Department for Education

Children’s services statistical neighbour benchmarking model

Technical report

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Summary

The Children's services statistical neighbour benchmarking (CSSNB) model helps benchmark local authority data. It gives each local authority in England 10 statistical neighbours that share similar socio-economic characteristics. The model is widely used by local authorities, Ofsted, LGA, ADCS, and the department. This report reintroduces the original model, and details the process of updating it.

Following the Children's Act 2004, the Every Child Matters framework set national outcomes for local authorities. These included 26 aims and priority targets. To benchmark progress, the Department for Education and Skills commissioned the model. Published in 2007, the CSSNB model provided comparators based on socio-economic characteristics.

The model has not been subject to a rebuild (involving the reselection of policy indicators or background variables). Further reasons for the update include:

- Legacy policy indicators which are no longer available.
- Make the model easier to update when local government reorganisations take place.
- Changes to the school and education service landscape.
- Rising demand and cost pressures across Children's Services.
- Significant shifts in local authority demographics.

The methodology used remained as close as possible to that set out in the original model. This method consists of the following steps:

- Source policy indicator and background variable data.
- Regression analysis to find background variables which are strong predictors of policy indicators.
- Correlation analysis on background variables from the previous step. This removes one of each pair of strongly correlated variables.
- Iterative weighting to assign each background variable in the final model a weight.
- Find the 10 nearest 'statistical neighbours' for each local authority.

The final model consists of 23 background variables - sourced mainly from the 2021 Census.

Introduction

Statistical neighbour models are a way for users to compare and benchmark local authority data (performance or otherwise) against meaningful comparators – those which are closest to them amongst selected characteristics.

The Children's Services Statistical Neighbour Benchmarking (CSSNB) model uses a range of carefully selected demographic and socio-economic characteristics to find meaningful comparators for the delivery of Children's Services in upper-tier local authorities in England. Each local authority receives a set of 10 statistical neighbours (SN). Local authorities and key stakeholders, including Ofsted, the Local Government Association (LGA), the Association of Directors of Children's Services (ADCS), and the department itself, have used these neighbours for several years.

This report gives a brief introduction to the original model and sets out the process undertaken to rebuild and update the model, whilst retaining the trusted and accessible original methodology.

History of the CSSNB model

Following the Children's Act 2004, Every Child Matters: Change for Children (HM Government, 2004) set out the national outcomes framework for change in local authorities. It included 26 aims related to five outcomes for children and young people, as well as priority national targets and other indicators. At the same time, inspections of children's services were changing. They aimed to be more outcome-focused, with Ofsted and the Commission for Social Care Inspection conducting joint Annual Performance Assessments and Joint Area Reviews.

To support the framework, the department (formerly Department for Education and Skills) commissioned the National Foundation for Educational Research (NfER) to develop a single, outcomes-focused statistical neighbour model. This model aimed to help track local authority progress across the Every Child Matters (ECM) framework.

In 2007, the researchers published the CSSNB model and shared a list of meaningful comparators for local authorities to benchmark ECM performance. These comparators were local authorities with similar demographic and socio-economic characteristics (background variables in this report). The background variables were selected as they were found to be strong predictors of ECM measures. It was assumed that local authorities with similar characteristics would perform or progress at a similar rate.

Need for update

The model has undergone a few changes (to reflect local government reorganisations), and data updates (from Census 2011, and other more frequently released sources) since its creation. It has not, however, been subject to an overall rebuild which involves the selection of new policy indicators or background variables.

Further reasons for exploring a rebuild of the model include:

- Legacy policy indicators: many indicators are no longer collected, or definitions have changed, as well as shifts in policy. For those indicators with up-to-date data, exploratory correlation analysis with the background variables in the original model showed weak associations.
- Attainment and outcome monitoring and governance has shifted away from Children's Services (academisation etc.).
- Children's Services delivery (CSC, SEND, Early Years, Family Help) face demand and cost pressures, which weren't adequately accounted for in the original model.
- Local government reorganisations (LGRs): several have taken place since the creation of the model. Whilst existing background variables have been updated, the model hasn't been 're-trained' with these new local authorities.
- Future LGRs: under either splits or mergers, the model should be flexible and easy to maintain.
- Demographics of local areas have shifted markedly over the last 20 years – so has the social and economic make-up of local authorities.

