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Connecting child maltreatment risk with crime and neighborhood disadvantage across time and place: A Bayesian spatio-temporal analysis

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Abstract

Child maltreatment is a major public health problem. Although maltreatment rates vary over time and are influenced by neighborhood characteristics, the unique effects of crime and disadvantage on risk are not well understood. This study utilized a Bayesian spatio-temporal approach to examine risk factors for substantiated child abuse and neglect over a 9-year period across zip codes in Davidson County, Tennessee. Risk for child sexual and physical abuse decreased from 2008 to 2016. In contrast, risk for child neglect increased from 2011 to 2014, followed by a rapid decrease in risk. Whereas higher percentages of families living in poverty were associated with higher risk for all maltreatment subtypes, higher unemployment rates were uniquely associated with risk for child neglect. Crime rates were positively associated with risk for child physical and sexual abuse but not neglect. Results have implications for tailoring prevention strategies according to geographic area and maltreatment subtype.

Keywords

child maltreatment; abuse; neglect; crime; socioeconomic; disadvantage

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Child maltreatment, which encompasses physical abuse, sexual abuse, and neglect, is a major public health concern in the United States that affects as many as 1 in 4 children (Fang, Brown, Florence, & Mercy, 2012; Finkelhor, Turner, Shattuck, & Hamby, 2013). Maltreatment rates exhibit variations across time and place (Ernst, 2000) due, in part, to structural features of the natural, built, and social environments (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Freisthler, Merritt, & LaScala, 2006; Maguire-Jack, 2014). Neighborhood disadvantage and crime are structural factors known to be associated with risk for maltreatment (Coulton, Korbin, & Su, 1999; Freisthler, Gruenewald, Remer, Lery, & Needell, 2007). Examining relations between structural factors and maltreatment rates over

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time has the potential to enhance prevention efforts by informing the design and dissemination of community-based programs, law enforcement activities, and policy initiatives.

According to social disorganization theory, neighborhood structural factors including economic deprivation and residential mobility could contribute to higher maltreatment rates by dismantling social networks and eroding informal social controls (Sampson & Groves, 1989; Shaw & McKay, 1942). Consistent with social disorganization theory, socioeconomic indicators are among the most reliable and robust structural correlates of child abuse and neglect. Higher maltreatment rates are generally associated with measures of neighborhood impoverishment, including children in poverty, rates of unemployment, income, and mortgage foreclosure rates (Coulton et al., 1999; Deccio, Horner, & Wilson, 1994; Frioux et al., 2014; Molnar, Buka, Brennan, Holton, & Earls, 2003; Smith, Kay, & Womack, 2017). Neighbors living in more disadvantaged neighborhoods tend to exhibit less willingness to cooperate and to intervene for the common good (Cohen, Inagami, & Finch, 2008; Sampson, Raudenbush, & Earls, 1997), which could reduce the likelihood of neighbors reporting suspected child maltreatment. According to routine activity theory, the confluence of motivated offenders and suitable targets in neighborhoods with low social control could increase risk for child abuse (Cohen & Felson, 1979). Neighborhood disadvantage may also affect risk for maltreatment by increasing the likelihood of harsh parental discipline and neglect due to elevated family stress levels (Conger, Ge, Elder, Lorenz, & Simons, 1994) and/or limited access to mental health and substance abuse services (Maguire-Jack, 2014).

Disadvantaged neighborhoods are more prone to ‘physical disorder’, which refers to overt signs of negligence or decay evident in abandoned cars and buildings, property damage, and garbage in the streets (Sampson & Raudenbush, 1999). Land use features such as abandoned buildings serve as crime ‘attractors’ (Brantingham & Brantingham, 2013; Wilson & Kelling, 1982). For example, vacant housing has been associated with higher rates of violent crime in general (Gracia, Lopez-Quilez, Marco, Lladosa, & Lila, 2015). Importantly, the density of vacant housing (Deccio et al., 1994; Zuravin, 1989) has also been associated with higher child maltreatment rates in particular. To date, few studies have examined longitudinal associations between neighborhood disadvantage indicators and risk for maltreatment (Gracia, Lopez-Quilez, Marco, & Lila, 2017).

Increases in rates of lesser crimes could forecast increases in rates of violent crimes and child maltreatment (Cohen, Gorr, & Olligschlaeger, 2007; Daley et al., 2016; Mustaine, Tewksbury, Huff-Corzine, Corzine, & Marshall, 2014). Social-ecological models propose that connections between criminal activities and child maltreatment may be explained, in part, by shared contextual risk factors (Wilkins, Tsao, Hertz, Davis, & Klevens, 2014). For example, domestic violence and child maltreatment frequently co-occur within families (Gracia, López-Quílez, Marco, & Lila, 2018; Jouriles, McDonald, Slep, Heyman, & Garrido, 2008); both are associated with violent crime (Basile, Hamburger, Swahn, & Choi, 2013; Raghavan, Mennerich, Sexton, & James, 2006; Sampson & Raudenbush, 1999) and actual or perceived exposure to violence (Coulton et al., 2007; Raghavan et al., 2006; Reed et al., 2009; Sampson, Morenoff, & Gannon-Rowley, 2002; Stith et al., 2009).

