Child Abuse & Neglect 146 (2023) 106501

Contents lists available at ScienceDirect

Child Abuse & Neglect

journal homepage: www.elsevier.com/locate/chiabuneg

# The neighborhood deprivation gradient and child physical abuse and neglect: A Bayesian spatial model

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ARTICLE INFO

*Keywords:*
Bayesian spatial model
Physical abuse
Neglect
Area level deprivation
Random effects
Stepwise regression

ABSTRACT

*Background:* Child abuse and neglect is a public health priority due to its long-term maladaptive consequences. No study in the USA has assessed the nature and magnitude of the social deprivation effect on substantiated child maltreatment risk.
*Objectives:* To examine linear and non-linear relationships between area level deprivation and the log-risk of both substantiated physical abuse and neglect while accounting for spatial and heterogeneous random effects.
*Methods:* Substantiated child maltreatment and population data (2008–2015) were aggregated to neighborhoods in Bernalillo County, New Mexico. The contribution of area level deprivation to the geographical variation in the log-risks of substantiated child physical abuse and neglect was modeled using Bayesian spatial regression.
*Results:* Forty-three percent and 46.4 % of the 153 neighborhoods recorded greater risk for either substantiated physical abuse or neglect compared to the county average. The most deprived 20 % of neighborhoods had 71 % and 72 % more cases of substantiated physical abuse and neglect, respectively, than would be expected if the substantiations were randomly distributed throughout the county. Area level deprivation explained 47 % of the variation in substantiated physical abuse and 51 % of the variation in substantiated neglect after controlling for both spatial autocorrelation and heterogeneity.
*Conclusions:* Implications from this study can be used to quantify disparities in substantiated child maltreatment attributed to regional differences in social deprivation and to identify priority areas for intervention.

## 1. Introduction

According to a recent report from the Annie E. Casey foundation, New Mexico has one of the highest child poverty rates in the nation. Across the state, 28 % of children under five years old live in poverty, 50 % of children live in low-income households characterized by high housing cost burden, and 35 % of children have parents who lack secure employment (ibid). New Mexico has ranked 49th or 50th on multiple measures of economic, family and community well-being each year since 2012 (Annie E. Casey Foundation, 2023). Given these statistics, it is not surprising that New Mexico also has one of the highest rates of substantiated child maltreatment in the country. In 2017, the substantiated child maltreatment rate for the state was 17.6 per 1000, a 177.8 % increase from 2004 (U.S. Department of Health and Human Services et al., 2019). Aggregate statistics, however, mask the substantial spatiotemporal heterogeneity and dependence in maltreatment risk across the region resulting from socioeconomic inequality

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https://doi.org/10.1016/j.chiabu.2023.106501
Received 24 March 2023; Received in revised form 28 July 2023; Accepted 5 October 2023
Available online 14 October 2023
0145-2134/

(Barboza-Salerno, 2020). Despite the public health significance that contact with the child welfare system has for children (Thomas et al., 2023), particularly those who live in New Mexico, no US-based study to date has isolated the deprivation effect of neighborhood socioeconomic disadvantage on substantiated child maltreatment. The goal of this study was to explore the variability associated with area level deprivation on the risk of substantiated child physical abuse and neglect risk using Bernalillo County, the most populous county in New Mexico, as the study setting.

## 2. Neighborhoods and child maltreatment

Decades of research has documented the ecological and community systems that are systematically associated with disparities in child welfare outcomes (Drake & Pandey, 1996; Webb et al., 2020). Researchers using an ecological perspective focus on elucidating the multi-level and structural factors that shape substantiated child maltreatment risk across diverse contexts. Operating within this framework, research has identified the socioeconomic conditions that are linked to higher rates of either alleged or substantiated child maltreatment. Earlier studies focused on the role of concentrated poverty as a risk factor for abuse and neglect (Coulton et al., 1995; Drake & Pandey, 1996; Garbarino & Sherman, 1980; Zuravin, 1989) theorizing that impoverished neighborhoods have less capacity to recognize common problems and act collectively. Other research has focused on the specific contexts that increase child maltreatment risk including alcohol outlets (Freisthler, 2004; Freisthler et al., 2003, 2007), housing vulnerability (Barboza-Salerno, 2020; Fromm, 2004), racial/ethnic heterogeneity (Barboza, 2019; Klein & Merritt, 2014), residential density (Zuravin, 1986) and immigrant concentration (Molnar et al., 2003). This research tends to attribute spatial heterogeneity in child maltreatment risk to geographic variations in socioeconomic contexts across various settings.

More recent work highlights the role of material hardship to better address the mechanisms by which limited resources hinder a household's ability to meet its basic needs (Bellair et al., 2021; Ouellette & Isaacs, 2004; Yang, 2015). For example, individuals living in lower income neighborhoods may report few, if any, material hardships whereas individuals living in less impoverished neighborhoods may be socially disadvantaged in other ways (Yang, 2015). In this framework, neighborhood poverty is insufficient to explain the heightened risk for substantiated child maltreatment and/or is mediated by other factors, such as high rent burden. Despite different conceptualizations and methodological orientations, the unifying theme of research on neighborhood effects and child maltreatment is the pattern of association found between levels of socioeconomic status and child welfare intervention rates which produce inequities in child welfare outcomes (Kim & Drake, 2018; Webb et al., 2020).

## 3. Area level deprivation and child welfare

Research has shown that multidimensional indicators better characterize a community's "socioeconomic position" compared to singular measures of economic poverty or income inequality alone (Purcell et al., 2021). Nevertheless, research has tended to "evaluate singular measures of the neighborhood in relation to child wellbeing rather than the constellation of neighborhood factors in tandem (Pearson et al., 2022, p. 2)." In particular, few research endeavors have sought to disentangle the association between child welfare involvement and area level deprivation, focusing instead on specific forms of child wellbeing such as low birth weight and/or physical and mental health (Doebler et al., 2022). One exception is a recent study conducted by Doebler et al. (2022) who used Poisson mixed effects models to analyze data on family court proceedings linked to information on area deprivation from 22 Welsh local authorities[1] (LAs). The authors found that an increased risk of becoming involved with care proceedings was statistically associated with four domains of deprivation: employment, income, education, and health. In a similar study of over 35,000 children, also conducted in the United Kingdom, researchers found a steep and consistent social gradient in the proportion of children on child protection plans or in care (Bywaters, n.d.; Skinner et al., 2023). In that study, children from the most deprived 10 % of neighborhoods were over 10 times more likely to be in state care or on protection plans compared to children from the least deprived 10 % of neighborhoods. Additionally, the study found that about 55 % of children involved in the child welfare system came from the most deprived 20 % of neighborhoods (Bywaters, n.d.). More recently, Bywaters et al. (2016) and Webb et al. (2020) have demonstrated evidence of an 'inverse intervention' law where, for any given level of deprivation in local neighborhoods, LAs with lower overall levels of deprivation intervened more often. In both studies, the data revealed very large inequalities in rates of child welfare interventions within and between LAs which were systematically related to levels of deprivation. In one of the few studies conducted in the United Sates, Eckenrode and colleagues used generalized additive models (GAMs) to explore the linear and nonlinear association between county-level substantiated maltreatment reports and area level deprivation (measured by income inequality and poverty) (Eckenrode et al., 2014). They found considerable variation between deprivation and substantiated child maltreatment rates at the county level even after controlling for neighborhood impoverishment (Eckenrode et al., 2014). As relevant to the present study, they found a linear association between child maltreatment rates and income inequality. Furthermore, they demonstrated that the association was stronger for counties with moderate to high levels of child poverty.

