Income Inequality & Child Welfare Interventions in England and Wales

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Funding source: This project received internal funding from the University of Sheffield and Cardiff University to cover the costs of commercial data used to estimate Gini coefficients. The authors wish to acknowledge the support of the Nuffield Foundation which funded the wider Child Welfare Inequalities Project (grant reference: KID 41935/03).

Potential Conflicts of Interest: The authors have no conflicts of interest relevant to this article to disclose.

Abbreviations: CLA = Children looked after, CP = Child Protection

What's known on the subject?
Within-area income inequality has been found to be associated with child maltreatment in the United States, as well as health and social problems globally. Evidence for the relationship between income inequality and child maltreatment outside the US is very limited.

What this study adds?
This study tests whether a relationship between child welfare interventions and income inequality can be observed in English and Welsh local authorities, contributing to international evidence that inequality is associated with greater rates of social problems and adverse health outcomes.

Abstract

Background: Previous research has identified a relationship between income inequality and child abuse and neglect in the United States. This association has received limited exploration outside the US.

Methods: Administrative data on child protection in 172 English and Welsh local authorities between 2013 and 2018 were combined with data on deprivation, ethnic density, and education from publicly available data sources. Commercial income data were used for Gini coefficient estimation. We tested whether similar evidence for three key findings from a US study could be found in England and Wales. These included: whether there was evidence of a relationship between income inequality and child maltreatment; whether this relationship was nonlinear; and whether this relationship varied dependent on the level of poverty.

Results: There was a significant non-linear relationship between income inequality and state care rates in England and Wales. Predicted state care rates were higher as income inequality increased, up until around average levels where the effect flattens. However, there was no significant relationship for models predicting child protection plan/register rates. Income inequality, income deprivation, ethnic density, and higher education were able to explain around 75 per cent of the variance in English and Welsh state care rates.

Conclusions: There is some evidence to support the claim of a relationship between income inequality and child maltreatment beyond the US in England and Wales, and a case for further comparative research, but there are significant limitations in the comparability of data.

Introduction

Social inequalities in population health and well-being are well evidenced internationally.[1,2,3,4] One aspect of these inequalities which is increasingly drawing the attention of researchers is the effect of income inequality within nations, regions, and administrative jurisdictions. Mental ill health, obesity, drug misuse, poor educational achievement, lack of trust, violence (including homicide), imprisonment, gender inequality and racism, have all been shown to have associations with income inequality and low social status.[4] Many of these associations have been found both in studies comparing different countries and in studies comparing US states. In reviewing the international evidence, Pickett and Wilkinson[5] conclude that the strength of evidence for the impact of income inequality on health is at a level where the relationship could be regarded as causal.

In the field of child abuse and neglect, there is a well-documented higher risk to children in deprived families of maltreatment[6,7] or out-of-home care.[8] We also see from ecological studies that there is a concentration of protective interventions in deprived neighbourhoods.[9,10]

Research in the United States by Eckenrode, Smith, McCarthy and Dineen[11] found that both income inequality and child poverty rates were associated with higher substantiated child maltreatment rates at the county level. Income inequality was measured by using Gini coefficients[12] and control variables included child poverty, adult qualifications and ethnic diversity. Eckenrode et al also found a significant non-linear relationship between income inequality and child maltreatment, with stronger associated increases as inequality reached its mean point and weaker increases after this. Further, the effect of inequality on child maltreatment rates was stronger in counties with high or moderate levels of poverty.

There are no international replications of Eckenrode et al.'s study to date, however, Webb et al.'s English study[13] found that greater income inequality in the local administrative region was associated with greater inequalities in child welfare intervention rates between more deprived and less deprived neighbourhoods. However, the sample size of local authorities was only 18, and there was no analysis of the relationship between income inequality and state interventions more generally. This article attempts to explore similar research questions to those of Eckenrode, et al.

Research Questions:

- Is there an association between income deprivation and income inequality and child welfare interventions in England and Wales?
- Are these associations non-linear?
- Is the effect of income deprivation moderated by income inequality, and vice versa?

Methods

Data Sources and Measures

Data were sourced from a combination of several publicly available resources from the Department of Education,[14,15] Department for Communities and Local Government,[16] the Office of National Statistics[17] and Welsh Government, at the upper-tier and county local authority level (N = 172).[18] Data on income bands were purchased from CACI Ltd. in the form of their 'Paycheck' dataset, which uses a range of geographic and survey data to estimate population income.[19] The Isles of Scilly and the City of London were omitted from the analysis because of small population sizes.

