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DCLG/DEFRA
Research into Drivers of Service Costs in Rural Areas

National Analysis of Unit Costs
Appendix A: Statistical Models

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1 Overview

1.1 This Appendix describes the development of the final statistical models referred to in the main report (National Analysis of Unit Costs – Main Report).

1.2 Regressions were carried out using the SPSS software package. The SPSS output for each model is provided in Appendix B, where each model is identified by the service code (e.g. A1, A2 etc.).

2 Highways and Transport

2.1 For Highways and Transport, unit costs were calculated using weighted road lengths as the denominator. The exception was Parking Services (A2), which used daytime population as the denominator. When carrying out regressions, traffic flow (HighwayFlow) was used as a control variable, rather than deprivation.

2.2 Adjustments were needed where expenditure was carried out by transport authorities, specifically the Greater London Authority (GLA) and the Integrated Transport Authorities (ITAs). This expenditure meant that local authorities' unit costs did not reflect the full cost of providing services in their local area, and therefore were not comparable with other local authorities.

2.3 To adjust for the expenditure by the GLA and the ITAs, the following exclusions were applied:

- The London boroughs were excluded from any regressions where the GLA had significant recorded expenditure, which was for all expenditure groupings except for Parking Service (A2) and Winter Services (A6).
- Expenditure by ITAs was primarily on Public Transport (A8), and so all metropolitan districts were excluded from this expenditure group.
- In addition, the Greater Manchester ITA recorded significant expenditure for Environmental, Safety and Routine Maintenance (A1), and so its member authorities were excluded from the regression analysis for this service. Similarly, the Merseyside ITA has significant expenditure for Transport, Planning, Policy and Strategy (A5), and so the Merseyside authorities were excluded from these regressions.

2.4 Regressions were carried out using the three basic sparsity measures (*SparsityDefra*, *SparsityLSOA* and *SparsityCarTime*), plus daytime population per kilometre (*HighwaysPopKm*). The latter is an increasing function of population density, rather than sparsity, and so the results of the models were interpreted accordingly.[1]

2.5 **Environmental, Safety & Routine Maintenance (A1):** For this service, the best model had a goodness-of-fit of 5.1% in which sparsity was found to have a negative, statistically significant (P<0.05) related to unit costs. The sparsity variable used in the final model was hectares per person (*SparsityLSOA*

[1] For example, where the coefficient on *HighwaysPopKm* is negative, we report this as a positive relationship between sparsity and unit costs.

2.6 **Parking Services (A2):** Sparsity was found to have a positive and highly statistically significant relationship to unit costs (P<0.01), with a goodness-of fit-of 24.3%.

2.7 The sparsity variable used in the final model was population per kilometre (HighwaysPopKm).[2] The final model excluded the traffic flow indicator (*HighwayFlow),* which ceased to be significant once population per kilometre (*HighwaysPopKm)* was introduced. Using *HighwaysPopKm* over the other sparsity indicators increased the model's goodness-of-fit from around 6% to over 22%.

2.8 Parking Services is one of the few services for which local authorities record large negative net current expenditure. It is possible that population sparsity is associated with higher unit costs due to fewer revenue raising opportunities in less-densely populated areas.

2.9 **Street Lighting (A3):** In all the models considered, sparsity was found to be negatively related to unit costs and highly statistically significant (p<0.01). The best model had a goodness-of-fit of 52.2%, using population per kilometre (*HighwaysPopKm*) as the sole explanatory variable.

2.10 **Structural Maintenance (A4):** Sparsity was positively related to unit costs in a number of models tested, but in no case was it found to be statistically significant.

2.11 **Transport Planning, Policy and Strategy (A5):** Sparsity was found to be negatively and significantly (p<0.05) related to unit costs. The model included population per km (*HighwaysPopKm*) and traffic flow (*HighwayFlow*) as explanatory variables, and had a goodness-of-fit of 14.8%.

2.12 **Winter Service (A6):** Two indicators of sparsity were found to be positively and significantly related to Winter Service unit costs. The final model had a goodness-of-fit of 10.8%, in which the variable *SparsityLSOA* was highly statistically significant (p<0.01).

