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Untangling Child Welfare Inequalities and the 'Inverse Intervention Law' in England

Calum Webb, the University of Sheffield
Paul Bywaters, Huddersfield University
Jonathan Scourfield, Cardiff University
Claire McCartan, Queen's University Belfast
Lisa Bunting, Queen's University Belfast
Gavin Davidson, Queen's University Belfast
Kate Morris, the University of Sheffield

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Abstract
This article addresses some potential limitations of key findings from recent research into inequalities in children's social services by providing additional evidence from multilevel models that suggest the socioeconomic social gradient and 'Inverse Intervention Law' in children's services interventions are statistically significant after controlling for possible confounding spatial and population effects. Multilevel negative binomial regression models are presented using English child welfare data to predict the following intervention rates at lower super output area-level: Child in Need (n = 2707, middle super output area [MSOA] n = 543, local authority [LA] n = 13); Child Protection Plan (n = 4115, MSOA n = 837, LA n = 18); and Children Looked After (n = 4115, MSOA n = 837, LA n = 18). We find strong evidence supporting the existence of a steep socioeconomic social gradient in child welfare interventions. Furthermore, we find certain local authority contexts exacerbate this social gradient. Contexts of low overall deprivation and high income inequality are associated with greater socioeconomic inequalities in neighbourhood intervention rates. The relationship between neighbourhood deprivation and children looked after rates is almost five times stronger in local authorities with these characteristics than it is in local authorities with high overall deprivation and low income inequality. We argue that social policy responses addressing structural determinants of child welfare inequalities are needed, and that strategies to reduce the numbers of children taken into care must address underlying poverty and income inequality at both a local and national level.

Keywords: social work, child protection, deprivation, income inequality, children's social care

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Highlights

- Multilevel models were used to reanalyse child welfare inequalities data
- Robust quantitative evidence for the 'inverse intervention law' and social gradient
- Findings are consistent, after controlling for confounding spatial and demographic factors

- The finding of an 'income inequality intervention law' mirrors international research on other social problems and on population health
- Low deprivation in local authorities and high income inequality exacerbate child welfare inequalities

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Abstract

This article addresses some potential limitations of key findings from recent research into inequalities in children's social services by providing additional evidence from multilevel models that suggest the socioeconomic social gradient and 'Inverse Intervention Law' in children's services interventions are statistically significant after controlling for possible confounding spatial and population effects. Multilevel negative binomial regression models are presented using English child welfare data to predict the following intervention rates at lower super output area-level: Child in Need (n = 2707, middle super output area [MSOA] n = 543, local authority [LA] n = 13); Child Protection Plan (n = 4115, MSOA n = 837, LA n = 18); and Children Looked After (n = 4115, MSOA n = 837, LA n = 18). We find strong evidence supporting the existence of a steep socioeconomic social gradient in child welfare interventions. Furthermore, we find certain local authority contexts exacerbate this social gradient. Contexts of low overall deprivation and high income inequality are associated with greater socioeconomic inequalities in neighbourhood intervention rates. The relationship between neighbourhood deprivation and children looked after rates is almost five times stronger in local authorities with these characteristics than it is in local authorities with high overall deprivation and low income inequality. We argue that social policy responses addressing structural determinants of child welfare inequalities are needed, and that strategies to reduce the numbers of children taken into care must address underlying poverty and income inequality at both a local and national level.

Introduction

Literature concerned with the relationship between family socio-economic status (SES), local contexts and social work interventions has continued to grow internationally in recent years (see, for example, Slack, et al., 2017; McAuley & Rose, 2019). In England, variations in children's chances of receiving a child protection intervention have been linked to socially structured inequalities (Bywaters, et al., 2014a; 2015). Pilot research using an inequalities lens led to a much wider project across the four United Kingdom countries which better evidenced the existence of both a strong social gradient in social work interventions and an 'inverse intervention law' in England (Bywaters, et al., 2014a; 2014b; 2015; 2018a; 2018b; Morris, et al., 2018).

The inverse intervention law refers to the finding that when comparing children living in neighbourhoods with equivalent levels of deprivation, a child in a less deprived local authority (larger geographical municipality) is more likely to experience a child protection intervention than a child in a more deprived local authority (*ibid*).[1] This is hypothesised to have resulted from differential levels of local authority (LA) expenditure relative to need, with less financially constrained, low deprivation LAs intervening more frequently in equivalent neighbourhoods as high cost interventions are rationed a little less stringently (Hood, et al., 2016). The findings of this research programme have been used in the development of new models for social work with families (Featherstone, et al., 2018) and the study has been replicated internationally, such as in Aotearoa New Zealand by Keddell, et al. (2019). Given this impact, the robustness of the study's main findings warrants further examination.

To date the evidence for these phenomena has come from descriptive data analyses that have not controlled for potential confounding factors. Arguments can be made that these SES-based child welfare inequalities may actually be artefacts of other relationships between other demographic characteristics and interventions that are well-documented in social work literature. Some of these competing explanations have been particularly absent in quantitative social work research. Narratives that reference spatial concentrations of child abuse and neglect are common among social workers (Morris, et al. 2018) but quantitative spatial analysis of child abuse and neglect is sparse, although there has been some research of this type in the US (Hillier, 2007). Building the strength of the socioeconomic inequalities argument in relation to child welfare intervention requires that these competing explanations are properly accounted for and, to the extent that the data allow, we address these here by presenting the findings of a complex model that controls for neighbourhood demographics and spatial autocorrelation.

We present some justification for the confounding factors we include in our analysis in a brief literature review below. We focus on six potential confounding factors that appear in the literature, all being covariates with poverty. These are: place, ethnicity, unemployment, infant mortality, income inequality, and population education. As an example, poverty is heavily geographically concentrated (Kavanagh, et al., 2016), and, as noted, previous research has highlighted that social workers often reflect heavily on locales themselves and less on their shared underlying characteristics like deprivation level (Morris, et al. 2018). Therefore, it may be reasonable to suggest that socioeconomic child welfare intervention inequalities actually reflect spatial closeness of children at risk, not an association between poverty and child protection. Even if this is unlikely, failure to address this weakness in our quantitative analysis means we cannot truly know whether socioeconomic evidence is robust. The effects need to be 'disentangled'.

Such confounding factors did not feature in the initial analysis of child welfare inequalities (e.g. Bywaters, et al., 2014a; 2018a; 2018b) as the quality of data precluded this. To some extent, the quality of data still obscures a full analysis of the chances of intervention for individual children. The main obstacle is that in the UK information is collected routinely on children in the child protection systems but no data – either demographic or socio-economic – is collected about parental or family circumstances. We therefore are limited to presenting a neighbourhood-level analysis by linking child protection data with lower super

[1] The name 'inverse intervention law' comes from a concept in health inequalities literature, the 'inverse care law' (Tudor Hart, 1971). We maintain this nomenclature to draw explicit parallels to health inequalities.

output area (LSOA) level data on deprivation using UK IMD scores. These scores capture relative income and employment deprivation as well as deprivation in the form of access to key services.

