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Understanding Social Disorganization and the Nonprofit Infrastructure; An Ecological Study of Child Maltreatment Rates

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Abstract

Advocates and researchers have emphasized the role of disorder in neighborhood processes, with serious consequences for families, however, neighborhood structures may also support families and reduce child maltreatment. Nonprofits maintain a range of strategies to support nearby families, including direct services, facilitation of social networks, and formalizing advocacy for increased attention from government. Using agency data on child maltreatment, nonprofit locations, and indicators of social disorganization, this article studies the role of nonprofit organizations in the spatial distribution of child maltreatment among Cuyahoga County Ohio census tracts ($N = 442$). Accounting for spatially structured and tract-specific variation with a hierarchical Poisson model implemented through a Bayesian methodology, the results indicate the presence of nonprofits is a protective factor: negatively associated with child maltreatment (posterior mean: −0.18, CI: −0.34, −0.03), with heterogeneity by type. The study highlights neighborhoods as a propitious site of intervention and emphasizes the intra-county distribution of nonprofits.

Keywords

neighborhood effects, child maltreatment, nonprofit density, neighborhood protective factors

Introduction

Child maltreatment remains a significant issue in the United States, and globally. In 2019, there were 656,000 victims of child abuse and neglect in the US. Nationally, the most common form was neglect, followed by physical and sexual abuse (Children's Bureau, 2022). Social disorganization theory (e.g., Shaw and McKay 1942) posits that structural factors such as low socio-economic status, residential mobility, and ethnic diversity, disrupt communities and explain variation in occurrences of crime, delinquency, and child maltreatment (Coulton et al. 2007). This has motivated a rich literature of ecological studies of child maltreatment rates that have assisted in identifying important risk factors which may

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degrade social control and increase disorder, as well as the overlap of child maltreatment with other social problems (Barboza-Salerno 2020; Coulton et al. 1995, 2007, 2018; Freisthler 2004; Gracia et al. 2018; M. C. Morris et al. 2019). Yet, social disorganization theory also suggests disorder in neighborhood processes may respond to supportive neighborhood structures. Extending social disorganization theory, Sampson and Groves (1989) show disorganization in neighborhood processes may result from, among others, sparse local friendship networks and low organizational participation. Consistent with this view, child maltreatment research has explored the availability of particular services, such as social services including early education, immigrant services, or substance use treatment, producing mixed results (Klein 2011; Maguire-Jack et al. 2018; Maguire-Jack and Klein 2015; Morton 2013; Seon and Klein 2021). Less is generally known about the role of nonprofit organizations in neighborhood processes and disorder. Although the presence of certain services may assist through direct provision, this literature has not studied the role of the nonprofit infrastructure, which may provide strong neighborhood anchors capable of enhancing social ties, increasing organizational participation, creating strong community actors (Brandtner and Dunning 2020; Marwell 2004; Ressler 2020; Sharkey et al. 2017), and consequently reducing child maltreatment rates. This article first discusses the role of structural features in the spatial distribution of child maltreatment rates by neighborhood, then situates nonprofit organizations as neighborhood anchors capable of reducing disorganization. Pairing multiple sources of administrative and public data, the paper then empirically explores the patterns of nonprofit density and the spatial distribution of child maltreatment rates, examining nonprofit density in aggregate and disaggregated by primary purpose.

Background

Race and the Child Welfare System

The US child welfare system is a group of services chiefly designed to promote safety, permanency, and the strength of families. To do this, the child welfare system endeavors to minimize child maltreatment, which includes different forms of abuse and neglect. However, reports, and subsequent involvement in the child welfare system are more prevalent among families that are economically disadvantaged or racial and ethnic minorities, particularly, families that are Black or African American. While the racial and economic disproportionality has been a demonstrated fact of the child welfare system for nearly 50 years, the reasons for this disproportionality continue to be debated among child welfare scholars (Dettlaff 2021), with possibilities ranging from caregiver risk factors to caseworker biases and forms of institutional racism (Cénat et al. 2021). For example, referrals may emerge from racialized perceptions of mental health and treatment of behaviors in the school system (Hill 2004). These are compounded at the neighborhood level, as clusters of reports may increase monitoring within the area, creating positive feedback (Fong 2020). Further, a high number of maltreatment reports may interact with the legacy of neighborhood, creating distrust among neighbors, normalizing reporting and involvement in the child welfare system, and further disrupting neighborhoods (Roberts 2008). Importantly, the conditions and perceptions of the neighborhood are often correlated with its racial and ethnic composition (Coulton et al. 1995). The following sections describe the role of neighborhood conditions.

Social Disorganization and Child Maltreatment

Social disorganization theory links structural factors, such as ethnic and racial diversity and economic status, with disorder in social processes (Shaw and McKay 1942). Coulton et al. (2007) extend this framework acknowledging that neighborhood structures influence social processes within neighborhoods, which in turn influence behaviors and residents, such as families and children. This framework links neighborhood structures with behaviors, and suggests resource deficits erode social support and organization which can destabilize families, increasing maltreatment rates, and explaining the clustering of social problems (Coulton et al. 2007; Sampson 1986). To this end researchers have investigated the relationship between poverty, unemployment, or other signals of economic need, revealing a consistent pattern: higher disorder predicts higher levels of maltreatment (Coulton et al. 1995, 2018; Freisthler 2004; Raissian 2015). Adverse neighborhood conditions take a toll on families by exacerbating risk factors while degrading protective factors and perceptions of the neighborhood (Coulton et al. 1999). There is also a burgeoning literature on the clustering of child maltreatment with other social problems that may respond to similar underlying neighborhood processes, including crime, domestic violence, and other indicators of risk for children (Gracia et al. 2018; Marco et al. 2020; M. C. Morris et al. 2019). This literature shows the importance of considering multiple social problems; residents in a region with widespread violence and resource deficits may experience a loss of efficacy and increased disorganization.

