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# In Defence of Ordinary Help: Estimating the effect of Early Help/Family Support Spending on Children in Need Rates in England using ALT-SR

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**Abstract**
Randomised controlled trials are often inappropriate for many forms of preventative children's services, as such, observational studies using administrative data can be valuable for evidence-based policymaking. However, estimates of effectiveness can be confounded by differences in thresholds of intervention and national policies that exert pressure on local trends. This study adjusted for these factors using methods developed in clinical psychology to control for individual traits and developmental trajectories, Autoregressive Latent Trajectory Models with Structured Residuals, to analyse the relationship between local authority preventative spending and Children in Need (CIN) rates in England. Higher spending was associated with significant decreases in CIN rates between 2010/11 and 2014/15, but not from 2014/15 onwards. In the first half of the decade, 1% increases in expenditure were associated with between 0.07% and 0.157% decreases in CIN rates. Based on average local authority spending cuts, this translates to an additional 13,000 to 16,500 children and young people put or kept at risk of developmental or health impairments nationally for each year between 2011 and 2015. These findings highlight the potential of early help/family support policies and concerns around how their effectiveness has changed consequent to prolonged austerity and a deliberate policy focus on 'what works'.

**Keywords:** austerity; social work; child welfare; social care; structural equation modelling; early intervention

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## Background

Under section 17 of the Children Act 1989, local authorities in England have a duty to provide services that 'safeguard and promote the welfare of children within their area who are in need'. Children who are at risk of having their health or development impaired without the provision of additional support are recorded in administrative data as 'Children in Need' (CIN). Support for these children their parents is often delivered through various forms of 'early help', 'early intervention', or 'family support' that typically aim to prevent existing or potential problems escalating to safeguarding concerns (Frost, et al. 2015). Greater reinvestment in early help and family support services, which have been diminished since 2010 (Webb & Bywaters, 2018), has been touted as a solution to the problem of growing rates of children in care (NCB, 2017; Featherstone, et al. 2019).

Analyses by the National Audit Office (NAO, 2016, 2019) and Ofsted (2016) reported there was no relationship between expenditure on preventative children's services and their quality or rates of child protection interventions. The implication of these findings has been that investment alone is inadequate for improving outcomes. In his 2016/17 annual report, the Chief Inspector of Ofsted wrote:

> *"We now know that: inadequacy is not a function of size, deprivation or funding, but of the quality of leadership and management."*
>
> Michael Wilshaw, Ofsted, 2016: 5, quoted in Lavalette, 2019: 28

A significant amount of evidence from Randomised Controlled Trials (RCTs) and meta-analyses generally concludes that family support services have beneficial impacts on children's social, emotional, and educational development, and on family functioning and parenting skills (Hutchings, et al., 2017; Axford, et al., 2015; Allen, 2011; Macmillan, et al. 2009; Melhuish, et al., 2008; Dunst, et al. 2007; Dagenais, et al. 2004; Layzer, et al. 2001), however, as indicated by the NAO's analyses, these may not necessarily translate into decreased state intervention rates. Commissioning more effective early intervention services based on high-quality evaluations has been an aim of UK government throughout the 2010s, outlined in the Allen Report (Allen, 2011) and reinforced in the establishment of the 'What Works Network' (DFE, 2013). Despite the Allen Report's ambition of only guiding new funding, and not threatening existing programmes, the 'quality' of evidence – as measured by how closely evaluations align to a framework that positions experimental and quasi-experimental methods as the 'gold-standard' – has become a significant policy driver in deciding what services are funded under austerity.

### *'What works?' and the defence of ordinary help*

Critics of what could be called the 'what works' paradigm have noted that many early help and family support services do not conform well to, or are ethically inappropriate for, RCT evaluations, particularly where these services are delivered in community settings or utilise less manualised or structured forms of support (Stewart-Brown, et al. 2011, 2012; White, et al. 2014). As White, et al. (2014: 83) state simply: "the more ordinary and relatively cheap the help, the less likely it is to yield to experimental methods". Thoburn, et al. (2013) highlight several features of 'ordinary help', including that it is flexible, adaptive, and sensitive to the context of multiple needs; it is relationship-based and includes help with pragmatic factors that can strain parenting. Jack and Gill (2010) highlight that it includes a range of activities that create informal social support structures, assuaging the mistrust and power imbalance between parents and social workers.

These services are often highly tailored to the needs of the population they support, sometimes explicitly because they originate from community self-organisation, which further complicates the appropriateness and generalisability of RCTs. Though there is no way to establish the size of reductions to the provision of services with experimental evidence against those without, the case of children's centres in England may serve as one example due to their area-based implementation, universality, and provision of multiple varied services. Smith, et al. (2018) report that between 2009 and 2017 more than 30 per cent of registered children's centres had closed and 55 per cent of local authorities reported reduced services, with increased focus on specialist provision for complex needs and reduced universal support (see also: Hood, et al. 2020b).

This is particularly acute when a distinction between 'early intervention' and 'early help' is made. While the two terms are used interchangeably, one pattern, but by no means absolute rule in England, is that 'early help' more generally refers to the need for intervention or support provided *early in the life of a problem*, whereas 'early intervention' often stresses the need for intervention on perceived risks *early in the life of a child*, as well as early in the life of a problem (White, et al. 2014; Featherstone, et al. 2019). Much experimental evidence comes from evaluations of interventions with very young children, especially in the field of neuroscience (Wastell & White, 2017; Featherstone, et al. 2019). Services for adolescents often focus on relationship-building with trusted adults and practical, long-term support, usually embedded in physical spaces like youth centres. This places services for older children in a particularly precarious position. The YMCA (2020) report that youth services funding has been cut by more than 70 per cent between 2010-11 and 2018-19, with the closure of 1 in 6 youth centres between 2012 and 2019.

Policy rationales for commissioning public services increasingly coalesce around causal evidence based on medical models of science (Wastell & White, 2017), economic justification (Featherstone, et al. 2019; Maron, 2021), and potential for financialisation (Wiggan, 2018; Jones, 2019). This can drive out community solutions that often lack the capital to demonstrate such outcomes. Of the Early Intervention Foundation's eight early help programmes that it rates as having the highest quality of evidence, seven were developed in the USA and one in Australia. Of these, five require license and training fees to be paid to private enterprises, two require paid training only, and one can only be offered exclusively through a UK non-governmental organisation (*author's analysis of EIF Guidebook, June 2020*).

### *'The trouble with thresholds': variation and rationing of 'need' in administrative data*

Establishing causal evidence through non-trial methods is complicated by several dynamics of administrative data. While statuses like 'in Need' are defined in legislation, it is the responsibility of local authority children's services to operationalise these definitions. This results in the ascription of 'need' differing between children's services. In England, each local authority employs differing thresholds for 'Child in Need' status, which can be affected by demand for services (Broadhurst, et al., 2010), type of risk (Devaney, et al., 2012; Hayes & Spratt, 2012), rationing in response to budget constraints (Devaney, et al. 2012; Devaney, 2019), and arrangement of referral systems (White, at al. 2015). Many drivers of changing thresholds, and therefore rates, are associated with national, rather than local, policy effects over time.

This introduces difficulties in drawing general conclusions from observational studies. Most forms of analysis, including those used by the NAO, rely on observing relationships between cases, for example, whether higher CIN rates are associated with lower expenditure. This relies on the assumption that 'in Need' means the same thing in every local authority. In practice, the most high-level forms of intervention become the focus of analysis, namely rates of children in care or child protection plans, because these interventions are bound by more universal thresholds such as family court rulings. This sets an unrealistic expectation on early help services when their focus is to address children's needs under section 17 of the Children Act 1989. The effects of early help on care rates or child protection plans may be small or incremental and therefore difficult to evidence in terms of 'statistical significance' when the number of children's services is finite and relatively small (Stewart-Brown, 2011). Additional observational approaches that avoid the pitfalls of administrative children's services data are required to fairly represent the value of services that do not conform well to experimental methods.