A primary contribution of this paper is in the addition of spatial autocorrelation and the parameterisation of the inverse intervention law as a cross-level interaction between local authority level deprivation and lower super output area deprivation, allowing the scale of the inverse intervention law to be quantified and for other types of contextual 'laws' to be tested. This allows us to answer whether the 'inverse intervention law' that has been identified in more descriptive work carries statistical significance and whether the relationship between income inequality and child welfare interventions mirrors similar relationships in public health literature. We argue that if contextual effects are large in scale policy responses at the local level only will have limited success in alleviating child welfare inequalities.

Literature Review

Child welfare inequalities are defined as occurring 'when children and/or their parents face unequal chances, experiences or outcomes of involvement with child welfare services that are systematically associated with structural social dis/advantage and are unjust and avoidable' (Bywaters et al., 2015: 100). Inequity can be seen, for example, in differences in the chances of children being taken into care depending on their ethnic heritage or their family's socioeconomic characteristics (Bywaters, et al., 2018a; 2019). Within these inequities are recurrent patterns of association between levels of socioeconomic status and child welfare intervention rates. This relationship is referred to throughout as the 'social gradient' in child welfare intervention (*ibid*). Further, the same research into child welfare inequalities found that this social gradient differs substantially depending on the levels of deprivation in the larger geographical area: there are greater inequalities in intervention rates between poorer and more affluent neighbourhoods when the overall level of deprivation in the wider administrative area is lower.

The first potential confusion to be disentangled refers to the spatial proximity of children subject to child protection interventions and the feasible argument that such interventions may be spatially concentrated, perhaps as a result of territorial stigma associated with certain neighbourhoods and communities that is often, but may not necessarily, be associated with deprivation (Hillier, 2007; Cummins, 2016; Wacquant, 2009; Wacquant, et al., 2014). Another spatially located issue is that of community assets in preventing child neglect and abuse, and the differential perceptions of communities held by social workers and residents (McDonell, et al., 2015; Maguire-Jack and Font, 2016; 2017; Maguire-Jack and Showalter, 2016; Gross-Manos, et al., 2018). As McDonell et al. (2015) summarise, there is some evidence that the care and support of children is improved where there are: good social networks and social engagement across families, schools and community institutions; higher perceived social cohesion; stronger social capital; and more involvement of neighbours. Such spatial clustering of low and high community assets may be entangled with deprivation and intervention.

Secondly, there is the well-documented if not necessarily well understood relationship between ethnicity and child welfare interventions (Barn, 2007; Bernard & Gupta, 2008;

Owen & Statham, 2009; Bywaters, et al., 2014b, 2017, 2019). Different ethnic groups often have divergent intervention rates with many Black, Asian, and Minority Ethic (BAME) groups being disproportionately represented in the child protection system. In England the social gradient appears to differ substantially between ethnic groups, with some minority ethnic groups experiencing higher rates of intervention in low deprivation areas but lower rates of intervention in high deprivation areas, relative to the White British child population (Bywaters, et al. 2019). Most BAME populations are also disproportionately at risk of poverty (Platt, 2007). As socioeconomic status, neighbourhood deprivation and ethnicity are so closely related we might expect a reasonable degree of confoundment. Furthermore, there is the issue of high levels of segregation between and within ethnic groups in England and Wales (Catney, 2017), a spatial factor that further undermines confidence in any socioeconomic social gradient argument without sufficient controls. It is difficult to say without a complex model whether deprivation-based child protection inequalities are simply reflections of wider ethnic inequalities or whether the two operate independently.

Parental education has emerged as a ubiquitous protective factor in programmes designed to reduce the incidence of child neglect and abuse, with strong evidence that low levels of both paternal and maternal education levels are associated with increased risks of child maltreatment (Sidebotham & Golding, 2001; Mulder, et al., 2018). However, many of these studies have historically neglected to incorporate structural factors such as poverty into their analysis (Metzler et al, 2017). Unsurprisingly, lower educational attainment is associated with lower income and a higher risk of poverty (Pantazis, et al., 2006). Therefore, it is not unreasonable to suggest that the social gradient may otherwise be reflecting the relationship between parental education and risk of child maltreatment and subsequent child welfare interventions, partcularly where parents with higher education backgrounds may be more comfortable navigating the child protection system. Effective policy recommendations are likely to be profoundly different if, in actuality, population education levels were a stronger predictor of social work interventions than deprivation.

Lastly, evidence by Eckenrode, et al. (2014) identified a relationship between income inequality and child maltreatment. This mirrors broader patterns of association between inequality and social problems that have been at the centre of public health debate for at least a decade (Pickett & Wilkinson, 2015; Uphoff & Pickett, 2018). Such a potential relationship has been of growing interest for understanding child welfare inequalities, where an increasing focus on seeing intervention through a social inequalities lens has been identified as a key priority for new research (Nichols, 2015; Featherstone, et al., 2018). Economic inequality has become demonstrably associated with a multitude of social problems, it is therefore important to assess whether the relationship between social problems and income inequality extends to child welfare interventions in a complex analysis.

Data & Method

This section outlines the methods and data used to answer the following research questions:

1. Is the social gradient identified in previous descriptive research statistically significant after controlling for possible confounding factors?
2. How strong is the 'inverse intervention law', and is it statistically significant?

3. Is local authority income inequality associated with significantly steeper social gradients in child welfare intervention?

This paper uses data from the Child Welfare Inequalities Project (Bywaters, et al., 2017b) linked to additional administrative data. Data sets included:

- Children's services data for all children assessed as 'in need' of services, including details about their age, gender, ethnicity, and whether they were subject to either child protection plan or looked after (in State care) interventions, at 31st March 2015, linked to the LSOA code of their family home, or the home address from which they entered care.
- LSOA-level data including 2015 Index of Multiple Deprivation (IMD) score and estimates of child population size and ethnic density (2011 Census adjusted for LSOA-level population growth). IMD consists of several domains of deprivation, weighted as follows: 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%); living environment deprivation (9.3%) (Department for Communities and Local Government, 2016).
- Local Authority level data including estimates of infant mortality from the Office for National Statistics, a five year average of Job Seeker's Allowance claimant rate from the Department of Education's Local Authority Interactive Tool (2013-2018), the proportion of the population with Level 4 or higher education qualifications (roughly equivalent to a foundation degree or above) from the 2011 Census, and estimates of income inequality before housing costs estimated from summary data of household income from CACI Limited's Paycheck data set (2019), as used in previous research on inequality (Fone et al. 2013).

'Child in need' status refers to children who have been identified as in need by their local authority under the statutory definition outlined in the Children's Act 1989 (S.17). Children are 'in need' if they are unlikely to 'achieve or maintain, or have the opportunity of achieving or maintaining, a reasonable standard of health or development without the provision for them of services by a local authority'; or, 'their health or development is likely to be significantly impaired, or further impaired, without the provision for them of such services'; or, if they are living with a disability (Department for Education, 2018: 5). The status of 'in need' is required in order to access certain kinds of help that may be welcomed by some families, though not all, as the category can also indicate professional concern about how a child is being cared for.

A child protection plan status reflects a step-up in intervention where a local authority has identified that a child is suffering abuse or neglect, or is at significant risk of harm and suffering, and is now working with the family to resolve this risk. Children looked after (CLA) status refers to children who are under the care of the state. Most have been separated from their birth families following child protection concerns and are living with foster parents or in an institutional setting. Some children are placed with extended family. Children who have been adopted or are on Special Guardianship Orders (longer-term kinship care) are not counted as 'children looked after' in official statistics. Of these three child welfare categories, child protection plans and children being looked after statuses usually involve considerably more involuntary arrangements than are found for a child involved with Children's Social Services because they are 'in need'.

