Supplementary appendix

This appendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

Appendix

Contents

National trends

Figure 1. National trends in child poverty rates, rates of children in care at 31st March, per 10,000, and rates of children entering care, per 10,000, in England.
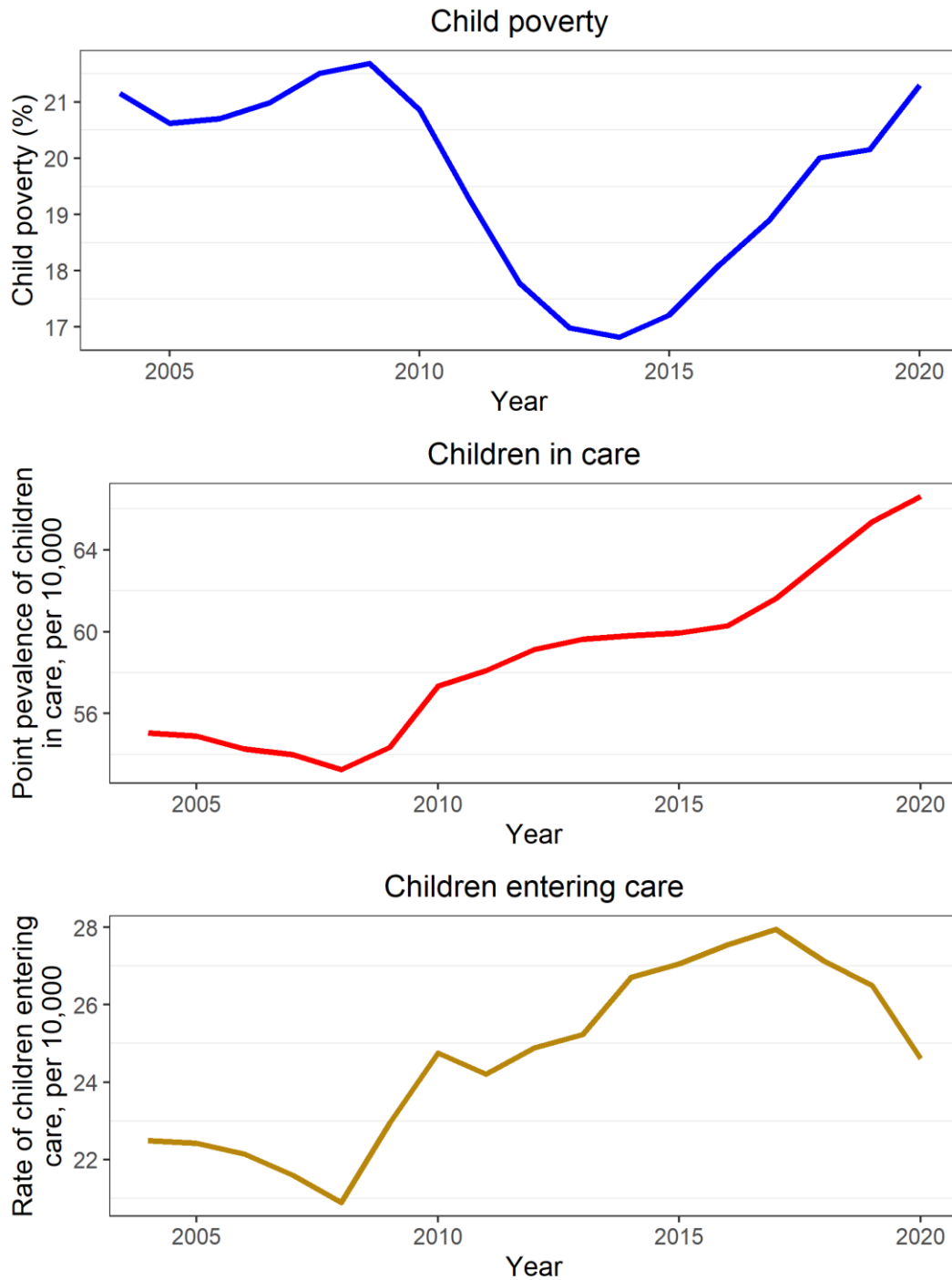
Note: Relative child poverty before housing costs data are taken from Households Below Average Income statistics, and represent three-year right-aligned rolling averages.

