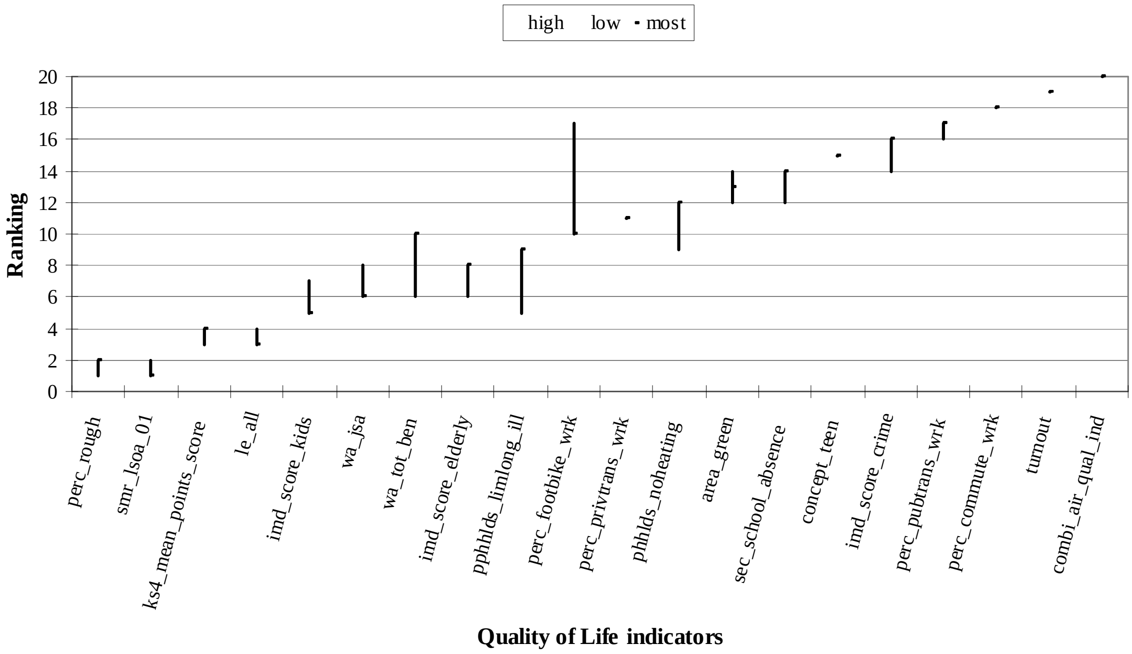
This suggests that there is some stability in the rankings of the quality of life variables with respect to the proportion of variation explained at higher levels since the bars are for the most part quite short. However the indicator percentage of people living rough (perc_rough) shows the greatest change in ranking depending on which needs variables and performance indicators are added to the model. This is not surprising given that this variable had the highest overall level of variance. Other variables with a higher coefficient of variation such as area of green space per head (area_green) also tend to show greater variability in rankings.

Figure 3: Changes in rankings of the proportion of variation attributable to higher levels (SHAs, PCTs) in quality of life indicators (across all variants of Model 4)



Moving away from Model 4, we show the same ranking results for Model 1 (Figure 4). This considers the local government context (with LSOAs or wards nested within Local Authorities and Governmental Regions introduced as dummy variables) and the overall trend across the five permutations also suggests that the greatest variation in most quality of life measures is at the small area level, although for the variables measuring air quality (combi_air_qual_ind) and election turnout (turnout), the greatest variation is at Local Authority area level. There is clearly much greater stability in rankings in this model since the bars are much shorter. (The stability in rankings is found in Models 2 and 3 too.)

Figure 4: Changes in rankings of the proportion of variation attributable to higher levels (LAs) in quality of life indicators (across all variants of Model 1)



When we summarise these results across all 4 models we tend to find that the same variables congregate to the left and right of the spectrum in terms of the proportion of variation attributable to higher levels. Variables further to the right of the spectrum may be more amenable to intervention from higher level PSOs than variables clustered to the left. We summarise in Table 5 the six quality of life indicators which tend to consistently fall to the left and right of the rankings across all four models. Those marked with a tick are in the top or bottom six rankings consistently. Indicators which tended to show greater variability in rankings have been marked with an asterisk.

This suggests that indicators which tend to have a large variation at small area level include the standardised mortality ratio (smr_lsoa_01), educational attainment (ks4_mean_points_score) and the percentage of individuals living rough (perc_rough). Whereas for variables such as air quality (combi_air_qual_ind), election turnout (turnout) and transport (perc_commute_wrk; perc_pubtrans_wrk), the majority of the variation is attributable to higher level PSOs, suggesting they may have a greater role to play in influencing outcomes on these variables.