2.13 **Traffic Management & Road Safety (A7):** For this service, every sparsity indicator had a negative and highly statistically significant (p<0.01) relationship with unit costs. The final model had a goodness-of-fit of 27.4% and incorporated sparsity (*SparsityDefra*) and traffic flow (*HighwayFlow*) as explanatory variables.

2.14 **Public Transport (A8):** As with the previous service, every sparsity indicator had a negative and statistically significant relationship with unit costs. The final model had a goodness-of-fit of 69.8%, with population per kilometre (*HighwaysPopKm*) as the explanatory variable, which was highly statistically significant (p<0.01). It should be noted that all London boroughs and all metropolitan districts were excluded from this model, given the role of the GLA and ITAs. For Highways and Transport, the unit cost per resident is the product of two factors: (i) road length per resident, and (ii) total cost per kilometre of road. The current funding system, which allocates funding primarily on the basis of road length, implicitly allocates more funding per capita to sparsely populated authorities (before the impact of other factors, such as traffic flows), as these authorities tend to have greater road distances per resident. The analysis carried out as part of this study assessed whether there was a relationship between sparsity, and costs per kilometre of road. For Public Transport, sparsity was associated with lower costs per kilometre of road. This could

[2] The coefficient on *HighwaysPopKM* was negative. Because population per kilometre is a measure of density, this translates to a positive relationship between sparsity and unit costs.

potentially be due to more densely populated urban authorities having a larger number of potential passengers per kilometre; this additional passenger volume could therefore translate to higher expenditure on public transport per kilometre (as the results of the regression analysis suggest).

3 Children's Social Care

3.1 For Children's Social Care, there was little evidence that local authorities in sparsely populated areas had higher unit costs. Of the seven expenditure categories in Children's Social Care, sparsity was found to be statistically significant in only one. For Other Children's and Families' Services, there was found to be a negative and statistically significant relationship between sparsity and unit costs.

3.2 **Children Looked After (B1):** A total of 12 models were estimated, using different combinations of sparsity and deprivation. The maximum goodness-of-fit that was achieved was only 2.6%, and in no case was the sparsity variable statistically significant.

3.3 **Children and Younger People's Safety (B2):** In most models, the coefficient on the sparsity variable was negative but not statistically significant, despite trending towards significance ($p<0.1$) when the travel time indicator was used. Overall, no statistically significant relationship was found.

3.4 **Commissioning & Social Work (B3):** While sparsity was positively correlated with unit costs in every model, it no case was it statistically significant. The maximum goodness-of-fit was 0.2%.

3.5 **Family Support Services (B4):** A positive relationship between sparsity and unit costs were observed for this expenditure group, but in none of the model was the relationship found to be significant.

3.6 **Service Strategy (B5):** A viable model could not be estimated for Service Strategy, with none of the estimated models having a goodness-of-fit greater than 0%.

3.7 **Youth Justice (B6):** A negative relationship between unit costs and sparsity was observed, but this was not found to be statistically significant in any of the models.

3.8 **Other Children's and Families' Services (B7):** Sparsity was found to be negatively related to unit costs in all models, and statistically significant in several. The best model had a goodness-of-fit of 8.6%, and the negative coefficient on sparsity (*SparsityCarTime*) was statistically significant ($p<0.05$).

4 Adult Social Care

4.1 A total of 50 models were estimated for Adult's Social Care, but little evidence could be found linking sparsity to higher unit costs. In only one model was a statistically significant relationship detected (Adults under 65 with Learning Disabilities), but these showed a negative correlation between sparsity and expenditure per client.

4.2 One area to note was a consistently negative relationship between unit costs and deprivation, the opposite of what might be expected. This raises questions regarding the appropriateness of the dependent variables, which measures net current expenditure per client. The fact that expenditure per client tended to be lower in more deprived areas may be evidence of unmet need, and/or may be indicative of higher quality or wider ranging services provided to clients in less deprived areas. This suggests that unit costs for adult social care may not be a reasonable proxy for assessing whether there are potentially additional unavoidable costs facing rural areas.