Whilst more sophisticated methods of finding statistical neighbours can be used, the methodology of the original model (see the Approach sub-section below for an overview) is transparent, and relatively easy to communicate – especially for non-technical users. For this reason, it was decided to recreate the methodology of the original model, whilst updating the policy indicator framework to reflect current policy direction and capturing the breadth of local authority characteristic data available.

Note on the Opportunity Mission

Every Child Matters was one of the key motivators for the creation of the original model – benchmarking local authority progress across the framework indicators. The review, collection of policy indicators, and updating of the new model, pre-dates the introduction of the current Mission-led approach (HM Government, 2024). One could surmise the use of statistical neighbour models could be of use to track and benchmark progress across the proposed milestones. The policy areas which use the CSSNB model (CSC, SEND, EY and FH) are key to the Opportunity Mission, specifically the Best Start in Life, Every

Child Achieving and Thriving, and the Keeping Children Safe pillars. The model is used to benchmark performance and progress across a much wider range of indicators than the specific metrics used in policy frameworks (ECM, pillar metrics etc.). Considering this, policy indicators have been selected which are not specific to any policy framework. Instead, they are of broad, continual interest. They will gauge the demand on, and capacity of, Children's Services. More fundamentally, the new model does not use metrics or indicators which have been proposed to measure progress across the Opportunity mission, because they have not yet been decided. There may be a need to compare indicator lists once the Opportunity Mission metrics have been decided and revisit the updated model.

Approach

Where viable, the methodology remains as close as possible to that set out in the original 2007 NfER technical report (Benton, Chamberlain, Wilson, & Teeman, 2007). For detailed reasoning as to why certain choices were made, please refer to that document. The method consists of the following steps:

- Source policy indicator and background variable data.
- Regression analysis to find those background variables which are strong predictors of the policy indicators.
- Correlation analysis on those background variables from the previous step, removing one of each pair of strongly correlated variables.
- Iterative weighting to assign each background variable in the final model a weight.
- Nearest Neighbours using a weighted Euclidean distance across each of the final background variables, find the 10 nearest 'statistical neighbours' of each local authority.

Results, and details of any departures from the original methodology, can be found in the next section (Methodology).

Methodology

This section provides more detail on the implementation of the original model as well as any deviations or changes in this update.

Policy indicator selection

The list of policy indicators is not used directly within the CSSNB model. Instead, it is used to select a small number of background variables from the potential longlist. This shortlist of background variables is selected because they are found to be good predictors of at least 1 policy indicator (in this model, via a regression technique).

The original model used 15 measures from the ECM framework as this start-point. Of these, 9 are no longer collected, or are no longer comparable. Statistical neighbour sets have been used to benchmark progress and performance across a large range of measures related to Children's Services, not just the initial ECM indicators.

The ECM framework included many measures relating to attainment, and performance of education services. The school landscape has changed significantly since the creation of the original model (when most schools were local authority maintained). Since 2010 the academisation of schools – largely taking them out of the control of local authorities – has increased rapidly. Prior to 2010 there were 203 academies, but during the 2010/11 academic year a further 600 opened (Department for Education, 2012). By the end of the 2023/24 academic year there were a total of 10,640 academies – accounting for 43.5% of all schools – but educating 56.2% of all pupils (Department for Education, 2024). This academisation rate has large geographical variation, with the proportion ranging from 0 to 100%. The attainment, outcomes, and experiences of children and young people are more strongly tied to other parts of local authority delivery, or services outside of local authorities' control.

Lastly, the ECM framework used in the original model had few service demand or pressure measures. It was understandably focused more on performance and outcomes. Including performance measures in the policy framework makes the model circular because it wrongly assumes that local authority performance is only a function of the demand and pressures in the local area. Local practice, strategies and policies, and funding decisions also influence performance and outcomes. If a performance gap is found between local authorities with similar characteristics (hence similar demands and pressures), it can be assumed to be due to these additional aspects. The policy indicators used to select background variables in the model should then ideally be demand or pressure focused.

The points above strongly favour a new set of policy indicators upon which to rebuild the Children's Services Statistical Neighbour model – based on demand or pressure measures related to CSC, SEND, EY and FH.

Workshops

To decide on a list of policy indicators for the model framework, analysts from relevant policy areas were invited to a series of workshops. With input from their policy teams, they discussed the measures and indicators important for planning, implementing, and tracking policy.