## 4. Present study

The present study extends Eckenrode et al. (2014) in several ways. First, by using a highly reliable and valid measure of area level

[1] Local authorities, or LAs are higher-level administrative units in England, comparable to counties in the United States.

deprivation that incorporates multiple socioeconomic indicators across several domains, including housing, income, and transportation (Singh, 2003). Second, the unit of analysis in the present study is not the county but rather the census tract, which is a well-established proxy for 'neighborhood' in area deprivation studies (Ford & Dzewaltowski, 2011; Stafford et al., 2008). Further, unlike Eckenrode, this study disaggregates child maltreatment into separate measures of substantiated physical abuse and neglect. Finally, this study incorporates both spatial and heterogeneous random effects in addition to fixed effects (i.e., it is not an aspatial model). By incorporating spatial dependence, it is possible to explore the extent to which the 'deprivation effect' reproduces hot spots of substantiated child maltreatment risk observed across the county (Martínez-Beneito & Botella-Rocamora, 2019).

A review of research did not result in any US-based study that quantified the linear and nonlinear effects of area level deprivation on distinct forms of substantiated child maltreatment using a Bayesian spatial framework. As such, the present study adds to the growing body of research on deprivation gradients conducted in other countries by (1) examining linear and nonlinear associations between deprivation and specific maltreatment types (i.e., physical abuse and neglect); (2) computing standardized incidence ratios (SIRs) (rather than rates) of physical abuse and neglect to determine which neighborhoods, if any, show excess risk in comparison to the county; and (3) implementing models that incorporate random effects (i.e., spatial dependence and heterogeneity) to determine the amount of variation in child maltreatment that can be attributed exclusively to the deprivation effect. The goal of this study is to quantify the functional form (i.e., linear or nonlinear) and relative contribution (i.e., variation) of the deprivation effect on substantiated child maltreatment risk. The expectation regarding the magnitude of the deprivation effect is that increasing levels of deprivation will be associated with increased risk of both substantiated physical abuse and neglect.

## 5. Methods

### 5.1. Study area

This study takes place in Bernalillo County, New Mexico which in 2015 was comprised of $N = 153$ census tracts. The study setting offers several advantages. Encompassing 1167 mile$^2$, it is the third smallest county by area; however, with a total population of 674,393 (U.S. Census Bureau, 2021) it is the most populous county in the state. In the 2020 Census, 37.5 % of the population in Bernalillo County self-identified as non-Hispanic White, 48.7 % as Hispanic or Latine, 4.5 % as American Indian and Alaska Native alone, and 2.6 % as non-Hispanic Black (U.S. Census Bureau, 2020). In 2015, the median family income was $63,700.50 (Std.Dev. = $27,809.71) and about 25 % of the total population lived 150 % below the federal poverty line (FPL) (see Supplementary Table 1). Bernalillo county is the focus of this investigation for a few reasons. First, it is the smallest yet most populous county and hence may drive the results of state level analyses. Also, Bernalillo County provides a good mix of both urbanicity (16.8 %) and rurality (83.2 %) making it unique. Finally, since the outcome is measured in terms of relative risk and not a rate, focusing on one county results in the interpretation being relative to the county-level risk (versus the state-level risk). This is important because even though the administrative framework for child welfare is through the state, counties are tasked with the provision of services.

### 5.2. Data description

#### 5.2.1. Dependent variable

*5.2.1.1. Substantiated child maltreatment.* Yearly counts of child maltreatment substantiations conducted between 2007 and 2015 were collected by the Protective Services Division of New Mexico's Department of Child Youth & Families (CYFD) and provided to the researcher by the New Mexico Community Data Collaborative.[2] The counts were aggregated by census tracts and spatially ordered. Because the number of children in each census tract is variable, population estimates of children under 18 years of age were downloaded from the American Community Survey (ACS) for the years 2006–2010 and 2011–2015. The number of substantiated physical abuse and neglect cases expected in each census tract was computed using the census tract specific population counts of children under 18 years old.

### 5.3. Area level deprivation

Created by the Health Resources & Services Administration (HRSA), the Area Deprivation Index (ADI; (Kind & Buckingham, 2018), is comprised of 15 factors that approximate the material and social conditions of a community across multiple domains including income, education, transportation, and housing quality. The index was constructed based on factor loadings and factor score coefficients used to weight the 15 indicators (see Supplementary Appendix Table 1), all of which loaded significantly on a single factor. The factor scale was then transformed into a standardized index with mean = 100 and standard deviation = 20. Higher values on the ADI are indicative of more deprivation. Previous research has shown that area deprivation index is both reliable and valid for describing the extent of economic inequality and deprivation (Singh, 2003). The ADI was downloaded at the census tract level for Bernalillo County, New Mexico, using the R function `get_adi` available from the `sociome` package (https://github.com/NikKrieger/

[2] These data are also publicly available from the New Mexico Community Data Collaborative at the Center for Health Innovation located here CHILD ABUSE AND NEGLECT TRENDS, 2007-2015, SMALL AREAS - Overview (arcgis.com)

sociome). The library includes arguments to download the census tract geometry, factor scores and all indicators for the ADIs for Bernalillo County (state = "NM") for the 5-year spanning 2011–2015 (see Appendix for R code used to download the ADI). More information regarding the calculation of the ADI is available online at https://www.neighborhoodatlas.medicine.wisc.edu/.

### 5.4. Statistical analysis

Geographic differences in the relative risk of both substantiated physical abuse and neglect in Bernalillo County neighborhoods (i.e., census tracts) using the ADI index were examined using Bayesian hierarchical models. One benefit of using Bayesian hierarchical modeling is that these models improve estimates by shrinking unstable risks toward the local mean risk by borrowing information between areas (Beale et al., 2008). Therefore, in the present analysis, the Bayesian hierarchical models estimate the 'smoothed' relative risks of child physical abuse and neglect for each neighborhood (i.e., census tract) by borrowing strength across adjacent census tracts. Bayesian Hierarchical models are also advantageous because they allow for the incorporation of both spatial dependence and heterogeneity via the inclusion of random effects (Martínez-Beneito & Botella-Rocamora, 2019). To model spatial dependence, an adjacency matrix containing adjacent neighborhood information across Bernalillo County census tracts was created using the `rgdal` library in R. The shared neighborhood boundaries were defined using the queen's contiguity method of first order.