Child Welfare Intervention Rates

There is no direct parallel to 'substantiated child maltreatment' in UK administrative data. Rather, the Department for Education and Welsh Government publicly release statistics about children on child protection plans (England) or on the child protection register (Wales) (CP), and children in state care (children looked after, CLA). Non-abuse- and neglect-related factors can result in children becoming looked after or placed on child protection plans/registers, for example, in the case of unaccompanied asylum seeking or child behaviour that parents cannot manage. This introduces some difficulty making international comparisons of results.

However, according to the Office for National Statistics,[20] for the five-year period this study covers, approximately 62 per cent of children looked after were placed in care *primarily* because of abuse or neglect. Many cases may include instances of child abuse and neglect as secondary or tertiary factors. No similar data are available for child protection plans/registers, as the only factors available to assign to cases are abuse/neglect-related.

The family of a child on a child protection plan or register will have supervised social work intervention because of a risk to the child's health, wellbeing, or development. A child who is 'looked after' is in the care of their local authority, usually subsequent to placement on a child protection plan/register. The outcome variables are five-year averages for child protection rates and children looked after rates per 10,000 population aged 0-17 at 31st March each year, the governmental reporting date to avoid double-counting children in year-long statistics.

Income inequality in England and Wales

There is one published dataset containing inequality estimates for UK local authorities, but these exist only for England and are not available at the aggregate level into which children's services are organised.[21] Nyanzu and Rae[22] provide an alternative methodology for estimating income inequality using national deciles of small-area income deprivation that we were able to successfully scale to LEA level,[23] but this measure had only a 0.25 correlation with Rae and Nyanzu's own Gini coefficient estimates. Because it uses deciles relative to national income, we believe this measure reflects a different type of inequality from within-area inequality. For example, using the Nyanzu and Rae[22] 20:20 index, a local authority where all small areas were in the poorest 20 per cent nationally would have an index score of 1 (most unequal), despite the fact that all small areas *within* that local authority shared similar traits. In other words, they are equal, but poor. Further, the index is created as a function of income deprivation, introducing almost complete concurvity (non-linear dependence) that make it inappropriate for general additive models (see Appendix 1).

Rather, our Gini coefficient estimation is similar to Nyanzu and Rae's with some improvements and disadvantages. Nyanzu and Rae calculate a Lorenz Curve and Gini coefficient using nine income bands for disposable income from PAYE data from the Office of National Statistics (pp. 8-9). We use 26 gross income bands and mean income data from CACI Ltd to create a simulation of the income distribution within a local authority. Gross income may inflate local area inequality generally and underestimate it in places with high cost of living.

Because the cut-off for income brackets is £200k, we also dynamically skewed the distribution to adjust for this by increasing the skew of this uppermost band until the simulated income distribution mean was approximately equal to the 'real' mean. Nyanzu and Rae do not make this correction. These simulations were repeated 1,000 times and the mean of all of the iterations was taken as the Gini coefficient. While under our license we are not permitted to share the CACI Ltd data, nor derivatives from this data, we have made the script used to calculate these Gini coefficient estimates publicly available.[24]

Income Deprivation

There is no measure of child poverty in the UK that is directly comparable to that used in the US. The US federal poverty line uses a semi-'absolute' definition of poverty based on whether the weighted expenses needed to meet a pre-defined dietary subsistence criterion exceeds one-third of a household's income, based on the Orshansky thresholds.[25] The UK uses a relative measure of poverty, income deprivation, which is the proportion of the population on low-income welfare benefits or in receipt of incomes that are less than sixty per cent of the national median income while receiving Working Tax and Child Tax credits.[16]

Other predictors

We aimed to include variables comparable to Eckenrode, et al.'s[11] study such as the proportion of the local authority population with National Vocational Qualification Level 4 or above (roughly equivalent to one year of study at Bachelor's degree level or higher); the proportion of the population claiming the unemployment benefit Job Seekers Allowance

(JSA); the infant mortality rate per 1,000 live births; and the proportion of the population from Asian (British, Indian, Bangladeshi, Pakistani or Other) and Black (British, African, Caribbean, or Other) ethnic groups. These ethnic groups do not mirror the social positions of African-American and Latino populations in the US, because of the two countries' very different histories, but the Asian and Black groups represent the two main ethnic minority categories in England and Wales and there are some similarities to those US minority populations in terms of their contact with child welfare systems.[9]