4.3 **Adults under 65 with Learning Disabilities (C1):** The best model had a goodness-of-fit of 18.1%, with hectares per person (*SparsityLSOA*) and the benefit recipient rate (*DepriveBenefitKey*) as explanatory variables, both of which were highly statistically significant ($p<0.01$). Both variables had a negative relationship with unit costs, which was not expected.

4.4 Negative and statistically significant coefficients on sparsity and deprivation were found in other model. This included models where different indicators were used for both the sparsity and the deprivation variables.

4.5 **Adults under 65 with Mental Health Needs (C2):** A viable model could not be estimated for this service, and with none of the estimated models had a goodness-of-fit greater than 0%.

4.6 **Adults under 65 with Physical Disabilities (C3):** None of the models tested showed a statistically significant relationship between sparsity and unit costs. The coefficient on deprivation was negative and statistically significant for a number of models.

4.7 **Older Adults (C4):** None of the models tested showed a statistically significant relationship between sparsity and unit costs. In most models, the deprivation indicators were positively and significantly associated with expenditure per client, as might be expected.

4.8 **Other Adult Social Care (C5):** A viable model could not be estimated for this service, with the maximum goodness-of-fit being 0.4%. Sparsity was not found to be statistically significant in any model.

5 Housing

5.1 In Housing, sparsity was positively associated with unit costs for Homelessness, and negatively related in the case of Housing Strategy, Advice, Advances etc. (though with a very poor goodness-of-ift).

5.2 **Homelessness (D1):** Expenditure per homeless household was positively related to sparsity. The best model had with a goodness-of-fit of 8.8%, in which sparsity (*SparsityLSOA*) was highly statistically significant ($p<0.01$). Deprivation was also positively correlated with unit costs, and highly statistically significant ($p<0.01$). It should be noted, however, that the number of homeless households is not a fixed proportion, but is directly affected by spending. Considering that a significant portion of spend on homelessness is preventative, and the ultimate aim of all spending is to bring people out of homelessness, this means that a local authority with a highly effective homelessness programme (i.e. few homeless households but a high spend) would also display a very high unit cost.

5.3 **Housing Benefits Administration (D2):** Sparsity was both positively and negatively associated with unit costs, depending on the model, but in no cases was found to be statistically significant.

5.4 **Housing Strategy, Advice, Advances etc. (D3):** Sparsity was found to be negatively related to unit costs statistically significant in two models, both of which had a very low goodness-of-fit (1.0%). The highest significance was obtained when *SparsityDefra* was entered as the sole explanatory variable ($p<0.05$).

5.5 **Supporting People (D4):** There was a consistent, negative relationship between sparsity and unit costs, but this was not found to be statistically significant in any of the models tested.

5.6 It should be noted that for this service, unit costs were calculated using the resident population as the denominator, as caseload data on Supporting People was not available at the local authority level.

6 Cultural & Related Services

6.1 For Cultural and Related Services, only Tourism showed a positive significant relationship between sparsity and unit costs. For all other services, the relationship was negative, and in most cases this was statistically significant. This was the first group of services to include dummy variables for shire districts and county councils, based on the expenditure splits that were shown in Figure 4.

6.2 **Culture & Heritage (E1):** The best model had a goodness-of-fit of 26.3%, which included *SparsityDefra* and *DepriveBenefitKey* as explanatory variables. The sparsity coefficient was negative and statistically significant (p<0.05). The coefficients for deprivation and the two dummy variables (for shire districts and county councils) were all of the expected sign and highly statistically significant (p<0.01).

6.3 **Libraries (E2):** For Libraries, the best model had a goodness of fit of 16.7%, with sparsity (*SparsityDefra*) as the sole explanatory variable. The coefficient on sparsity was negative and highly significant (p<0.01).