Four separate regression models with random effects for neighborhoods were estimated to fit the relative risk of child abuse and neglect over the region controlling for spatial heterogeneity and autocorrelation. The observed number of distinct cases of physical abuse or neglect, respectively, was aggregated into each of the $I = 153$ census tracts. Then, the number of children under 18 years of age was used to calculate the expected number of physical abuse and neglect substantiations in each census tract. In the model, $O_i$ and $E_i$ represent the observed and expected counts of the $i$-th census tract. Model 1 was specified with mixed effects for neighborhoods to fit the relative risk of substantiated child physical abuse and neglect separately without including the ADI. Then, the ADI, denoted as

**Table 1**
Descriptive statistics of study variables.

| | | Average | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| | Physical Abuse rate per 1000 | 4.95 | 4.31 | 0.00 | 22.41 |
| | Neglect rate per 1000 | 13.94 | 9.79 | 0.00 | 46.15 |
| | Physical Abuse SIR | 0.45 | 0.39 | 0.00 | 2.04 |
| Least Deprived 20 % of neighborhoods (Q1) | Neglect SIR | 0.40 | 0.28 | 0.00 | 1.33 |
| | Physical Abuse (N) | 113 | 3.13 | 0.00 | 15 |
| | Neglect (N) | 326 | 8.61 | 0.00 | 38 |
| | Area Deprivation Index | 73.1 | 8.75 | 50.3 | 83.9 |
| | Physical Abuse rate per 1000 | 8.70 | 5.93 | 0.00 | 26.79 |
| | Neglect rate per 1000 | 26.02 | 14.12 | 7.26 | 61.74 |
| | Physical Abuse SIR | 0.79 | 0.54 | 0.00 | 2.44 |
| Q2 | Neglect SIR | 0.75 | 0.41 | 0.21 | 1.78 |
| | Physical Abuse (N) | 259 | 5.67 | 0.00 | 21 |
| | Neglect (N) | 705 | 11.92 | 3 | 46 |
| | Area Deprivation Index | 89.1 | 2.63 | 84.4 | 93.2 |
| | Physical Abuse rate per 1000 | 11.63 | 6.87 | 0.00 | 30.97 |
| | Neglect rate per 1000 | 40.75 | 25.16 | 11.35 | 142.86 |
| | Physical Abuse SIR | 1.06 | 0.63 | 0.00 | 2.82 |
| Q3 | Neglect SIR | 1.17 | 0.72 | 0.33 | 4.11 |
| | Physical Abuse (N) | 292 | 5.98 | 0.00 | 29 |
| | Neglect (N) | 881 | 14.45 | 5 | 54 |
| | Area Deprivation Index | 98.3 | 3.33 | 93.5 | 104 |
| | Physical Abuse rate per 1000 | 13.91 | 6.98 | 3.02 | 28.74 |
| | Neglect rate per 1000 | 46.61 | 23.43 | 18.72 | 127.27 |
| | Physical Abuse SIR | 1.27 | 0.63 | 0.27 | 2.61 |
| Q4 | Neglect SIR | 1.34 | 0.67 | 0.54 | 3.66 |
| | Physical Abuse (N) | 396 | 7.52 | 3 | 29 |
| | Neglect (N) | 1267 | 19.70 | 9 | 96 |
| | Area Deprivation Index | 111 | 4.25 | 104 | 118 |
| | Physical Abuse rate per 1000 | 16.96 | 8.49 | 1.39 | 34.51 |
| | Neglect rate per 1000 | 59.51 | 28.66 | 1.39 | 124.58 |
| | Physical Abuse SIR | 1.54 | 0.77 | 0.13 | 3.14 |
| Most Deprived 20 % of Neighborhoods (Q5) | Neglect SIR | 1.71 | 0.82 | 0.04 | 3.59 |
| | Physical Abuse (N) | 669 | 14.02 | 1.00 | 54 |
| | Neglect (N) | 2287 | 46.15 | 1.00 | 165 |
| | Area Deprivation Index | 129 | 8.35 | 118 | 146 |
| | Physical Abuse rate per 1000 | 11.23 | 7.79 | 0.00 | 34.51 |
| | Neglect rate per 1000 | 37.38 | 26.56 | 0.00 | 142.86 |
| | Physical Abuse SIR | 1.022 | 0.71 | 0.00 | 3.14 |
| Total | Neglect SIR | 1.076 | 0.764 | 0.00 | 4.11 |
| | Physical Abuse (N) | 1729 | 10.05 | 0.00 | 54 |
| | Neglect (N) | 5466 | 32.42 | 0.00 | 165 |
| | Area Deprivation Index | 100 | 20 | 50.3 | 146 |

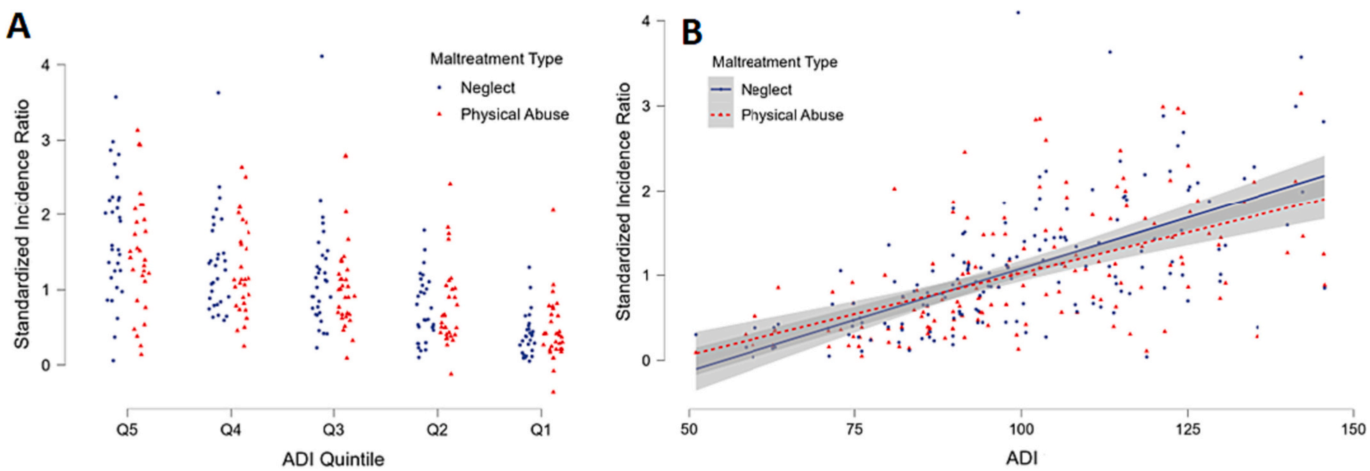


**Fig. 1.** Relationship between neighborhood deprivation index (2015) and child abuse and neglect in 153 census tracts of Bernalillo County, New Mexico 2008–2015. **A** Child maltreatment risk (2008–2015) by neighborhood deprivation index quintiles by maltreatment type (*Q1* = least deprived 20 % of neighborhoods, *Q5* = most deprived 20 % of neighborhoods); **B** Linear relationship between child maltreatment risk and area deprivation.