Suppressed data

In publicly available data, for the purposes of confidentiality, cell contents were supressed if the count of children was between 1 and 5 inclusive. Tables 1 and 2 show the count of local authorities for which data were supressed, by year and age group. There were fewer instances of suppression among children aged over 15 than among children in the relevant age groups, combined. And complete data on the total count of children entering care (all ages) were available for the period 2015-20. Therefore, to derive the count of children under 16 entering care, we randomly imputed an integer between 1 and 5 for children over 15 entering care (54 imputations), then subtracted counts for children over 15 from the total number of children entering care.

Complete data were available for children under 16 being made subject to a child protection plan and beginning an 'episode of need'. No imputation was necessary.

Table 1. Count of local authorities for which data are suppressed, by year and age groups of interest.

	Count of LAs for which data are suppressed				
	Age group				
Year	<1	1-4	5-9	10-15	Total
2015	9	4	7	1	21
2016	4	4	5	0	13
2017	5	6	3	2	16
2018	4	8	4	2	18
2019	5	7	7	2	21
2020	7	9	15	2	33
Total	34	38	41	9	122

Table 2. Count of local authorities for which data are suppressed, by year, for young people over the age of 15

	Count of LAs for which data are suppressed
Year	Age group >15
2015	15
2016	5
2017	6
2018	10
2019	6
2020	12
Total	54

Main model formula

Let:

- Y_{it} denote the sCLA / sCPP / sCIN rate, dependent on LA i and year t
- x_{1it} denote the child poverty rate, dependent on LA i and year t
- x_{2it} denote the employment rate, dependent on LA i and year t
- U_i denote LA random effects
- δ_t denote a series of dummy variables for each year t
- $\varepsilon_{it} \sim N(0, S_1)$ denote the random error for LA i in year t
- The overbar denote time-averages
- The superscript ^{w} or ^{b} denote decomposition into within- or between- LA effects of covariates

$$Y_{it} = \beta_0 + \beta_1^w(x_{1it} - \bar{x}_{1i}) + \beta_1^b(\bar{x}_{1i}) + \beta_2^w(x_{2it} - \bar{x}_{2i}) + \beta_2^b(\bar{x}_{2i}) + U_i + \delta_t + \varepsilon_{it}$$

Cost estimates

Corporate parenting costs associated with rising child poverty from 2015

Based on our estimates of the annual marginal difference between observed trends in sCLA rates, and trends that might have been expected had child poverty rates from 2015 remained stable, employment trends unaltered, we estimated the corporate parenting costs associated with the difference. We used 2015-20 data on mean weekly expenditure per child in care, compiled by the Local Government Association,[1] and data for the same period on the mean duration of last period of care for children leaving care, from the Department for Education.[2] For each year, we multiplied our difference estimates by the mean annual cost, and mean duration of placement. We summed costs over the time period to obtain our overall estimate.

Corporate parenting costs associated with the revocation of the £20-per-week Universal Credit uplift and minimum income floor

Using Legatum Institute estimates of the number of children protected from moving into poverty by the £20 weekly Universal Credit uplift and minimum income floor,[3] and Department for Work and Pensions data on the number of children in poverty in the UK,[4] we derived the percentage rise in child poverty represented by a revocation of these protective measures. We then multiplied this percentage rise by our model estimates to contextualise the impact of the revocation on children and families' involvement with children's social care.

Assuming that the relationship between child poverty and statutory child welfare interventions across the UK is comparable to that in England, and assuming comparable Social Metrics Commission and Households Below Average Income child poverty data, we estimate that the cut is likely to lead an additional 1,508 children entering care [95% CI 638–2,407]; 5,597 children becoming subject to a child protection plan [95% CI 3,596– 7,627]; and 15,138 additional children beginning an episode of need, or receiving some form of care and support from the local authority [95% CI 3,944–26,332], each year.