Higher perceived levels of violence in the community are associated with higher maltreatment rates (Lynch & Cicchetti, 1998). In addition, objective indicators of community violence (i.e., domestic violence, aggravated assaults, murders, drug crimes) are associated with increased risk for child neglect (Kim, 2004), parent-to-child physical aggression (Molnar et al., 2003), and predict risk for substantiated child maltreatment over and above poverty (Daley et al., 2016). Although prior cross-sectional research demonstrates a link between community violence and maltreatment, one important question remains unanswered: are crime rates associated with child maltreatment rates *over time* and after controlling for neighborhood disadvantage?

Bayesian spatio-temporal modeling offers unique advantages over frequentist approaches (i.e., more reliable risk and coefficient estimates) for addressing the challenges of spatial autocorrelation, overdispersion, temporal autocorrelation, and low count data that are inherent in crime datasets (Haining, Law, & Griffith, 2009; Law & Haining, 2004; Li, Haining, Richardson, & Best, 2013; Wheeler & Waller, 2009). Bayesian spatio-temporal models also offer two major advantages over cross-sectional Bayesian spatial models for elucidating maltreatment risk factors. First, spatial models aggregating data across multiple years can mask non-linear relations between neighborhood characteristics and maltreatment risk over time. Adding a temporal dimension can help to identify areas with stable high or low risk as well as areas with increasing or decreasing risk. Second, because Bayesian spatio-temporal models can be used to monitor changes in maltreatment risk over time across areas, this approach can be used to assess the effectiveness of prevention and intervention programs. Bayesian spatio-temporal modeling has been used to identify neighborhood risk factors (e.g., unemployment, poverty) for intimate partner violence (Cunradi, Mair, Ponicki, & Remer, 2011; Gracia, Lopez-Quilez, Marco, Lladosa, & Lila, 2014; Gracia et al., 2015), violent assaults (Mair, Gruenewald, Ponicki, & Remer, 2013), and property crime (Law & Chan, 2012). To our knowledge, only two studies have used Bayesian spatio-temporal modeling to examine predictors of child maltreatment. Results from one study showed that greater neighborhood disadvantage (i.e., lower property values, lower average education level) and greater policing activity were associated with higher risk for substantiated child maltreatment (Gracia et al., 2017). Results from another study showed that racial heterogeneity and social vulnerability interacted to predict risk of substantiated child abuse and neglect: for census tracts with higher social vulnerability, greater racial segregation was associated with higher risk for maltreatment (Barboza, 2016). The extent to which actual crime rates, vacant housing, and unemployment are associated with risk for subtypes of maltreatment (i.e., physical abuse, sexual abuse, neglect) has yet to be examined.

Present study

Research on risk factors for child maltreatment conducted in neighborhoods, block groups, zip codes, census tracts, counties, and states, has been limited by cross-sectional designs (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014; Smith et al., 2017). Failure to model ‘time’ could lead to misinterpretations of risk estimates because fluctuations in risk would be obscured by data aggregation (Gracia et al., 2017). Cross-sectional data also cannot disentangle the temporal order between child maltreatment and its correlates. The present study addressed this critical gap by examining how neighborhood disadvantage and crime were associated with risk for substantiated child maltreatment using annual data from 2008 to 2016 for zip codes in Davidson County, Tennessee. Focusing on potentially malleable risk factors for child maltreatment such as neighborhood disadvantage and crime can help to inform targeted prevention programs.

Based on prior work examining the role of neighborhood disadvantage, we hypothesized that higher percentage of families living in poverty, higher unemployment, and higher percentage of vacant housing would be associated with higher overall rates of substantiated child maltreatment as well as maltreatment subtypes (i.e., child sexual abuse, child physical abuse, child neglect) over time. Families living in impoverished neighborhoods can vary substantially in their exposure to crime (Brody et al., 2001), which suggests that rates of criminal offenses may predict unique variance in risk for child maltreatment above and beyond indicators of neighborhood disadvantage. We further hypothesized that crime rates would be positively associated with rates of substantiated overall child maltreatment as well as maltreatment subtypes, controlling for neighborhood disadvantage.

Method

Data Sources

Child maltreatment data for victims ages 18 years and younger were obtained from the State of Tennessee Department of Children's Services. Examining data at the child-level rather than the family-level allowed for estimating the prevalence of child victims. Data were aggregated for each year from 2008 to 2016 for populated zip codes in Davidson County, Tennessee (N = 31 out of 49 possible zip codes). Primary outcomes were substantiated cases of overall child maltreatment, child sexual abuse, child physical abuse, and child neglect. Overall maltreatment included the following: sexual abuse, physical abuse, psychological harm, abandonment, abuse-related deaths, drug-exposed child, drug-exposed infant, educational neglect, environmental neglect, lack of supervision, medical maltreatment, neglect-related death, and nutritional neglect. Child neglect was computed by summing across the following: abandonment, drug-exposed child, drug-exposed infant, educational neglect, environmental neglect, lack of supervision, medical maltreatment, neglect-related death, and nutritional neglect. Substantiations were selected to estimate cases of child maltreatment that were verified to have occurred. While prior research has indicated similar rates of recidivism regardless of substantiation status (Kohl, Jonson-Reid, & Drake, 2009), the current study aimed to understand confirmed cases of maltreatment rather than risk for future harm.