Early social disorganization theorists suggested ethnic diversity leads to increased social disorganization by decreasing the capacity of residents to align goals (Sampson and Groves 1989; Shaw and McKay 1942). Contacts with agencies and reporters, as well as the effects of low socio-economic status, may vary by the ethnic and racial composition of the neighborhood (Jonson-Reid et al. 2013; Korbin et al. 1998). Yet, Drake et al. (2009) show that maltreatment reporting did not differ after controlling for poverty, while poverty increased reporting rates across races. However, Klein and Merritt (2014) found a positive relationship between neighborhood diversity and child maltreatment rates, consistent with early social disorganization theorists, and while neighborhood diversity is a strong predictor, recent evidence suggests neighborhood diversity may present a protective factor (Barboza-Salerno 2020).

Service Availability

Clearly, poverty, instability, and the presence of social problems decrease the ability of neighborhoods mitigate social problems. Scholars have also considered the presence of social services as a possible "ecological intervention," a protective factor that enhances processes to reduce maltreatment rates. Despite a burgeoning area of research, the evidence in this area is mixed. Klein (2011) found a positive relationship between the density of childcare centers and referral rates, and Freisthler (2013) found social services (domestic violence and substance use) and maltreatment referrals are positively related, as well. Seon and Klein (2021) also found a positive relationship between the presence of immigration and other services, with maltreatment rates. While this literature may suggest a generally positive relationship between access to services and maltreatment rates, other research suggests maltreatment rates are positively associated with distance to a substance use facility (Maguire-Jack and Klein 2015; Morton 2013), and the density of child welfare services may be related to lower rates of referral (Freisthler 2013). These discrepancies have been under theorized in the existing literature, often attributed to regional differences or slight differences in measurement (Maguire-Jack and Klein 2015; Seon and Klein 2021). However, this literature has not incorporated theories from organizational studies, such as theories of market failure that explain the emergence of mission oriented organizations (Weisbrod 1977), and has considered only a limited class of organizations.

Nonprofit Organizations as Neighborhood Actors

The nonprofit sector encompasses a broad class of organizations that are essential to many aspects of everyday experience, particularly, the social safety net, education, as well as civic, and religious life. Although nonprofit organizations are a heterogenous group, they are distinct in several ways. In exchange for the benefits they receive, nonprofits cannot freely distribute capital, and are uniquely marked by their development around ambiguous core technologies which can render verification of outcomes challenging (Newman and Wallender 1978). These are important as they prohibit nonprofits from demonstrating legitimacy in ways typical among their for-profit counterparts, such as margins and profitability. In contrast, nonprofits often seek legitimacy through other means, and may require public trust and support to continue operations. The constraints on nonprofits, to distribute profits and demonstrate legitimacy, make the choice of location particularly important. In addition to relying on nearby regions for resources, nonprofits often acquire legitimacy from their location, and commonly benefit from a commitment to their location (Joassart-Marcelli and Wolch 2003; Ressler et al. 2020). Nonprofits are also neighborhood actors, assisting in the development of civic capacity, the facilitation of economic networks, and participating in governance (Brandtner and Dunning 2020), as well as through the work of organizational members. Organizational members are often inclined to improve the welfare of their neighborhoods, and receive positive feelings in return (Marwell 2004).

Nonprofits have become increasingly important to the social service system and civic life as governments have preferred contracting for a local implementation of services, a phenomenon that has become known in the public administration literature as the "hollow state" (see, for example, Milward and Provan 2000). Consequently, nonprofits often deliver services locally, reducing barriers for those nearby (Allard and Danziger 2002; Bielefeld et al. 1997). The logic is that local implementation allows organizations broader capability to tailor services to consumers using the information of their surroundings. As a result, nonprofits have become de-facto policy makers through discretion in implementation (Lipsky 2010). However, nonprofits are not passive instruments to implement government programs. Rather, they often prod government for increased attention and resources through advocacy, pilot programs, or demonstration projects (Young 2006). This suggests that regions dense with nonprofit organizations may receive enhanced services and greater access to government resources, rectifying resource deficits that may otherwise negatively impact social support (Coulton et al. 2007).

In addition to organizational participation and direct services, the strength of neighborhood processes and the ability of neighborhoods to establish common goals is a function of the strength of social ties present in the neighborhood (Sampson and Groves 1989). Nonprofit organizations can increase civil capacity by stimulating political engagement among residents and consumers (Sampson and Wilson 2012; Saxton and Benson 2005), and may otherwise facilitate the development and maintenance of social networks. Marwell (2004) showed community-based organizations such as churches create community participants, that are motivated to improve their neighborhood while maintaining a commitment to the organization. Increases in political engagement may further magnify government attention and bring additional resources, while the facilitation of social networks permits enhanced goal alignment and information sharing, resulting in increased educational and economic opportunities. This has implications for child maltreatment as the presence of nonprofit organizations may increase parental involvement (Ressler 2020) or increase social control resulting in lower violence (Sharkey et al. 2017; Wo et al. 2016).

Nonprofit Location. As nonprofits bring benefits to their regions, their location is of practical importance. It is also of importance to the study of child maltreatment; if nonprofits only locate in neighborhoods that are already well supported, the effects may not be detectable on maltreatment rates. Classic economic theories of the nonprofit sector suggest that nonprofit organizations emerge in response to a type of market failure, such as restricted access, under provision, or lack of verification or quality of goods or services. Nonprofits address these problems by shifting costs, specializing, or enhancing trust through legitimacy and the non-distribution constraint (Steinberg 2006; Weisbrod 1997). The founders of nonprofit organizations are a largely separate class of entrepreneurs, often never considering a for-profit corporation, and frequently acknowledge their efforts as a response to needs in their locale (Carman and Nesbit 2013). However, nonprofits, like all organizations, tend to locate near existing organizations to benefit from access to professional and economic networks (van Wissen 2004). Consistent with economic theories, several studies have found positive relationships between nonprofit density and poverty or other indicators of community need (Joassart-Marcelli and Wolch 2003; Peck 2008; Yan et al. 2014).