Overall, the data covered 52,179 Children in Need; 6,716 children on child protection plans, and 8,865 children looked after within 4115 LSOAs with each LSOA consisting of between around 470 and 1000 households. This figure equates to approximately 12 per cent of the total population of children on protection plans or looked after in England. Thirteen local authorities (8 per cent of all LAs) with adequate data on Children in Need were used in the CIN model and eighteen local authorities (12 per cent of all LAs) were used in the analysis of Child Protection Plan and Children Looked After rates. The reason for this discrepancy is that in the original Child Welfare Inequalities Project study only thirteen of the local authorities provided full, accurate data on children in need. The eighteen local authorities from the Child Welfare Inequalities Project were chosen using a stratified sampling frame, ensuring local authorities were selected from all regions in England with a range of levels of deprivation, population, geographical size and administrative structure. Nonetheless, the possible lack of representativeness of Children in Need data for the five local authorities excluded from the CIN analysis should be kept in mind when considering the findings, as we can be less confident of their generalisability.

Summary statistics for all variables included in the models are shown in table one. Income inequality estimates were based on 1,000 bootstraps of a simulation algorithm that extrapolates income distributions from detailed summary statistics of household income in bands of £5,000, iteratively adjusted for skew at the positive tail of income distributions. Gini coefficients - a commonly-used measure of inequality (De Maio, 2007) - were then calculated based on these simulated income distributions. The coefficients derived from this method were consistent with other attempts to estimate local-level income inequality in England (Bradshaw & Bloor, 2016).

Because of high correlations between the proportions of some ethnic minority groups living in LSOAs the initial number of ethnic categories (11) was reduced to five: Mixed Heritage, Asian Indian, Asian Pakistani, Asian Indian, Black British/African/Caribbean/Other. Population counts for different Mixed Heritage ethnic groups were combined, as were Black African, Black Caribbean, and Black Other population counts, due to their LSOA ethnic densities having correlations higher than $r = 0.85$. Ethnic density for different Asian groups were left disaggregated as correlations were not high enough to result in serious multicollinearity concerns ($r < 0.6$).

The analysis used multilevel spatial regression models to predict child welfare intervention rates within LSOAs. The choice of count model was informed by comparing relative model fit information criterion (AIC/BIC), and is explained in the results below. Dependent variables were the number of Children in Need (CIN), Children on Child Protection Plans (CPP), and Children Looked After (CLA) in each LSOA. An offset variable of the log of the child population divided by 10,000 was included to control for population size and to aid interpretation by standardising the output of predictions as the number of child welfare interventions per 10,000 child population, a commonly used denominator for children's services figures (Hilbe, 2012). All LSOA-level variables were centred and standardised around their local authority means and standard deviations to aid interpretation of effects and better separate effects at the local authority and LSOA level (Bell, et al., 2018). Local Authority level variables were grand mean centred and standardised.

We control for spatial correlation between LSOAs by including a matrix of spatially correlated random effects based on Euclidean distance between population weighted centroids for each LSOA, where spatial correlations fit a negative exponential distribution (a hypothesised exponential decay in the strength of the correlation in intervention rates as the distance between pairs of LSOAs increases) (Corrado & Fingleton, 2011; Kristensen, 2019). Population weighted centroid distances are used as opposed to shared borders as LSOA borders are usually not used in relation to service delivery nor are populations usually dispersed evenly throughout them. Moran's I statistics were calculated from residuals for models without spatial error terms to identify evidence of spatial autocorrelation (Fotheringham & Rogerson, 2008).

Multilevel models allow researchers to estimate and control for autocorrelation within grouping or clustering factors in data and provide corrected estimates for higher-level variables with lower sample sizes, both of which violate assumptions of general linear regression (Robson & Pevalin, 2015). In this instance it is necessary because lower super output areas are nested within middle layer super output areas (MSOAs), which are, in turn, nested within local authorities (LAs). LSOAs within the same local authority are also more likely to be similar to one another than LSOAs in different local authorities, especially considering different local authorities may use different social work practice models. Random intercepts were included at the MSOA and LA level.

Random effects can also be added under the assumption that there is normally distributed variance in the coefficients for lower-level variables depending on the higher-level group membership (Robson and Pevalin, 2005). The inverse intervention law is one such example of a lower-level effect that differs depending on group membership – neighbourhood deprivation has a stronger relationship with child welfare interventions in some local authorities than it has in others. Considering the emerging literature and unanswered questions concerning differential intervention for ethnic groups (Bywaters, et al., 2019), we also control for the eventuality that ethnic density may have differential effects in each local authority, and include this as a random effect.

Table 1: Summary statistics and ranges for variables

Variable	Mean	SD	Min	Max
LSOA Number of Children in Need	10.60	11.20	0.00	89.00
LSOA Number of Children on Child Protection Plans	1.53	2.71	0.00	28.00
LSOA Number of Children Looked After	1.97	3.18	0.00	46.00
LSOA IMD Score	21.9	15.80	1.18	82.60
LA IMD Score	22.0	8.14	8.86	41.20
LSOA Mixed Heritage %	2.21	2.09	0.00	14.90
LSOA Asian Indian %	3.42	7.74	0.00	71.50
LSOA Asian Pakistani %	1.32	3.64	0.00	53.60
LSOA Asian Bangladeshi %	0.53	1.68	0.00	35.70
LSOA Black African/Caribbean/Other %	3.27	6.65	0.00	57.20
LA JSA 5 Year Average %	1.65	0.92	0.72	4.14
LA Infant mortality per 1,000	3.57	1.28	1.20	6.70
LA Level 4 Qualification %	27.40	7.35	15.2	50.30

LA Gini coefficient	0.386	0.014	0.358	0.415

Interpretation of Results: One Standard Deviation Changes in Deprivation
While the Indices of Multiple Deprivation are used extensively in UK research and policy they can be difficult for an international audience to interpret without some explanation. IMD scores are only interpretable in a relative sense, where higher scores indicate greater levels of deprivation and lower scores indicate lower levels of deprivation, relative to other neighbourhoods. Although lower IMD score neighbourhoods are sometimes referred to as more affluent, this is not exclusively the case as IMD does not measure affluence, only the presence or absence of deprivation. It is assumed that a lack of deprivation is often associated with an increase in affluence. Strictly speaking, however, we should state that any references to affluence really relate to the absence of deprivation.

It can be difficult to meaningfully interpret the reality that changes in IMD scores represent because they are a composite of several measures. As outlined above, IMD scores in 2015 were based on seven indicators of deprivation. While the majority of these indicators have scores that are only meaningful in a relative sense, the two domains with the greatest weighting, income deprivation and employment deprivation, are expressed as a proportion of the population experiencing that domain of deprivation and have more straightforward explanations. The expected proportion of an LSOA population experiencing income and employment deprivation for different levels on our standardised LSOA IMD Score variable are presented in Table 2, to give readers a sense of the reality of a one-unit change in standardised IMD score for a neighbourhood.