Crime report data for victims ages 18 and over were obtained from the Metropolitan Government of Nashville and Davidson County Police Department. Although crime report incidents were geocoded at the block level, these data were aggregated for each year from 2008 to 2016 for zip codes in Davidson County, Tennessee, to match the spatial resolution of child maltreatment data (Cohen et al., 2007). Total criminal offenses, reported per 1,000 population, included non-sexual assaults (i.e., aggravated assault, harassment, intimidation, kidnapping/abduction, murder, non-negligent manslaughter, simple assault, justifiable homicide), sexual offenses (i.e., assisting or promoting prostitution, forcible fondling, forcible rape, forcible sodomy, indecent exposure, obscene conduct, peeping tom, pornography/obscene material, prostitution, sexual assault with an object, statutory rape), stalking incidents (i.e., stalking, violations of orders of protection), thefts (i.e., burglary, breaking and entering, robbery, bribery, embezzlement, counterfeiting/forgery, extortion/ blackmail, fraud), property damage (i.e., arson, destruction/damage/vandalism of property), and drug-related offenses (i.e., drug/narcotic violations, drunkenness, drug/narcotic equipment violations).

Neighborhood disadvantage data, including percentages of families living in poverty, unemployment rate, and percentage of vacant housing, were created from the US Census estimates, which are provided at the census block group level. The block group data were aggregated up to the zip code level, with values weighted based on the captured census block population, because block groups are not perfectly nested within zip codes. Study procedures were approved by the institutional review board.

Data Analytic Strategy

Advantages of Bayesian spatio-temporal modeling over the frequentist approach include the ability to simultaneously address spatial autocorrelation (i.e., tendency for maltreatment risk factors to cluster together geographically) and temporal dependence (i.e., tendency for maltreatment risk factors to correlate between years within zip codes) in the data. This data analytic strategy has increasingly been applied to the study of the ecology of social problems, including child maltreatment (DiMaggio, 2015; Freisthler, Kepple, & Holmes, 2012; Freisthler & Weiss, 2008; Gracia et al., 2017; Law, Quick, & Chan, 2014; Marco, Freisthler, Gracia, López-Quílez, & Lila, 2017). In the present study, four Bayesian spatio-temporal models were performed for overall child maltreatment, as well as for the maltreatment subtypes of child sexual abuse, child physical abuse, and child neglect. Conditionally independent Poisson distributions were used to model all outcomes. The number of minors with substantiated cases of child maltreatment was counted for each zip code and year. The following equation was used:

$$y_{it} \mid \eta_{it} \sim Po(E_{it}\exp(\eta_{it})), \quad i = 1, \dots, 31, t = 1, \dots, 9$$

where E_{it} defines the expected number of minors with substantiated cases of child maltreatment (adjusted for population under 18 years old in each zip code and year), and η_{it} is the log relative risk in each i-zip code and t-year.

An autoregressive model (Martínez-Beneito, López-Quilez, & Botella-Rocamora, 2008) was used to account for spatio-temporal effects, after showing a better fit for the data in terms of Deviance Information Criterion (DIC) compared to other less complex models (i.e., baseline model, spatial model, other spatio-temporal models). This type of model combines autoregressive time series and spatial modeling and can assess patterns of increases and decreases in risk within the study period. The autoregressive model determined relative risk for maltreatment in a particular zip code for a given year based on prior risk estimates for that zip code (i.e., temporal dependence) and risk estimates for neighboring zip codes in that year (i.e., spatial dependence) as well as in previous years (i.e., spatio-temporal dependence;

Martínez-Beneito et al., 2008). Recent studies have used this model to assess the spatio-temporal distribution of social problems (Gracia et al., 2017; Marco, Gracia, López-Quílez, & Lila, 2018; Marco, López-Quílez, Conesa, Gracia, & Lila, 2017). Neighborhood disadvantage variables (families in poverty, unemployment rate, and vacant housing) and total crime rate were included as predictors. The model was defined as follows:

$$\eta_{i1} = \mu + X_{it}\beta + \propto_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1})$$
$$\eta_{it} = \mu + X_{it}\beta + \propto_t + \rho \cdot (\eta_{i(t-1)} - \mu - \alpha_{t-1}) + \phi_{it} + \theta_{it}$$

where η_{i1} refers to the log relative risk for the first observed period (2008), and η_{it} refers to the log-relative risk for the following years, from 2009 to 2016. The parameter μ is the intercept, X_{it} represents a vector which includes the four independent variables in this study, β defines the vector of regression coefficients for these variables, $\propto_t$ is the mean deviation of the risk in the year t, ρ is the temporal correlation among years, and ϕ_{it} and θ_{it} define the structured and unstructured spatial random effects, respectively. If the structured spatial effect is stronger than the unstructured effect, this would indicate that accounting for spatial dependencies for both predictors and outcomes is important. Conversely, if the unstructured spatial effect is stronger than the structured effect, this would indicate that the spatial distribution of predictors and outcomes is more random.