Table 5: Summary of variability in rankings across models and proportion of variation explained

	Model 1	Model 2	Model 3	Model 4
Most variation at small area level				
smr_lsoa_01	✓	✓	✓	✓
ks4_mean_points_score	✓	✓	✓	✓
perc_rough	✓	✓	✓	✓ *
imd_score_kids	✓	✓	✓	✓ *
le_all	✓	× *	✓	✓
area_green	×	✓	✓ *	✓ *
Most variation at PSO level				
perc_pubtrans_wrk	✓	✓	✓	✓
perc_commute_wrk	✓	✓	✓	✓
turnout	✓	×	✓	✓
combi_air_qual_ind	✓	✓	✓	✓
concept_teen	✓	✓	✓	✓
imd_score_crime	✓	✓	✓ *	✓

* These QoL indicators show some variability in rankings within this model.

What influence can PSOs have at small area level then? The greatest residual variance that we find tends to be at the lowest levels, and this might be interpreted as just random variation in the data.[*] However, as explained earlier, LSOAs have been constructed specifically to take into account not only mutual proximity and population size but also "social homogeneity". It can be argued therefore that the variation at small area level is not just a statistical result or random variation, but represents some genuine variation which may be amenable to influence at a small area level (such as communities or neighbourhoods). However, the relative size of the variation given by the coefficient of variation on a variable such as life expectancy (le_all) was consistently very small compared to percentage of people living rough (perc_rough) and area of green space per head (area_green) which have high levels of total variance. This suggests that in order to reduce overall variation between small areas, the latter variables might be more amenable to intervention.

As we move in each case from our basic model to the additional explanatory variables in models A, B, C and D, the coefficient of variation decreases suggesting that introducing more needs and performance adjusters tends to reduce the amount of total variation in the models. This is to be expected since we are explaining more of the overall variation in each of the models as we add additional explanatory variables.

[*] We explored this statistically. Details are in the report on the CHE / PSP website.

The proportion of variation explained by the different levels in the hierarchy on the other hand, tends to be relatively stable.

We sought to replicate all the permutations of Model 1 for the MVML approach. However, given the enormity of the dataset and the complexity of the model, running the 17 quality of life indicators available at LSOA level simultaneously was impossible. We therefore ran two subsets of nine and eight indicators respectively. In addition, we could only run the basic model and variant A (with the overall IMD index), any additional adjusters were computationally infeasible.

In short, the estimates of the proportion of variation explained at each level in the MVML model (results not shown) were remarkably consistent with those from the individual ML models. This gave us reassurance that whilst the SUR model had suggested we should ideally model the quality of life indicators as a system of equations given the correlations between the different measures, the simpler and computationally more amenable approach of modelling each quality of life indicator using an individual ML, would provide similar and consistent answers. This is an important finding as it offers justification for a significant analytic and computational simplification.

Conclusions

We draw two sets of conclusions. First, from a methodological perspective, our work makes a distinctive contribution to the literature. It provides new evidence on the complex interactions between PSOs and the potential influence they may have on the quality of life of citizens at a local level. So far as we are aware, this is the first study of its kind to provide evidence on the sources of variation in quality of life indicators at small area level and to use advanced methods to disentangle this variation. We provide insights into whether the three approaches SUR, ML and MVML are suitable methods to examine the complex interplay between different hierarchical levels that are commonplace in all public services and point the way forward for future analysis in this area.

Second, from a policy perspective we have demonstrated that it is important to consider the influence of PSOs on quality of life in areas that fall outside their traditional domains. Moreover, our results give a flavour of the relative influence that health care and local government organisations may have on measures that span health, education, environment, safety, housing and others. We also illustrated the potential significance of considering the small area level in public policy making. The existence of substantial variation in quality of life measures at this level suggests that PSOs with responsibilities at higher level should be aware of the variation that exists at this level within their area and the differential impact their policies may have locally. As we outlined earlier, government policy highlights the importance of local communities and neighbourhoods and although there are no obvious PSOs that have responsibility for quality of life at small area level, the thrust of policy has been to encourage PSOs to become more responsive to local needs and to devolve to communities a greater role in decision-making, including the handling of resources at neighbourhood group and community level (Dept for Communities and Local Government, 2008). Also, as the literature suggests, fostering social capital can enhance the quality of life of citizens and protect them from social exclusion. Neighbourhood and community networks and relationships appear to play an important role in the creation and maintenance of social capital. Our results therefore suggest that policy attention to the local level may well be a fruitful approach if the aim is to enhance the overall well-being of citizens.

This project provides a good basis from which further research can be developed. Modelling of the error term at the lowest level into a deterministic and a random component would further explore the nature of the variation at small area level, although this would require information at smaller levels such as postcode.

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