6.4 **Open Spaces (E3):** While all other services used the resident population as the denominator, this expenditure grouping used local authority area (in hectares). The best model returned a goodness-of-fit of 47.2%, in which sparsity (*SparsityDefra*) was negative and highly significant (p<0.01). The coefficients on deprivation (*DepriveBenefit18Plus*) and the two dummy variables were all of the expected sign and highly statistically significant (p<0.01).

6.5 **Recreation & Sport (E4):** While sparsity was found to be negatively related to unit costs in all the models tested, it was not found to be significant when deprivation was controlled for (controlling for deprivation greatly improved the goodness-of-fit of the model, increasing it from less than 6% to over 22%).

6.6 **Tourism (E5):** Sparsity was consistently and positively related to unit costs. The final model had a goodness-of-fit of 12.6%, with sparsity (*SparsityLSOA*) being highly statistically significant (p<0.01). The model included a deprivation variable (*DepriveBenefit18Plus*) and a dummy variable for counties, both of which were of the expected sign and highly statistically significant (p<0.01). The dummy variable for shire districts was not statistically significant and was therefore omitted.

7 Environmental & Regulatory Services

7.1 For Environmental & Regulatory services, the relationship between sparsity and unit costs was positive in four service groupings, but negative in the remaining three.

7.2 **Community Safety (F1):** The best model returned a goodness-of-fit of 40.7%, in which sparsity (*SparsityDefra*) was negatively related to unit costs and was highly statistically significant. The model included a deprivation variable (*DepriveBenefitKey*) and dummies for shire districts and counties, all of which were of the expected sign and highly statistically significant (p<0.01).

7.3 **Regulatory Services (F2):** Sparsity was found to be positively related to unit costs for Regulatory Services. The best model had a goodness-of-fit of 35.2%, in which sparsity (*SparsityDefra*) was highly statistically significant (p<0.01). Other explanatory variables included deprivation (*DepriveBenefit18Plus*) and the dummy variable for shire counties, both of which were highly statistically significant (p<0.01) and of the expected sign. Unit costs for shire districts were not found to be significantly different and so the dummy variable was omitted from the model.

7.4 **Street Cleansing (F3):** Unit costs for street cleansing were found to be negatively related to sparsity (*SparsityDefra*). The final model returned a goodness-of-fit of 25.9%, with a statistically significant coefficient on sparsity (p<0.05). Unit costs were positively related to deprivation, which was highly statistically significant (p<0.01).

7.5 **Waste Disposal and Recycling (F4):** Sparsity was positively related to unit costs in most models tested, though most had a low goodness-of-fit. The best model had a goodness-of-fit of 2.6%, in which the car journey time indicator (*SparsityCarTime*) was statistically significant (p<0.05). A dummy variable for county councils, which was marginally significant (p<0.1), suggested lower expenditure in counties relative to unitaries; the lower unit costs for counties possible reflected the fact that some of the costs were being met by districts in two-tier areas.

7.6 For this service grouping, the Waste Disposable Authority levy was added to the total expenditure of local authorities for whom this was applicable.

7.7 **Waste Collection (F5):** Waste Collection unit costs also appeared to be positively related to sparsity. Sparsity (*SparsityDefra*) was highly statistically significant (p<0.01), with the final model giving a goodness-of-fit of 9.9%.

7.8 **Other Environmental & Regulatory (F6):** The coefficient on sparsity was positive and statistically significant in most models tested. The deprivation variables, however, were not found to be significant. The final model had a goodness-of-fit of 3.4% in which sparsity variable (*SparsityDefra*) was statistically significant (p<0.05).

8 Planning & Development Services

8.1 There was generally a positive correlation between sparsity and unit costs for Planning & Development services. The relationship was statistically significant for two of these expenditure groupings (Economic Research & Development and Environmental Initiatives). However, in one expenditure grouping, the relationship was negative (Development Control).

8.2 **Building Control (G1):** Sparsity was not found to be statistically significant in any of the models that were estimated for Building Control.

8.3 **Business Support (G2):** Sparsity was positively related to unit costs in each model, but these relationships were never statistically significant.