Following the Bayesian perspective, appropriate prior distributions were assigned for all parameters. The fixed effects β were specified as vague Gaussian distributions; we assigned an improper uniform distribution for μ. Regarding the random effects, a normal distribution $N(0,\sigma^2)$ was used for the unstructured effects (θ and $\propto$) and a conditional spatial autoregressive (CAR) model (Besag, York, & Mollie, 1991) was used for the structured effect (ϕ), defined as follows:

$$\phi_i \mid \phi_{-i} \sim N\left(\frac{1}{n_i}\sum_{j \sim i}\phi_j, \frac{\sigma_\phi^2}{n_i}\right)$$

where n_i represents the number of neighbors of the zip code i, ϕ_{-i} accounts for the values of the ϕ vector except the element i, $j \sim i$ refers to all units j that are neighbors of zip code i, and σ_ϕ defines the standard deviation parameter. The prior distribution of the standard deviation σ_ϕ was specified by a uniform distribution $\sigma_\phi \sim U(0,1)$.

Simulation was conducted using Markov Chain Monte Carlo techniques: 100,000 iterations were generated and the first 10,000 were discarded as 'burn in period'. The convergence diagnosis $\hat{R}$ (Gelman et al., 2013), used to assess the convergence of the models, was near 1.0 for all parameters. The software R and the WinBUGS package were used.

Results

Overall rates of substantiated child abuse and neglect in Davidson County, TN, fell from 7.3 children per 1,000 in 2008 to 4.3 children per 1,000 in 2016. Descriptive statistics for study variables, averaged across zip codes, are presented in Table 1. Bayesian spatio-temporal modelling was used to map the relative risk of child maltreatment, accounting for covariates and actual rates, as well as to assess changes in risk over time. Figure 1 shows the relative risk for the first, the fifth, and the last year of the study (2008, 2012, and 2016) for each child maltreatment type for descriptive purposes. This relative risk takes into account the risk of child maltreatment in each zip code in comparison to the overall risk for the county. Zip codes with higher-than-average relative risk (> 1) are darker, whereas zip codes with lower-than-average relative risk (< 1) are lighter. Descriptively, these maps reveal common patterns across the child maltreatment types: areas with higher levels of relative risk are located at the center and western parts of the county. However, some differences can be observed between child maltreatment types. For example, whereas child physical and sexual abuse risk is higher and more concentrated in the central area of the county, child neglect risk is higher in the central and western areas of the county. The parameter ρ indicated a high temporal correlation among years, and similar patterns of relative risk are depicted in the maps for 2008, 2012, and 2016. However, results did reveal an increase in the number of high-risk zip code areas from 2008 to 2016.

Autoregressive models were used to examine the temporal pattern of child maltreatment risk across years. Figure 2 shows the temporal effect ($\propto$) for each type of child maltreatment. For overall child maltreatment, sexual abuse, and physical abuse, temporal effects reveal a pattern of decreasing risk. However, important differences in the pattern of temporal effects were observed between child maltreatment subtypes. There was a steady decrease in relative risk for child sexual abuse across the study years. For child physical abuse, there was a pattern of decreasing risk from 2008 to 2010, followed by a four-year period of stability, and then another decrease in risk from 2013 to 2014. The temporal effect for neglect risk contrasted sharply with patterns for physical and sexual abuse: results revealed *increasing* risk that reached its maximum in 2014. Following 2014, there were decreases in child neglect risk.

Overall Child Maltreatment

Results of the four Bayesian Poisson autoregressive models are presented in Table 2. For determining the relevance of the covariates to the model, we considered the posterior probability distributions of the regression coefficients β being over or under zero. The advantage of the Bayesian approach is that it allows credible intervals to be interpreted in probability terms, so variables can be considered relevant if they reach a high probability (i.e., greater than 80% and 95%) of a positive or negative association (Carlin & Louis, 2008; Gelman et al., 2013; Gracia et al., 2015; Marco, Gracia, & López-Quílez, 2017). Thus, variables with a less-than-80% posterior probability of being over or under zero were considered irrelevant to the model.

Autoregressive models revealed that higher percentages of families in poverty, higher percentage of vacant housing, and higher rates of crime were uniquely associated with higher risk of overall child maltreatment. The unemployment rate was not associated with overall child maltreatment risk. In addition, results showed a stronger effect of the spatially structured term compared to the spatially unstructured term ($\sigma_{\phi} = .309$ and $\sigma_{\theta} = .185$, respectively), which indicates that risk factors for maltreatment were not randomly distributed across zip codes but tended to cluster together in neighboring zip codes. Moreover, the temporal effect was small (σ_{α} = .038), and the temporal correlation (ρ = .946) suggests that rates of child maltreatment in one year are highly correlated with maltreatment rates the previous year.

Child Sexual Abuse

Results revealed that higher percentages of families in poverty, higher percentages of vacant housing, and higher rates of crime were associated with higher risk of sexual abuse. Unemployment rates were not associated with sexual abuse. Similar to the overall child maltreatment model, there was a stronger effect of the spatially structured term compared to the spatially unstructured term (σ_{ϕ} = .205 and σ_{θ} = .162, respectively). The temporal effect was also small (σ_{α} = .053) and the temporal correlation ρ (ρ = .945) was high, indicating a higher correlation among years.