Accordingly, using data on mean weekly expenditure per child in care,[1] and mean duration of last period of care for children leaving care,[2] as above, we used 2020 data to estimate the corporate parenting costs associated with the additional children likely to enter care as a result of the revocation. This amounts to an additional £225.6 million [£95.4 million – £360.0 million], each year.

Robustness tests

Alternative data sources and measures

In robustness tests, as alternative measures of our exposure, we used: 1) absolute child poverty before housing costs, and 2) relative child poverty after housing costs. Absolute child poverty is measured against a static threshold that rises only with inflation, regardless of how the prosperity of a whole society may shift.[5] In official data this threshold is set to 2011, with absolute child poverty defined as the proportion of children living in households with less than 60% of the 2011 median income, adjusted for inflation.[6] Our measure of relative child poverty after housing costs is derived from before housing costs data by the Centre for Research in Social Policy. It takes into account the cost of rent, water, mortgage interest payments, buildings insurance payments, ground rent and service charges.[7]

Alternative modelling approaches

In our main analysis we used linear models: visually, we assessed that the relationship seemed to be more linear than log-linear. However, Poisson models may also be appropriate to the count data. We therefore also used an alternative modelling approach, fitting Poisson within-between regression models to data on the number of children experiencing the different interventions, with the log of the relevant child population as an offset in the analysis, instead of modelling intervention rates directly. In the Poisson models, we accounted for overdispersion by including observation-level random effects.[8]

Appendix

Excluding observations with extreme values

Using the Bonferroni outlier test,[9] we identified observations with extreme values that may be unduly influential in our models. We reran our main analyses, excluding each of these observations in turn.

Controlling for local authority prevention spend

Local authority spend on preventative children's services is intended to directly affect our outcome of interest by reducing the need for statutory interventions.[10] However, the relationship of prevention spend to our exposure may be more complex. Prevention spend may act as a mediator of the effect of child poverty on intervention rates: decisions about spend may be influenced by level of anticipated need in an area. This was our assumption in the main models; we deliberately do not control for likely causal mediators of the relationship of interest. However, prevention spend may also act as a confounder. Prevention strategies that target the social determinants of need, for example supporting families with benefits maximisation or finding employment, may alleviate child poverty, directly affecting both exposure and outcome.

We therefore conducted an additional robustness test, controlling for prevention spend per child in the previous financial year. Local authority finance data were taken from Section 251 spending returns.[11] In our measure of prevention spend per child under 18, we summed spend categories relating to early help and family support services (sure start and early years; family support services; services for young people; youth justice; other children and family services), and excluded categories relating to child protection social work or children already in care. The denominator was the population of children under 18, taken from Office for National Statistics (ONS) mid-year population estimates.

We hypothesised that prevention spend would likely have a lagged effect; this modelling decision ensures that prevention spend precedes the exposure so cannot be considered a direct mediator. Nevertheless, the correlation of observations across years within areas means that disentangling the potential pathways remains complex.

Discussion of robustness test results

Summary and full model output for robustness tests are shown in appendix tables 8-17. Robustness tests using alternative measures of our exposure show that, for our main outcome and more acute secondary outcome, findings are robust to the specification of poverty type

(appendix table 8). For children in need, however, the poverty measure accounting for housing costs revises the effect estimate downwards, with wide confidence intervals spanning the null.

The Poisson regression models validate our main finding of an association between child poverty rates and intervention rates within local authorities, across the spectrum of statutory interventions (appendix table 9). They additionally highlight the greater relative increase in children being placed on a child protection plan compared to our main outcome and less acute secondary outcome, for a given increase in the child poverty rate, holding employment rates constant.