Nonprofit density and child maltreatment share many of the same antecedents. Just as poverty may signal needs not met by government services, racial and ethnic heterogeneity may correspond to heterogeneous demands, creating unmet demands and increasing space in the market for nonprofits. Despite the theoretical framing, empirical evidence on this is mixed, Corbin (1999) found a positive relationship between racial diversity and nonprofit density, while other studies have found null or weak evidence for a relationship (Kim 2015; Wo 2018). The child maltreatment literature discussed above shows a strong relationship between forms of violence or crime, and child maltreatment. This relationship is mirrored in the nonprofit density literature (however less is known, in general) and while nonprofit density may respond to the presence of crime in neighborhoods, it currently unclear if organizations enter or exit in response (Wo 2018; Wolch and Geiger 1983).

The Current Study

Child maltreatment responds to neighborhood processes, such as changes in disorder, which may empower neighborhoods to alter environmental stressors (Coulton et al. 2007). In this framework, organizations provide supportive structures by direct services or by facilitating connections through organizational participation (Sampson and Groves 1989). The existing literature related to supportive organizations and child maltreatment has often focused primarily on substance use treatment and childcare centers (Klein 2011; Maguire-Jack et al. 2018; Maguire-Jack and Klein 2015; Morton 2013) with two main limitations: it has not integrated theories of market failure, and it has considered a limited number of organizational forms. These are significant limitations, as the literature has under-theorized organizational location, and may have been unable to capture unique relationships as organizations often cluster to obtain the benefits of economic networks (van Wissen 2004).

Nonprofit organizations are important neighborhood anchors that provide vital services, important cultural hubs, and may assist in facilitating the development or maintenance of social networks (Brandtner and Dunning 2020; De Vita et al. 1999; Marwell 2004). This suggests nonprofits may mitigate maltreatment by delivering services directly, for example, by increasing access to social welfare services, childcare, or substance use (Allard 2004; Allard and Danziger 2002; Klein 2011; Morton 2013). However, the literature shows nonprofits may also enhance neighborhood processes by fostering organizational participation, increasing the strength of social networks, familial ties, and collective efficacy (Brandtner and Dunning 2020; Marwell 2004; Ressler 2020; Sharkey et al. 2017; Wo et al. 2016).

This study contributes to literature related to neighborhoods and child maltreatment by studying patterns of nonprofit density and child maltreatment rates, incorporating theories of nonprofit location with theories of social disorganization. The existing theory and literature lead to the hypothesis of a negative relationship between nonprofit density and child maltreatment rates, which is tested using data from Cuyahoga County Ohio (USA). Scholars have largely studied nonprofit density as inclusive of organizations across purpose (Kim 2015; Saxton and Benson 2005; Wo 2018). The motivation is that organizations typically draw on a similar class of resources, leading them to cluster near one another, a concept known in organizational theory as density dependence (among others, see Carroll 1984). However, distinct organizational purposes may correspond to distinct relationships with child maltreatment. Organizations that benefit residents by enhancing social ties, such as churches and arts organizations, may behave differently than those that provide direct services, such as nonprofits focused on health and human services. Consequently, this study then decomposes nonprofit density using the National Taxonomy of Exempt Entities (National Center for Charitable Statistics 2007), examining heterogeneity by organizational purpose.

Methods and Materials

This study employs a cross-sectional ecological design to quantify the relationship between nonprofit density and child maltreatment in the neighborhood setting, as well as decompose the relationship by organizational type. The study region is Cuyahoga County Ohio, a US county with a population of roughly 1.25 million that covers an area of over 1,200 square miles. Defining neighborhoods for research is fundamentally challenging, however, the census tract is used to indicate a neighborhood in this study (Coulton et al. 2018; Klein 2011; Wo 2018). In 2016, Cuyahoga County contained 447 census tracts, five of which had estimates of zero children, resulting in a final sample of 442 tracts.

Dependent Variable: Substantiated and Indicated Child Maltreatment Cases

The dependent variable in this study is the rate of unduplicated maltreatment cases per child in the tract. This study seeks to understand the role of nonprofit organizations and neighborhood processes in the spatial distribution of child maltreatment, consequently focusing on substantiated and indicated cases of maltreatment (Coulton et al. 1995). A maltreatment report is considered substantiated when an agency determines that maltreatment has occurred based on a state law or other relevant policy. A report is considered indicated when the agency has a high level of suspicion that maltreatment occurred, however, may lack complete evidence or information. Data on the number of substantiated and indicated cases were retrieved from NEO CANDO, a tool provided by the Center on Poverty and Community Development at Case Western Reserve University, which provides unduplicated counts of child maltreatment reports based on information from the Department of Children and Family Services (*Substantiated and Indicated Child Maltreatment Cases* 2016). Unduplicated counts provide a strong measure of risk because they emphasize the number of children, rather than the number of reports. In 2016, there were 3,051 unduplicated cases of child maltreatment that were substantiated or indicated, the average child maltreatment rate was 1.39 percent (SD = 1.53).

Key Independent Variable: Nonprofit Density

This study proceeds first by measuring nonprofit density as the number of active nonprofits in the tract, then disaggregates the count by primary purpose, studying the relationship between maltreatment rates and the density of each organizational type. Measuring nonprofit density is difficult, information about services is generally unavailable and not all nonprofits submit financial information, however, scholars of nonprofit organizations have often identified the total number of nonprofit organizations as a strong measure of nonprofit density (Joassart-Marcelli and Wolch 2003; McDonnell et al. 2020; Wo 2018; Wolch and Geiger 1983).