Child Physical Abuse

Higher percentages of families in poverty and higher crime rates were associated with higher rates of physical abuse. Neither unemployment rates nor vacant housing were associated with physical abuse. There was a stronger effect of the spatially structured term compared to the spatially unstructured term (σ_{ϕ} = .243 and σ_{θ} = .056, respectively). The temporal effect was small (σ_{α} = .066) and the temporal correlation was high (ρ = .940).

Child Neglect

Higher percentages of families in poverty, higher unemployment rate, and higher percentage of vacant housing were associated with higher rates of child neglect. In contrast to findings for the other types of child maltreatment, crime rates were not related to child neglect. The spatially structured term was stronger than the spatially unstructured term, but both were more relevant than with the previous Bayesian spatio-temporal models (σ_{ϕ} = .524 and σ_{θ} = .331, respectively). In addition, the temporal term was more relevant than for other Bayesian spatio-temporal models and exhibited a higher value for the autoregressive standard deviation (σ_{α} = .224). The temporal correlation was lower (ρ = .838), indicating less stability across years than the other child maltreatment types.

Discussion

Child maltreatment rates vary across time and place and are associated with structural features of the natural, built, and social environments (Ernst, 2000). However, our understanding of the structural determinants of maltreatment has been limited by predominantly cross-sectional research studies (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014). The current study addressed this important gap in the literature by using Bayesian spatio-temporal models to examine how two important structural factors - neighborhood disadvantage and crime rates - are associated with substantiated child abuse and neglect over a 9-year period across zip codes in Davidson County, Tennessee. Although greater neighborhood disadvantage (i.e., poverty, vacant housing) and higher crime rates were associated with higher overall child maltreatment risk, distinct patterns of association emerged between these risk factors and sexual abuse, physical abuse, and neglect.

Greater neighborhood disadvantage was generally associated with higher risk for child maltreatment across zip codes and over time. One major contribution of the present study was identifying distinct patterns of associations among disadvantage indicators and risk for child physical abuse, sexual abuse, and neglect. Consistent with social disorganization theory (Sampson & Groves, 1989; Shaw & McKay, 1942), zip codes with higher percentages of families living in poverty were at higher risk for all child maltreatment subtypes. Poverty likely increases risk for child abuse and neglect via direct (e.g., elevated family stress levels) and indirect (e.g., limited service availability) mechanisms (Maguire-Jack, 2014). Notably, the other disadvantage indicators were only associated with specific subtypes.

Zip codes with higher percentages of vacant housing were at higher risk for child sexual abuse and neglect but not for child physical abuse, which extends findings from prior cross-sectional research (Deccio et al., 1994; Zuravin, 1989). Vacant housing could increase risk for sexual abuse directly by providing unsupervised settings where victimization could occur and/or indirectly via increases in opportunities for criminal activities (Brantingham & Brantingham, 2013; Wilson & Kelling, 1982). In addition, vacant housing could increase risk for specific forms of neglect, including drug exposure and contact with environmental hazards (Breysse et al., 2004). The presence of vacant lots and buildings are associated with higher crime rates, including prostitution, illegal drug sales/use, and illegal firearm storage (Spellman, 1993). Bayesian approaches highlight the spatio-temporal relation between vacant housing and risk for intimate partner violence (Gracia et al., 2015). The present findings contribute to a growing literature on shared risk factors for multiple forms of violence (Wilkins et al., 2014) by showing the additional relevance of vacant housing to risk for child sexual abuse and neglect. One potential avenue for future research is to determine whether ‘vacant lot greening’ interventions that have been successful in reducing crime rates and gun assaults (Garvin, Cannuscio, & Branas, 2013) could reduce rates of substantiated child sexual abuse and neglect. Future studies are also needed to replicate this pattern of findings and to determine why poverty - but not vacant housing – was associated with risk for child physical abuse.

Child neglect is the most commonly-reported maltreatment subtype; rates of substantiated neglect have declined more slowly than rates of substantiated physical and sexual abuse over the past three decades (U.S. Department of Health & Human Services, 2016). The present findings revealed that zip codes with higher unemployment rates were at increased risk for child neglect but not for child physical or sexual abuse. This finding extends prior research showing a positive correlation between unemployment rate and substantiated child maltreatment across counties (Frioux et al., 2014) and a spatio-temporal association between unemployment rates and intimate partner violence (Cunradi et al., 2011). The pathways that lead from unemployment to increased risk for substantiated child neglect could be direct (i.e., parents’ inability to take care of their children’s material, medical, and nutritional needs) and/or indirect (i.e., parents’ financial stress negatively impacting other risk factors for neglect including marital quality and mental health) (Berger, et al., 2015; Conger et al., 1994). Importantly, unemployment rates were associated with risk for substantiated child neglect over and above poverty. This suggests that the effect of unemployment on risk for substantiated neglect is not solely due to problems affording basic needs but is likely driven by other factors – for instance, uncertainty regarding transitions in and out of employment. One interpretation for the unique association observed between unemployment and substantiated neglect is that this type of economic instability increases the likelihood that all families – regardless of functioning – are unable to provide for their children's basic needs (direct path). In contrast, the relation between unemployment and child physical or sexual abuse could be weaker because it depends on other familial vulnerability/resilience factors, such as parenting practices.