The need to address these confounding factors in longitudinal analysis is not unique to the case of children's services, and techniques have been developed in clinical statistics to separate 'traits', – analogous to differential operationalisations of 'need' – 'trajectories', – analogous to change over time in rates associated with supra-local policies – and 'within-unit dynamics' – analogous to associated changes in need and service provision independent of local authority level trends and interpretations of legislation. This study uses Autoregressive Latent Trajectory Models with Structured Residuals (ALT-

SR) (Curran, et al. 2014; Mund & Nestler, 2019) that adjust for such confounding factors to examine the lagged effect of early help and family support expenditure in local authorities in England on CIN rates. The article contrasts estimates from an ALT-SR model to three frequently-used models.

## Methods

An ALT-SR model represents a combination of two routinely used models in structural equation modelling (SEM): the Cross-lagged Panel Model (CLPM) and the Latent Growth Model (LGM) or Latent Curve Model (LCM) (Curran, et al. 2014; Mund & Nestler, 2019). The purpose of a CLPM is to estimate the effects of multiple variables on one another over a series of sequential time points, while controlling for immediately prior values (autoregression) from each unit (individual or case measured over time) under observation. The purpose of Latent Growth Models (LGM) is to model the developmental trajectory of a variable over time (Duncan & Duncan, 2009). This is achieved using latent variables. In a simple example, latent variables may represent an intercept point and a linear slope; these variables can further have variance parameters estimated, which describe how the intercept and slope differ for each individual unit. This variance can further be regressed on or correlated with other variables, including latent growth factors associated with a second developmental trajectory to identify 'parallel processes'.

The autoregressive components of a CLPM fail to account for stable between-unit factors, which has been shown to bias the estimates for cross-lagged relationships and confound the extent to which they represent within-unit dynamics between two variables over time (Curran, et al. 2014; Hamaker, et al. 2015; Berry & Willoughby, 2017). There is a need to separate 'stable differences between units' from 'temporal, within-unit dynamics' (Mulder & Hamaker, 2020: 1). The need for a further decomposition of trajectories was highlighted by Curran, et al. (2014). They argue that because many variables exhibit some constant developmental process over time this should not be treated as a within-unit dynamic. This separation is important because, as Curran, et al. (2014) explain:

> *"[M]any contemporary theories ... posit complex reciprocal relations between multiple constructs at both within-person and between-person levels of influence, and these relations may vary in magnitude or form across time or over group. However, many traditional statistical models commonly used in practice are restricted to the estimation of between-person relations ... and thus may at times provide less than optimal empirical tests of our theoretically-derived research hypotheses."*
>
> *Curran, et al. (2014: 3)*

This logic is extended to local/national government, as developmental trends that are associated with supra-local developments, for example, austerity, should not be considered part of *within*-local authority dynamics and should be appropriately decomposed into a separate, *between*-unit part of the model. This can be achieved through the combination of a CLPM and an LGM. Figure 1 shows a basic ALT-SR as a path diagram and highlights the decomposition of variance to the *between*-unit and *within*-unit parts of the model.

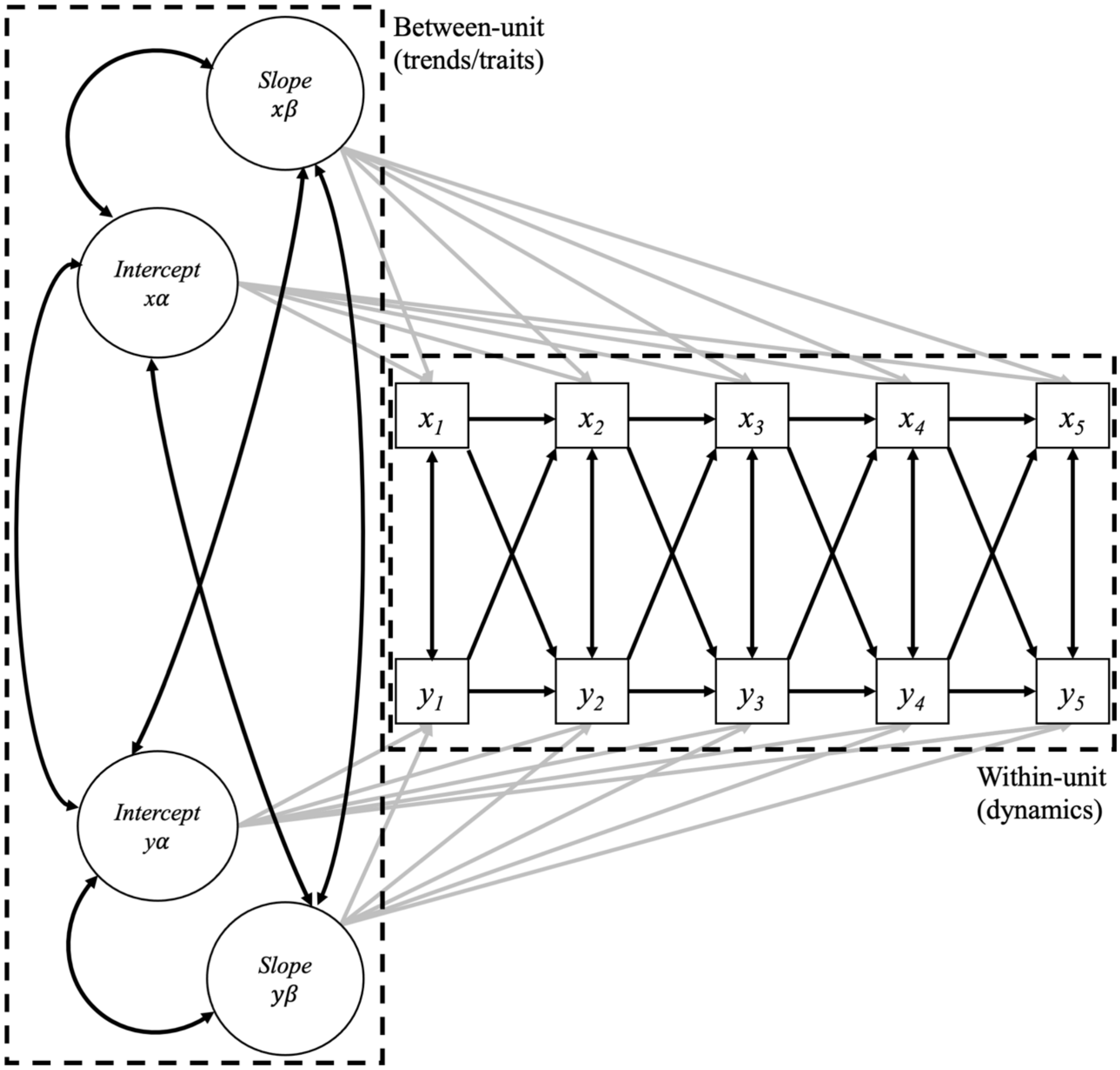


**Figure 1: The ALT-SR Model as a combination of a CLPM and LGM**

### *Visual Explanation*

Figure 2 provides a visual example illustrating the removal of variance associated with latent trends and the impact of this on the interpretation of cross-lagged relationships within a single case. Plot (a) represents data for expenditure and Children in Need rates at nine intervals between 2011 and 2019, with linear trend lines for each variable over time. Before adjusting for trends, the value of expenditure at 2012 represents a simple decrease, and this decrease is associated with a decrease in CIN rate in the following year.

Plot (b) shows how adjusting the values within the local authority for the larger trend over time changes the interpretation of values to be their fluctuation from an established trajectory. The residuals from this adjustment then form the cross-lagged component of the ALT-SR model to estimate within-unit effects of deviations in spending on CIN rates, and *vice versa*, above and below the general trajectory. Plot (c) labels one side of these cross-lagged relationships with curved arrows. One consequence of this is that positive expenditure residuals are now consistently associated with negative CIN rate residuals in the following year, better representing within-unit dynamics.

