Delinquency, Lead, and Nonprofit Organizations; A Spatio-Temporal Perspective

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Abstract

Juvenile delinquency has significant social costs for perpetrators, victims, as well as their communities. To understand the distribution of delinquency offenses, this study considers the clustering of social problems, hypothesizing that housing creates a connection between lead exposure and delinquency rates in neighborhoods, while nonprofits may support collective action and mitigate disorder in neighborhoods. Employing a longitudinal ecological design (N = 4,390) and a hierarchical model implemented in a Bayesian methodology that allows space-time interaction, the results show elevated blood lead levels and nonprofit density are positively and negatively related to the delinquency offense rate, respectively. The study emphasizes the isolation of neighborhoods with social problems and nonprofits as valuable community resources.

1 Introduction

Juvenile delinquency has significant social costs for perpetrators, victims, as well as their communities. Delinquency clearly has implications for the children that commit crime, as they may be less likely to complete college, and more likely to become unemployed and commit crimes later in life (Carter, 2019; Loeber & Farrington, 2000). Delinquency may also increase monitoring in the neighborhoods where it occurs, making contact with police or other workers more common, degrading perceptions of the neighborhood and normalizing negative interactions (Fong, 2020). This may re-enforce existing forces that create socially isolated neighborhoods dense with social problems (Sampson et al., 2002).

Delinquent behaviors have long been linked to their neighborhood through social disorganization theory, as neighborhood structures effect processes which can provide resources, often through their capacity to promote or inhibit social interaction, for residents to influence individual behaviors through social control, making the neighborhood a key site of study (Sampson & Groves, 1989; Shaw & McKay, 1942). Consistent with this theory, juvenile delinquency researchers have considered a range of structural characteristics, as well as social support and processes, and their implications for delinquent behaviors (Chung & Steinberg, 2006; Kurlychek et al., 2012; Sampson et al., 2002). However, this literature has paid less attention to the role of housing in children's health and behaviors, as well as the immense benefits nonprofits may provide to their communities (Jacobs, 2011; Mayer, 2023a). Contributing to the literature related to neighborhoods, delinquency, and the spatial distribution of social problems, this paper considers variables that are currently understudied in the delinquency literature: elevated blood lead level (EBLL) and nonprofit organizations. After discussing the extant literature and theoretical framework, this study employs a longitudinal design and an empirical approach which allows interaction between space and time over the spatial units, implemented in a Bayesian methodology, contributing to a burgeoning literature which considers approaches to crime from spatial epidemiology (Groff & Lockwood, 2014; Law et al., 2014; Matthews et al., 2010). The results show substantial variation over space and time in delinquency rates, and suggest that delinquency clusters with EBLL, however, is negatively related to nonprofit density.

2 Lead and the Clustering of Social Problems

Lead is a naturally occurring toxic heavy metal that when ingested at certain levels may significantly impact the health and behavior of children. A substantial body of work has demonstrated the range of implications of lead ingestion by children, for example, lead ingestion may decrease Intelligence Quotient (IQ), executive functioning, and academic performance (Bellinger et al., 1992; Canfield et al., 2003). Lead ingestion, however, may affect children in ways not explained entirely by decreases in IQ, as lead affected children may also experience behavioral differences and developmental disorders (Bellinger, 2008; Braun et al., 2006). Importantly, the damage lead ingestion causes may be linked to lower self-control, and in turn, increases in aggressive or deviant behavior and psychopathy (Nkomo et al., 2018; Wright et al., 2009). Aizer & Currie (2019) find elevated blood lead levels increase children's likelihood of suspension and detention from schools, and historical research suggests lead pipes predicted increases in violent crime (Feigenbaum & Muller, 2016).

Exposure and subsequent ingestion of lead often occurs from contact with structures built before 1978 (when lead-based paint was banned) through chipped paint and dust in older unremedied buildings. Often, this occurs during remodeling, removal, or in homes where that are not well maintained, implicating housing in determining lead exposure with implications for health and delinquency. The distribution of housing quality, however, is not uniform across neighborhoods, and Jacobs (2011) finds sub-standard housing is most common among non-Hispanic Black residents, followed by Hispanic residents, and least common among non-Hispanic White residents, and Bailey et al. (1994) finds risk of EBLL is more common in older housing and among Black or African American Families. Further, in their study of lead exposure and kindergarten readiness, Coulton et al. (2016) show lead exposure is correlated with housing quality and the neighborhood's poverty rate. Clearly, the children's housing is an important factor in determining the likelihood of lead exposure, with implications for their health and future. Yet, this literature suggests the etiology of lead exposure is tied deeply to the resident's neighborhood, and while lead may cause delinquent behavior, lead exposure is likely to be present in communities where social problems tend to cluster, such as isolated minority neighborhoods (Sampson et al., 2002). Consistent with this theory, this study hypotheses a positive relationship between EBLL and juvenile delinquency rates.

3 Nonprofit Organizations and Collective Efficacy

Social disorganization theory states that communities experience high crime rates due to their inability to effectively achieve consensus and maintain social controls as a result of structural characteristics (Sampson & Groves, 1989; Shaw & McKay, 1942). A socially organized community experiences low crime rates and is characterized by solidarity, cohesion, and integration (Kubrin & Wo, 2015). The existing literature has largely focused on risk factors and the concentration of social problems, while a smaller literature exists considering protective factors that may lead to higher levels of social organization (Sampson et al., 2002). Collective efficacy, often understood as shared expectations for action or intervention within a community, can reduce crime and disorder by encouraging community members to act toward the common good. Collective efficacy is undergird by networks which may provide opportunities for goal alignment, and increased confidence in community members ability to take action (Sampson et al., 1997).