Zip codes with higher crime rates were at greater risk for overall maltreatment and were specifically at risk for child sexual abuse and physical abuse. These findings are consistent with prior work linking crime to overall maltreatment rates (Daley et al., 2016) and to child physical abuse (Molnar et al., 2003). Although one national study found that crime rates were associated with a parent-report measure of neglectful behaviors over and above the effects of neighborhood disadvantage (Kim, 2004), the present Bayesian spatio-temporal approach suggests that this association does not extend to rates of substantiated child neglect. Crime rates could directly increase risk for physical and sexual abuse by placing children in community settings where they are more likely to be victimized and/or indirectly by increasing family stress levels (Conger et al., 1994) and, as a result, the likelihood of punitive parenting practices. One interpretation for the association between crime rates and abuse - but not neglect – is that the types of violence subsumed within child physical and sexual abuse could share vulnerability factors with other forms of violence against adults, including neighborhoods with lower cohesion and greater social isolation (Wilkins et al., 2014). A second interpretation is that the definition of child neglect is broad and does not distinguish between cases of well-intentioned parents who cannot provide for their children's needs and cases of parents who are either willingly or unwittingly neglectful due to substance abuse or mental health problems. That is, crime rates may be specifically associated with more extreme forms of neglect such as abandonment and drug exposure.

The frequent co-occurrence of child maltreatment subtypes within individuals (Herrenkohl & Herrenkohl, 2009) has prompted debate on the utility of drawing conceptual distinctions among child physical abuse, sexual abuse, and neglect. The present study demonstrated both shared (i.e., families in poverty) and unique risk factors for child physical abuse, sexual abuse, and neglect, which suggests that conceptual distinctions among subtypes may be warranted. These findings have at least two important implications for future research in this area. First, studies examining the causes and consequences of maltreatment should assess subtypes (Arata, Langhinrichsen-Rohling, Bowers, & O'Brien, 2007). Second, Bayesian spatio-temporal models can help to identify areas where risk for substantiated maltreatment subtypes is increasing as well as potentially malleable environmental factors contributing to increasing risk.

Limitations of this study provide directions for future research. First, this study examined aggregate rates of child maltreatment. Whether crime rates and neighborhood disadvantage indicators are associated with specific harsh or neglectful parenting behaviors requires longitudinal family studies. The results of ecological studies such as the current one cannot be assumed to apply at the individual family level. Second, while substantiated cases are a good source of information about the official victims of child abuse and neglect, these data likely undercount the true rates of child maltreatment. Third, the present findings were based on data obtained for a predominantly urban area and may require modification for more rural areas. Prior research has noted limitations in applying social disorganization theory to rural areas (Kaylen & Pridemore, 2013; Lynch, 2016). Fourth, the present study cannot account for the problem of neighborhood selection; that is, families at high risk for maltreatment may have been driven to reside in communities with higher crime rates (Cicchetti & Lynch, 1993). Fifth, the use of zip codes as the geographic level was required due to data limitations. Zip codes cover large geographic areas and as a result may have a great deal of variation therein. As a result, relying on zip codes as the unit of analysis could mask important variation and thus inhibit the ability to detect significant relations. Finally, the present study did not assess whether non-malleable neighborhood characteristics such as racial heterogeneity have a direct impact on risk for substantiated maltreatment or moderate relations between neighborhood disadvantage and risk for maltreatment. Klein and Merritt (2014) found that while neighborhood impoverishment and residential instability were related to referral rates for White and Hispanic children, only housing stress was relevant for Black children. Barboza (2016) found that greater racial segregation was associated with increased risk for substantiated child maltreatment in neighborhoods with higher social vulnerability.

The current study has important implications for public health efforts to prevent child maltreatment. Results revealed a relevant spatial structure for all subtypes of child maltreatment, which suggests that maltreatment was not randomly distributed across zip codes. Hence, interventions addressing community-level risk factors in areas with higher risk of child maltreatment could not only improve prevention efforts targeted to that area but may also have a positive spillover effect on the incidence of child abuse and neglect in neighboring areas. Relative risk maps showed different spatio-temporal distributions of child abuse and neglect subtypes across zip codes and Bayesian spatio-temporal models demonstrated unique combinations of risk factors associated with these subtypes. Taken together, these findings suggest new directions for tailored maltreatment prevention strategies. First, targeting high poverty areas with community-level prevention efforts could help to reduce risk for substantiated child maltreatment, regardless of subtype. Second, investing in programs that address vacant housing, such as vacant lot greening programs (Garvin et al., 2013), could be targeted to zip codes experiencing high and/or increasing relative risk for substantiated child sexual abuse or neglect. Third, programs addressing unemployment could be selectively implemented in zip codes experiencing high and/or increasing relative risk for substantiated child neglect. Finally, monitoring spatio-temporal patterns in annual crime report data can also help to identify zip codes at high and/or increasing relative risk for child sexual or physical abuse. Zip codes that experience upticks in crime could warrant greater investment in prevention strategies to disrupt this negative chain (Cohen et al., 2007; Daley et al., 2016; Mustaine et al., 2014). Longitudinal designs can also help to elucidate the temporal behavior of child maltreatment rates and provide a more accurate ecological description of this devastating social problem. The Bayesian spatio-temporal approach employed in the present study could be adapted for probabilistic child maltreatment forecasting (Cohen et al., 2007) and may also be useful for evaluating the success of tools to assess risk for child welfare involvement (e.g., Family Advocacy and Support Tool) and intervention strategies or policies implemented in specific areas (Yu et al., 2008).