Excluding from our analyses each observation with extreme values, identified from our models using the Bonferroni outlier test, suggests that no single observation is unduly influential (appendix tables 10-12). Overall, removal leads to slightly attenuated point estimates for the sCLA and sCPP models. This is to be expected given that the observations with extreme values tend to reflect more deprived local authorities experiencing greater increases in child poverty and intervention rates.

Across all outcomes, additionally controlling for local authority prevention spend per child in the previous year does not meaningfully alter our estimates (appendix table 13). In this robustness test, we considered prevention spend a confounder of the relationship of interest. However, if preventative services were in fact mediating the effect of child poverty by anticipating and addressing need, we might expect point estimates to be revised upwards when controlling for prevention spend. That our estimates are unaffected might indicate that, in the absence of national efforts to shift the distribution of children's exposure to poverty, local efforts to mitigate the consequences may simply be insufficient. Given the restricted time period for the analysis, our model may also be underpowered to detect the impact of preventative spend. Further research is needed to disentangle the respective roles of poverty and preventative services in determining children's outcomes.

Summary statistics

Table 3. Summary statistics for main outcome variable

Year	Main outcome variable			
	sCLA rate (per 100,000 children < 16)			
	Mean	Sd.	Min	Max
2015	280·05	110·91	98·28	678·29
2016	277·42	110·63	73·85	823·03
2017	290·52	132·43	58·53	996·18
2018	273·36	118·79	75·91	778·21
2019	262·07	125·49	87·95	693·29
2020	260·00	141·41	101·93	931·88

Table 4. Summary statistics for secondary outcome variables

Year	Secondary outcome variables							
	sCPP rate (per 100,000 children < 16)				sCIN rate (per 100,000 children < 16)			
	Mean	Sd.	Min	Max	Mean	Sd.	Min	Max
2015	605·70	220·05	159·34	1687·83	3374·99	1395·97	1269·09	7884·70
2016	623·70	244·42	173·61	1921·71	3295·18	1189·50	1120·76	7816·81
2017	640·42	250·79	216·42	2232·55	3317·60	1231·04	1241·81	9489·46
2018	651·59	254·26	223·29	1634·24	3299·84	1108·04	1221·51	6735·77
2019	617·13	241·93	160·96	1775·60	3262·75	1072·43	1114·47	6876·37
2020	622·71	271·87	167·88	1601·16	3234·23	1235·58	1041·92	8145·64

Table 5. Summary statistics for exposure variable

Year	Main exposure variable			
	Relative child poverty, before housing costs (%)			
	Mean	Sd.	Min	Max
2015	15·62	5·16	5·35	29·73
2016	16·41	5·75	5·21	32·41
2017	17·33	6·28	5·35	34·63
2018	18·48	6·55	6·26	37·42
2019	18·73	6·74	6·17	38·34
2020	19·75	7·24	6·88	38·63

Table 6. Summary statistics for control variable

Year	Control variable			
	Employment rate (%)			
	Mean	Sd.	Min	Max
2015	72·26	5·03	60·00	82·90
2016	73·31	4·87	60·40	84·20
2017	73·74	4·99	60·90	82·30
2018	74·52	4·89	58·70	84·40
2019	74·85	4·61	61·70	84·30
2020	75·56	4·58	64·50	84·20