Data on nonprofit organizations are drawn from the Business Master File (BMF) which contains a census of nonprofit organizations that submit any variety of tax forms or requests for exemption (e.g., forms 1023 and 1024, or any form-990). The Internal Revenue Service provides an updated BMF monthly, however, it is also provided by the National Center for Charitable Statistics (NCCS) which augments the IRS data with additional information to assist researchers (*Internal Revenue Service, Exempt Organizations Business Master File* 2016). To further increase the accuracy of the measure, organizations that have not submitted tax documents (any form of 990, including the EZ and N) in the past 2 years are excluded from the sample as they are unlikely to be active in their community. While excluding inactive organizations, this likely results in undercounting religious organizations, and those with few assets and low revenue (less than fifty thousand dollars). Private foundations and supporting organizations are excluded as well. These organizational types are often distinct from public charities in mission and management and may have different roles in their communities and correspond to different processes. The BMF provides the most current and complete information on nonprofit organizations and has been a valuable data source for measuring nonprofit density in the U.S. (Wo 2018; Yan et al. 2014). The organizations that met the inclusion criteria were geocoded using the address listed on the tax form and placed in their respective census tracts. In the event that an organization listed a post office box as their main address, the post office was used as the organization was likely nearby (Yan et al. 2014). Using this process, over 99 percent of active organizations were successfully geocoded, while the remainder were excluded. Beginning with 7,078 nonprofits, 1,603 were removed for inactivity, another 1,601 were removed for their classification as supporting organizations or private foundations, resulting in 3,788 nonprofits.

The second aim of this article is to quantify heterogeneity by organizational purpose. Disaggregating organizations by purpose is done with the National Taxonomy of Exempt Entity Codes (NTEE), a set of alpha-numeric codes developed by the NCCS in the 1980s to assist nonprofit researchers. NTEE codes have several levels, dividing nonprofits into categories of varying granularity. While organizations select classifications for themselves, the NCCS also provides a code based on their assessment of the organization's primary purpose. Coders are discouraged from relying on the organization's name and rather rely on tax submissions or requests for exemption (National Center for Charitable Statistics 2007). The highest level of NTEE classifications include arts (A), education (B), health (E-H), human services (I-P), and other (C, D, and Q-Z). Although this classification has been widely used in the nonprofit literature (for example, Jeong and Cui 2020; Kim 2015), separating out religious organizations (NTEE code X) is important in this study as they are a common site for service delivery and organizational participation (Marwell 2004; Owens and Smith 2005). Nonprofits may provide mission and non-mission related benefits. Focused on direct services, human service nonprofits contain nearly all the organizational types included in prior studies, such as child day care (P33), substance use treatment (F20), and ethnic and immigrant centers (P84). However, nonprofits focused on health may also provide important services, while arts and religious organizations may be more focused on indirect benefits such as enhancing social networks. Consequently, the analysis to address the second aim proceeds with six categories. In 2016, there were 3,788 nonprofits in Cuyahoga County that met the inclusion criteria, a plurality of which were human services (1,065), followed by arts (758), education (552), health (240), and religion (239), with 934 other organizations. Correlation by tract between types of organizations range from 0.09 (education and arts organizations) to 0.75 (education and other organizations), with an average correlation of 0.34. Figure 1 shows the distribution of nonprofits included in the sample over the study region, as well as the maltreatment rate per 1,000 children. The figure shows organizations are spread throughout the region, while 10 percent of the tracts included are home to zero organizations.

Control Variables

The extant literature reveals several important variables that may confound the relationship between nonprofit density and child maltreatment. Primarily, these include indicators of social disorganization such as the unemployment, vacancy, and poverty rates of the census tract (Coulton et al. 2018; Dollar et al. 2019; Raissian 2015; Wo 2018). High residential mobility may also disrupt collective goal setting and neighborhood processes (Shaw and McKay 1942), to control for this, the percent of the tract that resides in the same home they did 1 year ago is collected, as well. Additionally, racial and ethnic heterogeneity is often an important predictor of both maltreatment rates and nonprofit density (Barboza-Salerno 2020; Corbin 1999; Jeong and Cui 2020; Klein and Merritt 2014). The racial and ethnic composition of the tract is measured using three variables. These include the percent of the tract that identifies as Hispanic or Latino, the percent of the tract that identifies as Black or Latino, and a racial and ethnic diversity index is created by subtracting a Herfindahl index on four ethnic groups (White, Black, Latino, Asian), from one (Wo 2018). These variables are drawn from the US Census American Community Survey (2012–2016).

Crime and measures of violence are also strong predictors of child maltreatment and nonprofit density (M. C. Morris et al. 2019; Wo 2018). Currently, no ecological studies of child maltreatment and organizational presence control for a measures of violence. However, high quality crime data were unable for the county. To obtain a measure of violence that covers the entirety of Cuyahoga County Ohio, data were retrieved from The Gun Violence Archive, an organization that tracks gun-involved incidents from manual and automated searches of media sources, the existence of which are verified in a two stage process (*Total Number of Incidents* 2016). The Gun Violence Archive provides information on the number of persons injured or killed; however, this study employs the total number of gun-involved events aggregated by census tract. In 2016, there were 453 gun-involved events in census tracts included in the sample.

Table 1 shows the mean and standard deviations, names, and sources of each variable collected for the study. It shows that the average tract had just under seven cases of child maltreatment, one gun-involved event, and that nonprofit density shows great variation between tracts.

Empirical Model

The rate of substantiated and indicated child maltreatment cases is positive and unbounded ranging from 0 to .1, suggesting a Poisson model has the correct support. However, Table 1 shows that the standard deviation is slightly higher than the mean. The possibility of over dispersion is examined by comparing the Poisson model with homogenous rates to a model that includes a normally distributed, unstructured random effect, which results in Poisson log-normal mixing under the canonical log link. A characteristic of the study of neighborhoods and other small geographic units is their propensity to influence those in their proximity, such as their neighbors. In their review of ecological studies of child maltreatment, Coulton et al. (2007) identified spatial dependence as a key methodological issue. This issue is further complicated as such variation is unlikely to be constant over spatial units (Ernst 2001). A flexible Bayesian methodology is often advantageous in this setting, providing a natural framework for the propagation of uncertainty (Mayer and Fischer 2022). In a Bayesian framework, the addition of a latent spatial structure that varies over units can be specified with a conditional autoregressive prior (CAR), yet, the CAR prior may restrict the range of spatial dependence (Banerjee et al. 2003), an assumption relaxed by allowing complete spatial autocorrelation, resulting in the intrinsic conditional autoregressive prior (ICAR). The ICAR is an improper prior that estimates a smooth pattern over the spatial units by averaging the effects of a unit's neighbors, and is shown in equation (1a), where d_i are the number of neighbors for tract i and $[i]$ indexes the neighborhoods for i. The contingency matrix to specify the ICAR is generated using the "queen" method, allowing first order neighborhoods in each direction,