Transformations

As with Eckenrode et al.'s analysis, 5-year averages between 2013 and 2018 were used for all variables where possible. Due to the Census being completed only once every ten years, population growth adjusted estimates were used for 2015. CACI Ltd only provide income data for the current year, meaning 2018/19 data were used to calculate Gini coefficients. Indices of Multiple Deprivation are only calculated every five years, we used the 2015 release of the income deprivation subdomain of the IMD to measure poverty in England, and the 2014 income deprivation subdomain of the Welsh Indices of Multiple Deprivation to measure poverty in Wales.

Statistical Analysis

Figure one shows summary plots and statistics for all variables. Five-year average unemployment rates were very highly correlated with income deprivation (r = 0.855) and was therefore excluded from the analysis. The correlation between income deprivation and local authority Gini coefficients was reasonably strong (r = 0.67), more so than the correlation between child poverty and Gini coefficients in Eckenrode, et al.'s (p: 456) study (r = 0.49). This may introduce greater multicollinearity/concurvity in our regression models.

Shapiro-Wilks tests were used to examine whether distributions for response variables were sufficiently normal. Untransformed CLA and CP rates differed significantly from expected normal distribution (CLA: W = 0.951, p <0.001, CP: W = 0.948, p <0.001) and were transformed to logged rates. In the case of CP rates, one outlier was removed (Milton Keynes). The final log rates used in all models were normally distributed (CLA: W = 0.992, p = 0.476, CP: W = 0.992, p = 0.449).