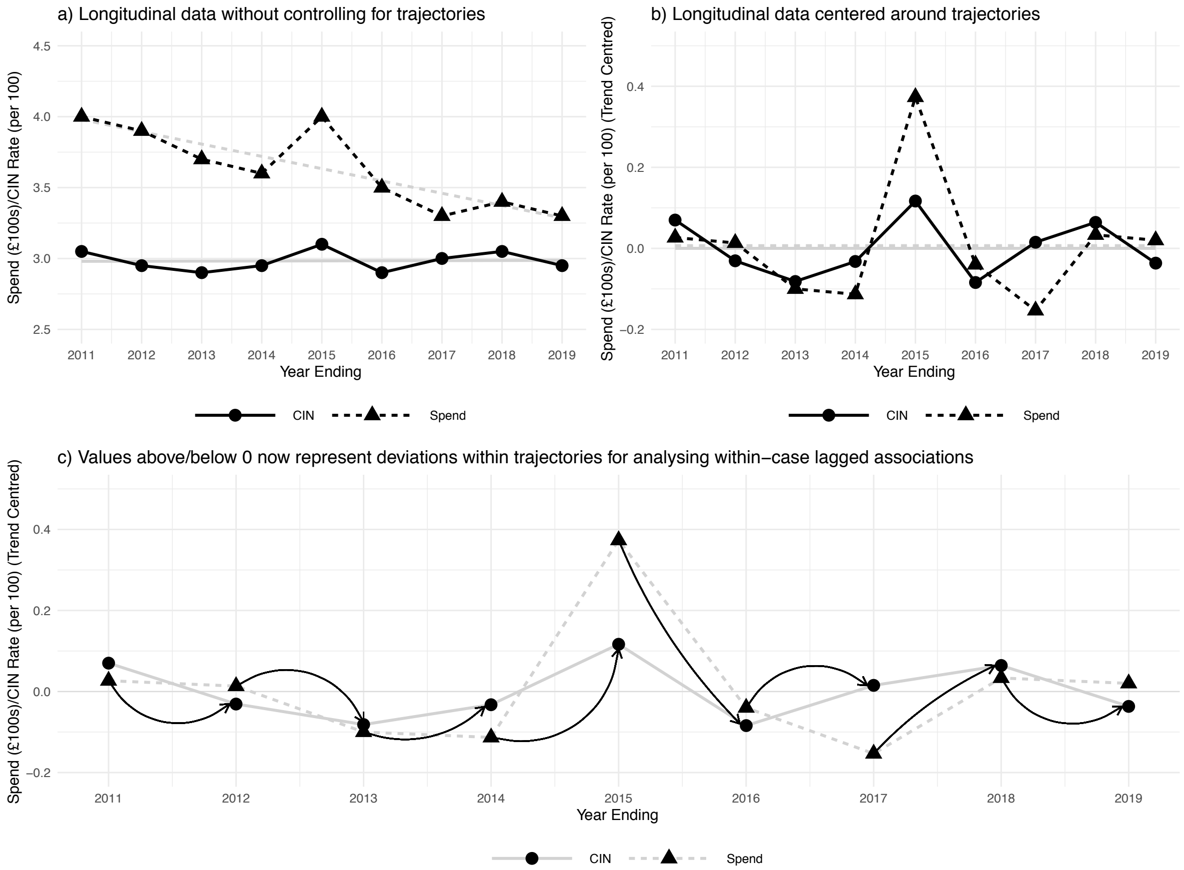


**Figure 2: A visual explanation of the effects of removing variance associated with case intercepts and slopes on the interpretation of lagged effects**

*Model Building and Selection*

While Curran, et al. (2014) prescribe no specific model building strategy, they demonstrate building an ALT-SR model by first establishing an appropriate function for growth over time in each variable, then testing autocorrelation and unidirectional cross-lagged associations between variables with both fixed and freely estimated effects over time. Model selection is achieved through the use of comparative fit.. In this study, the robust Comparative Fit Index (CFI), robust Tucker Lewis Index (TLI), the Standardised Root Mean Square Residual (SRMR), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) were used to gauge and compare model fit. A summary of these statistics can be found in Kenny (2020). Model selection and the model building process is reported in full in appendix A; the final ALT-SR model included random intercepts, random slopes, and a fixed quadratic growth curve for expenditure with no residual autocorrelation; a random intercepts, random slopes growth curve for CIN rate with residual autocorrelation; and freely estimated cross-lags between both variables.

*Assessing Model Fit*

Cut-off criteria established by Hu & Bentler (1999) are frequently used to determine whether models represent 'good' fits to data; these are set at values close to or greater than 0.95 for CFI/TLI and less than 0.08 for SRMR. The AIC and BIC have no cut-off criteria, and operate as relative indicators for competing models, with the BIC applying a larger penalty for complexity. Smaller values of AIC and BIC indicate better fit. Strict cut-offs for model rejection have been cautioned against due to their behaviour with different sample sizes and degrees of model complexity and misspecification (Marsh, et al. 2004; 2005; Nylund, et al. 2007; Neimand & Mai, 2018; Shi, et al. 2018). A simulation study by Shi et al. (2018) found that the CFI and TLI of correctly specified models falls as sample size decreases. They argue that "A sample of N = 200 observations only provides a reasonable estimate for CFI and TLI when [the number of observed variables is less than] 30" (Shi, et al. 2018: 330).

Neimand & Mai (2018) recommend the use of flexible cut-off values, but these cannot yet be readily calculated for models other than Confirmatory Factor Analysis (CFA). As an illustrative example, Neimand & Mai's (2018) cut-off values for CFI, TLI, and SRMR for a CFA with a sample size and number of observed/latent variables equal to that of this study are 0.927, 0.913, and 0.066 respectively. This adjustment makes the requirements for good fit under CFI and TLI indices less stringent, but requirements under the SRMR more stringent, due to its bias towards small samples. While this is not necessarily a suitable adjustment for an ALT-SR model, it provides an approximate indication of the extent to which claims of good fit below Hu & Bentler's cut-offs may be inappropriate.

### *Comparison to other lagged effects models*

A number of approaches have confronted the same challenges addressed by ALT-SR. In addition to a comparison with a CLPM, this study also shows differences in estimation between the ALT-SR model and a Fixed Effects Linear Panel Model (FE-LPM), as well as a Maximum Likelihood Dynamic Panel Model (ML-DPM) (Allison, et al. 2017). For each of the models where such specification is possible, both fixed and free lagged effects were estimated. For the FE-LPM, models were estimated with and without a lagged dependent variable (Allison, 2015). Each of these models offered only a partial separation of *between*-unit relationships from *within*-unit dynamics. The FE-LPM model allowed for the inclusion of differing case-level intercepts and linear trajectories in the dependent variable through the inclusion of local authority fixed-effects and interaction effects, but lagged effects could then only be estimated as fixed over time. The ML-DPM allowed adjustment for differing intercepts of CIN rate and their covariance with expenditure at each time point, but not for trajectories.

### *Estimation*

Model estimation for structural equation models was performed using the *lavaan (0.6-7)* package in *R* version 3.6 (Rosseel, 2012; R Core Team, 2019). Estimation of FE-LPM was performed using the *fixest (0.7.1)* package (Bergé, 2018). Structural equation models were first estimated using a maximum likelihood estimator with robust standard errors, then bias-corrected 95 per cent confidence intervals were calculated from 10,000 bootstrap samples per model. For FE-LPM, clustered standard errors were used to calculate 95 per cent confidence intervals. As there is no external package for estimating ML-DPMs in *R*, these were specified manually in *lavaan* using code from Allison, et al. (2017). ALT-SR models included time-adjacent residual covariance parameters to control for the effects of unobserved time-varying covariates (Grilli & Varriale, 2014; Isiordia & Ferrer, 2018); missing data was handled using Full Information Maximum Likelihood (Little, et al. 2014). All data and analysis code are published in an online repository: [https://github.com/cjrwebb/cin-spend-rv](https://github.com/cjrwebb/cin-spend-rv)

## Data

Data on local authority Children in Need rates are from England's Children in Need Census (Department for Education, 2019) and data on expenditure is taken from Section 251 local government spending returns (Department for Education, 2020). Non-safeguarding, non-children looked after expenditure was the total expenditure spent on the following categories: Sure Start and early years;

family support services; services for young people; youth justice; and ‘other’ children’s and families’ services. As such, this largely captures early help and family support services as opposed to child protection social work activities or services for children in care. Precise early help and family support expenditure categories are not possible to derive due to inconsistency in reporting between local authorities and changes to spending categorisation over time (Webb & Bywaters, 2018). Per capita estimations of spending were calculated using ONS population estimates for people aged 0-17 by local authority. Expenditure and CIN rates were transformed to their natural log values, meaning cross-lagged regression coefficients represent percentage changes in the one variable for a one per cent increase in the other. Descriptive statistics for all untransformed variables are provided in table 1.