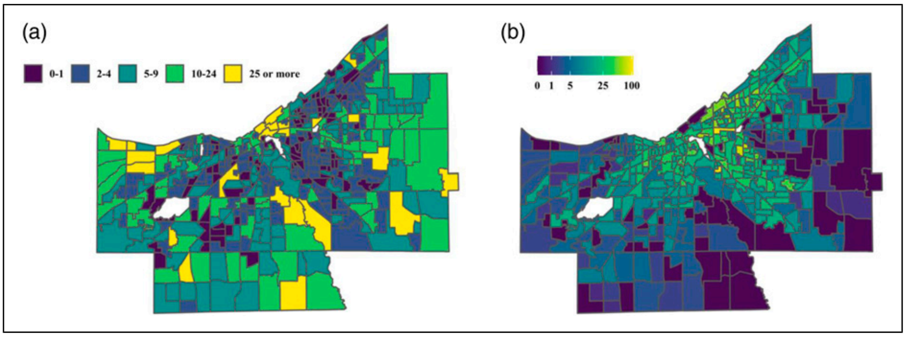

Figure 1. Maps of key variables by census tract. All active nonprofit organizations in Cuyahoga County Ohio, included in the sample (panel A), and the observed maltreatment rates per 1,000 children (panel B).

tracts have an average of just over 6 neighbors. However, including only spatially structured effects constitutes an informative prior which can be relaxed through convolution with an unstructured non-spatial effect (Congdon 2019)

$$\phi_i \middle| \phi_{[i]} \sim N\left(\frac{\sum_{[i]}\phi_i}{d_i}, \frac{\sigma_\phi}{d_i}\right) \tag{1a}$$

Specifying priors for the standard deviation of spatial and non-spatial random effects is complicated as the ICAR is scaled while the unstructured effect is not. Typically, priors that equally weight spatial and non-spatial variation typically must be carefully chosen to be "fair," equating spatial and non-spatial variation a-priori (Bernardinelli et al. 1995; Congdon 2019). Riebler et al. (2016) provide an alternative approach which allows meaningful priors to be placed on each parameter and shrinks to a known base model, penalizing complexity. This approach is shown in equations (2a)–(2c), where y_i is the number of child maltreatment cases, and c_i is the number of children in tract i. The variable o_i is the number of nonprofit organizations where δ is the parameter of interest, X_i is a matrix of controls, and γ_i is the convolution prior. In (2c), ρ governs the ratio of spatial and non-spatial variance, ϕ is the ICAR from equation (1a), s is the scaling factor to ensure the variance of ϕ_i is approximately 1, θ is standard normal as the neighborhood graph is fully connected, and σ_γ is the standard deviation of the combined effects

$$y_i \sim Poisson(\lambda_i) \tag{2a}$$

$$\ln(\lambda_i) = \ln(c_i) + \delta o_i + X_i\beta + \gamma_i \tag{2b}$$

$$\gamma_i = \left[\left(\phi\sqrt{\rho/s}\right) + \left(\sqrt{1-\rho}\right)\theta\right]\sigma_\gamma \tag{2c}$$

Priors, Model Comparison, and Posterior Inference. The non-conjugate approach to the full Bayesian methodology is convenient when a hierarchical model is desired and can be facilitated through the probabilistic programming language Stan. Stan uses an implementation of Hamiltonian Monte Carlo (Stan Development Team n.d, 2019) that is particularly sensitive to degeneracies and offers a wide range of checks for mixing and convergence, with efficient implementations of several spatial models (M. Morris et al. 2019). This study builds up from a homogenous Poisson model to the model shown in (2a)–(2c), evaluating the necessity of each component. In all models, the fixed effects (δ and β) are given normal priors with standard deviation of 0.5, a prior that regularizes each parameter toward zero (Gelman et al. 2003). In the intermediate model, the Poisson model with an unstructured random effect, the standard

Table 1. Descriptive Statistics for All Variables by Census Tract in Cuyahoga County Ohio (N = 442).

Variable	Mean	Standard deviation	Source
Child maltreatment cases: Substantiated or indicated[a]	6.90	7.57	Cuyahoga county children and family services
Neighborhood characteristics			
Number of children	614.25	343.45	US Census Bureau, ACS
Gun violence	1.22	2.01	Gun violence archive
Poverty (%)	22.50	17.89	US Census Bureau, ACS
Unemployment (%)	12.55	9.91	US Census Bureau, ACS
Vacancy (%)[a]	14.96	10.74	US Census Bureau, ACS
Residential mobility (%)	84.12	8.87	US Census Bureau, ACS
Diversity index[a]	0.67	0.20	US Census Bureau, ACS
Black or African American (%)[a]	37.54	36.37	US Census Bureau, ACS
Hispanic or Latino (%)	5.61	8.61	US Census Bureau, ACS
Nonprofit organizations			
Nonprofit density[b]	8.57	24.69	NCCS BMF
Human services[b]	2.41	3.85	NCCS BMF
Education[b]	1.25	3.83	NCCS BMF
Religion[b]	0.54	3.25	NCCS BMF
Health[b]	0.55	1.33	NCCS BMF
Arts[b]	1.72	18.23	NCCS BMF
Other[b]	2.11	4.48	NCCS BMF

Note: Based on 442 census tracts included in the study. The network of tracts (constructed using "queen" adjacency) is fully connected with a minimum of 2 connections, while the average tract had 6.05 connections. ACS = American Community Survey. NCCS BMF = National Center on Charitable Statistics Business Master File.
[a]Unduplicated count, analysis provided by the Center on Urban Poverty and Community Development, Jack, Joseph and Morton Mandel School of Applied Social Sciences, Case Western Reserve University.
[b]Includes only active public charities, excluding foundations.

deviation of the unstructured effect is given an exponential(1) prior which places most probability mass on zero, shrinking toward a simpler model. The final model compared is described in (2a)–(2c), which requires priors on the fixed effects as well as σ_γ and ρ, the total variance and the share of that is spatially structured. A diffuse prior of Γ (1,1) is placed on σ_γ, with a β (1,1) prior for ρ, corresponding to diffuse belief about the amount and source of variation. Model comparison is carried out using the Leave One Out Information Criterion (LOOIC), a criterion that fails less frequently and is more diagnosable than comparable methods, namely, WAIC (Vehtari et al. 2017).