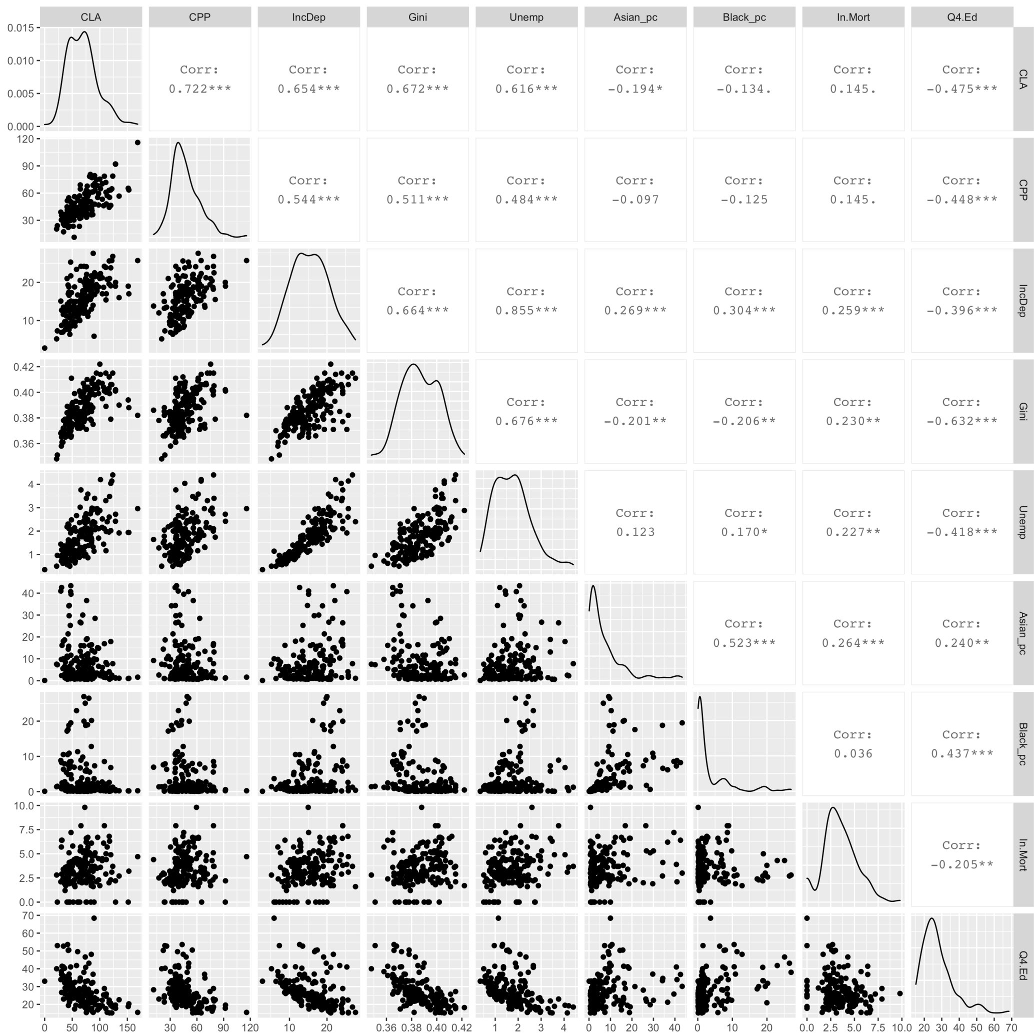

Figure 1: Correlation pair-plots and densities for variables included in analysis.

We used six iterative models to answer the research questions listed above, presented in table one, using model fit, postestimation of marginal effects, and post-hoc analysis of differences in effects to determine the appropriate specification of the final general additive models (GAMs). All statistical analysis was completed using R[26] and general additive models were fit using the MGCV package.[27] Thin plate regression splines were used for modelling nonlinear relationships. Full models for each stage are included in Appendix 2-3.

The first stage involved creating a baseline general linear model (GLM) with linear associations between income deprivation, income inequality, and the outcome measure, including fixed effects for country (Model 1). The second and third stage tested whether smoothed nonlinear effects of income deprivation (Model 2) and income inequality (Model 3) using thin-plate regression splines in a generalised additive model (GAM) offered justifiable improvements in model fit compared to a linear regression. To determine this, we compared Akaike Information Criterion (AIC) and performed a likelihood ratio test (LRT) between the linear model and each non-linear model. Models with smaller AIC and significant LRT p-values were considered justified improvements in model fit and, in cases where the change in AIC was minimal and the LRT was non-significant, the most parsimonious model, the model with fewest degrees of freedom, was retained.

Next, we tested whether the effects of income deprivation and income inequality differed significantly between the two countries (Model 4). If the model coefficients for income deprivation and inequality were not significantly different between countries, the fixed effect for Wales was removed. The resulting model (Model 5) was the final GAM reported. Following Eckenrode, et al., we constructed a GLM equivalent for each model based on the effective degrees of freedom (*edf*) in their GAM counterpart. This was necessary to test whether there is an interaction between income deprivation and income inequality.

All residuals were normally distributed and *k*-index significance indicated that smoothing was appropriate. Concurvity was below 0.8 for all smoothed estimates. We present plots of the non-linear effects of income deprivation and income inequality on back-transformed CLA and CP rates to illustrate the shape and strength of the relationship. As with Eckenrode, et al., we also include standardised coefficients for the linear and polynomial components of a GLM with the closest approximate functional form.

Results

Table one includes model comparison statistics and postestimation results, table two reports results from the final GAMs. Full results from each of the models referenced in table one are available in an online appendix. The final CP model can explain around 47.2 per cent of the variance in child protection plan/register rates. The CLA model is able to explain around 75.3 per cent of the variation in CLA rates.

== Table 1 ==

== Table 2 ==

Table 1: Model fit statistics, Likelihood Ratio Tests, post-hoc analyses, postestimation of marginal effects, and key regression coefficients and significance tests for model selection. Full models for each intervention are provided in appendix 2-3.

Child Protection Plan/Register Models

Model	*Description*	*AIC*	*df*	R^2	*LRTp*	*HSDp*	*Est.*	*SE*	*p*
Model 1	Baseline GLM including fixed effects for Wales	16.238	11	0.432					
Model 2	GAM to test income deprivation nonlinearity against baseline	15.928	11.476	0.449	0.123[1]				
Model 3*	GAM to test Gini coefficient (income inequality) nonlinearity against baseline	12.598	13.901	0.475	**0.027**[1]				
Model 4*	GAM with Tukey HSD to test significance of Wales interaction fixed effects	12.598	13.901	0.475	**0.027**[1]				
	Income Deprivation × Country					0.405	0.144	0.173	
	Gini × Country					**0.011**	-1.21	0.471	
Model 5	Final GAM based on results of above models, used to test significance of effects	11.569	12.796	0.472	0.326[2]				
Model 6	GLM closest fit to Model 5 to test significance of interaction effects between Gini and income deprivation	16.215	18.000	0.477	0.409[3]				
	Income Deprivation × Gini (England) *Postestimation of three-way interaction*						-0.014	0.017	0.422
	Income Deprivation × Gini (Wales) *Postestimation of three-way interaction*						1.460	0.963	0.130
	Income Deprivation × $Gini^2$ (Wales only)						-1.600	1.001	0.112
	Income Deprivation × $Gini^3$ (Wales only)						-3.818	2.718	0.162
	Income Deprivation × $Gini^4$ (Wales only)						4.078	2.305	0.079