A community's nonprofit infrastructure is essential in this conceptualization of collective efficacy. Organizations may result from collective action, creating a template of successful collective action on behalf of the community (Greve & Rao, 2012; Sampson & Wilson, 2012). Once established, nonprofit organizations continue to be valuable community assets, as they often provide vital services or other highly valued amenities (Ressler et al., 2021). Importantly, they also provide community spaces which can encourage community members to act toward the common good as well as foster ties to maintain social and economic networks and facilitate goal alignment, increasing social control (Brandtner & Dunning, 2020; Marwell, 2004). Sampson (2004) argues "a strong institutional infrastructure and working trust among organizations help sustain capacity for social action in a way that transcends traditional personal ties" (p. 109). Consistent with this notion, recent evidence suggest a negative relationship between a number of categories of crime and nonprofits among US cities (Sharkey et al., 2017; Wo et al., 2016). Furthermore, using block groups, Wo (2019) finds nonprofits effect crime in neighboring regions, as well. However, social disorganization may have a disproportionate impact on children and families, which can be mitigated by organizational participation (Sampson & Groves, 1989), and a related line of research has shown nonprofits bring immense benefits to families and reduce child maltreatment through service access, norm concretization, and enhancing social capital (Mayer, 2023c, 2023a; Morton, 2013). Consistent with this literature, this study hypothesizes a negative relationship between nonprofit density and juvenile delinquency rates.

4 Current Study Overview

Delinquency remains a serious social problem with implications for children, families, and communities. This study investigates two underexplored links between delinquency and neighborhood structures, particularly, lead (EBLL) and nonprofit organizations. Lead provides a mechanism which links housing, where children are typically exposed to lead, and delinquency, while nonprofits may build on existing social networks and enhance the neighborhoods capacity to act and solve collective action problems, such as juvenile delinquency. Accordingly, this study hypothesizes a positive relationship between EBLL and juvenile delinquency rates, and a negative relationship between nonprofit density and juvenile delinquency rates. The study investigates these questions using 10 years of data, aggregated by census tract, in Cuyahoga County Ohio, with an empirical model that addresses spatial and temporal variation in juvenile delinquency rates.

5 Methods and Materials

Data for this study cover a 10-year period, from 2010 to 2019, in Cuyahoga County Ohio (USA) a US county with a resident population of roughly 1.25 million that covers an area of over 1,200 square miles, and contains the city of Cleveland, which regularly ranks among the country's poorest big cities, as well as a mix of high-, middle-, and low-income neighborhoods. The unit of analysis in this study is the census tract, a widely used measure of neighborhoods, and corresponds more closely to the size of neighborhoods reported by residents (Coulton et al., 2013; Mayer, 2023c; Wo, 2018).

5.1 Dependent Variable: Juvenile Delinquency

The dependent variable in this study is the number of juvenile delinquency offenses in the tract and year. These data come from the Cuyahoga County Juvenile Court, which are updated annually (*Juvenile Court Indicators*, 2010). A delinquency case occurs when a juvenile is charged with a crime that would be considered criminal if committed by an adult, including, among others, violent, drug, and conspiracy offenses, and has at least one hearing with a judge or magistrate. This excludes “unruly” offenses, which although processed by the juvenile court, would not be considered criminal if committed by adults. Importantly, the juvenile offenses are mapped to the offender’s residence, rather than the location of the incident, properly mapping to the structural characteristics of the home and neighborhood.

5.2 Independent Variables

The two key independent variables in this study are EBLL and nonprofit density. EBLL is measured as the unduplicated count of children under six years of age with a confirmed elevated blood lead level test, defined as above five milligrams per deciliter, within the tract and year, and come from the Ohio Department of Health (*Health Indicators*, 2010). A confirmed tests includes at least one venous test within a year, or two or more capillary tests conducted within six weeks. Like juvenile offenses, the data correspond to the tract of the child’s residence at the time of the test. Although there is no safe amount of lead ingestion (Bellinger, 2008), five milligrams per deciliter represents the current reference set by the Centers for Disease Control and Prevention to identify children with lead levels higher than most children’s, corresponding to the highest two and half percent of children from the National Health and Nutrition Examination Survey. The second key variable in this study is nonprofit density, defined as the number of active nonprofit organizations in the tract and year (Mayer, 2023c; Wo, 2018). Corresponding to the Internal Revenue Source (IRS) definition, an active nonprofit is defined as one which has submitted a form-990 within the past two years. Nonprofit data for this study are drawn from the National Center for Charitable Statistics business master file (NCCS BMF), which provides updated versions of IRS records with additional information to assist researchers. The NCCS BMF contains a census of organizations that submit any variety of tax forms or requests for exemption (e.g., forms 1023 and 1024, or any form-990), and has been used widely by researchers interested in geocoding and smaller geographic units (Crubaugh, 2020; Mayer, 2023c, 2023a; Wo, 2018). Focused on nonprofits and neighborhoods, this study excludes private foundations and supporting organizations, which may distort counts by including organizations that have a different relationship with their environment. The organizations that met these inclusion criteria were geocoded using the address listed on the tax form and placed in their respective census tracts. Following this process, over 99 percent of active nonprofits were successfully geocoded, while the few remaining organizations were excluded.

5.3 Control Variables

This paper's focus is on the relationship between juvenile delinquency, EBLL, and nonprofit density, however, other variables must be considered which may confound the relationships of interest. These include the tract's poverty rate, rate of owner-occupied housing, and the racial and ethnic composition of the tract, all drawn from the American Community Survey. Juvenile delinquency is more likely to occur in regions that are economically under-resourced, such as neighborhoods with high poverty rates (Rekker et al., 2015; Shaw & McKay, 1942). Neighborhoods with higher rates of poverty may also have housing stock that is older, or less well maintained, leading to higher rates of lead exposure (Bailey et al., 1994; Coulton et al., 2016). Similarly, nonprofits are not equally distributed over space, and neighborhoods with higher rates of poverty may be home to fewer nonprofits (Joassart-Marcelli & Wolch, 2003; McDonnell et al., 2020). Homeowners have been the site of intervention reducing the prevalence of lead exposure through maintenance and education (Korfmacher & Hanley, 2013), making owner-occupation an important consideration. Delinquency offenses may also cluster in neighborhoods with lower rates of owner-occupied housing, possibly due to transience which may make building social networks and effecting collective action more challenging (Kubrin & Wo, 2015; McAllister & Mason, 1972). Finally, the racial and ethnic diversity of the tract must be considered as the over-representation of minority children has long been a fact in the juvenile justice system (Bishop & Leiber, 2011). Due to historical processes and structural disadvantages, predominately minority neighborhoods may experience higher rates of social problems, such as child maltreatment, which may increase monitoring and surveillance (Fong, 2020). Due to a concentration of social problems, these neighborhoods may be more likely to have housing which has not been properly maintained, raising the possibility of lead exposure for children (Bailey et al., 1994). Yet, nonprofit density is also a function of the racial and ethnic composition of the neighborhood. Nonprofits tend to cluster together to benefit from economic networks, and these clusters are less common in minority neighborhoods (Mayer, 2023b; Wo, 2018). The racial and ethnic composition of the census tract is measured using three variables: the percent of the tract that identifies as Black or African American, Hispanic or Latino, and a Herfindahl–Hirschman Index constructed from the share of the tract that is white, Hispanic or Latino, Asian, and Black or African American, which is subtracted from one such that higher values indicate more racially and ethnically diverse areas (Mayer, 2023c; Wo, 2018).