In these workshops, attendees first discussed the proposed methodology behind the model update (SNs are used across all these policy areas), compiled lists of indicators which are currently used, and identified cross-cutting measures. Attendees were then asked to filter indicators from their policy area with a set of selection criteria (found in the Selection criteria sub-section) and rank their indicators in order of importance/priority of inclusion in the model.

Selection criteria

The following criteria were used to filter policy indicators during the workshops:

- Regular: annual, bi-annual, termly, or a longer timescale.
- Easily calculated from source: rates, percentages, or unit costs for example
- Publicly available/published measures.
- Pressure related: demand, capacity or finance measures – avoid performance/outcomes measures.
- Aligned to Children's Services policies/strategies: acknowledging that some areas may not have available data (i.e. Family Help), and that some measures are of constant interest.

Measures in model

The workshops yielded the following list of policy indicators – the policy area which selected each indicator can be found in brackets:

- Children and young people per capita spending (CSC, FH)
- Children in Need rate, per 10,000 0–17-year-olds (CSC)
- Children Looked After rate, per 10,000 0–17-year-olds (CSC)
- Under-18 conception rate, per 1,000 15–17-year-olds (FH)
- CS Workforce agency worker rate, proportion of total workforce (Full-time equivalent FTE) (CSC Workforce)
- CS Workforce agency workers covering vacancies, proportion of agency workforce FTE (CSC Workforce)

- 3-year % change in Dedicated Schools Grant carry-forward (SEND)
- 3-year % change in number of children and young people (CYP) with Education and Health Care Plans (EHCPs) (SEND)
- CYP with EHCPs, proportion of 2–18-year-olds (SEND, FH)
- Registered Early Years Places, per 1,000 0–4-year-olds (EY)
- Take-up rate of targeted childcare offer, proportion of eligible 2-year-olds (EY)
- Take-up rate of universal childcare offer, proportion of all 3–4-year-olds (EY)

Background variable selection

When the original model was being designed, the development team ran workshops with local authorities and other stakeholders to construct a list of data sources from which to gather background local authority variables. Where possible, variables have been sourced from the same sources as the original model, as well as from further relevant sources that describe local authority characteristics (demographics, socio-economic, physical, geographic, access to services, etc.). This list of sources was shared with local authorities through the National Performance and Information Managers Group (NPIMG), with a request for feedback and any sources missed.

Selection criteria

It is our hope that the updated model will be used as widely, and for as long as the original model. Criteria for the selection of data sources and background variables were designed with the intent to make the final model:

- Transparent: to make the inputs accessible to non-technical users.
- Have a simple methodology: the chosen regression technique is relatively easy to explain but limits the types of data which can be used. For example, no categorical data can be used as it would need more complex methods.
- Easy to maintain: updating the original model with new data, or to account for LGRs, is not straightforward.

These criteria are as follows:

- Updated annually: but recognising it is likely most background variables will be derived from Census data (conducted every 10 years).
- Simple: Counts, Totals, Percentages/Proportions, Rates, Averages etc. – avoid complex compound measures.
- Continuous: measures which can take any value (theoretically), not discrete (i.e. Ranks, Classifications).

- Available at geographies lower than upper tier local authorities (UTLA): ideally Lower/Middle Super Output Area (L/MSOA) or lower tier local authority (LTLA). This allows 'new' data to be aggregated/split for local authorities resulting from LGRs
- Not directly or indirectly used to calculate a compound measure.
- Not used to calculate policy indicators.

Sources

Using those criteria, sources from the original model as a starting point, our own data exploration and sector input, over 270 background variables were collected from the following sources:

- Census 2021 (ONS)
- Connected Nations and infrastructure reports (Ofcom)
- Air Information Resource (Defra)
- Annual Survey of Hours and Earnings (ONS)
- Children in Low Income Families (DWP)
- Universal Credit Statistics (DWP)
- Vehicles Statistics (DfT)
- Schools, pupils and their characteristics (DfE)
- National Child Measurement Programme (PHE/DHSC)
- Labour Market Overview (ONS)
- Natural Capital (ONS)

Whilst the sources are similar to the original model, the number of potential background variables is over 4 times larger (63).

Regression analysis

The regression analysis step is used to identify a subset of background variables from the longlist, which are the strongest predictors of local authority policy indicators. Those background variables with little to no association to the policy indicators were removed from the model.