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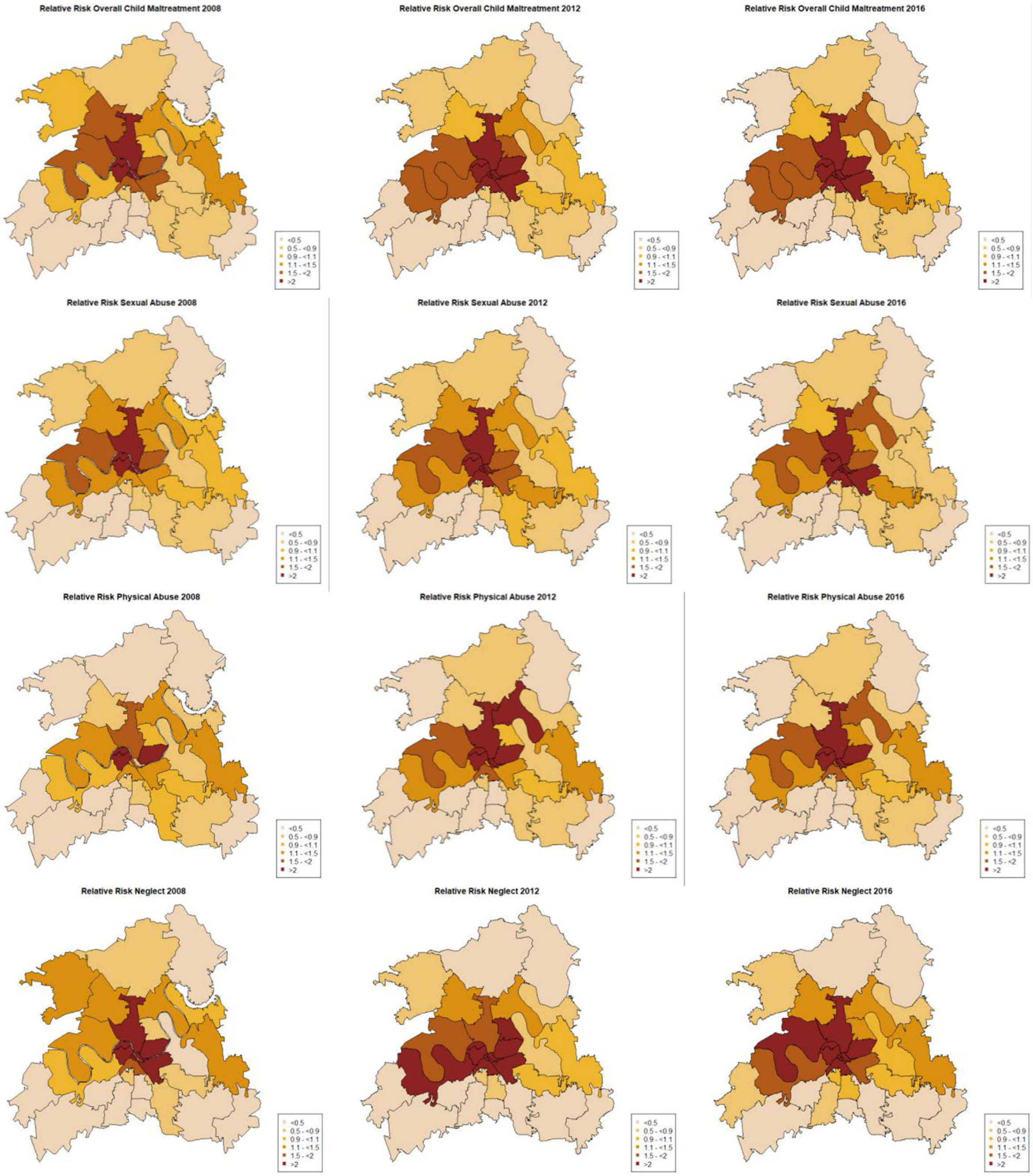

Figure 1.

Maps of relative risk of child maltreatment types by zip code in the first, the fifth, and the last year of study (2008, 2012 and 2016).