5.4 Empirical Model

There are several complications with empirical studies of neighborhoods or other small geographic units that must be accounted for in an empirical approach. Spatially structured variation has long been a concern among neighborhood and community researchers, as neighborhood processes, such as communication and disorder, typically do not obey boundaries imposed by researchers (Coulton, 2005; Coulton et al., 2007). Furthermore, spatial confounding by noise can often make the detection of effects of interest more challenging as spatial units become smaller, and ignoring spatial confounding can lead to biased or inefficient inference

(Elliott & Wartenberg, 2004). In longitudinal studies, assuming the spatial effects are constant over the study period and units may be overly restrictive and fail to represent the changing dynamics of communities, and robustness to this is particularly important when the outcome is rare (Congdon, 2019). This study addresses these complications with a model that accounts for the spatial network, as well as variation in the spatial effects over time, using a Bayesian methodology, Integrated Nested Laplace Approximation (INLA), which provides an approximate posterior through optimization (Rue et al., 2009, 2017). The Bayesian methodology has distinct advantages in neighborhood effects studies, particularly for its ability to propagate uncertainty representing spatial dependence structures (Gracia et al., 2017; Marco et al., 2022; Mayer & Fischer, 2022).

This study accounts for spatial effects using the intrinsic conditional autoregressive prior (ICAR). The ICAR is an improper prior that estimates a latent, smooth, conditionally normal, pattern over the spatial network by averaging the effects of a unit's neighbors (Besag, 1974). However, entertaining only spatially structured variation can be viewed as a strong prior on the source of variation, which can be relaxed by introducing an unstructured source of variation among the spatial units (Besag et al., 1991). The resulting prior mixes the variance components, however, may also introduce a series of problems which Riebler et al. (2016) resolve in a complexity penalizing framework by introducing a novel parameterization of the convolution with a single parameter governing the mixing, which is used in this study.

The analysis proceeds through model comparison using the Watanabe–Akaike Information Criterion (WAIC), which integrates over the posterior and provides an estimate of predictive error in new data (asymptotically equivalent to Leave-One-Out Cross Validation) with a penalty applied for the effective number of parameters (Gelman et al., 2014). The model is first specified with a Poisson likelihood, which provides the correct support and allows the child population to be included as an offset, modeling the tract's rate of juvenile delinquency offenses as a function of the covariates. Two random effects are then introduced, allowing correlated deviations from the population average constant and linear time trends. The model then enters the convolution prior, modeling a constant spatial and nonspatial effects which vary over units as described in Riebler et al. (2016) as $x_i = \sqrt{\tau}^{-1}(\sqrt{1-\phi}\ \upsilon + \sqrt{\phi}\ \mu)$ where i indexes the tract, υ and μ are standardized, and τ is the marginal precision, and ϕ is the proportion explained by the spatial structure. The assumption of constant variance components in the convolution prior is relaxed by estimating them as independent and identically distributed (iid) with common variance. Finally, the model entertains increased variation in the convolution prior through a first order autoregressive process between years, specified as $x_{ij} = \rho x_{ij-1} + \sqrt{1-\rho^2}\epsilon_{ij}$ where ρ governs smoothing between years, and ϵ_{ij} is standard normal (Blangiardo & Cameletti, 2015). Priors are also required in the full Bayesian methodology, and in this study all fixed effects are assigned standard normal priors, providing regularization by a constant amount (Gelman & Hill, 2006). The precision parameters for the random effects, as well as the AR1 parameter, are given a diffuse log-Γ(.1,.1) prior, while the precision matrix for the random effects is assigned a Wishart prior with four degrees of freedom. Note that while INLA parametrizes models in terms of precision, for lucidity, this study reports standard deviations.

6 Results

The data used in this study include 439 tracts, each measured over 10 years resulting in 4,390 total observations. Table 1 shows select descriptive statistics for the variables used in this study: the mean, standard deviation, as well as the first and third quantiles. The table shows the average tract experienced 12 delinquency offenses, 5 cases of EBLL, and was home to 10 nonprofits per year over the study period. Delinquency offenses and nonprofit density, however, show a large amount of variation, suggesting they may be concentrated in some tracts.

[Table 1]

Although table one helps to understand the observed distribution of many of the key study variables, it does not consider variation by space and time, which are important dynamics when considering neighborhood processes and juvenile delinquency. The trends of the three key variables over time are shown in figure 1. The figure shows that over the 10-year period covered in this study, Cuyahoga County experienced substantial reductions in juvenile delinquency offenses and confirmed cases of EBLL as their 2019 totals represent 52 and 58 percent reductions from 2010, respectively. The number of active nonprofits in the county among the included tracts, however, increased 10 percent from 2010 to 2019, although is lower than the peak of over 4,700 in 2016.

[Figure 1]

Figure one shows the importance of considering time trends in the key variables; however, the geography of delinquency shows distinct patterns which have also changed over time. Figure two shows maps of the total number of juvenile delinquency offenses by year in Cuyahoga County tracts. The figure reveals several geographic regions in which delinquency is concentrated, suggesting spatial variation which varies over tracts. However, the figure also shows the patterns of delinquency over time, while stable in some areas, can also change dramatically between years. The map from 2010 shows several regions of the county experienced high rates of delinquency, yet as the rates decrease over time, cases become more concentrated in certain areas of the map. Particularly, the outer suburban areas experience fewer delinquency cases over time. Taken together, these figures suggest changes in space and time are important components of studying delinquency.

[Figure 2]

Model comparison supports the descriptive evidence that variation over space and time is an important component of juvenile delinquency, as model comparison using WAIC suggests the most complex model under consideration, random effects for slop and intercept, as well as the convolution prior with an AR(1) process governing the change in the compounding effects between years, is the best in terms of WAIC. Table 2 summarizes the results of the five models considered in this study, which gradually increase in complexity, and reveal substantial improvements with each additional component.