Children Looked After Models

Model	*Description*	*AIC*	*df*	R^2	*LRTp*	*HSDp*	*Est.*	*SE*	*p*
Model 1	Baseline GLM including fixed effects for Wales	-34.846	11	0.726					
Model 2	GAM to test income deprivation nonlinearity against baseline	-38.330	13.739	0.754	**0.029**[1]				
Model 3	GAM to test Gini coefficient (income inequality) nonlinearity against baseline	-40.684	11.865	0.752	**0.006**[1]				
Model 4	GAM with Tukey HSD to test significance of Wales interaction fixed effects	-40.976	14.424	0.760	**0.009**[1]				
	Income Deprivation × Country					0.140	-0.337	0.254	
	Gini × Country					0.676	-0.065	0.156	
Model 5	Final GAM based on results of above models, used to test significance of effects	-42.938	11.047	0.753	**0.009**[2]				
Model 6	GLM closest fit to Model 5 to test significance of interaction effects between Gini and income deprivation	-28.422	14	0.725	0.354[3]				
	Income Deprivation × Gini						0.070	0.046	0.124
	Income Deprivation × $Gini^2$						-0.032	0.026	0.217
	$Gini^2$ *× Income Deprivation*						0.019	0.026	0.468
	$Income\ Deprivation^2 \times Gini^2$						0.002	0.011	0.874

In LRTp column: [1] = Likelihood Ratio Test p-value against Model 1, [2] = Likelihood Ratio Test p-value against Model 4, [3] = Likelihood Ratio Test p-value against Model 5.
AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, df = (effective) degrees of freedom, LRTp = Likelihood Ratio Test p-value, HSDp = Tukey Honest Significant Difference test p-value
* Model 3 and Model 4 share identical model structures as there was no evidence of non-linearity in Model 2 and evidence of non-linearity in Model 3. See appendix 2 for futher details.

Table 2: GAM predicting Log Child Protection Plan/Register rate per 10,000 and Log Children Looked After rate per 10,000 in England and Wales

	Log CP Rate per 10,000					**Log CLA Rate per 10,000**				
Predictors	*Est./edf*	*Std. Est.**	*SE*	*95% CI*	*p*	*Est./edf*	*Std. Est.**	*SE*	*95% CI*	*p*
(Intercept)	3.815	0	0.020	3.775 – 3.854	**<0.001**	4.142	0	0.017	4.108 – 4.176	**<0.001**
Wales = 1	0.277	-0.116	0.345	-0.404 – 0.959	0.422	0.185	0.149	0.052	0.082 – 0.288	**0.001**
Asian Population % z-score	-0.049	-0.155	0.025	-0.099 – 0.000	0.050	-0.101	-0.254	0.022	-0.144 – -0.057	**<0.001**
Black Population % z-score	-0.039	-0.124	0.028	-0.095 – 0.017	0.171	-0.029	-0.090	0.026	-0.080 – 0.022	0.268
Infant Mortality z-score	0.030	0.092	0.021	-0.012 – 0.071	0.159	0.033	0.079	0.018	-0.002 – 0.068	0.063
Q4 Education % z-score	-0.043	-0.132	0.028	-0.097 – 0.012	0.125	-0.029	-0.061	0.024	-0.078 – 0.019	0.230
Smooth term: Income Deprivation % z-score						1.946	0.614^{1} -0.059^{2}			**<0.001**
Smooth term: Gini coefficient z-score						2.101	0.194^{1} -0.095^{2}			**0.022**
Income Deprivation % z-score	0.160	0.504	0.035	0.091 – 0.228	**<0.001**					
Smooth term: Gini coefficient z-score (England)	1.000	0.030^{1}			0.808					
Smooth term: Gini coefficient z-score (Wales)	3.797	2.54^{1}** -0.477^{2}** -0.829^{3}** 0.995^{4}**			0.058					
Observations	171					172				
R^2 Nagelkerke	0.472					0.753				
AIC	11.569					-42.938				