Local authorities exhibiting large changes in exposure and outcomes

Figure 2. Associations between the change in the child poverty rate between 2015 and 2020, and intervention rates for each of our outcomes between 2015 and 2020, in each local authority, with 95% confidence intervals. Extreme values are labelled with the name of the corresponding local authority.
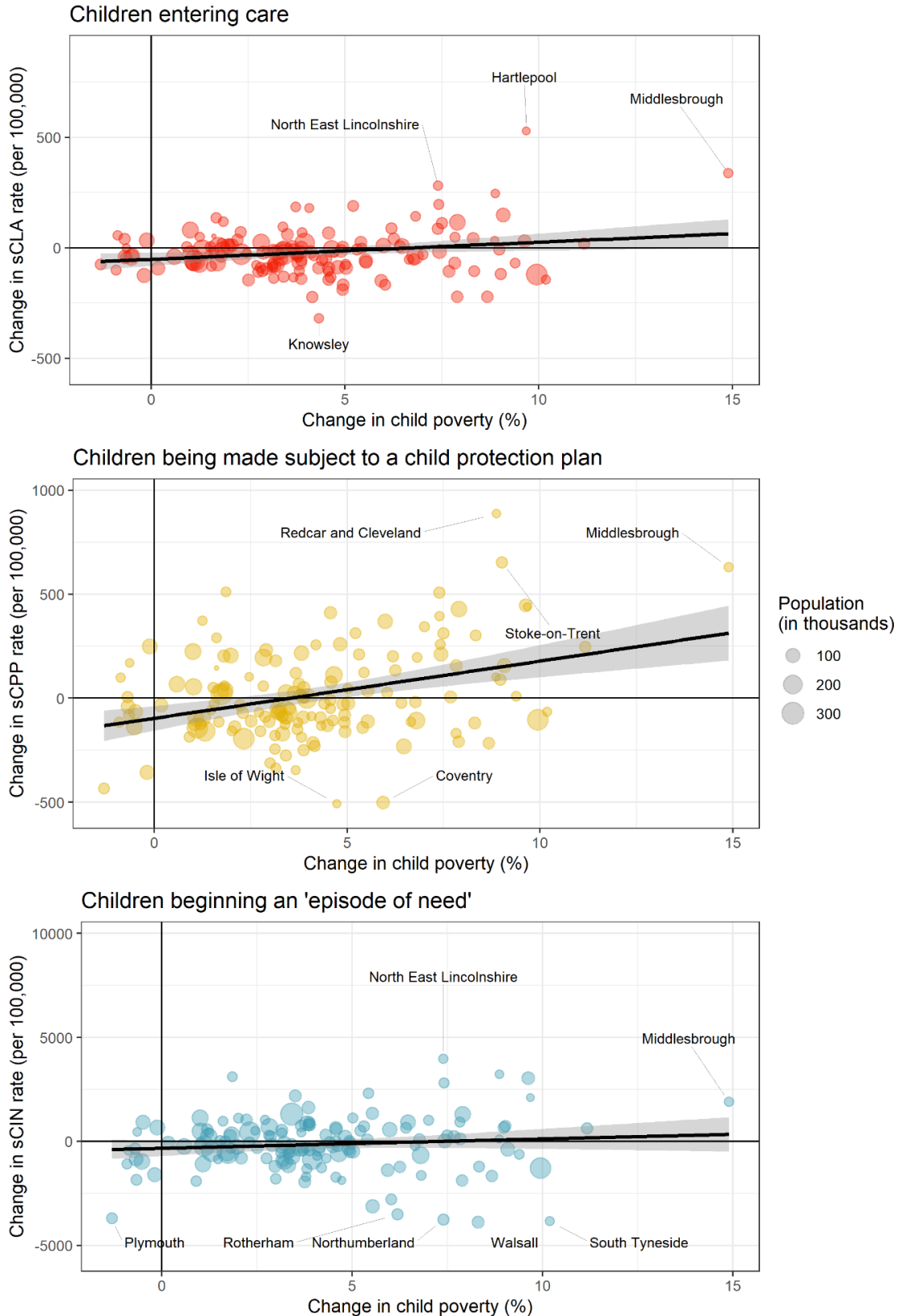
Full main linear regression model output

Table 7. Full main linear regression model output.