[Table 2]

The full results of model five are shown in table 3, which includes the mean, standard deviation, as well as the 25^{th}, 50^{th}, and 75^{th} percentiles of the posterior for each parameter. Note that all variables, other than year, are mean centered and scaled to variance of one, consequently, the constant reflects the delinquency rate in 2010 with the covariates and random effects set to zero. The results show EBLL is positively related to the rate of delinquency offenses and suggests an increase of seven confirmed cases of EBLL, holding other variables constant, predicts an increase in the rate of delinquency offenses between 3 and 11 percent. Nonprofit density, however, is negatively related to the delinquency rate: an increase of 25 nonprofits in the tract predicts a decrease between 6 and 15 percent in the rate of delinquency offenses.

While not the focus of this study, several other variables show clear relationships with the delinquency rate, the effect for year shows the negative trend averaged over tracts, and the control variables show higher delinquency rates are found in tracts with higher rates of poverty, while the tract's racially and ethnic diversity and the percent that identify as Black or African American are positively related to the delinquency rate, as well. The random effects suggest greater variation is captured within tracts over time, than between tracts on average, as the random effect for time shows tracts within one standard deviation may increase over the study period. The standard deviation for the convolution prior suggests substantial variation is found across units, while the posterior for ϕ suggests most of this variation is unstructured. Finally, ρ shows the convoluted effects are positively related between years.

[Table 3]

7 Discussion

Scholars have long emphasized the clustering of social problems, and the isolation of neighborhoods that experience high rates of social issues such as juvenile delinquency, due to a range of structural features that may degrade social control or collective efficacy (Kubrin & Weitzer, 2003; Kubrin & Wo, 2015; Sampson et al., 2002). Contributing this body of literature, this study investigated the connection between lead exposure, nonprofit organizations, and juvenile delinquency rates using a rich longitudinal design from 2010-2019 and an empirical model developed in the epidemiology literature capable of addressing confounding by spatial and temporal heterogeneity (Besag, 1974; Elliott & Wartenberg, 2004; Riebler et al., 2016). The study tested two key hypotheses: 1) a positive relationship between EBLL and delinquency rates and 2) a negative relationship between nonprofit density and delinquency rates. The results show support for both hypotheses, with substantial estimates that are robust to the inclusion of heterogeneity over space and time.

Juvenile delinquency and lead exposure are severe social problems that can have negative long-term implications for those involved or effected. This study hypothesized a link between lead exposure and delinquency through housing, as neighborhood sorting behaviors along socio-economic lines expose minorities and impoverished residents to sub-standard housing and lead exposure (Bailey et al., 1994; Jacobs, 2011), and lead exposure may induce delinquent behavior (Aizer & Currie, 2019; Feigenbaum & Muller, 2016). The evidence presented in this study supports this theory, and suggests substantial benefits may accrue, at the neighborhood level, from the provision of modern housing or lead abatement strategies to residents. As abatement strategies have begun in some areas around the country (Korfmacher & Hanley, 2013), future research is needed to understand their impact on these patterns.

One way residents may enact change is through nonprofit organizations, as nonprofits can concretize or enforce norms, and support social networks, enhancing social capital and collective efficacy (Mayer, 2023a, 2023c; Sharkey et al., 2017; Wo et al., 2016). Accordingly, this study hypothesized a negative relationship between nonprofit density and juvenile delinquency. The results supported this hypothesis, building on the extant literature related to the benefits nonprofit organizations can bring to their communities. However, nonprofits are not equally distributed over space, and recent evidence suggests they may be less likely to locate in disadvantaged neighborhoods (McDonnell et al., 2020; Wo, 2018), where they are needed most. More research is needed on the location choices of nonprofits among small geographic areas, as well as the reasons for their choices.

This study has used administrative and agency data in a rich longitudinal design, however, reliance on these data are not without limitations. Administrative data on delinquency offenses and EBLL cover only those that are caught or undergo testing. Consequently, populations subject to higher levels of monitoring may be more likely to appear in these data. The data source for nonprofit density used in this study, the form-990, is also an administrative data source, and while it has been widely used by nonprofit researchers for decades, it was not designed for research purposes. Importantly, it conflates organizations and establishments, and may undercount those not required to submit tax documents, such as small organizations and some religious nonprofits. Finally, the census tract, while also widely used as a measure of neighborhood, may not reflect the lived experience of neighborhood life. Future research may consider a survey methodology to obtain a different picture of victimization, perpetration, and neighborhood life.

8 Conclusion

This study has considered juvenile delinquency, lead exposure, and nonprofit organizations. The results suggest lead and nonprofit organizations provide countervailing forces in neighborhood life, as lead may disrupt neighborhood processes and further disadvantage isolated communities, while nonprofits may support collective action and mitigate disorder. The link between housing, lead, and delinquency builds upon the established body of evidence highlighting the significant public health implications associated with housing. Particularly, isolating disadvantaged residents in neighborhoods with low quality housing can alter the trajectory of their lives through lead exposure and an increased likelihood of delinquent behaviors. The results of this study suggest the neighborhood is an important consideration when considering the mitigation of disorder.

9 References

Aizer, A., & Currie, J. (2019). Lead and Juvenile Delinquency: New Evidence from Linked Birth, School, and Juvenile Detention Records. *The Review of Economics and Statistics*, *101*(4), 575–587. https://doi.org/10.1162/rest_a_00814

Bailey, A. J., Sargent, J. D., Goodman, D. C., Freeman, J., & Brown, M. J. (1994). Poisoned landscapes: The epidemiology of environmental lead exposure in Massachusetts children 1990–1991. *Social Science & Medicine*, *39*(6), 757–766. https://doi.org/10.1016/0277-9536(94)90037-X

Bellinger, D. C. (2008). Very low lead exposures and children's neurodevelopment. *Current Opinion in Pediatrics*, *20*(2), 172–177. https://doi.org/10.1097/MOP.0b013e3282f4f97b

Bellinger, D. C., Stiles, K. M., & Needleman, H. L. (1992). Low-level lead exposure, intelligence and academic achievement: A long-term follow-up study. *Pediatrics*, *90*(6), 855–861.