$x$, was included as a covariate in the model, such that $x_i$ represents the ADI score in each of the $i = 1, \ldots, 153$ tracts. Thereafter, the model was formulated as follows:

$$O_i \sim \text{Poisson}(E_i\theta_i), i = 1, \ldots, I$$

$$log(\theta_i) = \mu + f(x_i\beta) + g(\varphi)_i,$$

where $\mu$ = the intercept, $f(x_i\beta)$ models the contribution of the covariate to the geographical variation of the log-risks of child maltreatment, and $g(\varphi)$ is the vector of random effects representing the variation in the log-risks of child maltreatment that cannot be explained by area deprivation (see Martínez-Beneito & Botella-Rocamora, 2019 for more information about this modeling framework). The random effects were comprised of two components: a spatially unstructured term which captures random variation around $\mu$ and a spatially structured conditional autoregression term which captures local dependence. The prior of $\varphi$ was modeled as a conditional autogressive (CAR) distribution to incorporate spatial correlation.

Model 2 assumed a linear relationship between the ADI and the log-risks for each census tract. In order to explore a more flexible alternative beyond the linear relationship between deprivation and the log-risks, the ADI was categorized into discrete groups using a stepwise function. The cutpoints used in the stepwise function split the ADI into equal groups with the same number of census tracts in each group (e.g., quintiles when $Q = 5$). The stepwise functions used for models 3 and 4 categorized the ADI into $K - 1$ equal groups $\{Q_1, Q_2, \ldots, Q_{K-1}\}$ where $K = 5$ and 10 respectively. For example, when $K = 5$ (Model 3) the ADI covariate was categorized into quintiles where $Q_1$ corresponds to the least deprived 20 % of neighborhoods and $Q_5$ to the most deprived 20 % of neighborhoods. When $K = 10$ (Model 4), the ADI was cut into deciles before being added to the model. In models 3 and 4, the $\beta$'s were defined as a first order random walk to model dependency on nearby intervals of the stepwise function using an improper uniform prior when $k = 1$ but when $k = 2, \ldots$ $K$ then $\beta_K \sim N\left(\beta_{k-1}, \sigma_\beta^2\right)$ (see Martínez-Beneito & Botella-Rocamora, 2019).

The models were run using the `pbugs` library in R which runs WinBugs through the R interface. Markov-Chain Monte Carlo (MCMC) simulations were implemented, and parameter means and associated 95 % credible intervals (CrIs) were estimated from a chain of 150,000 iterations after a burn-in of 50,000 iterations. The Brooks-Gelman-Rubin statistic, the effective sample size, and an examination of the simulated chains were used to evaluate the convergence of the identifiable variables in the model (Brooks & Gelman, 1998; Gelman & Rubin, 1992). The Brooks-Gelman-Rubin statistic was <1.1 (Rhat = 1.00), and that the effective sample size was >100 for all variables in every model. The convergence diagnostics indicated that all of the samples for the parameters of interest converged appropriately. To interpret the model results the exponentiated coefficients associated with the ADI are interpreted as incidence density ratios with associated 95 % CrI's.

## 6. Results

### 6.1. Descriptive characteristics

The mean total child population in each census tract was 1028.23 (Std.Dev. = 626.43; Range = [35–3143]). Table 1 shows the summary statistics for key study variables. There was a total of 1729 unique cases of substantiated physical abuse and 5466 unique cases of substantiated neglect over the study period. The average rate of substantiated physical abuse and neglect was 11.23 and 37.38 per 1000 children, respectively. The SIR compares the observed number of substantiations to the number that would be expected given the distribution of children under 18 in each neighborhood. An SIR >1 indicates more cases were observed than expected whereas an SIR <1 indicates fewer cases were observed than expected. The SIRs were 1.022 and 1.076 for physical abuse and neglect, respectively. This means that there were 2.2 % and 7.6 % more observed cases of substantiated child abuse and neglect than would be expected in the county if the cases were randomly distributed.

Table 1 disaggregates the study variables within ADI quintiles. The results suggest substantial heterogeneity across levels of deprivation. For example, there were almost 6 times as many child physical abuse cases in the most deprived 20 % of neighborhoods over the 8 year period compared to the least deprived 20 % (669/113). The rate of substantiated physical abuse in the least deprived neighborhoods was 4.95 compared to 11.23 in the most deprived neighborhoods. Similarly, the rate of substantiated neglect in the least deprived neighborhoods was 13.94 per 1000 compared to 59.51 per 1000 in the least deprived. The table demonstrates a clear gradient effect in which the magnitude of substantiated physical abuse and neglect cases for each level of ADI is greater than the next lowest quintile. The SIR for substantiated physical abuse and neglect in the most deprived neighborhoods shows 54 % and 71 % more cases than would be expected given the child population of each area. In contrast, in the least deprived neighborhoods, the SIR shows 65 % and 60 % *fewer* cases than expected based on the number of exposures. Other comparisons can be read from the table. This is strong evidence that the cases are highly clustered in the most deprived neighborhoods.

Fig. 1 shows the relationship between SIRs and area deprivation by maltreatment type. Fig. 2a provides the cloud plot of the SIRs within deprivation quintiles. The plot demonstrates the substantial variation in SIRs within ADI quintiles. An analysis of the variation within quintiles compared to the total variation across all quintiles reveals that the variation in SIRs is greater within the most deprived 20 % of neighborhoods for both types of maltreatment. However, the variation within the least deprived 20 % of neighborhoods is significantly smaller compared to the total variation across all quintiles (see Supplementary Table 2). Fig. 2b shows the strong, positive linear relationship between each SIR and area deprivation. The Pearson correlation coefficient between the SIR for physical abuse was 0.54 ($p < .001$) and for neglect was.63 ($p < .001$). A unit increase in the ADI was associated with a .02 increase in the SIR for both physical abuse ($\beta = .021, t = 7.94, p < .001$) and neglect ($\beta = .024, t = 9.98, p < .001$).