Given the aims of this study, the focus of posterior inference is the hypothesis of a negative relationship between nonprofit organizations and child maltreatment rates. This is evaluated with conventional 95 percent credible intervals and further by computing $p(\delta < 0)$, where δ is the parameter corresponding to nonprofit density in equation (2b). All models were first run with three chains, for three thousand sampling iterations, with one thousand warm-up iterations to evaluate mixing. Final models are run with one chain for seven thousand sampling iterations with one thousand warm-up iterations.

Results

Nonprofits in Aggregate

Sampling was unproblematic for all models, with no divergent transitions and R-hat's of 1 for all parameters. Results for the relationship between aggregate nonprofit density and child maltreatment are shown in Table 2. Model comparison in Table 2 shows the random effects are an important component of the model, where the LOOIC favors more flexible models and model 3 is the best under consideration. The difference in expected point wise density between model 3 was sizable when compared to models 1 and 2 (−230.0, SE = 34.3 and −27.1, SE = 8.1, respectively).

Table 2 shows that although mobility and unemployment appeared important in model 1, the estimates were consistent with zero after accounting for spatial and non-spatial variation. However, there are several positive relationships between indicators of disorder and child maltreatment across the three models. Model 3 suggests a 12 percent increase in the expected child maltreatment rate for an increase of 2 incidents of gun violence, as well as an increase of nearly 15 and 35 percent for a one standard deviation increase in the percent under the poverty line and vacancy rate, respectively. Two measures of the racial and ethnic composition of the tract show clear patterns, as model 3 shows more diverse tracts and those with a higher share of Black or African American residents tend to have lower and higher child maltreatment rates, respectively. Finally, a one standard deviation increase in nonprofit density predicts a decrease of nearly 16 percent in the expected child maltreatment rate, a result consistent across models. As nonprofit organizations have a standard deviation of just over 24, this suggests a decrease of nearly 1.5 percent for every two organizations in the tract.

Model 3 shows the standard deviation of the random effects is .63, the majority of which is captured in the spatial effects. The implications of the model and the variance captured in these effects can be understood further by mapping the posterior means of the estimates. Figure 2 shows the posterior means for the estimated rates (panel A), the sum of the random effects (panel B), as well as the spatial and non-spatial effects (panels C and D, respectively). Consistent with the patterns shown in Figure 1, panel A in Figure 2 shows that the model predicts higher maltreatment rates around the north-central and north-east regions of Cuyahoga County. The conditions that predict child maltreatment, such as crime and poverty, are present in these areas at high rates. This is further emphasized by panel C, which shows the random effects contribute little to estimates these regions, rather, the covariates capture the variation in child maltreatment.

Disaggregating Nonprofits

Models 1–3 average effects over the population of nonprofit organizations; the second aim of this study requires decomposing the effects by organizational type. Table 3 shows the results for the same class of models with organizations disaggregated by subsectors. The LOOIC as well as the indicators of disorganization and violence have similar estimates to those found in Table 2, and consequently are not commented on again. In model 4, the density of education, religious, human services, and arts organizations all show a clear negative relationship with child maltreatment. Several of the credible intervals include zero in model 6. Yet, the posterior probability that the estimates are negative for these parameters are over 95 percent. While the parameter for health and religious organizations had just over 90 percent of their probability mass above zero and below zero, respectively.

Based on the posterior mean, holding other covariates constant, model 6 predicts decreases of 10, 19, 8, and 26 percent in the child maltreatment rate for one standard deviation increases in education, human services, religion, and arts organizations, respectively, based on posterior means. This suggests that the largest effects for one organization, holding others constant, comes from religious organizations, with a predicted decrease of just over 6 percent in the expected child maltreatment rate per religious organization.

Discussion

Prior studies have produced decidedly mixed results about the relationship of organizations and maltreatment rates (Freisthler 2013; Maguire-Jack and Klein 2015; Seon and Klein

Table 2. Posterior Inference and Model Comparison for Models of Child Maltreatment and Aggregate Nonprofit Density (N = 442).

	Model 1			Model 2			Model 3		
Variable	Mean	CI		Mean	CI		Mean	CI	
Constant[a]	2.21	2.16	2.25	2.08	2.00	2.15	2.07	2.01	2.13
Nonprofit density[a]	−0.15	−0.24	−0.06	−0.26	−0.44	−0.08	−0.18	−0.34	−0.03
Gun violence[a]	0.12	0.08	0.15	0.14	0.06	0.22	0.12	0.04	0.20
Poverty (%)	0.30	0.23	0.37	0.31	0.16	0.45	0.14	−0.01	0.30
Unemployment (%)	−0.09	−0.16	−0.01	−0.10	−0.25	0.05	−0.11	−0.25	0.04
Vacancy (%)[a]	0.21	0.16	0.26	0.24	0.15	0.35	0.30	0.17	0.41
Residential mobility (%)	0.05	0.01	0.10	0.03	−0.06	0.12	0.06	−0.03	0.14
Diversity index[a]	−0.12	−0.16	−0.07	−0.12	−0.22	−0.03	−0.13	−0.25	−0.01
Black or African American (%)[a]	0.40	0.33	0.48	0.41	0.27	0.54	0.58	0.38	0.79
Hispanic or Latino(%)	0.17	0.13	0.22	0.19	0.09	0.28	0.04	−0.08	0.17
σ[b]				0.57	0.50	0.64	0.63	0.54	0.74
ρ							0.75	0.51	0.95
LOOIC	2678.8 (90.7)			2273.1.8 (38.0)			2218.9 (39.3)		

Note: All models include the number of children as an offset. All variables are mean centered and scaled to unit variance. Posterior inference based on 7,000 sampling iterations. LOOIC = Leave One Out Information Criteria. CI = 95 percent Credible Interval.
Model 1 is a Poisson with homogenous rates. All fixed effects have Normal(0,.5) priors.
Model 2 is model 1 with unstructured random effect. The standard deviation has an exponential(1) prior.
Model 3 is the Poisson model with the convolution prior described in equations (2a)–(2c). Priors are Normal(0,.5) for all fixed effects, β (1,1) for ρ and Γ (1,1) for the standard deviation.
[a]Posterior probability of being over or under 0, in all models, is greater than .95.
[b]Standard deviation of the unstructured effect in model 2 and the shared scale parameter in model 3.