Besag, J. (1974). Spatial Interaction and the Statistical Analysis of Lattice Systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, *36*(2), 192–236.

Besag, J., York, J., & Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*, *43*(1), 1–20. https://doi.org/10.1007/BF00116466

Bishop, D. M., & Leiber, M. J. (2011). Racial and Ethnic Differences in Delinquency and Justice System Responses. In D. M. Bishop & B. C. Feld (Eds.), *The Oxford Handbook of Juvenile Crime and Juvenile Justice* (p. 0). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195385106.013.0020

Blangiardo, M., & Cameletti, M. (2015). *Spatial and Spatio-temporal Bayesian Models with R-INLA*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118950203

Brandtner, C., & Dunning, C. (2020). Nonprofits as urban infrastructure. In W. W. Powell & P. Bromley (Eds.), *The nonprofit sector: A research handbook* (Third edition, pp. 270–291). Stanford University Press.

Braun, J. M., Kahn, R. S., Froehlich, T., Auinger, P., & Lanphear, B. P. (2006). Exposures to environmental toxicants and attention deficit hyperactivity disorder in U.S. children. *Environmental Health Perspectives*, *114*(12), 1904–1909. https://doi.org/10.1289/ehp.9478

Canfield, R. L., Henderson, C. R., Cory-Slechta, D. A., Cox, C., Jusko, T. A., & Lanphear, B. P. (2003). Intellectual impairment in children with blood lead concentrations below 10 microg per deciliter. *The New England Journal of Medicine*, *348*(16), 1517–1526. https://doi.org/10.1056/NEJMoa022848

Carter, A. (2019). The Consequences of Adolescent Delinquent Behavior for Adult Employment Outcomes. *Journal of Youth and Adolescence*, *48*(1), 17–29. https://doi.org/10.1007/s10964-018-0934-2

Chung, H. L., & Steinberg, L. (2006). Relations Between Neighborhood Factors, Parenting Behaviors, Peer Deviance, and Delinquency Among Serious Juvenile Offenders. *Developmental Psychology*, *42*(2), 319–331. https://doi.org/10.1037/0012-1649.42.2.319

Congdon, P. D. (2019). *Bayesian Hierarchical Models: With Applications Using R, Second Edition* (2nd edition). Chapman and Hall/CRC.

Coulton, C. J. (2005). The Place of Community in Social Work Practice Research: Conceptual and Methodological Developments. *Social Work Research*, *29*(2), 73–86. https://doi.org/10.1093/swr/29.2.73

Coulton, C. J., Crampton, D. S., Irwin, M., Spilsbury, J. C., & Korbin, J. E. (2007). How neighborhoods influence child maltreatment: A review of the literature and alternative pathways. *Child Abuse & Neglect*, *31*(11–12), 1117–1142. https://doi.org/10.1016/j.chiabu.2007.03.023

Coulton, C. J., Jennings, M. Z., & Chan, T. (2013). How big is my neighborhood? Individual and contextual effects on perceptions of neighborhood scale. *American Journal of Community Psychology*, *51*(1–2), 140–150. https://doi.org/10.1007/s10464-012-9550-6

Coulton, C. J., Richter, F., Kim, S.-J., Fischer, R., & Cho, Y. (2016). Temporal effects of distressed housing on early childhood risk factors and kindergarten readiness. *Children and Youth Services Review*, *68*, 59–72. https://doi.org/10.1016/j.childyouth.2016.06.017

Crubaugh, B. (2020). Neighborhood Development Organizations and Neighborhood Disadvantage: Race, Resources, and Inequality in Chicago. *Nonprofit and Voluntary Sector Quarterly*, *50*(1), 27. https://doi.org/10.1177/0899764020941928

Elliott, P., & Wartenberg, D. (2004). Spatial epidemiology: Current approaches and future challenges. *Environmental Health Perspectives*, *112*(9), 998–1006. https://doi.org/10.1289/ehp.6735

Feigenbaum, J. J., & Muller, C. (2016). Lead exposure and violent crime in the early twentieth century. *Explorations in Economic History*, *62*, 51–86. https://doi.org/10.1016/j.eeh.2016.03.002

Fong, K. (2020). Getting Eyes in the Home: Child Protective Services Investigations and State Surveillance of Family Life. *American Sociological Review*, *85*(4), 610–638. https://doi.org/10.1177/0003122420938460

Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9780511790942

Gelman, A., Hwang, J., & Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. *Statistics and Computing*, *24*(6), 997–1016. https://doi.org/10.1007/s11222-013-9416-2

Gracia, E., López-Quílez, A., Marco, M., & Lila, M. (2017). Mapping child maltreatment risk: A 12-year spatio-temporal analysis of neighborhood influences. *International Journal of Health Geographics*, *16*(1), 38. https://doi.org/10.1186/s12942-017-0111-y

Greve, H. R., & Rao, H. (2012). Echoes of the Past: Organizational Foundings as Sources of an Institutional Legacy of Mutualism. *American Journal of Sociology*, *118*(3), 635–675. https://doi.org/10.1086/667721

Groff, E. R., & Lockwood, B. (2014). Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence about the Spatial Extent of Facility Influence. *Journal of Research in Crime and Delinquency*, *51*(3), 277–314. https://doi.org/10.1177/0022427813512494

Health Indicators (Census Tract). (2010). Center on Poverty and Community Development, Jack, Joseph and Morton Mandel School of Applied Social Sciences, Case Western Reserve University. http://neocando.case.edu

Jacobs, D. E. (2011). Environmental Health Disparities in Housing. *American Journal of Public Health*, *101*(Suppl 1), S115–S122. https://doi.org/10.2105/AJPH.2010.300058

Joassart-Marcelli, P., & Wolch, J. R. (2003). The Intrametropolitan Geography of Poverty and the Nonprofit Sector in Southern California. *Nonprofit and Voluntary Sector Quarterly*, *32*(1), 70–96. https://doi.org/10.1177/0899764002250007

Juvenile Court Indicators (Census Tract). (2010). Center on Poverty and Community Development, Jack, Joseph and Morton Mandel School of Applied Social Sciences, Case Western Reserve University. http://neocando.case.edu