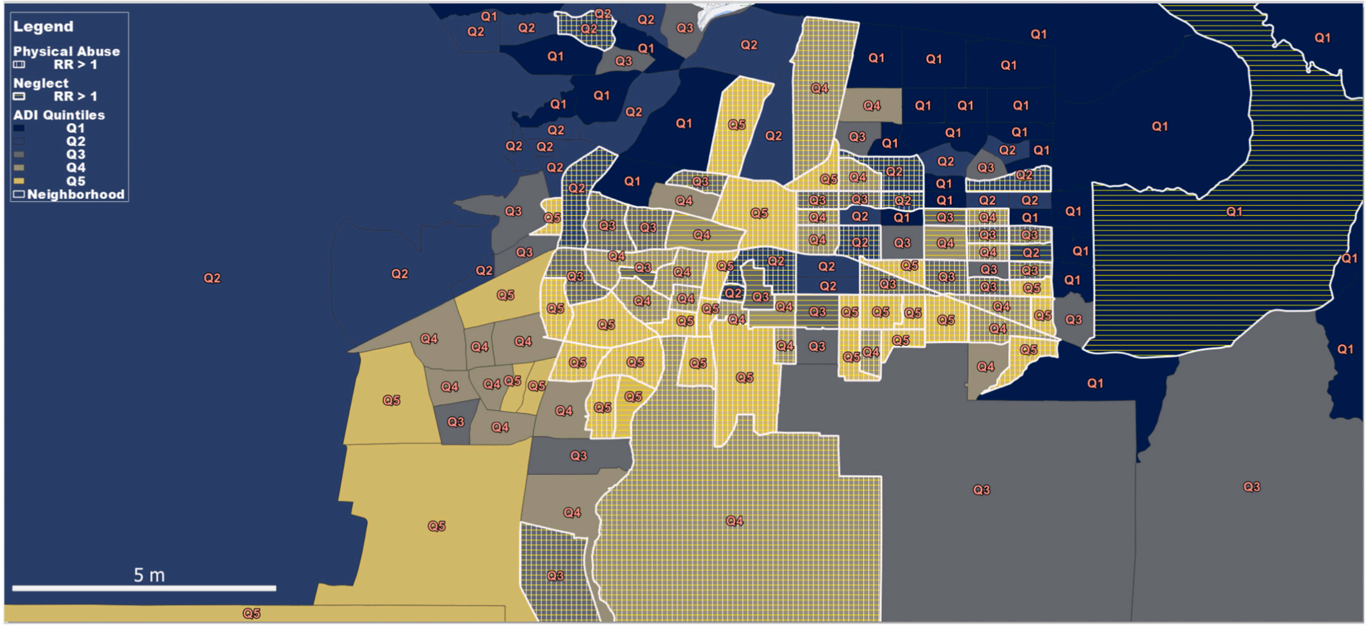


**Fig. 2.** Map of neighborhoods with relative risk greater than the county average for physical abuse (horizontal hatches) and neglect (vertical hatches). All areas with greater relative risk for physical abuse are also areas of greater relative risk for neglect (checker board hatches). Q1 = least deprived 20 % of neighborhoods; Q5 = most deprived 20 % of neighborhoods.

Fig. 2 shows the areas that had higher risk for substantiated physical abuse and neglect than the county overlaid onto a quintile map of area level deprivation. The vertical hatches show areas that had higher risk for physical abuse and the horizontal hatches show areas that had higher risk for neglect. Therefore, areas that have a checkerboard design indicate areas that have higher values for both physical abuse and neglect. Forty-three percent and 46.4 % of the 153 neighborhoods recorded greater risk for either substantiated physical abuse or neglect compared to the county average while 39 % of the neighborhoods demonstrated greater risk for both substantiated physical abuse *and* neglect (see Fig. 1). The map shows that the relative risk is higher in the most deprived 40 % of neighborhoods but there are a few exceptions to this pattern. Whereas areas with higher risk for both physical abuse and neglect are generally associated with the most deprived neighborhoods and areas with the lowest risk are associated with the least deprived neighborhoods, some high risk neighborhoods are located in areas of least deprivation.

Model comparisons were made based on the DIC scores shown in Table 2. The fit for the unadjusted model was relatively worse compared to models 2–4 (Physical abuse DIC = 842.47; Neglect DIC = 1062.36). Model 3 (quintile) fit was slightly improved (lower DIC score) compared to models 2 and 4 for neglect (DIC = 1058.31) but the linear fit (model 2) was slightly better for physical abuse (DIC = 831.17) compared to models 3 and 4. The differences between models 2 and 3 for both substantiated physical abuse and neglect are small. Fig. 3 shows the posterior mean predictions from the quintile (*y*-axis) and linear (*x*-axis) models of substantiated physical abuse and neglect. Due to the observed similarities, the results from both models 2 and 3 are compared.

The ADI coefficient for model 2 has an exponentiated posterior mean of 1.02 (95 % crI [1.01, 1.02]). Therefore, each one unit increase in the ADI increases the relative risk of child maltreatment by 2 %. To more fully interpret this finding, the impact should be explored over more meaningful ranges of the ADI such as the standard deviation and range. A standard deviation increase (i.e., 20 units) in the ADI is associated with a.48 increase in the SIR for each maltreatment type. The maximum ADI score (i.e., the most deprived census tract in the county) is 145.72 and the minimum ADI score is 51.11. Therefore, the relative risk of substantiated child physical abuse across the range of deprivation (high versus low) is about 6.88 (crI = [4.17, 12.42]). Similarly, a standard deviation change in the ADI increases the relative risk by about 50 %. Model 3 similarly demonstrates the deprivation gradient effect on substantiated child maltreatment relative risk across quintiles (Table 3). The exponentiated posterior means corresponding to the ADI quintiles for physical abuse are Q1 = 0.454 (crI = [0.365, 0.572]), Q2 = 0.854 (crI = [0.713, 1.033]), Q3 = 1.121 (crI = [0.9579, 0.1.327]), Q4 = 1.333 (crI = [1.122, 1.555]), and Q5 = 1.724 (crI = [1.455, 2.052]). This means that children living in the least deprived 20 % of tracts have a 100*(1–0.454)% = 54.6 % lower chance of being substantiated for physical abuse whereas children living in the most deprived 20 % of tracts have a 72.4 % *higher* chance. The results are similar for neglect.

The top right map in Figs. 4 and 5 show the standardized incidence ratios (SIRs) for substantiated child physical abuse and neglect risk across neighborhoods. The plot reveal the unequal distribution of substantiated child maltreatment risk revealed by the model, with the highest risks associated with areas in the central part of the county. The two maps on the bottom of Figs. 4 and 5 represent the variance decomposition associated with area level deprivation, on the one hand, and the random effects on the other (i.e., the variability that remains once the effect of deprivation is removed). This decomposition is possible since the SIR $= exp(log(\theta)) = exp(\mu + \beta ADI_i + \varphi) = \exp.(\mu) + exp(\beta ADI_i) + exp(\varphi)$, for $i = 1, \ldots$ 153. The maps can be read together by noting that areas with the same color on the map suggest that the ADI effect is either stronger (map C) or weaker (map D), respectively. As shown by the bottom left map in Figs. 4 and 5, the deprivation component reproduces many of the high risk areas demonstrated by the SIR map which correspond to the most deprived 40 % of census tracts. The bottom right map shows some areas, however, that are not highlighted in the SIR map that are mainly associated with the larger tracts on the edges of the county. These are areas that remain high risk once deprivation has been partialled out.