Parameter	sCLA		sCPP		sCIN	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part						
β_0 Intercept	335·81	230·17	429·19	458·52	8957·33	2088·45
β_1^w Relative poverty	5·21	1·55	19·35	3·57	52·17	19·69
β_1^b Relative poverty	8·85	1·99	18·01	3·97	38·84	18·09
β_2^w Employment	0·48	1·17	0·73	2·68	-20·86	14·79
β_2^b Employment	-2·71	2·72	-1·36	5·41	-83·71	24·63
δ_{2015}Year	-	-	-	-	-	-
δ_{2016}Year	-7·28	6·67	1·84	15·35	-99·38	84·68
δ_{2017}Year	0·85	7·18	0·58	16·51	-115·58	91·08
δ_{2018}Year	-22·72	8·26	-11·21	19·00	-177·54	104·79
δ_{2019}Year	-35·45	8·60	-50·66	19·78	-220·44	109·11
δ_{2020}Year	-43·21	9·87	-65·43	22·71	-287·74	125·26
Parameter	Estimate	Std. Dev.	Estimate	Std. Dev.	Estimate	Std. Dev.
Random part: LA level						
Intercept variance	7913	88·95	30720	175·3	611019	781·7
Random part: observation level						
Residual variance	3051	55·24	16148	127·1	491319	700·9
Deviance	9992·2		11419·5		14375·4	
Log likelihood	-4996·1		-5709·5		-7187·7	
Number of local authorities	147		147		147	
Number of observations	882		882		882	
Note: the outcome is the intervention rate, per 100,000 children						

Summary robustness test results

Table 8. Linear regression model output, using alternative measures of our exposure. For full model output, see tables 14-15.

Poverty measure	Within-LA effects: Annual change in the rate per 100,000 for a 1 percentage point increase in child poverty, controlling for employment rates [95% CI]		
	Children starting to be looked after	Children made subject to a child protection plan	Children beginning an episode of need
Relative poverty, before housing costs (main model)	5·2 [2·2, 8·3]	19·3 [12·4, 26·3]	52·2 [13·6, 90·8]
Absolute poverty, before housing costs	5·6 [1·9, 9·4]	22·9 [14·3, 31·5]	60·1 [12·6, 107·6]
Relative poverty, after housing costs	5·9 [3·3, 8·5]	16·3 [10·3, 22·4]	18·6 [-15·0, 52·3]

Table 9. Poisson regression model output, using our main exposure, relative child poverty before housing costs. For full model output, see table 16.

	Children starting to be looked after	Children made subject to a child protection plan	Children beginning an episode of need
Within-LA effects: Percentage change in the rate for a 1 percentage point increase in child poverty, controlling for employment rates [95% CI]	1·3% [0·3%, 2·2%]	2·4% [1·3%, 3·5%]	1·6% [0·5%, 2·6%]
Between-LA effects: Percentage change in the rate for a 1 percentage point increase in average child poverty rates between LAs, controlling for employment rates [95% CI]	3·8% [2·5%, 5·1%]	3·4% [2·2%, 4·6%]	1·3% [0·3%, 2·4%]

Table 10. sCLA linear regression model output, excluding observations with extreme values, as identified using the Bonferroni outlier test.

Mean-shift outliers, identified using the Bonferroni outlier test		sCLA model estimates excluding outlier observation
Local authority	Year	Within-LA effects: Annual change in the sCLA rate per 100,000 for a 1 percentage point increase in child poverty, controlling for employment rates [95% CI]
Hartlepool	2015	4.5 [1.6, 7.5]
Middlesbrough	2020	4.0 [1.0, 7.1]
Hartlepool	2020	4.5 [1.5, 7.5]
North East Lincolnshire	2020	4.6 [1.6, 7.6]
Kingston upon Thames	2018	5.2 [2.2, 8.3]

Table 11. sCPP linear regression model output, excluding observations with extreme values, as identified using the Bonferroni test

Mean-shift outliers, identified using the Bonferroni outlier test		sCPP model estimates excluding outlier observation
Local authority	Year	Within-LA effects: Annual change in the sCPP rate per 100,000 for a 1 percentage point increase in child poverty, controlling for employment rates [95% CI]
Blackpool	2017	19.0 [12.1, 26.0]
Redcar and Cleveland	2020	18.2 [11.3, 25.1]

Table 12. sCIN linear regression model output, excluding observations with extreme values, as identified using the Bonferroni test