Income deprivation refers to the proportion of the population that were in receipt of income-related welfare support including income based Jobseeker's Allowance (JSA) and those receiving Employment and Support Allowance (ESA). It also includes adults and children in receipt of Child Tax Credit or Working Tax Credit whose income falls below 60 per cent of the median income for England – the relative poverty line (Smith, et al. 2015). In a statistically 'average' LSOA, with a standardised LSOA IMD score of 0, we would expect around 14.5 per cent of the population to be in income deprivation. In a more deprived LSOA, with an IMD score one standard deviation higher than the average, we would expect almost a quarter of the population to be living in income deprivation. By contrast, in a less deprived LSOA with an IMD score one standard deviation lower than the average, we would expect less than one-twentieth of the population to be living in income deprivation.

Table 2: Expected proportion of people in income and employment deprivation for standardised changes in overall IMD Score

Variable	**Standardised LSOA IMD Score** -1 (Less Deprived)	0 (Avg Deprivation)	+1 (More Deprived)
Per cent of people in income deprivation	4.6	14.5	24.5
Per cent of people in employment deprivation	4.6	11.9	19.2

We see similar figures when comparing the expected proportion of the population living in employment deprivation at different levels of the overall multiple deprivation score.

Employment deprivation is calculated based on the proportion of the population claiming welfare benefits related to employment, including Jobseeker's Allowance, Employment and Support Allowance, Incapacity Benefit, and Carer's Allowance (Smith, et al. 2015). We would expect around one-fifth of the population in high-deprivation LSOAs to be claiming one or more of these benefits, but less than one-twentieth in the low-deprivation LSOAs. The expected rate for an LSOA with an average IMD score is around 12 per cent.

The range between negative one and positive one on a standardised scale includes approximately 68 per cent of cases. This means that the majority of our neighbourhoods will have scores within this range, with minus one and plus one standard deviation operating as a reasonable approximation of an average 'low score' and 'high score' on the scale. Approximately 95 per cent of cases lie between the range of minus two and plus two standard deviations, enabling comparisons between neighbourhoods at the extreme ends of the spectrum of deprivation. Readers should keep this in mind when interpreting the findings below – in short, a change of one standard deviation in the IMD score of an LSOA reflects quite a large difference in the relative privations of the population. LSOAs and LAs with scores one standard deviation below the mean would be approximately at the mid-point of the third least deprived LAs/LSOAs, and those with scores one standard deviation above the mean would be at approximately the mid-point of the third most deprived.

Results

We first consider decisions related to statistical model choice and justifications for a multilevel spatial model structure before describing the substantive models for each intervention. As well as the inverse intervention law, the analysis considers the 'income inequality intervention law', a hypothesized phenomenon where the strength of the social gradient in child welfare interventions is contingent on the level of income inequality in a local authority. The amount of variance in local authority intervention rates and social gradients that can be explained by the inverse intervention law and income inequality intervention law is shown in the online appendices, which includes tables showing models with increasing complexity for each of the intervention measures. The comparison of these models shows the size of the suppression effect between the two intervention laws.

Choice of model distribution family and random intercepts

Alkaike and Bayes's Information Criterion statistics (AIC and BIC) were used to assess the most appropriate from a family of probability distributions for generalised linear models (Vrieze, 2012), and then to assess the significance of the inclusion of random intercepts at the MSOA and LA level. These are presented in table 2. The first stage of selecting the most appropriate general linear model involves determining whether a negative binomial model fits the distribution of the dependent variable better than a Poisson model. If so, the following step involves assessing which negative binomial dispersion parameter better fits the data, one where variance increases quadratically versus one where it increases linearly (Hardin & Hilbe, 2007). Decreases in the AIC and BIC values indicate an improvement in model fit.

Table 2: Relative Model Fit for determining model distribution family and multilevel random intercepts						
	CIN Model		**CPP Model**		**CLA Model**	
Distribution	AIC	BIC	AIC	BIC	AIC	BIC
Poisson	30072.9	30078.8	18000.7	18007.0	19793.9	19800.3
Negative binomial 2 $\sigma^2 = \mu\left(\frac{1+\mu}{\varphi}\right)$	17772.9	17784.7	12825.3	12838.0	14858.1	14870.7
Negative binomial 1 $\sigma^2 = \mu(1+\varphi)$	17800.5	17812.3	12775.2	12787.9	14837.2	14849.9
Selection:	Negative binomial 2		Negative binomial 1		Negative binomial 1	
Random effects	AIC	BIC	AIC	BIC	AIC	BIC
MSOA only	17175.1	17192.8	12511.9	12530.9	14452.8	14471.8
MSOA & LA	17099.4	17123.0	12476.7	12502.0	14393.6	14418.9
Spatial correlation	Moran's I	p-value	Moran's I	p-value	Moran's I	p-value
Null model	0.127	<0.001	0.037	<0.001	0.056	<0.001
Model with covariates	0.057	<0.001	0.015	<0.001	0.006	<0.001
Selection:	MSOA & LA Random Intercepts. Indication of spatial dependence.		MSOA & LA Random Intercepts. Indication of spatial dependence.		MSOA & LA Random Intercepts. Indication of spatial dependence.	

Negative binomial models far outperformed Poisson models for predicting rates of intervention, with a dispersion parameter of variance increasing quadratically with the mean in the CIN model fitting best but a linear relationship fitting slightly better for the CPP and CLA models (CIN ΔAIC = -12,300, ΔBIC = -12,294.1; CPP ΔAIC = -5,225.5, ΔBIC = -5,219.1; CLA ΔAIC = -4,956.7, ΔBIC = -4,950.4). Inspection of model fit for the inclusion of random intercepts implies that there are non-trivial clustering effects within MSOAs and Local Authorities, and that a multilevel model is preferable.

Moran's I statistics were calculated for testing spatial autocorrelation amongst residuals in the multilevel models with MSOA- and LA-level random effects and then for models containing all covariates. A statistically significant Moran's I value greater than zero indicates spatial clustering, whereas a value less than zero indicates spatial dispersion; a value of zero indicates spatial randomness. The findings suggest that there is statistically significant spatial clustering in the multilevel models, and that a spatial model to control for spatial patterns in intervention rates is necessary. However, the size of the spatial correlation after including the covariates in the model is very small for CPP, and almost negligible for CLA. As they were still significant the spatial correlation matrix was retained, but the very low spatial correlation in the CLA model meant that the parameters for exponential decay could not be calculated. Spatial correlation summaries are provided in the online appendix table A4 and parameters for the extracted exponential decay function are included in table 3.