A stepwise regression technique was performed on each of the policy indicators – testing against all the background variables. The algorithm finds the smallest number of variables to explain the indicator data. This can usually be performed in one of two ways: forward selection, where at each step the variable which contributes the greatest improvement to the regression model is added, until no statistically significant improvement can be made; or backward elimination, where the model starts with all the variables available and iteratively eliminates variables until no statistically significant improvement can be made. Whilst the original technical report doesn't specify, bidirectional stepwise regression was used – which is a combination of the two processes above. After each variable is added, the model is tested to see if a previously added variable is no longer contributing a statistically significant improvement to the model. This is continued until the addition or elimination of variables yields no further improvement.

An adjusted R-squared test statistic was used to measure the goodness-of-fit of each final policy indicator regression model i.e. how well the included variables explain the variation in the policy indicator. Like the original SN model, any policy indicator with an adjusted R-squared value less than 0.1 was removed from further analysis. No indicators fell below this threshold, but inspection of the adjusted R-squared values showed that indicators in two policy areas had generally lower values than others – SEND and CSC workforce.

These policy areas are very important currently and are likely to be over the lifetime of the model. It is unacceptable the model is potentially less valid for benchmarking local authorities in these policy areas than others. To bolster these areas, two further policy indicators were included. These additional indicators had the highest adjusted R-squared values from their respective policy areas, but didn't make the top of the list in the policy indicator workshop. These additional measures were:

- CS Workforce vacancy rate, proportion of social worker FTE plus vacancy FTE (CSC Workforce)
- Pupils with SEN Support, proportion of all pupils (SEND)

Using the results of these regression analyses, all proposed background variables – which appeared in any of the final regression models (for the original 12 indicators and the additional 2 above) – were ranked by their largest standardised regression coefficient. 'Largest' was taken to mean the magnitude or absolute value of the standardised regression coefficients – variables with strong negative coefficients would be ranked above those with weaker positive coefficients.

The original technical report removed several background variables with the smallest absolute standardised regression coefficients, but they did not specify the cut-off point. Generally, standardised regression coefficients less than 0.5 is a medium effect size, and less than 0.2 is weak (Acock, 2014). There were 50 background variables with standardised regression coefficients greater than 0.5 – a comparable number at this stage in the original analysis.

Variables describing ethnicity

In the original CSSNB model analysis, variables describing the ethnic make-up of local authorities had some of the smallest standardised regression coefficients (if they were even selected in regression models). Except for the variable describing the proportion of residents who are white, no ethnicity variable had a coefficient greater than 0.2.

This finding is believed to arise because:

- Ethnicities not in the white ethnic group have different and varying levels of interaction with CSC, SEND, etc. (some are over-represented, others are under-represented, relative to their proportion of the population).
- Individual ethnicities are unevenly spread across local authorities, so will result in the model running on small numbers of local authorities and being irrelevant to the rest.

The over, or under, representation of certain ethnicities in CSC (Ahmed, James, Tayabali, & Watson, 2022) or SEND (Lindsay, Pather, & Strand, 2006), is less significant when controlling for deprivation (Webb, Bywaters, Scourfield, Davidson, & Bunting, 2020) (Fitzsimons, James, Shaw, & Newcombe, 2022). Whilst an important aspect of practice in local authorities with less heterogeneous ethnic makeup, deprivation and cultural isolation are higher-order predictors of demand for Children's Services (Bywaters, et al., 2018) (Bywaters, Skinner, Cooper, Kennedy, & Malik, 2022) – these aspects are adequately captured by the variables included in the model at this stage.

Unlike the original model which kept some ethnicity variables in the model, the revised model does not. An ONS cluster and statistical neighbour model for general local authority characteristics across England, Scotland and Wales takes a similar approach, using only the proportion of residents who are white (ONS, 2025).

Correlation analysis

With the remaining background variables, two steps were carried out to diminish the impact of multicollinearity, reduce redundancy, and limit potential confusion:

- Examination of pairwise correlations and removal of one variable from highly correlated pairs
- Removal of variables with similar meanings

Pairwise correlation analysis identified several pairs of measures with high correlation (Pearson correlation coefficient > 0.9). Including multiple highly correlated variables in a model can create redundancy, where the effects of these variables are 'double-counted', and can lead to model over-fitting (multicollinearity). A few variables were found to be highly correlated with more than one other variable. To address this, similar to the original model, the following criteria were used to select variables for inclusion, discarding the other half of each correlated pair. Additionally, a new criterion was added to handle variables correlated with multiple others:

- Simple measures (percentages) over complex (indices etc.).
- Measures updated frequently, over those from the census.
- Additional criterion: preferring measures strongly correlated with more than one variable.
- If the above criteria didn't separate variables, the variable with the largest standardised regression coefficient from the initial regression analysis was selected.