Korfmacher, K. S., & Hanley, M. L. (2013). Are Local Laws the Key to Ending Childhood Lead Poisoning? *Journal of Health Politics, Policy and Law*, *38*(4), 757–813. https://doi.org/10.1215/03616878-2208603

Kubrin, C. E., & Weitzer, R. (2003). New Directions in Social Disorganization Theory. *Journal of Research in Crime and Delinquency*, *40*(4), 374–402. https://doi.org/10.1177/0022427803256238

Kubrin, C. E., & Wo, J. C. (2015). Social Disorganization Theory's Greatest Challenge. In *The Handbook of Criminological Theory* (pp. 121–136). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118512449.ch7

Kurlychek, M. C., Krohn, M. D., Dong, B., Hall, G. P., & Lizotte, A. J. (2012). Protection From Risk: Exploration of When and How Neighborhood-Level Factors Can Reduce Violent Youth Outcomes. *Youth Violence and Juvenile Justice*, *10*(1), 83–106. https://doi.org/10.1177/1541204011422088

Law, J., Quick, M., & Chan, P. (2014). Bayesian Spatio-Temporal Modeling for Analysing Local Patterns of Crime Over Time at the Small-Area Level. *Journal of Quantitative Criminology*, *30*(1), 57–78. https://doi.org/10.1007/s10940-013-9194-1

Loeber, R., & Farrington, D. P. (2000). Young children who commit crime: Epidemiology, developmental origins, risk factors, early interventions, and policy implications. *Development and Psychopathology*, *12*(4), 737–762. https://doi.org/10.1017/S0954579400004107

Marco, M., López-Quílez, A., Gracia, E., & Maguire-Jack, K. (2022). The Spatio-temporal Epidemiology of Child Maltreatment: Using Bayesian Hierarchical Models to Assess Neighborhood Influences. In K. Maguire-Jack & C. Katz (Eds.), *Neighborhoods, Communities and Child Maltreatment: A Global Perspective* (pp. 9–29). Springer International Publishing. https://doi.org/10.1007/978-3-030-93096-7_2

Marwell, N. P. (2004). Privatizing the Welfare State: Nonprofit Community-Based Organizations as Political Actors. *American Sociological Review*, *69*(2), 265–291.

Matthews, S. A., Yang, T.-C., Hayslett, K. L., & Ruback, R. B. (2010). Built Environment and Property Crime in Seattle, 1998–2000: A Bayesian Analysis. *Environment and Planning A: Economy and Space*, *42*(6), 1403–1420. https://doi.org/10.1068/a42393

Mayer, D. J. (2023a). Social Capital and the Nonprofit Infrastructure: An Ecological Study of Child Maltreatment. *Journal of Community Psychology*, *51*, 16. https://doi.org/10.1002/jcop.22984

Mayer, D. J. (2023b). Understanding Location and Density; A Spatial Analysis of Cuyahoga County Ohio’s Nonprofit Sector. *Nonprofit and Voluntary Sector Quarterly*, 23. https://doi.org/10.1177/08997640231171074

Mayer, D. J. (2023c). Understanding Social Disorganization and the Nonprofit Infrastructure; An Ecological Study of Child Maltreatment Rates. *Social Currents*, 19. https://doi.org/10.1177/23294965231159317

Mayer, D. J., & Fischer, R. L. (2022). Can a measurement error perspective improve estimation in neighborhood effects research? A hierarchical Bayesian methodology. *Social Science Quarterly*, *103*(5), 13. https://doi.org/DOI: 10.1111/ssqu.13190

McAllister, J., & Mason, A. (1972). A Comparison of Juvenile Delinquents and Children in Care: An Analysis of Socio-Economic Factors. *The British Journal of Criminology*, *12*(3), 280–286.

McDonnell, D., Mohan, J., & Norman, P. (2020). Charity Density and Social Need: A Longitudinal Perspective. *Nonprofit and Voluntary Sector Quarterly*, *49*(5), 1082–1104. https://doi.org/10.1177/0899764020911199

Morton, C. M. (2013). The Moderating Effect of Substance Abuse Service Accessibility on the Relationship between Child Maltreatment and Neighborhood Alcohol Availability. *Children and Youth Services Review*, *35*(12), 1933–1940. https://doi.org/10.1016/j.childyouth.2013.09.019

Nkomo, P., Naicker, N., Mathee, A., Galpin, J., Richter, L. M., & Norris, S. A. (2018). The association between environmental lead exposure with aggressive behavior, and dimensionality of direct and indirect aggression during mid-adolescence: Birth to Twenty Plus cohort. *Science of The Total Environment*, *612*, 472–479. https://doi.org/10.1016/j.scitotenv.2017.08.138

Rekker, R., Pardini, D., Keijsers, L., Branje, S., Loeber, R., & Meeus, W. (2015). Moving in and out of Poverty: The Within-Individual Association between Socioeconomic Status and

Juvenile Delinquency. *PLOS ONE*, *10*(11), e0136461. https://doi.org/10.1371/journal.pone.0136461

Ressler, R. W., Paxton, P., Velasco, K., Pivnick, L., Weiss, I., & Eichstaedt, J. C. (2021). Nonprofits: A Public Policy Tool for the Promotion of Community Subjective Well-being. *Journal of Public Administration Research and Theory*, *31*(4), 822–838. https://doi.org/10.1093/jopart/muab010

Riebler, A., Sørbye, S. H., Simpson, D., & Rue, H. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research*, *25*(4), 1145–1165. https://doi.org/10.1177/0962280216660421

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *71*(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Rue, H., Riebler, A., Sørbye, S. H., Illian, J. B., Simpson, D. P., & Lindgren, F. K. (2017). Bayesian Computing with INLA: A Review. *Annual Review of Statistics and Its Application*, *4*(1), 395–421. https://doi.org/10.1146/annurev-statistics-060116-054045

Sampson, R. J. (2004). Neighbourhood and community: Collective efficacy and community safety. *New Economy*, *11*, 106–113.