2021). Motivated by social disorganization theory (Coulton et al. 2007; Sampson and Groves 1989; Shaw and McKay 1942), this study contributes to the literature related to neighborhood structures and child maltreatment by broadening the mechanism from social services to include the auxiliary benefits of nonprofit organizations, including the creation and maintenance of social ties, the facilitation of parental engagement, and enhanced political activity (Brandtner and Dunning 2020; Marwell 2004; Ressler 2020; Sharkey et al. 2017). This study hypothesized a negative relationship between nonprofit density and child maltreatment. The results shown in Table 2 supported this hypothesis, suggesting a decrease of over half a percent in the expected child maltreatment for an increase of one nonprofit organization, holding other variables constant. This study then decomposes the effects by organizational type showing substantial heterogeneity. In addition to identifying different relationships with child maltreatment, the results of this decomposition suggest it is unlikely that the effects are driven entirely by human services nonprofits, the focus of much prior research, with substantial effects estimated for education and religious organizations, as well. These organizational types are primarily, although not exclusively, concerned with promoting civic life and fostering social ties. For example, the presence of educational nonprofits presents community support and education opportunities that increase parental involvement (Ressler 2020), while religious institutions are strong community builders (Marwell 2004). This raises the possibility that social ties and organizational participation may be as propitious intervention point as direct services, however, more research is needed. The results of this study also re-iterate

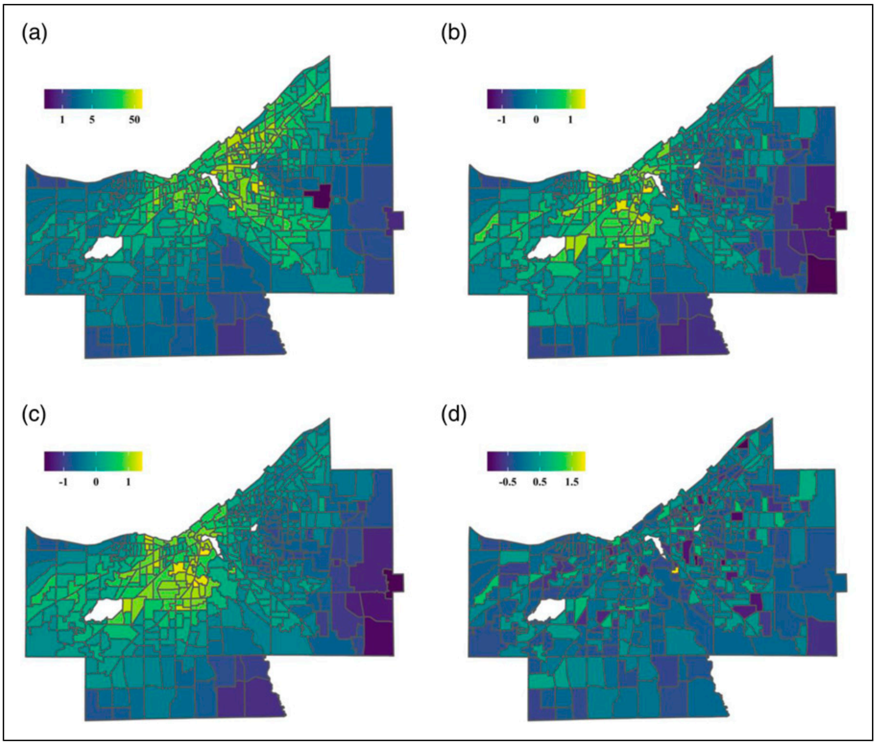

Figure 2. Maps of posteriors means for tract-specific effects estimated from model 3. Estimated maltreatment rates per 1,000 children (panel A), the convolution of spatial and non-spatial effects (panel B), the ICAR component (panel C), and the non-spatial random effect (panel D) from equations (2a)–(2c). White space indicates tracts with zero children.

several familiar patterns in the neighborhood effects child maltreatment literature, including the relationship between crime and child maltreatment and race (Coulton et al. 1995, 2018; M. C. Morris et al. 2019), as well as other forms of disorder (Coulton et al. 1999). Future research may benefit from investigating indirect effects of nonprofit density on child maltreatment, through their relationship with crime or other indicators of disorder (Sharkey et al. 2017; Wo et al. 2016).

This study contributes to the burgeoning literature emphasizing the importance of community-nonprofit relations, the location of nonprofit organizations, and the significance of a healthy nonprofit sector (Bielefeld et al. 1997; Ressler et al. 2020; Sharkey et al. 2017; Wo 2018). Nonprofit organizations may provide unique support to their communities, enhancing access to services, facilitating the development of social networks, and formalizing advocacy efforts—political or otherwise (Allard and Danziger 2002; Marwell 2004; Sampson and Wilson 2012; Young 2006). Nonprofits also provide a propitious avenue of intervention for child welfare advocates, crossing economic development and social services. Nonprofits take many features into account when selecting a location, either moving their operations, or through founding, such as unmet need, price, and access to other resources (Baum and Oliver 1996; Carman and Nesbit 2013). Policy makers and other community actors (i.e., chambers of commerce) have a range of tools to support or attract organizations into under-resourced neighborhoods, such as tax abatements or the use of opportunity zones. The attraction of nonprofit

Table 3. Posterior Inference and Model Comparison for Models of Child Maltreatment Including Disaggregation by Organizational Type (N = 442).