Several variables with sufficiently similar meanings or names to other variables were also removed to avoid confusion. Many of these pairs came very close to the threshold for removal in the correlation analysis but fell short due to small differences in methodology or definition. The same criteria listed above were used to select the variable to keep.

These steps reduced the number of background variables in the model from 50 to 23.

Examples:

The variable describing the proportion of households with dependent children deprived in 3 of the 4 deprivation dimensions was very strongly correlated with the following measures:

- Proportion of households with dependent children deprived in 3, or all, of the 4 deprivation dimensions.
- Proportion of households with dependent children deprived in the employment dimension.
- Proportion of households with dependent children deprived in the housing, education, and health dimensions.

These 3 variables all have lower standardised regression coefficients than the initial measure. Most of the information these 4 variables provide to the model (and not double or triple count the effect of deprivation dimensions) can be captured by only selecting the initial variable.

After the correlation analysis there were 3 variables describing the access to private gardens of residences:

- Proportion of all residences with private gardens
- Proportion of flats with private gardens (generally shared/communal)
- Proportion of houses with private gardens

These measures didn't meet the threshold to be examined for very strong correlation – but they measure a similar characteristic (all residences is the sum of houses and flats). Only the variable describing the proportion of all residences with private gardens in the model was kept.

Variable weighting

In the original CSSNB model each background variable is assigned a weight – how much importance is given to that variable. Due to how the model calculates statistical neighbours, variables with higher weights 'stretch' the distance between local authorities – small differences are exaggerated, so only local authorities with extremely similar values are likely to be neighbours, at least due to the influence of that variable.

Assigning different weights to each variable would result in differing, sometimes massively so, sets of statistical neighbours – so how to choose which 'family' of weights? The original model designed a model criterion to find the optimal set of weights (as well as decide on the number of neighbours to assign).

Model criterion

This criterion is determined by first asserting that the model which produces statistical neighbours, such that the performance of each local authority is closest to the average actual performance of its statistical neighbours, is the model that performs best in terms of matching the expected values of performance. This stems from the purpose and design of our statistical neighbour model – to find local authorities which have similar characteristics and should therefore have similar patterns of service demand and pressures (our policy indicators). This criterion is calculated with the following formula:

$$\text{Criterion} = \sum_{ij} \left(Y_{ij} - \tilde{Y}_{ij}\right)^2 / NJ$$

Where:

Y_{ij} is the standardised performance of local authority i on policy indicator j

$\tilde{Y}_{ij}$ is the average standardised performance of statistical neighbours of local authority i on policy indicator j, for the given statistical neighbour model

N is the number of local authorities

J is the number of policy indicators

The criterion can be expressed plainly as the average squared difference between the performance of each local authority and the average performance of its statistical neighbours across all performance indicators. With 2 different statistical neighbour models, the model which results in the lowest criterion value should be the one picked.

Weighting optimisation

The weights which result in the lowest model criterion are found with the following procedure:

- Assign each background variable in the model a random weight (a whole number) – note, weights can be 0.
- With these weights and the standardised background variables, calculate the 10 closest neighbours for each local authority (see the next subsection – Neighbour Selection for more details).
- Calculate the average of each local authority's statistical neighbours in each of the policy indicators.
- Calculate the model criterion – compare this to the previous model criterion, if lower save the weights.
- Repeat the steps above many times (over 2 million times for the final model).
- Across all the iterations find the set of model weights which resulted in the lowest model criterion.

The original model removes several measures with weights equal to or close to 0. In our own optimally weighted model, there were no variables with weights equal to 0, but several with weights of 1 – these variables were kept.

Neighbour selection

With the final background variables and their assigned weights from the iterative weighting optimisation, the 10 closest statistical neighbours for each local authority were calculated.