Sampson, R. J., & Groves, W. B. (1989). Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology*, *94*(4), 774–802. https://doi.org/10.1086/229068

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "Neighborhood Effects": Social Processes and New Directions in Research. *Annual Review of Sociology*, *28*(1), 443–478. https://doi.org/10.1146/annurev.soc.28.110601.141114

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science*, *277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918

Sampson, R. J., & Wilson, W. J. (2012). *Great American City: Chicago and the Enduring Neighborhood Effect*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226733883.001.0001

Sharkey, P., Torrats-Espinosa, G., & Takyar, D. (2017). Community and the Crime Decline: The Causal Effect of Local Nonprofits on Violent Crime. *American Sociological Review*, *82*(6), 1214–1240. https://doi.org/10.1177/0003122417736289

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas* (pp. xxxii, 451). University of Chicago Press.

Wo, J. C. (2018). Understanding the density of nonprofit organizations across Los Angeles neighborhoods: Does concentrated disadvantage and violent crime matter? *Social Science Research*, *65*(7), 56–71. https://doi.org/10.1016/j.ssresearch.2018.01.001

Wo, J. C. (2019). Revisiting the Crime Control Benefits of Voluntary Organizations: Organizational Presence, Organizational Capacity, and Crime Rates in Los Angeles Neighborhoods. *Crime & Delinquency*, *65*(7), 916–940. https://doi.org/10.1177/0011128718787517

Wo, J. C., Hipp, J. R., & Boessen, A. (2016). Voluntary Organizations and Neighborhood Crime: A Dynamic Perspective. *Criminology*, *54*(2), 212–241. https://doi.org/10.1111/1745-9125.12101

Wright, J. P., Boisvert, D., & Vaske, J. (2009). Blood Lead Levels in Early Childhood Predict Adulthood Psychopathy. *Youth Violence and Juvenile Justice*, *7*(3), 208–222. https://doi.org/10.1177/1541204009333827

Table 1. Mean, standard deviation, and quantiles for study variables by census tract 2010 – 2019 (N = 4,390)

Variable	Mean	SD	25 %	75 %
Total child population	640.706	347.698	388.000	817.500
Delinquency offenses	11.456	13.542	4.000	16.000
EBLL	4.881	6.993	0.000	7.000
Nonprofit Density[a]	9.637	25.233	3.000	10.000
Residents under the FPL (%)	21.866	16.899	7.357	34.006
Owner occupied housing (%)	56.707	23.952	38.727	76.471
Diversity index (1-HHI)[b]	0.326	0.204	0.145	0.522
Black or African American (%)	38.294	36.578	4.28	76.436
Percent Hispanic or Latino (%)	5.616	8.731	0.748	5.690

Note. Data cover 439 tracts over 10 years. SD = Standard Deviation. EBLL = Elevated blood lead level. EBLL = Elevated blood lead level.
[a] Includes active public charities, excluding supporting organizations.
[b] Includes the percent of the tract that identifies as white, Black/African American, Asian, and Hispanic/Latino.

Table 2. Model Comparison for juvenile delinquency rate

	Model	WAIC	Δ_{waic}
1	Homogenous Poisson with covariates	580909.331	557788.746
2	Correlated Random effects (intercept and slope)	34406.583	11285.998
3	Convolution prior (spatial and nonspatial effects)	27704.723	4584.138
4	IID convolution between years	23247.908	127.323
5	AR1 convolution between years	23120.584	0.000

Note. WAIC = Watanabe–Akaike Information Criterion. Δ_{waic} is the relative performance of the model: the difference in information criteria between the current model and the best model under consideration. Models include features found in prior models.

Table 3. Posterior summary model 5, lead, nonprofits, and juvenile delinquency (N = 4,390)

Variable	Mean	SD	Posterior Interval		
			2.5 %	50 %	97.5 %
Constant	-5.638	0.05	-5.737	-5.638	-5.539
Year	-0.103	0.007	-0.116	-0.103	-0.09
EBLL	0.068	0.016	0.034	0.068	0.101
Nonprofit Density[a]	-0.112	0.028	-0.167	-0.112	-0.057
Residents under the FPL (%)	0.164	0.030	0.102	0.164	0.226
Owner occupied housing (%)	0.053	0.032	-0.009	0.053	0.115
Diversity index (1-HHI)[b]	0.853	0.132	0.593	0.853	1.111
Black or African American (%)	0.491	0.033	0.425	0.491	0.556
Percent Hispanic or Latino (%)	0.050	0.028	-0.005	0.050	0.106
σ_{tract}	0.092	0.004	0.085	0.092	0.100
σ_{time}	0.663	0.268	0.337	0.596	1.360
$\sigma_{convolution}$	0.560	0.016	0.530	0.559	0.593
ϕ[c]	0.019	0.008	0.011	0.017	0.041
ρ[d]	0.675	0.023	0.629	0.676	0.717

Note. Child population is included as an offset term. All variables other than year are mean centered and scaled to variance of one. SD = Standard Deviation. EBLL = Elevated blood lead level. HHI = Herfindahl-Hirschman Index.
[a] Includes active public charities, excluding supporting organizations.
[b] Includes the percent of the tract that identifies as white, Black/African American, Asian, and Hispanic/Latino.
[c] Marginal spatial effect in the convolution prior.
[d] Autoregressive prior on the convolution term, governing between year smoothing between years.

Figure 1. Yearly totals of juvenile delinquency, EBLL, and nonprofit organizations, 2010-2019