The standard deviation of the ADI component on substantiated physical abuse is 0.409 and the standard deviation for residual variability is 0.436. This means that the ADI component explained 46.72 % of the variation in the log-risk for substantiated physical abuse. Similarly, in the stepwise model corresponding to substantiated neglect, the ADI component explained 51.9 % of the variation in log-risk. Finally, the results show that both random effects are important to include in the model. The spatial dependence parameters for each model provides statistical evidence that both substantiated child physical abuse and neglect demonstrate strong spatial clustering, as indicated previously.

## 7. Discussion

This is the first study to explore the neighborhood deprivation effect in the US context for distinct types of child maltreatment in a Bayesian spatial framework. Prior studies have focused on other countries (e.g., England, Wales), used aspatial regression methods (e.g., Poisson, GAMs) or used larger administrative units (e.g., counties). The results of this study show that during the time frame under

**Table 2**
Model fit statistics.

| | Physical Abuse | | | Neglect | | |
|---|---|---|---|---|---|---|
| | D | pD | DIC | D | pD | DIC |
| Unadjusted Model 1 | 748.05 | 94.41 | 842.47 | 934.72 | 127.63 | 1062.36 |
| Linear Model 2 | 750.09 | 81.09 | 831.17 | 940.47 | 119.37 | 1059.84 |
| Quintile Model 3 | 750.95 | 80.61 | 831.57 | 938.78 | 119.52 | 1058.31 |
| Decile Model 4 | 750.42 | 82.00 | 832.42 | 939.72 | 120.93 | 1060.66 |

D = Deviance; pD = effective number of parameters; DIC = Deviance Information Criteria. Models with lower DIC score indicate better fit.

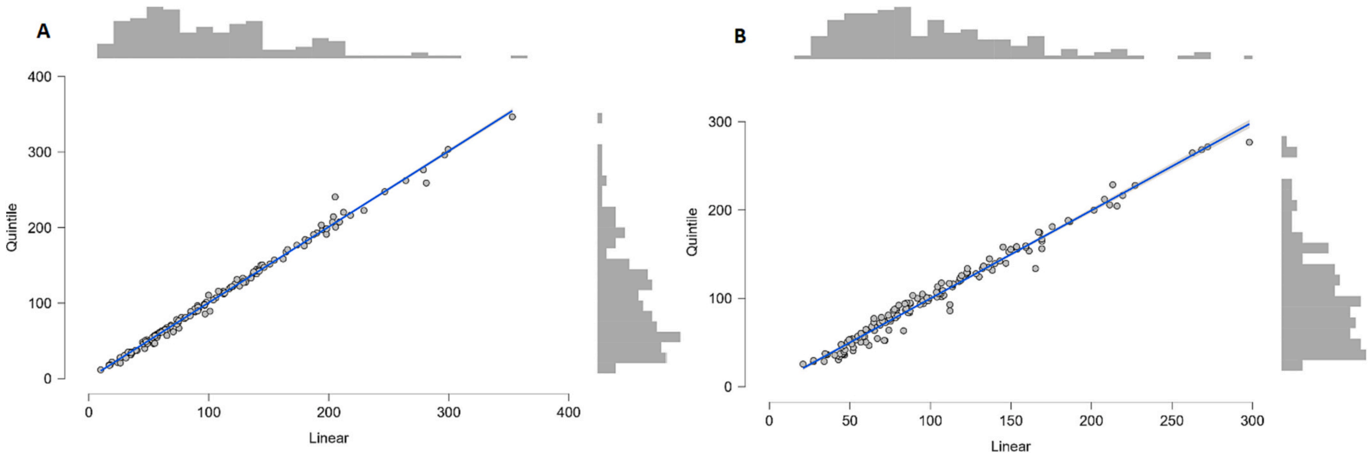


**Fig. 3.** Posterior mean of the standardized incidence ratios (SIRs) (multiplied by 100) from model 2 (linear; *x*-axis) and model 3 (quintile; *y*-axis) for substantiated neglect (A) and physical abuse (B) across $N = 153$ census tracts.

**Table 3**
Bayesian Hierarchical Model: unadjusted and adjusted beta coefficients (95 % CrI for the associations).

| | Physical Abuse RR (95%CrI) | Neglect RR (95%CrI) |
|---|---|---|
| Model 2: | | |
| Continuous ADI | | |
| 1 unit | 1.02 [1.01, 1.02] | 1.02 [1.02, 1.03] |
| 1 SD | 1.50 [1.35, 1.70] | 1.56 [1.36, 1.73] |
| ΔRange | 6.88 [4.17, 12.42] | 8.22 [4.32, 13.4] |
| ΔIQR (Q3 – Q1) | 1.49 [1.35, 1.70] | 1.45 [1.30, 1.58] |
| Random Effects | | |
| Spatial dependence | 0.654 [0.361,0.929] | 0.708 [0.452, 0.924] |
| Unstructured heterogeneity | 0.220 [0.030, 0.379] | 0.276 [0.184, 0.402] |
| Model 3: | | |
| ADI Quintile | | |
| Q1 | 0.46 [0.365, 0.572] | 0.44 |
| Q2 | 0.85 [0.713, 1.033] | 0.84 [0.706, 0.989] |
| Q3 | 1.13 [0.9579, 0.1.327] | 1.10 [0.963, 1.292] |
| Q4 | 1.33 [1.122, 1.555] | 1.42 [1.187, 1.629] |
| Q5 | 1.72 [1.455, 2.052] | 1.71 [1.44, 2.04] |
| Random Effects | | |
| Spatial dependence | 0.653 [0.356, 0.931] | 0.782 [0.477, 1.050] |
| Unstructured heterogeneity | 0.214 [0.027, 0.376] | 0.254 [0.068, 0.412] |

RR = exp.(beta); crI = Credible Interval; IQR = Interquartile Range; Q = Quintile; ADI = Area Deprivation Index

investigation, children living in Bernalillo County were being substantiated for maltreatment at levels that were significantly higher than the number of exposures (i.e., the population of children under 18 years old). Importantly, this finding is based on relative risk, defined as the ratio of the number of substantiations to the expected number of substantiations given the population under age 18. Of the 153 neighborhoods in Bernalillo County, 46.4 % recorded greater relative risk for either physical abuse or neglect compared to the county average while 39 % of the neighborhoods demonstrated greater risk for both substantiated physical abuse *and* neglect.