Mean-shift outliers, identified using the Bonferroni outlier test		sCIN model estimates excluding outlier observation
Local authority	Year	Within-LA effects: Annual change in the sCIN rate per 100,000 for a 1 percentage point increase in child poverty, controlling for employment rates [95% CI]
City of Nottingham	2017	39.7 [1.6, 77.9]
South Tyneside	2015	60.0 [21.7, 98.2]
NE Lincolnshire	2020	45.0 [6.8, 83.3]
Northumberland	2015	55.2 [17.0, 93.5]

Table 13. Summary of regression coefficients for the within-area change in our primary and secondary outcomes associated with a change in the child poverty rate, controlling for employment rates and prevention spend per child. For full model see table 18.

	Annual change in the rate per 100,000 for a 1 percentage point increase in child poverty, controlling for employment rates <u>and</u> prevention spend per child [95% CI]
Children starting to be looked after	5·3 [2·2, 8·3]
Children made subject to a child protection plan	19·6 [12·6, 26·6]
Children beginning an episode of need	51·9 [13·2, 90·5]

Full linear regression model output, using <u>absolute poverty before housing costs</u> as the exposure

Table 14. Full linear regression model output, using absolute poverty before housing costs as the exposure

Parameter	sCLA		sCPP		sCIN	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part						
β_0 Intercept	348·37	229·00	384·52	453·45	8670·51	2065·15
β_1^w Absolute poverty	5·61	1·91	22·87	4·40	60·06	24·23
β_1^b Absolute poverty	9·83	2·26	20·60	4·48	46·38	20·39
β_2^w Employment	0·57	1·17	1·07	2·69	-19·98	14·81
β_2^b Employment	-3·01	2·70	-1·39	5·35	-81·94	24·37
δ_{2015} Year	-	-	-	-	-	-
δ_{2016} Year	-1·01	6·60	25·93	15·20	35·05	83·78
δ_{2017} Year	13·60	6·81	49·30	15·66	14·69	86·31
δ_{2018} Year	-5·60	7·01	53·15	16·13	-4·63	88·88
δ_{2019} Year	-18·55	7·13	12·32	16·41	-50·79	90·42
δ_{2020} Year	-23·83	7·55	5·69	17·37	-95·32	95·73
Parameter						
Random part: LA level						
Intercept variance	7949	89·16	30592	174.9	608359	780·0
Random part: observation level						
Residual variance	3062	55·34	16198	127.3	491902	701·4
Deviance	9995·5		11421·2		14375·7	
Log likelihood	-4997·7		-5710·6		-7187·9	
Number of local authorities	147		147		147	
Number of observations	882		882		882	
Note: the outcome is the intervention rate, per 100,000 children						

Full linear regression model output, using <u>relative poverty after housing costs</u> as the exposure

Table 15. Full linear regression model output, using relative poverty after housing costs as the exposure

Parameter	sCLA		sCPP		sCIN	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part						
β_0 Intercept	1247·63	205·27	2435·98	409·09	9935·57	1752·71
β_1^w Relative poverty	5·91	1·34	16·33	3·10	18·64	17·15
β_1^b Relative poverty	-0·52	1·57	-2·67	3·13	27·15	13·41
β_2^w Employment	0·70	1·16	1·35	2·69	-20·14	14·87
β_2^b Employment	-12·72	2·31	-23·23	4·60	-99·94	19·70
δ_{2015} Year	-	-	-	-	-	-
δ_{2016} Year	-7·00	6·58	6·55	15·24	-70·10	84·30
δ_{2017} Year	-0·92	7·06	4·12	16·35	-60·20	90·45
δ_{2018} Year	-20·70	7·52	8·53	17·40	-68·84	96·26
δ_{2019} Year	-33·16	7·75	-28·96	17·94	-102·13	99·26
δ_{2020} Year	-36·71	8·20	-27·03	19·00	-119·54	105·09
Parameter						
Random part: LA level						
Intercept variance	9040	95·08	35199	187·6	612705	782·8
Random part: observation level						
Residual variance	3018	54·94	16183	127·2	495216	703·7
Deviance	10002·5		11439·6		14381·7	
Log likelihood	-5001·3		-5719·8		-7190·9	
Number of local authorities	147		147		147	
Number of observations	882		882		882	
Note: the outcome is the intervention rate, per 100,000 children						

Full <u>Poisson</u> regression model output

Table 16. Full Poisson regression model output.