Indices of Multiple Deprivation (IMD) scores were sourced from the Ministry of Housing, Communities & Local Government as a measure of local deprivation (MHCLG, 2015). The IMD is not comparable between years, and is calculated every five years. IMD scores are based on income deprivation (22.5%); employment deprivation (22.5%); education, skills and training deprivation (13.5%); health deprivation and disability (13.5%); crime (9.3%); barriers to housing and services (9.3%); and living environment deprivation (9.3%). IMD scores were standardised for all analyses. A one-standard deviation increase in IMD score is approximately equal to an increase of 10 per cent of the population with equivalised household incomes that are less than 60 per cent of the median national income (Webb, et al. 2020).

**Table 1: Descriptive Statistics for Expenditure, Children in Need rates, and IMD Score (pre-transformation)**

| Variable | N | Missing | Complete Rate | Mean | SD | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|---|---|---|---|
| Non-Safeguarding, non-Looked After Spend per Child 2011 | 149 | 0 | 1 | 481.98 | 194.5 | 341.81 | 449.35 | 573 |
| Non-Safeguarding, non-Looked After Spend per Child 2012 | 149 | 0 | 1 | 383.56 | 135.09 | 304.05 | 353.02 | 450.9 |
| Non-Safeguarding, non-Looked After Spend per Child 2013 | 149 | 0 | 1 | 354.56 | 138.73 | 265.62 | 323.63 | 405.29 |
| Non-Safeguarding, non-Looked After Spend per Child 2014 | 149 | 0 | 1 | 329.49 | 116.86 | 250.09 | 304.27 | 373.53 |
| Non-Safeguarding, non-Looked After Spend per Child 2015 | 149 | 0 | 1 | 309.21 | 119.68 | 235.14 | 280.63 | 349.35 |
| Non-Safeguarding, non-Looked After Spend per Child 2016 | 149 | 0 | 1 | 277.25 | 99.54 | 219.31 | 252.2 | 312.92 |
| Non-Safeguarding, non-Looked After Spend per Child 2017 | 149 | 0 | 1 | 250.74 | 94.77 | 189.73 | 237.91 | 282.54 |
| Non-Safeguarding, non-Looked After Spend per Child 2018 | 149 | 0 | 1 | 234.69 | 91.32 | 178.13 | 219.29 | 276.74 |
| Non-Safeguarding, non-Looked After Spend per Child 2019 | 149 | 0 | 1 | 229.17 | 93.01 | 173.23 | 214.74 | 265.11 |
| Children in Need Rate per 10,000 2011 | 145 | 4 | 0.97 | 362.6 | 105.48 | 286.9 | 352.8 | 419.7 |
| Children in Need Rate per 10,000 2012 | 147 | 2 | 0.99 | 351.23 | 110.53 | 260.58 | 340.36 | 419.75 |
| Children in Need Rate per 10,000 2013 | 146 | 3 | 0.98 | 358.27 | 113.07 | 273.12 | 344.22 | 423.86 |
| Children in Need Rate per 10,000 2014 | 148 | 1 | 0.99 | 369.67 | 117.22 | 285.25 | 358.8 | 428.95 |
| Children in Need Rate per 10,000 2015 | 149 | 0 | 1 | 363.06 | 105.79 | 279.7 | 348.6 | 422.3 |
| Children in Need Rate per 10,000 2016 | 149 | 0 | 1 | 363.61 | 104.62 | 295.4 | 343.2 | 416.3 |
| Children in Need Rate per 10,000 2017 | 149 | 0 | 1 | 356.05 | 97.3 | 295.1 | 336.5 | 411.4 |
| Children in Need Rate per 10,000 2018 | 149 | 0 | 1 | 365.87 | 101.3 | 295.53 | 349.85 | 434.17 |
| Children in Need Rate per 10,000 2019 | 149 | 0 | 1 | 361.14 | 102.72 | 292.05 | 339.03 | 418.79 |
| Indices of Multiple Deprivation Score | 149 | 0 | 1 | 23.09 | 8.06 | 17.16 | 23.09 | 28.57 |

Data corresponds to the 152 upper-tier local authorities that children’s services are organised into. Two local authorities were excluded: the City of London and the Isles of Scilly. Both of these local authorities serve very small populations and are not generally representative of typical local authorities in the country. Further, Haringey was excluded from the analysis due to it being a very significant Children in Need rate outlier in 2010/11, having almost twice as high CIN rates in that year than the second highest local authority. This was likely a consequence of the serious case review into the death of Peter Connolly in the years immediately prior (Jones, 2014). Two very affluent local authorities had values for expenditure and Children in Need rates in some years that were noticeably low. Model coefficients did not change significantly if these outliers were removed.

## Results and Interpretation

### *Comparison to CLPM, FE-LPM and ML-DPM*

Model fit, cross-lagged regression estimates, and latent variable means and correlations are shown alongside 95 per cent bias-corrected bootstrap confidence intervals in table 2. The ALT-SR model differs in model fit, point estimates, size of confidence intervals, and inference of significance on their basis from all other models. Estimates from each alternative model were not consistent with one another but the ways that the models differed was consistent with what would be expected given their differential treatment of unit intercepts and trends.

Estimates for the effects of expenditure in a given year on CIN rates trended upwards of ALT-SR estimates in the freely estimated lagged effects CLPM, in the fixed CLPM, in both FE-LPMs, and in the fixed ML-DPM. In particular, the significant *negative* estimates for the effect of lagged expenditure on CIN rates in the ALT-SR models were estimated to be significant in a *positive* direction in most cases for the CLPM, where there is no within/between decomposition of variance (Hamaker, et al. 2015). In the FE-LPMs, where adjustments are made for individual intercepts and slopes for CIN rate only, the lagged effect of expenditure was negative but not statistically significant regardless of whether an autoregressive parameter was included ($\beta_{y_t x_{t-1}}$= -0.04[-0.112, 0.032]). The ML-DPMs estimated lagged effects that were more positive than the ALT-SR before 2014/15-2015/16 and more negative after. This matches what would be expected given how the ML-DPM adjusts for random intercepts in the dependent variable and their association with values of the independent variable but does not consider growth, therefore likely overestimating effects at earlier time points and underestimating later time points when trends are negative.

This comparison shows that ALT-SR models may be valuable for estimating cross-lagged effects in studies where there is theorised to be a large influence from wider trends that exist either at the level of local government or from national policies. There are many such cases in social policy, where national policymaking, or even global trends, can confound variations in data at the local level, where policy implementation can often diverge and become a valuable source of natural variation. In such cases, it may be undesirable for these effects to be present in the analysis when *within*-unit relationships, such as the effectiveness of local services, are of interest. This may be especially true if such effects are hypothesised to influence both predictor and outcome variables in an analysis and may not be possible to fully control for using other approaches.