Table 3: Multilevel Negative Binomial Models predicting Intervention rates per 10,000 Children (standardised independent variables)

	Children in Need				Child Protection Plans				Children Looked After			
LSOA Level	**B**	**Exp(B)**	**SE**	***p***	**B**	**Exp(B)**	**SE**	***p***	**B**	**Exp(B)**	**SE**	***p***
LSOA IMD Score	0.4392	1.551	0.0251	***	0.5542	1.741	0.0247	***	0.5293	1.698	0.0289	***
Mixed Heritage %	0.0276	1.028	0.0212		0.0723	1.075	0.0446	***	0.1051	1.111	0.0245	***
Asian Indian %	0.0047	1.005	0.0229		0.0458	1.047	0.0394		0.0506	1.052	0.0315	
Asian Pakistani %	0.0162	1.016	0.0167		-0.0198	0.980	0.0319		-0.0087	0.991	0.0201	
Asian Bangladeshi %	0.0117	1.012	0.0167		-0.0079	0.992	0.0285		-0.0112	0.989	0.0213	
Black African/ Caribbean/Other %	0.0060	1.006	0.0200		-0.0366	0.964	0.0479		0.0218	1.022	0.0327	
LA Level												
LA IMD Score	0.3453	1.412	0.1623	*	0.0565	1.058	0.1663		0.2723	1.313	0.0660	***
JSA 5 Year Average %	-0.1065	0.899	0.1551		0.0732	1.076	0.1785		-0.1146	0.892	0.0678	
Infant mortality per 1,000	0.0857	1.089	0.0372	*	-0.0012	0.999	0.0570		0.0403	1.041	0.0209	
Level 4 Qualification %	-0.0794	0.924	0.0835		0.0553	1.057	0.0913		-0.1329	0.876	0.0274	***
Gini coefficient	-0.1024	0.903	0.0958		0.0832	1.087	0.1432		0.0627	1.065	0.0391	
Cross-level interactions												
LA IMD * LSOA IMD	-0.0752	0.928	0.0320	*	-0.0584	0.943	0.0370		-0.1313	0.877	0.0389	***
Gini * LSOA IMD	0.1183	1.126	0.0321	***	0.1661	1.181	0.0375	***	0.1683	1.183	0.0383	***
Intercept	5.4952	243.516	0.0495	***	3.4500	31.499	0.2584	***	3.6940	40.204	0.0221	***
N LSOA	2707				4115				4115			
N MSOA (LA)	543(13)				837(18)				837(18)			

Random effects	**s²**	**s**	**y*0***	**y*f***	**nl(α)**	s²	**s**	**y*0***	**y*f***	**nl(α)**	**s²**	**s**	**y*0***	**y*f***	**nl(α)**
MSOA	0.1269	0.3562				0.2355	0.4853				0.1526	0.3907			
LA	~0	~0				~0	~0				~0	~0			
LA – Mixed Heritage %	0.0509	0.2256				0.1336	0.3655				0.0005	0.0235			
LA – Asian Indian %	0.0565	0.2376				0.1102	0.3319				0.0912	0.3020			
LA – Asian Pakistani %	0.0286	0.1691				0.0659	0.2568				0.0001	0.0104			
LA – Asian Bangladeshi %	0.0389	0.1973				0.0655	0.2560				0.0437	0.2090			
LA – Black A/C/O %	0.0422	0.2055				0.1485	0.3854				0.0830	0.2881			
LA – LSOA IMD Score	0.0741	0.2722				0.0315	0.1775				0.0866	0.2943			
Spatial covariance (exp)	0.3065	0.5536	0.99	0.01	-9.2	0.4348	0.6594	1	<.01	-12.4	0.2998	0.5476	†	†	†

. = p < .1, * = p < .05, ** = p < .01, *** = p < .001. y*0* = exponential decay start parameter, y*f* = exponential decay end parameter, nl(α) = log rate of decay. † = Singular gradient.

Table 3 shows the results from the final multilevel spatial models. We describe the key findings related to the social gradient - the relationship between area-level deprivation and child welfare interventions – and the inverse intervention and inequality intervention laws below. Most of the control variables were not found to be statistically significant, with the exception of infant mortality rates (in the CIN model) and the proportion of the population with higher education qualifications (NVQ level 4 or higher) within the LA in the CLA model. A 7.3 per cent increase in the proportion of the LA population with NVQ4 or higher qualifications was associated with around 12.5 per cent lower rates of children looked after, holding all else constant. This raises some important questions regarding the role of cultural capital in relation to care proceedings (Houston, 2002; Dillon, 2019), that we are unable to fully explore in this paper.

The Social Gradient: Neighbourhood Deprivation and Intervention Rates
LSOA-level deprivation score was the single strongest predictor of intervention rates across all three levels of intervention. In all three types of intervention, LSOA-level deprivation was statistically significant at the 0.1 per cent level. As LSOA-level deprivation increases, the rates of Children in Need, children on Child Protection Plans, and Children Looked After all increase. The relationship between deprivation and intervention was strongest when looking at Child Protection Plans (B = 0.5542) and Children Looked After (B = 0.5293) and weakest in relation to Children in Need (B = 0.4392). However, all three coefficients represent large changes in the rates of intervention.

The strength of this relationship can be described using exponentiated coefficients, which represent the expected multiplicative change in the rates of intervention for an increase of one standard deviation in indices of multiple deprivation score (for example, whether the expected rate would double, triple, or halve). As mentioned, a one standard deviation increase in deprivation is associated with an additional 10 per cent of the population in the neighbourhood living in income deprivation (Table 2), as defined by being in receipt of income-related benefits and/or having an income less than 60 per cent of the median national income, as well as associated increases in health, employment, and other types of deprivation measured by the IMD. These multiplicative changes can be considered a single-number indicator of the social gradient.

An increase of one standard deviation in LSOA IMD score was associated with a 55 per cent increase in the expected Children in Need rate in the LSOA ($e^b = 1.551$), a 74 per cent increase in the expected Child Protection Plan rate ($e^b = 1.741$), and a 70 per cent increase in the expected Children Looked After rate ($e^b = 1.698$). We would expect to see much higher levels of intervention in more deprived neighbourhoods than in less deprived neighbourhoods, holding all else equal. This means the social gradient is approximately this strong *after* controlling for other characteristics that may differ between neighbourhoods, such as differences in ethnic densities, local authority membership, different proximities to high or low intervention areas, different proportions of university educated residents in the population, and so on.

The social gradient is slightly stronger for CIN (B = 0.538, Appendix Table A1) and CLA (B = 0.5576, Appendix Table A2) rates before controlling for other factors like population education and ethnic population, demonstrating the importance of analysing the relationship between deprivation and child welfare interventions using a sufficiently complex statistical approach. These results demonstrate that more descriptive findings from earlier research showing the relationship between deprivation and child welfare interventions (Bywaters, et al., 2014a; 2014b; 2015; 2018a; 2018b) stand up under higher levels of statistical scrutiny.

Inverse Intervention and Inequality Intervention

We find evidence for the inverse intervention law and for a newly hypothesized 'inequality intervention law', with some provisos that warrant further investigation with better data. Before considering these limitations, we present the results under their conceptualisation in previous research (Bywaters, et al. 2018a). We urge readers to carefully read the limitations of this approach to defining the inverse intervention law in the section below.

The inverse intervention law is parameterised as an interaction effect between LA-level IMD score and LSOA-level IMD score. The inequality intervention law is parameterised as an interaction between LA-level Gini coefficient and LSOA level IMD score. One standard deviation changes in LA-level IMD score and LA-level Gini coefficient are used as reference points for low, average, and high levels of LA deprivation and income inequality, as they are roughly equivalent to the average local authority in the bottom, middle, and top tertile of all local authorities respectively. The means and standard deviation values for these variables are shown in table one. For example, our reference point for a high deprivation LA IMD score is 22 (the mean) plus 8.14 (one standard deviation). An LA with this level of deprivation would be in the most deprived third of local authorities, whereas an LA with an overall level of deprivation one standard deviation below the mean would be in the least deprived third of all LAs. The interpretation of the IIL parts of the model is therefore "how much does the social gradient change in different local authority contexts, such as in an overall more deprived or more unequal local authorities respectively".