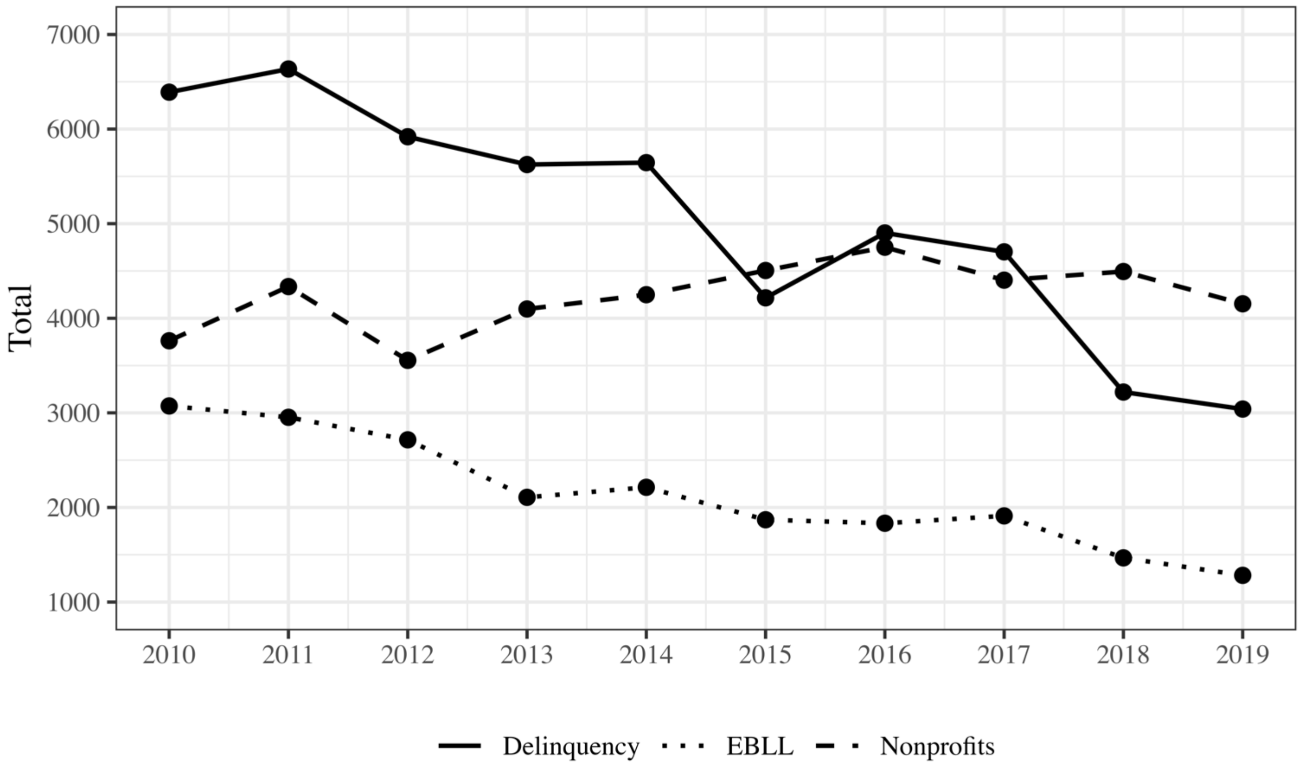

Fig 1. Cuyahoga County annual totals of key variables, juvenile delinquency, EBLL, and nonprofit organizations

Figure 2. Observed juvenile delinquency offenses by year across tracts, 2010-2019

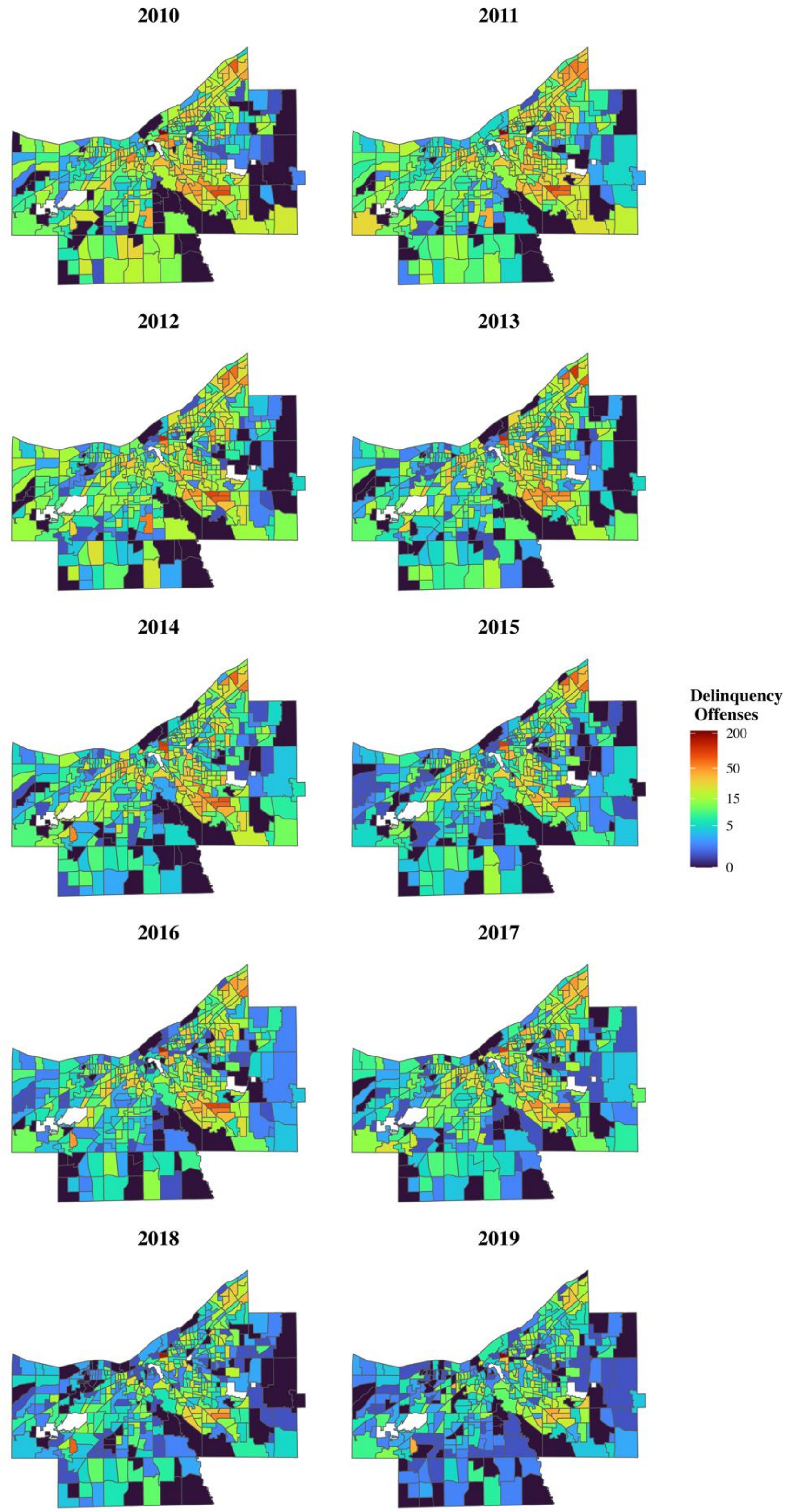

Fig 2. The spatial distribution of delinquency offenses by year in Cuyahoga County Ohio