## Table 2: Comparison of ALT-SR, CLPM, FE-LPM, and ML-DPM

| | ALT-SR Free Lags [95% BCa Bootstrap] | ALT-SR Fixed Lags [95% BCa Bootstrap] | CLPM Free Lags [95% BCa Bootstrap] | CLPM Fixed Lags [95% BCa Bootstrap] | FE-LPM LDP [95% Clustered CI] | FE-LPM No LDP [95% Clustered CI] | ML-DPM Free Lags [95% BCa Bootstrap] | ML-DPM Fixed Lags [95% BCa Bootstrap] |
|---|---|---|---|---|---|---|---|---|
| **Model Fit** | | | | | | | | |
| Robust CFI | 0.964 | 0.955 | 0.959 | 0.957 | | | 0.924 | 0.968 |
| Robust TLI | 0.955 | 0.950 | 0.953 | 0.956 | | | 0.888 | 0.952 |
| SRMR | 0.054 | 0.058 | 0.093 | 0.113 | | | 0.287 | 0.201 |
| AIC | -1777.58 | -1762.76 | -1801.96 | -1809.22 | -1392.08 | -1380.90 | -1628.56 | -1775.46 |
| BIC | -1580.49 | -1606.85 | -1690.18 | -1738.62 | 129.14 | 137.52 | -1378.52 | -1522.48 |
| **Coefficients** | | | | | | | | |
| Autoregression CIN $\beta_{yy}$ | **0.191 [0.082, 0.297]** | **0.109 [0.053, 0.180]** | **0.826 [0.783, 0.861]** | **0.827 [0.784, 0.862]** | **0.093 [0.016, 0.171]** | | **0.623 [0.515, 0.723]** | **0.625 [0.51, 0.729]** |
| Autoregression Spend $\beta_{xx}$ | | | **0.854 [0.800, 0.895]** | **0.852 [0.797, 0.895]** | | | | |
| Lag Spend → CIN 2011/12 $\beta_{y_2x_1}$ | **-0.159 [-0.248, -0.068]** | **-0.107 [-0.174, -0.053]** | **0.092 [0.018, 0.176]** | **0.053 [0.026, 0.083]** | -0.040 [-0.112, 0.032] | -0.044 [-0.119, 0.031] | 0.012 [-0.064, 0.088] | -0.027 [-0.085, 0.023] |
| Lag Spend → CIN 2012/13 $\beta_{y_3x_2}$ | **-0.131 [-0.208, -0.05]** | .. | **0.116 [0.046, 0.191]** | .. | .. | .. | 0.03 [-0.047, 0.106] | .. |
| Lag Spend → CIN 2013/14 $\beta_{y_4x_3}$ | **-0.097 [-0.165, -0.024]** | .. | -0.012 [-0.083, 0.054] | .. | .. | .. | -0.09 [-0.177, -0.012] | .. |
| Lag Spend → CIN 2014/15 $\beta_{y_5x_4}$ | -0.07 [-0.135, 0.002] | .. | 0.07 [-0.013, 0.156] | .. | .. | .. | -0.021 [-0.118, 0.064] | .. |
| Lag Spend → CIN 2015/16 $\beta_{y_6x_5}$ | -0.039 [-0.106, 0.036] | .. | 0.061 [-0.002, 0.127] | .. | .. | .. | -0.014 [-0.085, 0.056] | .. |
| Lag Spend → CIN 2016/17 $\beta_{y_7x_6}$ | -0.011 [-0.088, 0.075] | .. | 0.022 [-0.071, 0.108] | .. | .. | .. | -0.063 [-0.163, 0.037] | .. |
| Lag Spend → CIN 2017/18 $\beta_{y_8x_7}$ | 0.026 [-0.067, 0.127] | .. | 0.056 [-0.005, 0.118] | .. | .. | .. | -0.037 [-0.116, 0.034] | .. |
| Lag Spend → CIN 2018/19 $\beta_{y_9x_8}$ | 0.056 [-0.056, 0.174] | .. | 0.042 [-0.018, 0.103] | .. | .. | .. | -0.036 [-0.114, 0.039] | .. |
| Lag CIN → Spend 2011/12 $\beta_{x_2y_1}$ | **-0.041 [-0.075, -0.007]** | **-0.021 [-0.028, -0.014]** | -0.016 [-0.114, 0.099] | **0.077 [0.042, 0.124]** | | | | |
| Lag CIN → Spend 2012/13 $\beta_{x_3y_2}$ | -0.043 [-0.103, 0.018] | .. | 0.066 [-0.016, 0.165] | .. | | | | |
| Lag CIN → Spend 2013/14 $\beta_{x_4y_3}$ | -0.023 [-0.104, 0.06] | .. | 0.071 [-0.006, 0.152] | .. | | | | |
| Lag CIN → Spend 2014/15 $\beta_{x_5y_4}$ | 0.015 [-0.086, 0.121] | .. | 0.029 [-0.046, 0.117] | .. | | | | |
| Lag CIN → Spend 2015/16 $\beta_{x_6y_5}$ | 0.065 [-0.057, 0.199] | .. | 0.068 [-0.028, 0.169] | .. | | | | |
| Lag CIN → Spend 2016/17 $\beta_{x_7y_6}$ | 0.133 [-0.018, 0.303] | .. | **0.162 [0.077, 0.260]** | .. | | | | |
| Lag CIN → Spend 2017/18 $\beta_{x_8y_7}$ | **0.226 [0.032, 0.444]** | .. | **0.132 [0.029, 0.248]** | .. | | | | |
| Lag CIN → Spend 2018/19 $\beta_{x_9y_8}$ | **0.343 [0.093, 0.618]** | .. | 0.090 [-0.011, 0.205] | .. | | | | |
| **Latent Variable Means** | | | | | | | | |
| CIN Intercept Mean $\mu_{Y_\alpha}$ | **5.847 [5.801, 5.894]** | **5.851 [5.807, 5.897]** | | | | | | |
| CIN Slope Mean $\mu_{Y_\beta}$ | **-0.178 [-0.301, -0.053]** | -0.007 [-0.015, 0.001] | | | | | | |
| Spend Intercept Mean $\mu_{X_\alpha}$ | **6.107 [6.046, 6.166]** | **6.108 [6.048, 6.168]** | | | | | | |
| Spend Slope Mean $\mu_{X_\beta}$ | 0.083 [-0.141, 0.305] | **-0.087 [-0.109, -0.064]** | | | | | | |
| Spend Quadratic Mean $\mu_{X_\delta}$ | **-0.053 [-0.089, -0.018]** | 0.001 [-0.002, 0.003] | | | | | | |
| **Latent Variable Correlations** | | | | | | | | |
| CIN Intercept & CIN Slope $\rho_{Y_\alpha Y_\beta}$ | **-0.673 [-0.82, -0.439]** | **-0.485 [-0.647, -0.269]** | | | | | | |
| Spend Intercept & Spend Slope $\rho_{X_\alpha X_\beta}$ | **-0.44 [-0.628, -0.185]** | -0.254 [-0.452, 0.014] | | | | | | |
| CIN Intercept & Spend Intercept $\rho_{Y_\alpha X_\alpha}$ | **0.789 [0.681, 0.872]** | **0.740 [0.645, 0.833]** | | | | | | |
| CIN Intercept & Spend Slope $\rho_{Y_\alpha X_\beta}$ | **-0.405 [-0.609, -0.156]** | **-0.213 [-0.436, -0.015]** | | | | | | |
| Spend Intercept & CIN Slope $\rho_{Y_\beta X_\alpha}$ | **-0.493 [-0.716, -0.193]** | **-0.237 [-0.456, -0.002]** | | | | | | |
| CIN Slope & Spend Slope $\rho_{Y_\beta X_\beta}$ | 0.078 [-0.185, 0.356] | 0.262 [-0.021, 0.599] | | | | | | |

Bolded estimates represent Bias Corrected Confidence Intervals that do not cross zero