The main goal of this study was to determine the nature and magnitude of the deprivation effect in child maltreatment risk. Significant stepwise associations and high levels of correlation between area level deprivation and substantiated child maltreatment risk were noted. The linear model performed slightly better for physical abuse, but the quintile model performed slightly better for neglect. Regardless, both models revealed a clear deprivation effect best expressed as a gradient such that areas associated with the highest level of deprivation assume substantially more risk compared to areas with the next highest level of deprivation and so forth. For example, the analysis revealed that the relative risk for child physical abuse and neglect in the most deprived 20 % of neighborhoods was substantially lower relative to the exposed population whereas the risk of experiencing maltreatment in the most deprived 20 % of neighborhoods was substantially higher. This is consistent with international studies demonstrating a social gradient in child welfare involvement and entry into foster care (Bywaters et al., 2016; Doebler et al., 2022; Eckenrode et al., 2014).

The analysis extends previous research be revealing the magnitude of the deprivation effect which is very large (Figs. 4 and 5). The deprivation effect accounted for between 46 and 51 % of the variation in child maltreatment risk across the county. However, despite significant associations between area deprivation and child maltreatment risk, the magnitude of the variation in risk was only greater than the differences in average risk across deprivation quintiles within the most deprived 20 % of neighborhoods. The least deprived 20 % of neighborhoods had much smaller variability in risk such that the magnitude within the least deprived 20 % of neighborhoods was smaller than the average risk across all deprivation quintiles (see Fig. 1b, Supplementary Table 2). This finding is important because it means that some of the variability in child maltreatment risk is not explained by the ADI and therefore alternative factors must be at play. However, it also means that relatively more of the variability in child maltreatment risk was unaccounted for in the most deprived 20 % of neighborhoods compared to the least deprived 20 % of neighborhoods. Therefore, despite the large amount of variation explained by the deprivation effect, additional factors are relevant to explain the variability of risk within the most deprived quintiles. Access to parks, grocers, and health-related amenities and/or racial/ethnic composition and language barriers have been shown to comprise separate indices of deprivation beyond socioeconomic measures and would be good to consider in future studies (Eibner & Sturm, 2006).

It is worth noting that in New Mexico about 90 % of child maltreatment substantiations can be attributed to physical or supervisory neglect.[3] Also, under New Mexico law, as in most states, the definition of child maltreatment includes the failure of a parent, guardian, or custodian to provide proper care or basic necessities, such as food, shelter, medical care or education, to a child under 18 years old; or the inability of a parent to care for a child due to parental incarceration, hospitalization, or physical or mental disorder or incapacity (Abuse and Neglect Act (32 A-4-2, NMSA, 1978)). Clearly, the legal definition of neglect and the operationalization of deprivation overlap to a large extent. Therefore, the present study is consistent with the proposition that extreme social deprivation, and the social isolation that results, are neighborhood conditions that place constraints on a family's ability to meet the needs of their children

[3] If medical neglect is included in the calculation the figures are even higher, ranging from 93.6 to 98.9 % see https://cwoutcomes.acf.hhs.gov/cwodatasite/pdf/new%20mexico.html. These percentages are calculated against the number of unique victims.

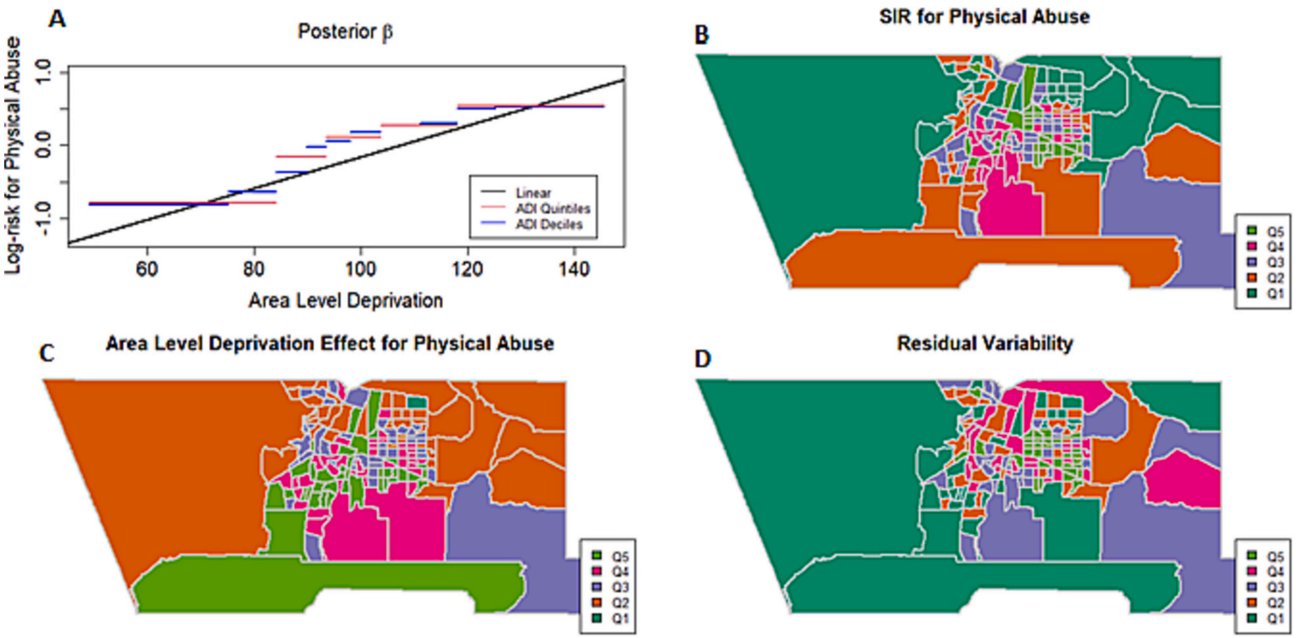


**Fig. 4.** Bayesian Hierarchical Model Results for Linear and Stepwise Regression Models estimating the effect of ADI on physical abuse: (A) Linear and stepwise associations between Area Deprivation and Log-risk of child physical abuse; (B) SIR = Standardized Incidence Ratios for child physical abuse; (C) The deprivation gradient effect representing the effectof area deprivation quintiles on child physical abuse; (D) the amount of residual variation in child physical abuse that is not accounted for by the deprivation gradient.