8.4 **Community Development (G3):** Sparsity was found to be positively related to unit costs, but was not found to be statistically significant in any of the models (despite trending towards significance with $p<0.1$).

8.5 **Economic Research & Development (G4):** Sparsity was consistently and positively related to unit costs for Economic Research & Development. The best model had a goodness-of-fit of 32.9%, in which sparsity (*SparsityCarTime*) was statistically significant ($p<0.05$). The coefficients on deprivation and the two dummy variables were also statistically significant.

8.6 **Planning Policy (G5):** Sparsity was positively related to unit costs in each model, but these relationships were never statistically significant.

8.7 **Environmental Initiatives (G6):** For Environmental Initiatives, sparsity was positively and significantly related to unit costs; however, this was not found to be statistically significant in any of the model (despite trending towards significance with $p<0.1$).

8.8 **Development Control (G7):** Sparsity was negatively related to unit costs for Development Control. The best model had a goodness-of-fit of 3.3%, for which the coefficient on sparsity (*SparsityDefra*) was negative and highly statistically significant ($p<0.01$).

8.9 For Development Control, the unit cost denominator was the number of district-level planning decisions. County councils were excluded, as the nature (and number) of their planning decisions were not comparable to those of shire districts. A dummy for shire districts was included in the final model, described above, suggesting that shire districts had higher unit costs than unitaries. The dummy variable was highly statistically significant ($p<0.01$).

9 Fire and Rescue Services

9.1 Sparsity was found to be negatively correlated with unit costs for Community Fire Safety, but no statistically significant relationship was found in the case of Fire Fighting & Rescue Operations.

9.2 **Community Fire Safety (H1):** The best model had a goodness-of-fit of 21.0%, in which the coefficient on sparsity (*SparsityLSOA*) was negative and statistically significant ($p<0.05$). The model also included deprivation as an explanatory variable (*DepriveBenefitKey*), which was positively related to unit costs and was statistically significant ($p<0.05$).

9.3 **Fire Fighting & Rescue Operations (H2):** There was generally a positive relationship between sparsity and unit costs, but this was not found to be statistically significant in any of the models tested (despite approaching significance with $p<0.1$).

10 Central Services

10.1 Within Central Services, sparsity was positively related to unit costs for two expenditure groupings (Coroners' Court Services and Corporate & Democratic Core). A statistically significant relationship could not be found in the remaining three expenditure groupings.

10.2 **Coroners' Court Services (I1):** Sparsity was positively related to unit costs for Coroners' Court Services. The best model had a goodness-of-fit of 22.6%, with a coefficient on sparsity (*SparsityDefra*) that was highly statistically significant ($p<0.01$). Deprivation (*DepriveBenefitKey*) was entered as a control variable; this was also positively related to unit costs and highly statistically significant ($p<0.01$)

10.3 **Corporate & Democratic Core (I2):** Sparsity was also positively related to Corporate & Democratic Core unit costs. The best model had a goodness-of-fit of 21.3%, with the sparsity (*SparsityLSOA*) coefficient being highly statistically significant ($p<0.05$). The coefficients on deprivation (*DepriveBenefitKey*) and the dummy variables for shire districts and county councils were all of the expected sign and highly statistically significant ($p<0.01$).

10.4 **Local Tax Collection (I3):** Sparsity appeared to be negatively related to unit costs for Local Tax Collection, but was not found to be statistically significant in any of the models tested.

10.5 **Elections (I4):** Sparsity also appeared to be negatively related to unit costs for Elections, but was not found to be statistically significant in any of the models.

10.6 **Other Central Services (I5):** For Other Central Services, sparsity was positively related to unit costs in every model tested, but in no cases was it statistically significant.

11 Education (excl. Schools)

11.1 Regression analysis was carried out on Education expenditure groupings, but excluded school spending which was outside the scope of the analysis.

11.2 Two service groupings were considered: Services to Young People and Other Learners (J1) and Other Strategic Functions (J2). In neither case was there found to be a statistically significant relationship between sparsity and unit costs, even when controlling for relative deprivation levels.