## Table 3: Model Output for Final ALT-SR Models

| | ALT-SR Model (No IMD) | | | | | ALT-SR Model (IMD) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 95% BCa Bootstrap CIs | | | | | 95% BCa Bootstrap CIs | |
| | Est. | SE | p | Lower | Upper | Est. | SE | p | Lower | Upper |
| **Model Fit** | | | | | | | | | | |
| Robust CFI | 0.964 | | | | | 0.963 | | | | |
| Robust TLI | 0.955 | | | | | 0.953 | | | | |
| SRMR | 0.054 | | | | | 0.052 | | | | |
| AIC | -1777.6 | | | | | -1911.1 | | | | |
| BIC | -1580.5 | | | | | -1702.3 | | | | |
| **Autoregression** | | | | | | | | | | |
| Autoregression CIN $\beta_{yy}$ | 0.191 | 0.055 | 0.001 | 0.082 | 0.297 | 0.188 | 0.056 | 0.001 | 0.076 | 0.296 |
| **Cross-Lagged Regressions** | | | | | | | | | | |
| Lag Spend → CIN 2011/12 $\beta_{y_2x_1}$ | -0.159 | 0.046 | p<0.001 | -0.248 | -0.068 | -0.157 | 0.046 | 0.001 | -0.246 | -0.063 |
| Lag Spend → CIN 2012/13 $\beta_{y_3x_2}$ | -0.131 | 0.040 | 0.001 | -0.208 | -0.050 | -0.129 | 0.040 | 0.001 | -0.205 | -0.046 |
| Lag Spend → CIN 2013/14 $\beta_{y_4x_3}$ | -0.097 | 0.036 | 0.006 | -0.165 | -0.024 | -0.097 | 0.036 | 0.007 | -0.164 | -0.023 |
| Lag Spend → CIN 2014/15 $\beta_{y_5x_4}$ | -0.070 | 0.034 | 0.041 | -0.135 | 0.002 | -0.070 | 0.034 | 0.040 | -0.135 | 0.002 |
| Lag Spend → CIN 2015/16 $\beta_{y_6x_5}$ | -0.039 | 0.036 | 0.278 | -0.106 | 0.036 | -0.039 | 0.035 | 0.263 | -0.105 | 0.034 |
| Lag Spend → CIN 2016/17 $\beta_{y_7x_6}$ | -0.011 | 0.041 | 0.788 | -0.088 | 0.075 | -0.012 | 0.040 | 0.758 | -0.088 | 0.070 |
| Lag Spend → CIN 2017/18 $\beta_{y_8x_7}$ | 0.026 | 0.049 | 0.586 | -0.067 | 0.127 | 0.025 | 0.047 | 0.597 | -0.065 | 0.120 |
| Lag Spend → CIN 2018/19 $\beta_{y_9x_8}$ | 0.056 | 0.058 | 0.328 | -0.056 | 0.174 | 0.054 | 0.055 | 0.329 | -0.053 | 0.165 |
| | | | | | | | | | | |
| Lag CIN → Spend 2011/12 $\beta_{x_2y_1}$ | -0.041 | 0.017 | 0.018 | -0.075 | -0.007 | -0.042 | 0.017 | 0.014 | -0.075 | -0.008 |
| Lag CIN → Spend 2012/13 $\beta_{x_3y_2}$ | -0.043 | 0.031 | 0.163 | -0.103 | 0.018 | -0.044 | 0.030 | 0.144 | -0.103 | 0.017 |
| Lag CIN → Spend 2013/14 $\beta_{x_4y_3}$ | -0.023 | 0.042 | 0.587 | -0.104 | 0.060 | -0.024 | 0.041 | 0.556 | -0.102 | 0.058 |
| Lag CIN → Spend 2014/15 $\beta_{x_5y_4}$ | 0.015 | 0.052 | 0.772 | -0.086 | 0.121 | 0.014 | 0.052 | 0.794 | -0.083 | 0.117 |
| Lag CIN → Spend 2015/16 $\beta_{x_6y_5}$ | 0.065 | 0.065 | 0.316 | -0.057 | 0.199 | 0.064 | 0.064 | 0.320 | -0.055 | 0.194 |
| Lag CIN → Spend 2016/17 $\beta_{x_7y_6}$ | 0.133 | 0.082 | 0.104 | -0.018 | 0.303 | 0.132 | 0.080 | 0.100 | -0.016 | 0.299 |
| Lag CIN → Spend 2017/18 $\beta_{x_8y_7}$ | 0.226 | 0.104 | 0.030 | 0.032 | 0.444 | 0.226 | 0.102 | 0.027 | 0.037 | 0.436 |
| Lag CIN → Spend 2018/19 $\beta_{x_9y_8}$ | 0.343 | 0.132 | 0.010 | 0.093 | 0.618 | 0.344 | 0.129 | 0.008 | 0.103 | 0.609 |
| **Latent Variable Means** | | | | | | | | | | |
| CIN Intercept Mean $\mu_{Y_\alpha}$ | 5.847 | 0.024 | p<0.001 | 5.801 | 5.894 | 5.848 | 0.019 | p<0.001 | 5.811 | 5.884 |
| CIN Slope Mean $\mu_{Y_\beta}$ | -0.178 | 0.063 | 0.005 | -0.301 | -0.053 | -0.174 | 0.061 | 0.004 | -0.292 | -0.050 |
| | | | | | | | | | | |
| Spend Intercept Mean $\mu_{X_\alpha}$ | 6.107 | 0.030 | p<0.001 | 6.046 | 6.166 | 6.107 | 0.022 | p<0.001 | 6.065 | 6.149 |
| Spend Slope Mean $\mu_{X_\beta}$ | 0.083 | 0.114 | 0.465 | -0.141 | 0.305 | 0.089 | 0.112 | 0.426 | -0.135 | 0.306 |
| Spend Quadratic Mean $\mu_{X_\delta}$ | -0.053 | 0.018 | 0.003 | -0.089 | -0.018 | -0.054 | 0.017 | 0.002 | -0.089 | -0.020 |
| **Latent Variable Correlations** | | | | | | | | | | |
| CIN Intercept & CIN Slope $\rho_{Y_\alpha Y_\beta}$ | -0.673 | 0.098 | p<0.001 | -0.820 | -0.439 | -0.709 | 0.081 | p<0.001 | -0.828 | -0.509 |
| Spend Intercept & Spend Slope $\rho_{X_\alpha X_\beta}$ | -0.440 | 0.113 | p<0.001 | -0.628 | -0.185 | -0.093 | 0.144 | 0.515 | -0.351 | 0.214 |
| | | | | | | | | | | |
| CIN Intercept & Spend Intercept $\rho_{Y_\alpha X_\alpha}$ | 0.789 | 0.049 | p<0.001 | 0.681 | 0.872 | 0.557 | 0.101 | p<0.001 | 0.331 | 0.727 |
| CIN Intercept & Spend Slope $\rho_{Y_\alpha X_\beta}$ | -0.405 | 0.116 | p<0.001 | -0.609 | -0.156 | -0.050 | 0.129 | 0.702 | -0.303 | 0.211 |
| Spend Intercept & CIN Slope $\rho_{Y_\beta X_\alpha}$ | -0.493 | 0.133 | p<0.001 | -0.716 | -0.193 | -0.442 | 0.137 | 0.001 | -0.677 | -0.140 |
| CIN Slope & Spend Slope $\rho_{Y_\beta X_\beta}$ | 0.078 | 0.138 | 0.573 | -0.185 | 0.356 | -0.080 | 0.168 | 0.632 | -0.406 | 0.256 |
| **Latent Variable Regressions** | | | | | | | | | | |
| Std. IMD Score → CIN Intercept $\beta_{Y_\alpha z}$ | | | | | | 0.191 | 0.018 | p<0.001 | 0.157 | 0.227 |
| Std. IMD Score → CIN Slope $\beta_{Y_\beta z}$ | | | | | | -0.007 | 0.003 | 0.032 | -0.013 | -0.0005 |
| | | | | | | | | | | |
| Std. IMD Score → Spend Intercept $\beta_{X_\alpha z}$ | | | | | | 0.234 | 0.022 | p<0.001 | 0.195 | 0.278 |
| Std. IMD Score → Spend Slope $\beta_{X_\beta z}$ | | | | | | -0.018 | 0.005 | p<0.001 | -0.027 | -0.009 |

*Interpretation of Lagged Effects*

Model output for key parameters of ALT-SR models with and without the inclusion of IMD score are presented in table 3. Full model output, which includes variance and covariance estimates as well as factor loadings, is supplied in appendix B. A 1 per cent increase in expenditure in 2010/11 was associated with a -0.159 per cent decrease in CIN rate in 2011/12 ($\beta_{y_2x_1}$= -0.159 [-0.248, -0.068]). In the following years, a 1 per cent increase in expenditure was associated with a -0.131 per cent decrease in CIN rate ($\beta_{y_3x_2}$= -0.131 [-0.208, -0.050]) and for 2012/13–2013/14 a 1 per cent increase in expenditure was associated with a -0.097 per cent decrease in CIN rate ($\beta_{y_4x_3}$= -0.097 [-0.165, -0.024]). The effects of years following this were not significant according to bootstrapped confidence intervals, though the value for the regression of CIN rates in 2014/15 on expenditure in 2013/14 was significant according to a conventional p-value ($\beta_{y_5x_4}$= -.070 [-0.135, 0.002], p=0.040), and therefore may reflect a meaningful effect size through to 2014/15.

As the interpretation of coefficients for logged variables is relative it is necessary to scale coefficients to assess whether efficacy of services has decreased. Equivalent percentage increases required to match a 1 per cent increase in expenditure in 2010/11 were calculated for years from 2011/12 onwards to scale coefficients. Absolute changes in CIN rate were calculated using these scaled coefficients based on average CIN rates for each year. Scaled coefficients and average absolute change is presented in table 4. This shows that the efficacy of expenditure on reducing CIN rates fell absolutely as well as relatively throughout the decade from a -0.551 per 10,000 change in CIN for a £4.82 increase in spending per child to a -0.254 per 10,000 reduction for the same amount spent in 2013/14.