The inverse intervention law was statistically significant for both Children in Need rates and Children Looked After rates, but not for Child Protection Plan rates. The inequality intervention law was statistically significant for all forms of intervention. The overall change in the size of the social gradient conditional on local authority level deprivation and income inequality was quite substantial in most cases, even when only looking at one standard deviation changes in income inequality and overall deprivation. Examples of social gradients for different levels of LA income inequality and overall deprivation, and different combinations of these contexts, are presented in table four.

In a high deprivation local authority, the social gradient for CIN rates was roughly 44 per cent, meaning that an increase of one standard deviation in neighbourhood deprivation was associated with a 44 per cent increase in CIN rate. In a low deprivation local authority an equivalent increase in neighbourhood level deprivation would be associated with a 67.2 per cent increase in the neighbourhood CIN rate. For CLA rates the change in the social gradient was more pronounced for different LA contexts. High deprivation local authorities had social gradients of 49 per cent and low deprivation local authorities had social gradients of 94 per cent. In other words, equivalent changes in neighbourhood deprivation were associated with almost doubled CLA rates in low deprivation authorities but only a 1.5 times increase in high deprivation authorities.

In local authorities with high income inequality an increase of one standard deviation in neighbourhood deprivation was associated with a 75 per cent increase in CIN rate, a 106 per cent increase in CPP rates, and a 101 per cent increase in CLA rate. By contrast, local authorities with low income inequality had much weaker associations between neighbourhood deprivation and interventions. Increases in neighbourhood deprivation in low income inequality authorities were associated with a 37.8 per cent increase in CIN rates, a 47.5 per cent increase in CPP rates, and a 43.5 per cent increase in CLA rates.

Higher local authority level deprivation and lower income inequality was associated with weaker associations between neighbourhood deprivation and intervention rates. This suggests that poverty may be less of a determining factor in state intervention in authorities that are more equal and where deprivation is more visible. Furthermore, combinations of different LA contexts show that in cases where deprivation is high and income inequality is low, we would expect the social gradient to be as low as 26 to 40 per cent depending on the type of intervention. In the opposite context, where deprivation is low and income inequality is high, we would expect social gradients between 88 per cent and 129 per cent. Local authority context appears to substantially change the relationship between deprivation and child welfare interventions, and in some comparisons, this is quite pronounced. At the extremes, we would expect a low deprivation, high income inequality local authority to have a social gradient around five times stronger (129 per cent increase) than the social gradient in a high deprivation, low income inequality local authority (25.8 per cent increase).

Table 4. How increases in intervention associated with one standard deviation changes in neighbourhood deprivation (the social gradient) change in different LA contexts (multiplicative social gradient)

	LA-Level Context			
	Low Deprivation	High Deprivation	Low Income Inequality	High Income Inequality
CIN Social Gradient	1.672	1.438	1.378	1.746
CPP Social Gradient	1.846*	1.642*	1.475	2.056
CLA Social Gradient	1.936	1.489	1.435	2.009

	LA-Level Combined Contexts			
LA IMD	High Deprivation	Low Deprivation	High Deprivation	Low Deprivation
LA Gini Coefficient	High Income Inequality	High Income Inequality	Low Income Inequality	Low Income Inequality
CIN Social Gradient	1.619	1.882	1.278	1.486
CPP Social Gradient	1.939	2.179	1.391	1.563
CLA Social Gradient	1.762	2.291	1.258	1.636

* = Not Statistically Significant

We also direct readers to the appendices to show an additional point in relation to the identification of the two 'IIL's. The inverse intervention law is not a statistically significant interaction effect unless the inequality intervention law is also included in the model (Appendix Tables A1 – A3). This is due to the fact that both laws operate in opposition to one another. More deprived areas typically have a more pronounced gap between the low income population and the middle-income population, creating a somewhat paradoxical situation where greater local equality is usually the result of a smaller gap between the middle-earning subset of the population and the low-earning subset.

This is at odds with our usual understanding of national or international inequality as being largely determined by the excessive wealth of very few people at the top of the income distribution. These types of earners tend not to be resident in the most deprived regions at a local level, and hence do not feature in the calculation of local inequality. In this sense, greater local income equality can be found when either the majority of the population is on a low income or when the entire population has incomes more closely distributed around the middle of the income distribution, usually in London boroughs where cost of living is most expensive. Inequality is usually associated with a large divide between the average income of low-income households and the average income of middle-income households. Although contrary to our intuition, this pattern is consistent with other researchers' estimates of local-area inequality in England (Bradshaw & Bloor, 2016). This may imply that the economic capital of social workers in more equal local authorities is likely to be closer to that of service users than it would be in more unequal local authorities, possibly leading to a greater convergence of lived experience.

Limitations

This represents close to the limits of complex quantitative analysis that can be done with a reanalysis of the Child Welfare Inequalities Project administrative data. As identified earlier, a primary weakness is the absence of individual level demographic or socio-economic data about parents, as this is not captured by services. In addition, even if these data were captured, the absence of linked data for children not known to children's services means that individual-level statistical models are an impossibility at this time (even linking to a more universal resource such as the National Pupil Database would exclude many children [Emmot et al., 2019]). This means that we cannot confidently make statements about individual socioeconomic circumstances and how they relate to child welfare interventions. A full analysis of individual children's likelihoods of intervention conditional on their family socioeconomic circumstances is essential for a complete understanding of the relationship between deprivation and child welfare interventions. At this stage we can only reliably talk about patterns related to neighbourhoods and what this might mean for social work while urging further developments in data linkage.

Secondly, it should be stated explicitly that child welfare interventions are not purely punitive outcomes. Being classified as 'In Need' is a prerequisite condition to accessing support from services, which may well be welcomed by families. Further, local authorities have a statutory duty to protect children from living in abusive or neglectful circumstances. However, we question whether circumstances resulting in some types of more coercive intervention, like children being taken into care, might have been better and more justly avoided if possible underlying conditions like poverty were addressed on a structural level. Again, this requires better data and further research that explores the relationship between preceding socioeconomic circumstances and subsequent interventions in relation to the reasons for intervention. Our intention is to continue to draw attention to the social determinants of child welfare interventions in a similar way to how authors have drawn attention to the social determinants of health (Wilkinson & Marmot, 2003; Bywaters, 2020).

The use of LSOA-level IMD scores may introduce potential errors in the specification of the inverse intervention law. It is not ideal, in a technical sense, for us to rely on the use of a higher-level aggregate of a lower-level variable, even after centering variables appropriately, as this introduces a risk of multicollinearity. This is another reason why individual-level socioeconomic data are necessary to strengthen evidence of the inverse intervention law.

Lastly, it is necessary to state that the experimental method used to derive local authority income inequality coefficient estimates will require future validation. While this method relies on simulations from very detailed summary data in local authorities that effectively adjusts for skew, there are ongoing debates around whether income inequality at the local level is a meaningful concept and the implementation of inequality measures for local areas in the UK is somewhat underdeveloped (Bradshaw & Bloor, 2016; Wilkinson & Pickett, 2006). This research has, however, used the most advanced possible approach to estimating Gini coefficients which leverages specialist commercial survey data. If nothing else, the findings here demonstrate that local area inequality may have profound effects on social work intervention and this alone should warrant greater methodological developments in the measurement of income inequality in the UK.