	Model 4			Model 5			Model 6		
Variable	Mean	CI		Mean	CI		Mean	CI	
Constant[a]	2.18	2.12	2.22	2.04	1.96	2.13	2.05	1.98	2.11
Nonprofit density									
Education[a]	−0.21	−0.34	−0.09	−0.18	−0.34	−0.02	−0.11	−0.22	0.01
Health	0.09	0.03	0.14	0.04	−0.06	0.15	0.06	−0.04	0.16
Religion[a]	−0.17	−0.35	−0.01	−0.25	−0.54	0.02	−0.21	−0.48	0.02
Human services[a]	−0.09	−0.17	−0.02	−0.08	−0.20	0.06	−0.08	−0.20	0.02
Arts	−0.37	−0.81	0.02	−0.52	−1.15	0.06	−0.31	−0.82	0.09
Other	0.07	−0.01	0.16	0.09	−0.04	0.23	0.05	−0.07	0.16
Neighborhood characteristics									
Gun violence[a]	0.11	0.08	0.15	0.12	0.04	0.20	0.11	0.04	0.19
Poverty (%)[a]	0.27	0.20	0.35	0.29	0.14	0.44	0.13	−0.02	0.28
Unemployment (%)	−0.09	−0.17	−0.02	−0.10	−0.24	0.05	−0.09	−0.24	0.05
Vacancy (%)[a]	0.23	0.18	0.27	0.25	0.15	0.36	0.30	0.18	0.42
Residential mobility (%)	0.05	0.01	0.10	0.03	−0.06	0.12	0.06	−0.03	0.14
Diversity index[a]	−0.13	−0.17	−0.08	−0.13	−0.22	−0.03	−0.13	−0.24	−0.01
Black or African American (%)[a]	0.39	0.32	0.47	0.41	0.28	0.55	0.57	0.37	0.77
Hispanic or Latino(%)	0.16	0.11	0.21	0.18	0.08	0.28	0.04	−0.09	0.16
σ[b]				0.57	0.50	0.64	0.63	0.54	0.73
ρ							0.73	0.49	0.95
LOOIC	2661.2 (88.3)			2265.4 (37.5)			2220.4 (39.3)		

Note: All models include the number of children as an offset. All variables are mean centered and scaled to unit variance. Posterior inference based on 7,000 sampling iterations. LOOIC = Leave One Out Information Criteria. CI = 95 percent Credible Interval.
Model 4 is a Poisson with homogenous rates. All fixed effects have Normal(0,.5) priors.
Model 5 is model 1 with unstructured random effect. The standard deviation has an exponential(1) prior.
Model 6 is the Poisson model with the convolution prior described in equations (2a)–(2c). Priors are Normal(0,.5) for all fixed effects, β (1,1) for ρ and Γ (1,1) for the standard deviation.
[a]Posterior probability of being over or under 0, in all models is greater than .95.
[b]Standard deviation of the unstructured effect in model 5 and the shared scale parameter in model 6.

organizations can also be considered in the broader scope of economic development and a piece of any neighborhood re-investment strategy. It is possible that incentivizing nonprofit organizations to change their choice of location to lower resourced neighborhoods is easier than for-profit corporations, as nonprofit organizations often draw legitimacy from their location and are often in a constant pursuit of reduced overhead and operating costs (Joassart-Marcelli and Wolch 2003; Newman and Wallender 1978).

There are several limitations to this study that are worth emphasizing. This is a cross-sectional ecological study and as such is unable to leverage repeated measures to control for other unobservable characteristics that are likely important for child maltreatment (Coulton et al. 2018; Raissian 2015), further, inference for tracts may not extend to individual residents. A richer design, such as one with repeated measures, may also decrease the variance and yield a more precise estimate for the effects of nonprofit density. By focusing on a single county, this study conditioned on government nonprofit relations in the region, however, this leaves the role of government size and their emphasis on nonprofit development or program implementation through nonprofit organizations unexamined. Future research may wish to explicitly include these to compare regions. There are also limitations to the use of the agency data for child maltreatment reports, as maltreatment not reported to the agency, or screened out by caseworkers, are not present in these data. Further, child welfare researchers have suggested neighborhoods may have a greater impact on reporting of child maltreatment than on behavior (Coulton et al. 2007), and future research may consider pairing administrative and primary data.

Limitations also come with reliance on form-990 submissions and the measure of nonprofit density used in this study. Tax documents may conflate organizations and establishments, and the measure of nonprofit density employed in this study, while widely used, focuses on one dimension of nonprofit activity in the neighborhood. Organizations differ greatly in size, scope, and service footprint. Future research may benefit from addressing alternative dimensions of nonprofit activity, using financial information or longevity. The measure is also limited insofar as it does not capture the activity of informal organizations, or for-profit organizations that maintain a social mission (e.g., social enterprises). Future research may consider augmenting these data with information on such organizations to obtain a clearer picture of the role of organizations in intricate neighborhood processes.

Conclusion

This study has discussed the role of nonprofit organizations in supporting neighborhood processes and reducing disorder. Nonprofit organizations have a broad class of mechanisms to support nearby families, including direct services, facilitation of social networks, or formal advocacy by prodding government. The study then tested this theory in data from Cuyahoga County Ohio, coupling data on nonprofit density, resident characteristics, violence, and other indicators of social disorganization. The results show a negative relationship between nonprofit density and child maltreatment, across a range of specifications. The relationship was then disaggregated by organizational type, uncovering heterogeneity and raising the possibility that organizations focused on community building and social ties may have a stronger relationship to child maltreatment than those focused on direct services. This broadly supports the theory that nonprofit organizations may support families in their neighborhood and provide a protective factor at the neighborhood level. This encourages entering the nonprofit sector into re-investment strategies for local officials and those interested in business attraction as well as a broader focus on the distribution of nonprofit organizations.

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