Parameter	sCLA		sCPP		sCIN	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part						
β_0 Intercept	-6·46	0·74	-6·23	0·68	-1·90	0·62
β_1^w Relative poverty	0·01	0·00	0·02	0·01	0·02	0·01
β_1^b Relative poverty	0·04	0·01	0·03	0·01	0·01	0·01
β_2^w Employment	0·00	0·00	0·00	0·00	-0·00	0·00
β_2^b Employment	-0·00	0·01	0·01	0·01	-0·02	0·01
δ_{2015} Year	-	-	-	-	-	-
δ_{2016} Year	-0·02	0·02	0·00	0·02	-0·02	0·02
δ_{2017} Year	-0·00	0·02	0·01	0·03	-0·02	0·03
δ_{2018} Year	-0·07	0·03	0·00	0·03	-0·03	0·02
δ_{2019} Year	-0·13	0·03	-0·06	0·03	-0·05	0·03
δ_{2020} Year	-0·17	0·03	-0·09	0·04		
Parameter	Estimate	Std. Dev.	Estimate	Std. Dev.	Estimate	Std. Dev.
Random part: LA level						
Intercept variance	0·08	0·28	0·07	0·26	0·05	0·23
Random part: observation level						
Intercept variance	0·02	0·16	0·03	0·19	0·04	0·19
Deviance	8693·6		10283·3		13161·4	
Log likelihood	-4346·8		-5141·7		-6580·7	
Number of local authorities	147		147		147	
Number of observations	882		882		882	
Note: the outcome is the log of the intervention rate per 100,000 children						

Linear regression model output, <u>controlling for local authority prevention spend</u>

Table 17. Linear regression model output, additionally controlling for prevention spend per child the year before

	sCLA		sCPP		sCIN	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part						
β_0 Intercept	26·14	249·84	-80·24	502·02	5906·89	2255·14
β_1^w Relative poverty	5·25	1·55	19·56	3·57	51·86	19·70
β_1^b Relative poverty	9·96	1·98	19·82	3·98	49·82	17·89
β_2^w Employment	0·47	1·17	0·63	2·68	-20·71	14·80
β_2^b Employment	0·31	2·86	3·57	5·74	-53·81	25·78
β_3^w Prevention spend per child the year before	0·04	0·06	0·21	0·13	-0·30	0·73
β_3^b Prevention spend per child the year before	0·27	0·10	0·44	0·20	2·70	0·87
δ_{2015} Year	-	-	-	-	-	-
δ_{2016} Year	-6·91	6·70	3·92	15·38	-123·51	93·03
δ_{2017} Year	1·83	7·33	6·02	16·84	-189·58	108·70
δ_{2018} Year	-21·24	8·56	-2·95	19·68	-232·46	112·85
δ_{2019} Year	-33·96	8·89	-42·42	20·43	-298·46	127·87
δ_{2020} Year	-41·89	10·08	-58·08	23·15		
Parameter	Estimate	Std. Dev.	Estimate	Std. Dev.	Estimate	Std. Dev.
Random part: LA level						
Intercept variance	7486	86·52	29589	172.0	569096	754.4
Random part: observation level						
Residual variance	3049	55·22	16094	126.9	491203	700.9
Deviance	9984·1		11411·9		14366·1	
Log likelihood	-4992·0		-5705·9		-7183·0	
Number of local authorities	147		147		147	
Number of observations	882		882		882	
Note: the outcome is the intervention rate, per 100,000 children						

Appendix references

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Appendix

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