Conclusions

We find a strong and statistically significant relationship between levels of deprivation and rates of child welfare interventions in LSOAs while holding ethnic demographics, unemployment levels, infant mortality rates, population higher education rates, spatial correlations, and local authority inequality constant. Higher deprivation is associated with higher rates of children in need, children on a child protection plans, and children looked after. However, this relationship appears to differ depending on contextual factors at the local authority level. In local authorities with low deprivation overall and high-income inequality, the relationship between neighbourhood deprivation scores and intervention rates is much stronger than it is in local authorities with high overall deprivation and low income inequality.

The quantitative evidence presented here supports the findings that emerged from the earlier descriptive work by Bywaters and others (2014a, 2014b, 2015, 2018a; 2018b; Morris, et al., 2018), from which evidence of the social gradient in child protection interventions and the inverse intervention law in England emerged. This provides the much needed statistical scrutiny to carry child welfare inequalities arguments onwards into policy. The social gradient appears to be robust after controlling for theoretically confounding relationships and differs substantially depending on local authority socioeconomic contexts. It is important to state here that to fully understand ethnic inequalities a more complex methodology is needed, which we aim to present in a related paper. Here, we have only controlled for a possible confounding relationship between IMD scores and ethnic density and have not examined differences between ethnic populations.

Variations in the social gradient in child welfare interventions are far more complicated than they first appear. Socioeconomic relationships are subject to at least two moderating LA-level factors that often suppress one another. We have named them the 'inverse intervention law' and the 'income inequality intervention law', in keeping with health inequalities nomenclature (Tudor Hart, 1971). The new identification of the 'income inequality intervention law' may explain why international replications of the Child Welfare Inequalities Project have, to date, found limited evidence for the 'inverse intervention law' (Keddell, et al., 2019).

With regards to variations in intervention rates, the evidence about the social gradient demonstrates that these are not the result of a 'postcode lottery'. Far from it. Contextual effects of income inequality and overall deprivation are consistent determinants of socioeconomic inequalities in intervention rates. In particular, income inequality exacerbates existing socioeconomic inequalities, mirroring the kind of relationship identified by Eckenrode, et al. (2014) and demonstrating the need for child protection to be included in wider discussions about inequality and social problems. This is just one part of a growing body of evidence that highlights the way that the ordering of many parts of children's services provision is associated with socioeconomic status including, for example, the funding of and recent cuts to children and young peoples' services (Webb & Bywaters, 2018; Hood, et al., 2016; Devaney, 2018; Jones, 2018).

Research, policy and practice that addresses the structural inequalities between poorer and more affluent children, families, neighbourhoods, and local authorities should therefore be central in efforts to ensure that all children have an equal chance of a good enough childhood. The way that contextual factors at different geographies shape socioeconomic inequalities in children's social care is too great to be ignored. We estimate that a local authority in the bottom tertile of deprivation and the top tertile of inequality will have a social gradient around five times steeper than a local authority in the top tertile of deprivation and the bottom tertile of income inequality. The findings presented here demonstrate that the relationship at a structural level between child welfare interventions and deprivation is both substantial and significant, a relationship that cannot be disregarded as one that simply reflects demographic differences. Although such demographic differences undoubtedly play a role, a very large piece of the puzzle in explaining variations in intervention rates can be explained by socioeconomic structures.

Of course, socioeconomic and demographic factors associated with child welfare interventions are only one part of the social work landscape. Leadership and practice culture undoubtedly play a part in variation between areas. In the 1960s, Packman's (1968) research noted the important role of departments' policies, practices and philosophies in explaining variation in intervention rates. Under the current UK regime, Wijedasa, Warner and Scourfield (2018) found that as well as changing low-income rates in English local authorities, Ofsted judgements and participation in the Innovation Programme were also correlated with change over time in rates of children looked after.

Social 'determinants' are not considerations in opposition to other dimensions in this complex landscape, but are essential, pervasive underlying factors which have received too little attention. Inequity on the basis of socioeconomic background is an undesirable feature of a just child protection system. If the social work profession believes that a family's socioeconomic background should not prejudice their chances of having their children taken into care the answer is not to ignore these very large socioeconomic inequalities. Rather, these inequalities need to be engaged with. While socioeconomic discrimination may have no place in individual social workers' ethos and practice, it appears to creep into the patterning of interventions and is linked to wider societal structures and systems. As with health inequalities, child welfare inequalities require a multi-level response; changing social work practice, culture or leadership styles is best done alongside changing underlying structural contexts.

We may not know yet precisely how much income inequality or geographic poverty needs to change to remove the socioeconomic inequalities in child welfare interventions, nor do we have a sufficient understanding of the mechanisms that lead from poverty to risk of or substantiated child abuse and neglect and subsequent removal (although this body of evidence is slowly growing; Cooper & Stewart, 2013, 2017; Mason & Bywaters, 2016). However, we do know in which direction we need to move on a structural level to reduce interventions and socioeconomic child welfare inequalities. Interventions are lower in neighbourhoods with lower deprivation, no matter their demographic makeup or proximity to other low-intervention areas. Poor neighbourhoods seem to stand out more as sites for intervention in local authorities where deprivation is more uncommon. High income inequality is associated with greater disparities in intervention rates between neighbourhoods. The evidence suggests that reducing deprivation may be a very effective way to reduce the rates of children being taken into care, and that reducing income inequality would result in less pronounced socioeconomic inequalities in intervention rates. The policy implications of more deprived local authorities having less steep social gradients is quite not as intuitive, and comparative research is ongoing, but this may be the result of historically higher levels of spending on early help services in more deprived local authorities (Webb & Bywaters, 2018) and the needs and community strengths in more deprived areas.

Inequalities in children's chances of receiving a child welfare intervention are a product of both demand factors affecting their likelihood of a good enough family life and supply factors which affect the choices local authorities' make about how, when and where to intervene (Bywaters et al., 2015). For both demand and supply, key influences are structural and systemic rather than individual or random. The extent to which a local authority reinforces or reduces structural inequalities in children's life chances is strongly linked to the contexts created by national policies and their legacy, affecting both local resources and how the role of children's services is conceptualised and judged. This evidence suggests that the current context is resulting in a strong reinforcement of socioeconomic inequalities at the local level.

Families need sufficient individual and communal resources to eliminate the socioeconomic factors associated with risk, and we must be aware of the systemic conditions that may lead to institutions knowingly or unknowingly placing their poorest neighbourhoods under inequitable levels of scrutiny. This is an especially important consideration for policy. If national and local responses to high and rising levels of state intervention in family life are to promote greater equity in children's life chances they must address the impact of underlying socio-economic structures on families and on communities. Child protection strategies which fail to respond to social and economic inequalities and the contexts that exacerbate them risk being ineffective or even self-defeating.