* Standardised estimates for linear terms from closest approximation GLM. For smoothed functions, footnote equals polynomial (e.g. ^{1} = linear part, ^{2} = quadratic part)

** Linear beta coefficient uninformative due to high number of polynomials in GLM equivalent (4)

There was a statistically significant linear relationship between income deprivation and logged child protection plan/register rates, and a significant non-linear relationship between income deprivation and logged children looked after rates (CP: B = 0.16 [0.091 – 0.228], $p < 0.001$; CLA: *edf* = 1.946, $p < 0.001$). While non-linearity offered a significantly better fit for the CLA model, this was largely because of the log-transformation of rates, as can be seen in figure two. Income deprivation was the strongest linear predictor in both models (CP = 0.504; CLA = 0.614). The income deprivation effect did not differ significantly between England and Wales in either model (CP: Tukey HSD B = 0.144, p = 0.405; CLA: Tukey HSD B = -0.337, p = 0.140).

Income inequality was not a significant predictor of CP Plan/Register rates, although the non-linear estimate for Wales approached significance (England: *edf* = 1.000, p = 0.808, Wales: *edf* = 3.797, p = 0.058). The low number of Welsh local authorities and high *edf* suggests this may be a consequence of overfitting. Income inequality was a statistically significant non-linear predictor of logged CLA rates in England and Wales (*edf* = 2.101, p = 0.022). The effect of income inequality on logged CLA rates was quadratic in form, with approximately zero effect beyond slightly higher than average levels of inequality. It did not differ significantly between England and Wales (Tukey HSD = -0.065, p = 0.676). The standardised coefficient for the linear component of the effect, taken from an equivalent GLM, was 0.194, making the strength of the association approximately one-third that of income deprivation.

There was no evidence that the effect of either Gini coefficient or income deprivation was moderated by the other. The direction of the coefficient in the CLA model did correspond with the one found by Eckenrode, et al. (B = 0.070, p = 0.124) and, given the comparatively small number of administrative units in England and Wales (N = 174), this may reflect an inadequate sample size to detect the moderating effect rather than the lack of such an effect.[28]