**Table 4: Scaled Coefficients for Lagged Expenditure Effects**

| Year | 1% Increase (£ per child) | 2010/11 Equivalent Increase (%) | Scaled Coefficient (%) | Absolute CIN change (N per 10,000) |
|---|---|---|---|---|
| 2010/11 | 4.82 | 1.00 | -0.157 | -0.551 |
| 2011/12 | 3.84 | 1.26 | -0.161 | -0.462 |
| 2012/13 | 3.55 | 1.36 | -0.131 | -0.359 |
| 2013/14 | 3.29 | 1.46 | -0.102 | -0.254 |
| 2014/15 | 3.09 | 1.56 | -0.060 | -0.142 |
| 2015/16 | 2.77 | 1.74 | -0.021 | -0.043 |
| 2016/17 | 2.51 | 1.92 | 0.048 | 0.091 |
| 2017/18 | 2.35 | 2.05 | 0.110 | 0.195 |

Table 5 presents the size of the effects based on average reductions in expenditure from 2010/11, as recent reductions in expenditure far exceed £4.82 per child. This provides a more policy-relevant estimate of the impact of real changes in funding over the decade, holding trajectories over time constant. It is important to state when using ALT-SR models that this is not necessarily an indication of how 'austerity-free' CIN rates may have looked, because national trends likely condition rationing within LAs, but an insight into the extent to which cuts to preventative services have contributed to rates of Children in Need if the thresholds and other trends that emerged under austerity are held constant.

Between 2010/11 and 2011/12 expenditure on non-safeguarding, non-children looked-after services fell by around £98.42 per child in an average local authority, a 20.4 per cent reduction. The expected increase in CIN rate within local authorities the following year is estimated to be around 3.65 per cent or 12.8 CIN per 10,000. For 2012/13, 2013/14 and 2014/15, the three years where the effect of lagged expenditure on CIN rates was significant or close to significant, the expected increase in CIN rates was approximately 14.5, 13.9, and 11.5 per 10,000 respectively. This represents between 3.16 to 4.04 per cent increases each year. Because the effects beyond 2015 were not statistically significant, we would not expect to see a consistent change in CIN rates.

**Table 5: Expected Effects for Average Reductions in Expenditure under Austerity**

| Year | Change in Spending from 2010/11 (£) | Change from 2010/11 Spending (%) | Expected CIN Rate Change (%) | Expected CIN Rate Change (N per 10,000) |
|---|---|---|---|---|
| 2010/11 - 2011/12 | -98.42 | -20.4 | 3.65 | 12.8 |
| 2011/12 - 2012/13 | -127.42 | -26.4 | 4.04 | 14.5 |
| 2012/13 - 2013/14 | -152.49 | -31.6 | 3.76 | 13.9 |
| 2013/14 - 2014/15 | -172.77 | -35.8 | 3.16 | 11.5 |
| 2014/15 - 2015/16 | -204.73 | -42.5 | 2.18 | 7.9 |
| 2015/16 - 2016/17 | -231.24 | -48.0 | 0.79 | 2.8 |
| 2016/17 - 2017/18 | -247.29 | -51.3 | -1.78 | -6.5 |
| 2017/18 - 2018/19 | -252.81 | -52.5 | -3.94 | -14.2 |

This is important considering the apparent emerging reciprocal lagged effect of CIN rates on expenditure that is significant since 2016/17. A 1 per cent increase in CIN rate in 2016/17 was associated with a 0.226 per cent increase in expenditure in 2017/18 ($\beta_{x_8 y_7}$= 0.226 [0.037, 0.436]). This increased to around 0.344 per cent in 2018/19 ($\beta_{x_9 y_8}$= 0.344 [0.103, 0.609]). This may indicate that a greater number of local authorities are responding to increases in CIN rates by increasing their expenditure on early help and family support services. There is a concern that services are now reinvesting into a preventative system that has become ineffectual.

### *Trends in Spend and CIN Trajectories Over Time*

Previous research has identified that expenditure on non-safeguarding, non-children looked-after services reduced dramatically in the first half of the decade (Webb & Bywaters, 2018). Because the model used logged values and quadratic components, which can be difficult to interpret, predicted trends for each local authority, and for high, low, and average levels of deprivation, have been back-transformed and are plotted in figure 3 to examine whether this trend appears to have continued throughout the rest of the decade.

Holding within-local authority dynamics constant, expenditure has continued to decrease throughout the 2010s in England. These decreases were larger for more deprived local authorities and smaller for less deprived local authorities ($\beta_{X_\beta z}$ = -0.018 [-0.027, -0.009]). Higher deprivation was associated with higher expenditure intercepts ($\beta_{X_\alpha z}$= 0.234 [0.195, 0.278]). The combination of these two patterns means that variation associated with deprivation has reduced over time, reflecting a more equal but perhaps less equitable distribution of resources from central government.

Trends in CIN rates have also been negative over the decade. Rates were generally higher in high deprivation local authorities and lower in low deprivation local authorities in 2010/11 ($\beta_{y_\alpha z}$= 0.191 [0.157, 0.227]), and have fallen faster in high deprivation local authorities than in low deprivation local authorities over the decade ($\beta_{y_\beta z}$= -0.007 [-0.013, -0.0005]). This may reflect decreasing need at a national level over time, but based on existing evidence may more likely reflect higher CIN thresholds related to rationing of services (Devaney, 2019, Hood, et al. 2020a, 2020b, Smith, et al. 2018). Lastly, the ALT-SR model tests for correlations between trends that are not already attributable to IMD score. Local authorities that had higher expenditure intercepts also had significantly larger 'reductions' in CIN rates over time ($\rho_{Y_\beta X_\alpha}$ = -0.442 [-0.677, -0.140]). Given the interpretation above, this may imply that local authorities with higher expenditure in 2010/11 were less able to retain lower thresholds for offering early help services to families.