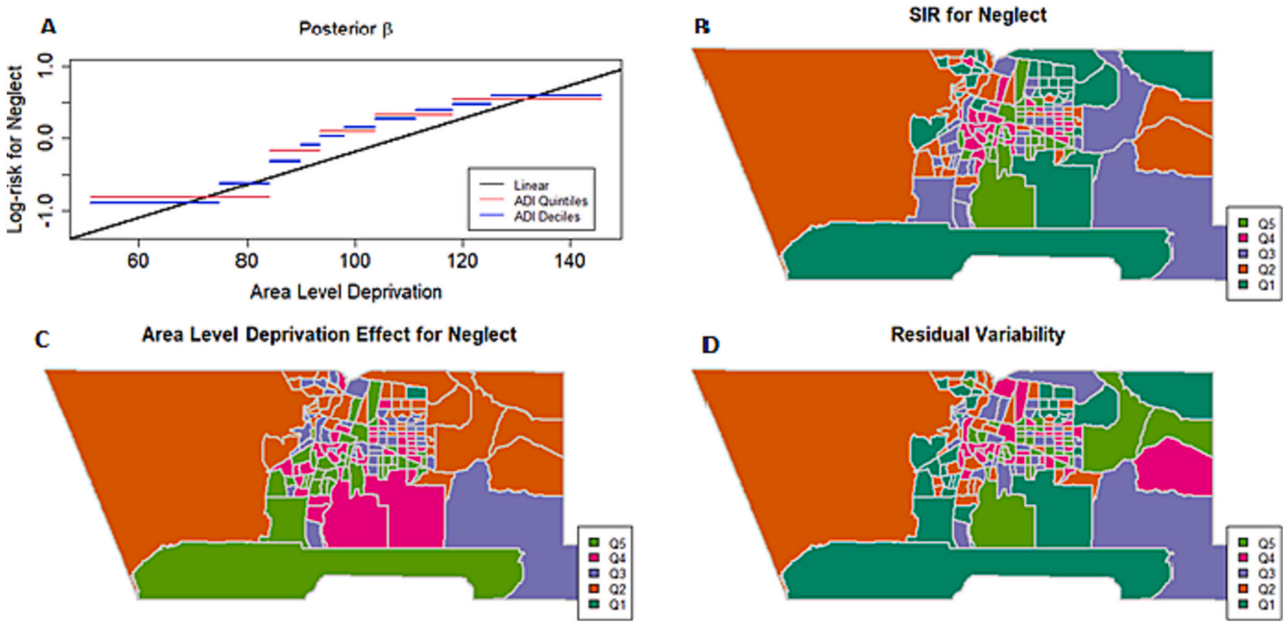


**Fig. 5.** Bayesian Hierarchical Model Results for Linear and Stepwise Regression Models estimating the effect of ADI on Neglect: (A) Linear and stepwise associations between Area Deprivation and Log-risk of child neglect; (B) SIR = Standardized Incidence Ratios for child neglect; (C) The deprivation gradient effect representing the effectof area deprivation quintiles on child neglect; (D) the amount of residual variation in child neglect that is not accounted for by the deprivation gradient.

(Bellair et al., 2021). These constraints have resulted from government sanctioned policies such as de jure segregation and redlining that continue to compromise the health and well-being of children through a process of systematic neighborhood disinvestment (Rothstein, 2017; Berg et al., 2022; Thomas et al., 2023). A clear implication pertains to the need for local governments to prioritize the consequences of historic disinvestment and lack of resources as spatial sources of social deprivation (Berg et al., 2022). Further, while past research suggests that the indicators of deprivation interact with individual level risk factors and social processes (Chandler et al., 2020) that are not yet fully understood (Molnar et al., 2016), multiple measures of deprivation must be properly accounted for and modeled in studies that seek to understand those social processes in context. A useful direction for future research is to explore the specific components of the ADI that exert the largest impact on increasing substantiated maltreatment risk. This study only focused on documenting the disparities in substantiated child maltreatment risk resulting from extreme disadvantage and restricted access to social resources, i.e., the deprivation effect.

Despite the novelty of the question posed, the present study is not without limitation. This study used the "common research practice of using only substantiated reports from maltreatment registries" (Leiter et al., 1994, p1). Part of the rationale for using substantiated child physical abuse and neglect stems from the large body of previous work finding that CPS substantiations are spatially concentrated into high risk areas driven by unique community characteristics that should be targeted for specific interventions (Barboza, 2019; Barboza-Salerno, 2020; Fong, 2019; Freisthler, 2004; Gracia et al., 2017; Marco et al., 2020; Molnar et al., 2016; Zhou, 2006). The strongest rationale for using substantiated child maltreatment reports versus screened in reports is provided by research supporting the adequacy of the substantiation process for measuring the serious of maltreatment (Leiter et al., 1994), similar behavioral and developmental outcomes of children with unsubstantiated and substantiated maltreatment reports (Hussey et al., 2005), and analyses demonstrating very strong spatial correlations between substantiated and unsubstantiated child maltreatment risks (Marco et al., 2020). Further, whereas there are many external factors involved in the decision to substantiate that are not captured by the present study, these same factors are considerations in the decision to report regardless of the outcome. Additionally, the reliance on substantiated child maltreatment using administrative data rather than maltreatment potential using measures of parenting behavior means that these results must be carefully interpreted. Specifically, the results from this study demonstrate the significant linear and nonlinear effects of neighborhood deprivation on the risk of substantiated child abuse and neglect from Child Protective Services (CPS) and not the risk of child maltreatment more generally. Consequently, the present results do not suggest that higher levels of area deprivation increase the risk of child maltreatment, but rather increase the risk of a case being substantiated. This distinction is critical. Whereas research has shown that disproportionate CPS intervention reflects underlying differences in child maltreatment risk (i.e., the two are clearly related), there is substantial evidence that the assessment of risk is based on child welfare practices that reinforce and legitimize stereotypes based on race and class (Fong, 2019; Lee, 2016). Another limitation is the use of ecological regression based on aggregate data compiled over a 9-year period. As with all neighborhood studies, there is the potential to commit the ecological fallacy and draw faulty conclusions that are not tied to the unit of observation (i.e., the neighborhood). In this paper, the interpretation of results is limited to the neighborhood unit and no individual-level differences are drawn. Regarding the unit of analysis, even though census tracts are generally considered to be good approximations of neighborhoods (Ross et al., 2000), census tract boundaries are arbitrary and change over time. Future studies may seek to replicate these findings using smaller administrative units, such as census block groups, for which the ADI is available. Also important is that the goal of the study was to reveal the variations in risk across deprivation percentiles using a mixed model parameterization to capture the "deprivation effect." On this basis, no other covariates were considered in the modeling framework. Future research would benefit from considering additional factors apart from socioeconomic deprivation that may impact substantiated maltreatment risk as suggested above. Although these results are based on many years' worth of data, the most recent year of data analyzed is now almost 8 years old. A reanalysis using more current administrative data may change the relationships reported here particularly considering the potential impact of the COVID-19 pandemic. Another limitation is the restriction of the population to a single county that is unique in terms of its social and demographic characteristics. In this case, small area-based spatial analyses focusing on the most populous county in the state with one of the largest share of welfare involved youth offers several advantages including the ability to identify how the ADI influences substantiated maltreatment risk on a neighborhood scale in a predominantly urban setting (Greves Grow et al., 2010). Nevertheless, future work should consider replicating this study using a sample that is more representative of the US population.

In conclusion, this study demonstrates the stepwise nature of neighborhood level deprivation and its strong association with child maltreatment risk. The approach offers a flexible methodology that can easily be adapted to explore other patterns of associations in other contexts to focus preventive interventions in places where they are most needed.

## Data availability

Links to the data are provided in the manuscript. All data used are publicly available.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chiabu.2023.106501.

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