First, the data was standardised – to make variables with differing ranges and scales comparable. After standardisation the mean of each standardised variable is 0 and the standard deviation is 1. The formula to standardise a variable is as follows:

$$X_j = (x_j - \tilde{x}_j) \,/\, std_j$$

Where:

X_j is the standardised variable j

x_j is the raw variable j

$\tilde{x}_j$ is the mean of variable j

std_j is the standard deviation of variable j

For each target local authority, the distance from itself to all other local authorities was calculated with a weighted Euclidean distance on the standardised background variables. In 2 dimensions consider two points with co-ordinates (x1, y1) and (x2, y2) – the unweighted Euclidean distance is:

$$\mathrm{d} = \sqrt{(\mathrm{x}_1 - \mathrm{x}_2)^2 + (\mathrm{y}_1 - \mathrm{y}_2)^2}$$

The optimised weights can be introduced and generalized to further dimensions. A local authority's values in the background variables can be thought of as it's co-ordinates in x and y (if there were only 2 variables).

The 10 closest local authorities, based on the average weighted Euclidean distance per standardised variable, are found for each local authority.

The same thresholds as the original model were used when categorising the proximity of statistical neighbours:

- Extremely Close: < 0.25 weighted Euclidean distance per standardised variable
- Very Close: < 0.55 weighted Euclidean distance per standardised variable
- Close: < 0.85 weighted Euclidean distance per standardised variable
- Somewhat Close: < 1.15 weighted Euclidean distance per standardised variable
- Not Close: >= 1.15 weighted Euclidean distance per standardised variable

Final model

Table 1: Model variables, weights and sources

Variable	Weight	Source
% matched premises with UFBB (100Mbit/s) availability	3	Ofcom (2022)
% residences with private gardens	1	ONS (2020)
Prevalence of obese or overweight children in Year 6	2	PHE (2022)
Prevalence of obese or overweight children in Reception	15	PHE (2022)
% infants taking a free school meal	1	DfE (2022)
% dependent children[1] with a bedroom occupancy rating of 1 (under-occupied)	3	Census 2021
% dependent children deprived in 1 dimension	22	Census 2021
% dependent children deprived in 3 dimensions	5	Census 2021
% dependent children where 0 persons are disabled whose day-to-day activities are limited	21	Census 2021
% dependent children where 1 or more adults are employed	16	Census 2021
% dependent children where 1 or more persons have a non-limiting long-term physical or mental health condition	2	Census 2021
% households with a single family - dependent child	1	Census 2021
% households where the property is owned (outright or with a mortgage)	10	Census 2021
% households where HRP[2] travels less than 60km to work	17	Census 2021
% HRP of working age who are unemployed but have worked in the last 12 months	19	Census 2021
% HRP of working age who have no qualification	21	Census 2021
% HRP of working age who have a highest qualification level of 2	7	Census 2021
% HRP of working age in a routine NS-SEC occupation	1	Census 2021
% HRP of working age, with dependent children, who work part time - less than 30 hours a week	19	Census 2021
% HRP of working age, with dependent children, in a lower managerial or professional NS-SEC occupation	17	Census 2021
% residents aged over 3 where English is their first language	23	Census 2021
% residents with religion - Christian	22	Census 2021
% households in whole house accommodation	11	Census 2021

Table 1 details the background variables in the final model, along with their assigned weights from the weighting optimisation. Like the original model, variables from the

[1] Dependent children is shorthand for Households with dependent children
[2] Household Reference Person

Census make up a significant proportion of the total. Most of these variables won't be updated until the next Census (2031) data is released.

With the removal of 8 variables describing the ethnic diversity of local authorities, there are more variables covering the health and deprivation level in households with children, the economic activity of households with children, and family/household structure.

When LGRs take place, the non-Census variables can be updated, and data for new local authorities can be aggregated (in mergers) or disaggregated (in splits) from the MSOA or LTLA data available for all these variables.

Table 2 lists the number of statistical neighbours by proximity count (the 5 categories detailed in the Weighting optimisation section:

Table 2: Statistical neighbour proximities

Proximity	Count
Extremely Close	16
Very Close	823
Close	507
Somewhat close	134
Not Close	50

For a comparison between the old and new models please refer to the Children's services statistical neighbour benchmarking tool - update note which can be found on the LAIT landing page.

Data for the background variables, their weights, and statistical neighbours for each local authority, can be found in the excel-based Children's services statistical neighbour benchmarking tool (also on the LAIT landing page) as well as in the Local Authority Interactive Tool.

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