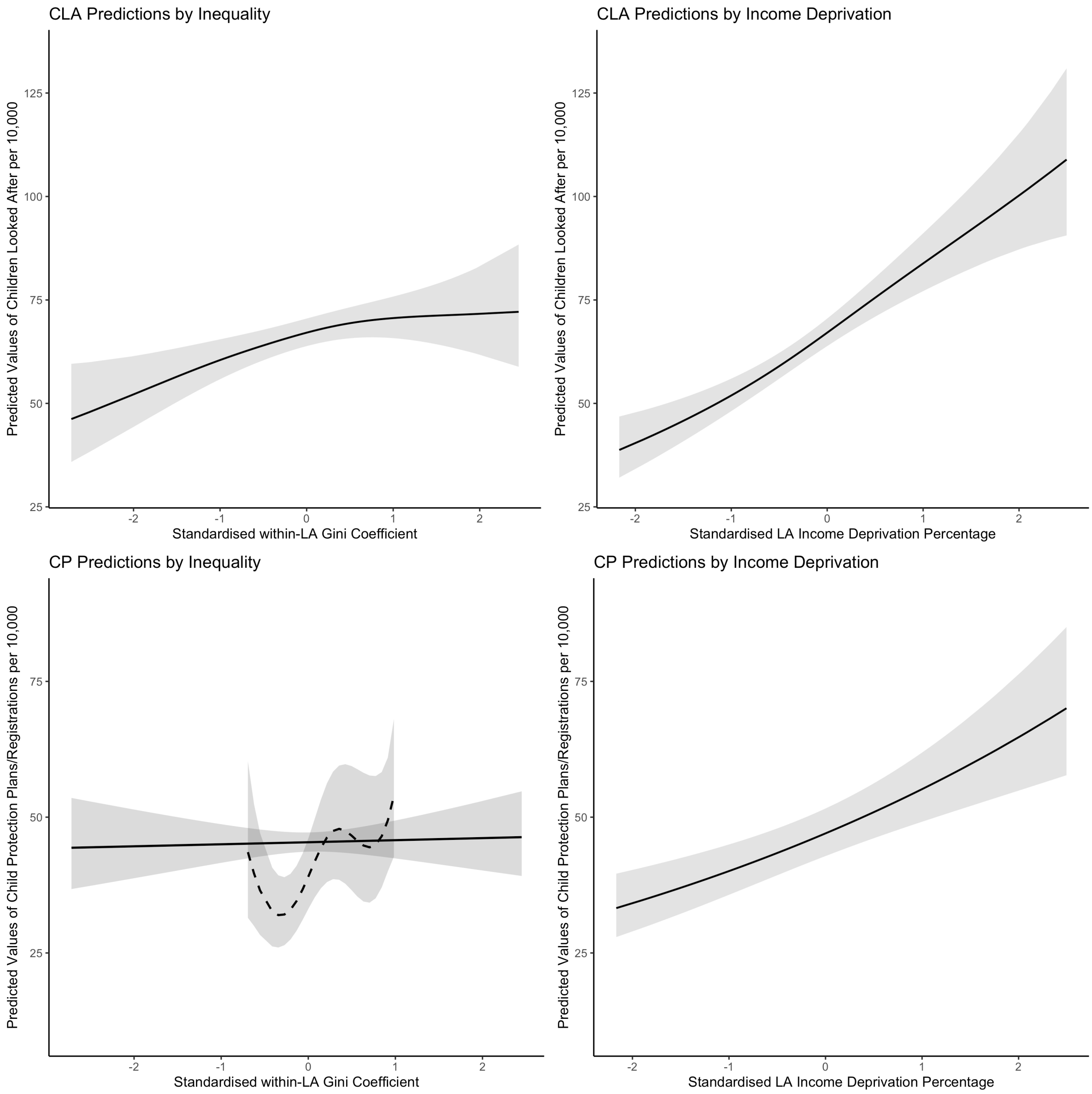

Figure 2: Predicted values of CLA and CP Plan/Register rates per 10,000 children by standardised income inequality and income deprivation. Dashed lines represent predictions and standard error estimates for Wales, when Welsh and English trends differed significantly.

Discussion

This study has found that there is mixed evidence to support the international application of findings from Eckenrode et al.'s US study.[11] This suggests that the relatively recent addition of child maltreatment to the list of adverse consequences of income inequality is tenable beyond the US, but the fact that it is not observable across different forms of child protection intervention raises further questions as to how exactly this adversity operates.

Despite children looked after and child protection plan/register rates having similar associations with income deprivation, income inequality was only a significant predictor of children looked after rates. While this may be a result of inadequate isolation of maltreatment cases in our children's services data, this finding may also be important for understanding where income inequality-related effects emerge. This includes questioning whether income inequality effects emerge downstream through, for example, differences in family court decisions to grant care orders, differences in the decisions of services to issue care proceedings, or differences in the substantiation of abuse by agencies, on the *service*-side of child welfare interventions, rather than upstream as a predicating stressor to abusive and neglectful parenting.

Limitations are also imposed by the lack of comparability between US and UK poverty measures. Relative measures such as income deprivation have a much higher correlation with income inequality, which may introduce difficulties in establishing the unique contributions of poverty and inequality, as the two concepts are closely linked within a relativist approach.[29] As the use of Orshansky thresholds are so unique to the US, this may raise further difficulties for other comparative research.

The study has, however, stayed close to the approach taken by Eckenrode et al.[11] where possible and some issues therefore remain unexplored. These include whether or not the proportion of children in the CP and CLA categories who have not been subject to maltreatment is random with respect to local authority income inequality; and the effect of austerity-related cuts to public services, which have been deeper in more deprived local authorities.[30] These would be interesting avenues to explore in future studies.

With limitations in mind, our study suggests that the rates of children in state care in England and Wales are higher in local authorities that are poorer or that have greater income inequality, or both, holding other factors constant. Further, these factors alongside some demographic variables can explain a very large proportion of the variation in rates of intervention. If inequality and poverty can explain between half and three-quarters of differences in serious welfare interventions, substantial macro-economic and social policies are required in response.

Conclusions

To our knowledge, this is the first study to explore the associations found in Eckenrode, et al. outside of the US context. More comparative studies are needed before we can refine our conceptual lens of inequality at the subnational level to provide constructive insights. We find tentative support for the claim of an independent association between income inequality and child welfare for England and Wales.

Lack of corresponding administrative data creates a significant barrier to comparative research in this field, but this evidence shows that the relationship between child maltreatment and income inequality may be a global one, and will prompt developments in international comparative research with more refined measurements. Our models suggest that income inequality is a risk to children's safety and/or right to family life in England and Wales, as it is in the US.

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