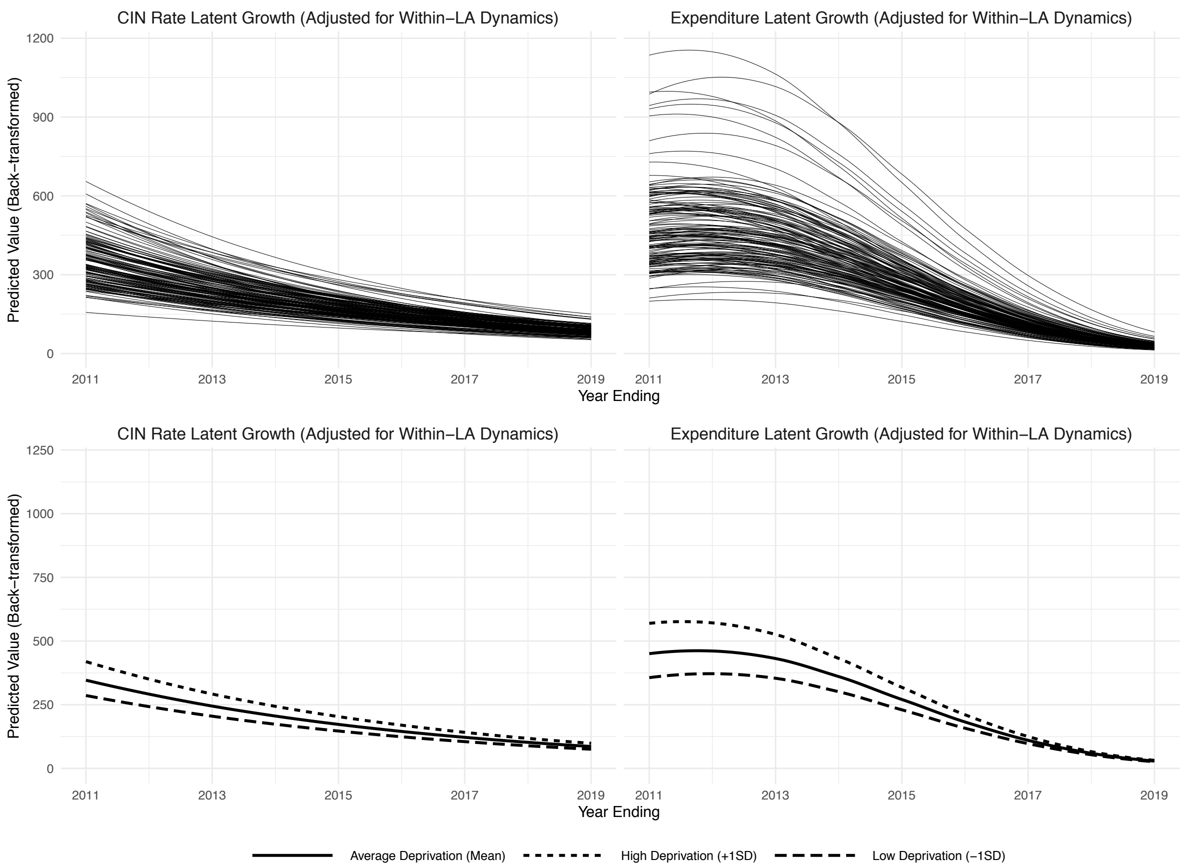


**Figure 3: Predicted trajectories over time from latent growth variables in ALT-SR model**

## Discussion

*The legacy of the Allen Report for Children in Need: ten years on*

An ambition of the Allen Report was to improve the effectiveness of support provided to children and families through greater use of early interventions that have high-quality evaluations. This ambition has influenced UK policy, including in the funding of the 'What Works for Children's Social Care' centre. The new evidence presented here suggests that increased effectiveness from investment in 'what has been shown to work' over the past ten years has not materialised, at least not in terms of reduced rates of children at risk of health or developmental impairments for equivalent levels of spending. Concerningly, effectiveness appears to have declined.

This decline in effectiveness may reflect an unintended consequence of this form of evidence-based policymaking under austerity. Severe cuts have fallen on preventative services (Webb & Bywaters, 2018), and a patchwork of evidence suggests that reductions in provision have been exacted on services that do not meet the 'gold-standard' of evidence; including children's centres and youth centres (Smith, et al. 2018, YMCA, 2020). There is evidence that the support retained has created a shift away from universal, open-access provision and 'ordinary help' and towards provision of programmes for multiple complex needs with targeted families (Smith, et al. 2018, Hood, et al. 2020b). In years where these services were more plentiful the effectiveness of local authority spending to prevent risks to child health and development appears to have been greater. The fears of researchers at the time, that this epistemological paradigm might diminish the effectiveness of children's services, appears to have been well-founded (Stewart-Brown 2011, 2012; White, at el. 2014).

## *Many trees, few forests: the need for an ecological view of early help and support*

Despite being ostensibly comprised of a larger proportion of services with 'gold-standard' evidence of effectiveness, the system as a whole seems to be achieving less in regard to reducing rates of Children in Need than it was before 2015. This could be a consequence of underfunding in general, if any service stretched thin enough becomes unable to address more universal needs of the population and must consequently fire-fight more complex problems (Devaney, 2019; Hood, et al. 2020a). However, these findings could also indicate some erroneous assumptions in child welfare policy.

The assumption that multiple high-quality interventions can be reliably scaled into an effective service ignores the complex ecology of child welfare services and children's lives (Bronfenbrenner, 1979). While much attention has been directed towards answering what makes an effective intervention, comparatively little has addressed what makes an effective *system*; nor have the methods that are needed been developed in the ways they have in clinical studies. As a result, it becomes easy to make the assumption that preventative services as a whole are equal to the effectiveness of their individual programmes. However, the diversity of services may create compounding benefits for addressing family needs – policymakers may benefit from a willingness to tolerate services with diverse forms of evidence.

More 'ordinary help' provided over long periods of time may help families address underlying problems such as poverty and enable more productive engagement with interventions that address acute or complex needs. Ordinary help provision may also reduce the impact of failure demand on costly early interventions by providing practical and community resources that can prevent problems from escalating to the point they require referral to an acute or crisis service. Creating better harmony between intervening early in a child's life and intervening early in the life of a problem, regardless of the age of the child or family circumstances, may create far more effective preventative systems on the whole than an intentional or unintentional focus on one or the other. Indeed, this might have happened if the Allen Report's recommendations that evaluation quality should only guide new funding, and not be the basis for dismantling existing forms of provision, had been possible to follow. National policies, including the decimation of the local authority central grant, made this impossible, and 'quality of evidence' has become a bigger requirement for justifying the continued existence of many services. Holistic assessments of different forms of evidence, and a 'systems-eye view' through the use of methods like ALT-SR, are recommended to create effective ecosystems for addressing need without putting services that provide ordinary help at risk.

*Limitations*

We remain unable to reliably investigate more nuanced categories of expenditure to explore which types of spending may be most effective for reducing CIN rates. While this article focuses on cross-referencing these findings with the policy focus on effectiveness and early intervention of the past decade, child welfare and policy change over this period has been complex and multi-faceted, and explorations of alternative or additional explanations should be encouraged. Further, this study does not examine how preventative spending might have affected other outcomes over time. These services might have become more effective at reducing rates of other state interventions like child protection plans or child removal into state care, which are salient concerns for local authorities, though this would still imply a failure to meet duties to children under the Children Act 1989.

We are also unable to disaggregate CIN into more specific categories before 2012, such as into Children in Need because of a risk of neglect compared to Children in Need because of disability. This may result in underestimating the effect of spending on reducing maltreatment or neglect related risk as children with disabilities remain 'in Need' under section 17 until adulthood. A profoundly different outcome measure is needed to assess the efficacy of preventative services for improving the lives of disabled children. Lastly, the study only observed one-year time lags, but it is possible that there are additional or cumulative effects over shorter or longer spans of time.

## Conclusions

Early help and family support expenditure funds many services that may not conform well to randomised controlled trials and, as such, this puts potentially effective services at risk of retrenchment (Stewart-Brown et al. 2011, 2012, White et al. 2014). Wider trends and individual case traits in administrative data mean that estimating system-level effects accurately can be difficult, and this is particularly acute in the case of assessing the impact of preventative spending on Children in Need rates. ALT-SR models are able to separate *within*-unit effects from *between*-unit effects beyond existing alternative models to address this problem. Doing so shows that investment in preventative support services was associated with significant and contextually large decreases in CIN rates before 2014/15: between 11.5 and 14.5 additional Children in Need per 10,000 per year within local authorities are attributable to adjacent-year effects of spending reductions under austerity between 2010 and 2015.

According to the UK Census, there were 11.3million people aged under 18 living in England in 2011, suggesting an additional 13,000 to 16,500 children and young people each year between 2010 and 2015 were put or kept at risk of developmental or health impairments as a result of local authority funding cuts to early help and family support services, after adjusting for differential and changing thresholds over time. As many of these children will have recurrent 'in Need' episodes in future years but not all of these will be the result of further preventative services expenditure cuts, it is reasonable to expect there is a significant cumulative impact of preventative spending cuts on total CIN rates in later years, though this is impossible to accurately estimate. For example, if every child remained in need for the five year duration, they would account for between 1-in-8 (13.3%) to 1-in-6 (16.9%) of all 390,000 CIN in England in 2015. Investment in early help and family support can reduce rates of Children in Need if policies are able to design effective systems.

However, despite the ambitions of the Allen Report (Allen, 2011) and the establishment of the 'What Works Network' to drive effectiveness in UK early intervention, it appears to have declined. These findings highlight the importance of routinely assessing local services as more than the sum of their parts and developing robust methods that enable such analyses. Going forward, the task of designing children's services may be better served by identifying effective ecosystems of support and the way that their internal components work together. Intentionally or unintentionally designing systems by scaling-up interventions with 'gold-standard' evidence without consideration of wider contexts may be a poor basis for policy, as others forewarned (Stewart-Brown, 2011, White, et al. 2014).

There are applications for ALT-SR models in social policy research beyond the example of child welfare services. Many areas of research use data at local government department, state, region, county, or country level that can be similarly confounded by larger individual differences and global trends that should be adjusted for to reliably estimate *within*-unit dynamics. ALT-SR's flexibility within a structural equation modelling framework means that related *between*- and *within*-unit research questions can be explored simultaneously to test multi-layered hypotheses.

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