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Online Appendices

Table A1: Multilevel Negative Binomial Model predicting Children in Need rates per 10,000 Children (standardised independent variables)

	Model 1		Model 2		Model 3		Model 4		Model 5	
LSOA Level	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***P***
LSOA IMD Score			0.5380	***	0.5278	***	0.5125	***	0.4392	***
Mixed Heritage %					0.0377	*	0.0389	*	0.0276	
Asian Indian %					-0.0025		0.0007		0.0047	
Asian Pakistani %					0.0179		0.0193		0.0162	
Asian Bangladeshi %					0.0016		0.0015		0.0117	
Black African/ Caribbean/Other %					-0.0032		-0.0091		0.0060	
LA Level										
LA IMD Score					0.1965		0.2280	.	0.3453	*
JSA 5 Year Average %					0.0192		0.0304		-0.1065	
Infant mortality per 1,000					0.0491		0.0394		0.0857	*
Level 4 Qualification %					0.0167		-0.0222		-0.0794	
Gini coefficient							-0.0763		-0.1024	
Cross-level interactions										
LA IMD * LSOA IMD					0.0049		-0.0927	***	-0.0752	*
Gini * LSOA IMD							0.1342	***	0.1183	***
Intercept	5.5576	***	5.4930	***	5.4439	***	5.4552	***	5.4952	***
Random effects	**s²**	**s**	**s²**	**s**	**s²**	**s**	**s²**	**s**	**s²**	**s**
MSOA	0.2676	0.5173	0.0556	0.2358	0.0479	0.2189	0.0479	0.2188	0.1269	0.3562
LA	0.0799	0.2828	0.0834	0.2888	0.0259	0.1610	0.0244	0.1563	~0	~0
LA – Mixed Heritage %					0.0009	0.0296	0.0007	0.0268	0.0509	0.2256
LA – Asian Indian %					0.0019	0.0433	0.0019	0.0433	0.0565	0.2376
LA – Asian Pakistani %					0.0006	0.0239	0.0005	0.0231	0.0286	0.1691
LA – Asian Bangladeshi %					0.0005	0.0222	0.0006	0.0239	0.0389	0.1973
LA – Black A/C/O %					0.0007	0.0271	0.0011	0.0334	0.0422	0.2055
LA – LSOA IMD Score			0.0128	0.1129	0.0129	0.1137	0.0019	0.0432	0.0741	0.2722
Spatial correlation (exp)									0.3065	0.5536

. = p < .1, * = p < .05, ** = p < .01, *** = p < .001. N = LSOA: 2707, MSOA: 543, LA: 13

Table A2: Multilevel Negative Binomial Model predicting Child Protection Plans per 10,000 Children (standardised independent variables)

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
LSOA Level	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***p***
LSOA IMD Score			0.5576	***	0.5670	***	0.5609	***	0.5542	***
Mixed Heritage %					0.0643		0.0640		0.0723	***
Asian Indian %					0.0433		0.0439		0.0458	
Asian Pakistani %					0.0251		-0.0221		-0.0198	
Asian Bangladeshi %					0.0110		-0.0093		-0.0079	
Black African/ Caribbean/Other %					0.0389		-0.0359		-0.0366	
LA Level										
LA IMD Score					0.1231		0.0886		0.0565	
JSA 5 Year Average %					0.0047		-0.0316		0.0732	
Infant mortality per 1,000					-0.0358		-0.0086		-0.0012	
Level 4 Qualification %					-0.1090		-0.0409		0.0553	
Gini coefficient							0.1198		0.0832	
Cross-level interactions										
LA IMD * LSOA IMD					0.0527		-0.0664	.	-0.0584	
Gini * LSOA IMD							0.1673	***	0.1661	***
Intercept	3.8212	***	3.4321	***	3.4083	***	3.4076	***	3.4500	***
Random effects	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**
MSOA	0.3159	0.5620	0.0950	0.3082	0.0711	0.2666	0.0068	0.0261	0.2355	0.4853
LA	0.1047	0.3236	0.0926	0.3043	0.0502	0.2241	0.0039	0.0197	~0	~0
LA – Mixed Heritage %					0.0202	0.1420	0.0017	0.0130	0.1336	0.3655
LA – Asian Indian %					0.0086	0.0927	0.0011	0.0106	0.1102	0.3319
LA – Asian Pakistani %					0.0050	0.0705	0.0004	0.0064	0.0659	0.2568
LA – Asian Bangladeshi %					0.0033	0.0571	0.0003	0.0056	0.0655	0.2560
LA – Black A/C/O %					0.0234	0.1529	0.0020	0.0141	0.1485	0.3854
LA – LSOA IMD Score			0.0250	0.1580	0.0147	0.1212	1.016e-09	3.187e-05	0.0315	0.1775
Spatial correlation (exp)									0.4348	0.6594

. = p < .1, * = p < .05, ** = p < .01, *** = p < .001. N = LSOA: 4115, MSOA: 837, LA: 18

Table A3: Multilevel Negative Binomial Model predicting Children Looked After per 10,000 Children (standardised independent variables)										
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
LSOA Level	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***p***	**B**	***p***
LSOA IMD Score			0.5576	***	0.5085	***	0.5098	***	0.5293	***
Mixed Heritage %					0.1019	***	0.1010	***	0.1051	***
Asian Indian %					0.0454		0.0480		0.0506	
Asian Pakistani %					-0.0057		-0.0045		-0.0087	
Asian Bangladeshi %					-0.0123		-0.0096		-0.0112	
Black African/ Caribbean/Other %					0.0193		0.0160		0.0218	
LA Level										
LA IMD Score					0.2854	***	0.2529	***	0.2723	***
JSA 5 Year Average %					-0.0966		-0.0968		-0.1146	
Infant mortality per 1,000					0.0311		0.0358	.	0.0403	
Level 4 Qualification %					-0.1639		-0.1320		-0.1329	***
Gini coefficient							0.0601		0.0627	
Cross-level interactions										
LA IMD * LSOA IMD					-0.0019		-0.1202	***	-0.1313	***
Gini * LSOA IMD							0.1629	***	0.1683	***
Intercept	3.8212	***	3.4321	***	3.6829	***	3.6842	***	3.6940	***
Random effects	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**	**s^2**	**s**
MSOA	0.3159	0.5620	0.0950	0.3082	0.0035	0.0186	0.0032	0.0180	0.1526	0.3907
LA	0.1047	0.3236	0.0926	0.3043	7.335e-10	2.708e-05	1.466e-10	1.211e-05	~0	~0
LA – Mixed Heritage %					7.257e-10	2.694e-05	4.724e-10	2.174e-05	0.0005	0.0235
LA – Asian Indian %					6.702e-03	0.0082	7.247e-03	0.0085	0.0912	0.3020
LA – Asian Pakistani %					4.240e-10	2.059e-05	5.386e-10	2.321e-05	0.0001	0.0104
LA – Asian Bangladeshi %					1.530e-03	0.0039	2.082e-03	0.0046	0.0437	0.2090
LA – Black A/C/O %					4.736e-03	0.0069	4.918e-03	0.0070	0.0830	0.2881
LA – LSOA IMD Score			0.0250	0.1580	0.0024	0.0155	0.0004	0.0062	0.0866	0.2943
Spatial correlation (exp)									0.2998	0.5476

. = p < .1, * = p < .05, ** = p < .01, *** = p < .001. N = LSOA: 4115, MSOA: 837, LA: 18

Table A4. Spatial correlations for child welfare interventions in LSOAs (distance between LSOA population weighted centroids)			
Distance between LSOAs	**Children in Need**	**Child Protection Plans**	**Children Looked After**
Less than 10km	0.631	0.979	<0.001
Between 10km and 50km	0.098	0.889	<0.001
Between 50km and 100km	0.002	0.721	<0.001
Greater than 100km	<0.001	0.363	<0.001