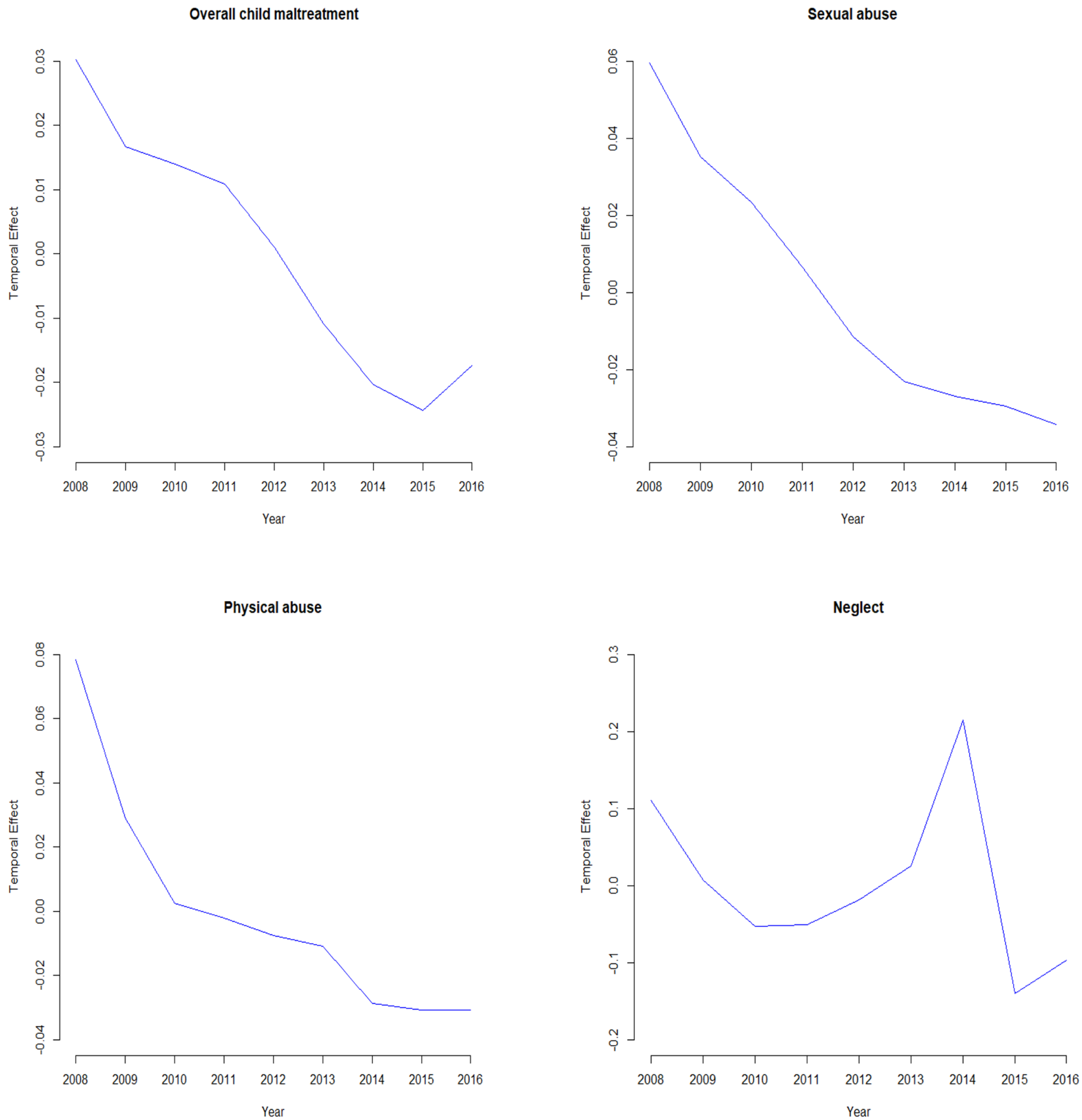

Figure 2.
Temporal effect for each year (2008-2016) for child maltreatment types.

Table 1.

Descriptive Statistics for Study Variables Across Zip Codes in Davidson County, Tennessee

	Annual Summary Mean (*SD*)								
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Overall child maltreatment	22.9 (27.25)	21.65 (22.65)	19.23 (22.35)	17.23 (17.47)	17.68 (18.47)	22.97 (23.50)	19.32 (22.45)	18.00 (23.95)	9.65 (10.29)
Sexual abuse	7.58 (9.08)	5.80 (6.75)	6.61 (8.84)	5.55 (5.28)	5.52 (6.29)	5.65 (6.28)	5.55 (6.95)	4.61 (5.33)	3.55 (4.80)
Physical abuse	3.94 (4.53)	5.26 (5.80)	4.48 (5.97)	4.07 (4.93)	4.56 (5.84)	3.68 (4.56)	3.16 (3.92)	2.23 (3.43)	1.71 (2.07)
Neglect	10.35 (13.38)	10.26 (10.99)	7.84 (9.06)	7.32 (8.51)	7.58 (7.91)	13.13 (13.37)	9.97 (12.65)	10.58 (15.33)	4.097 (4.34)
Families in poverty (%)	24.6 (9.9)	22.6 (9.6)	19.7 (8.4)	18.9 (7.9)	19.2 (7.9)	17.2 (9.2)	15.6 (8.3)	13.5 (6.5)	11.0 (5.6)
Unemployment rate	41.1 (8.1)	42.0 (7.8)	42.0 (7.7)	42.9 (7.8)	42.9 (7.4)	43.2 (7.8)	43.3 (7.9)	43.8 (8.1)	44.0 (8.0)
Vacant housing (%)	5.3 (2.2)	5.7 (2.2)	6.3 (2.5)	6.1 (2.4)	5.9 (2.3)	5.5 (2.1)	5.4 (2.0)	4.6 (1.7)	3.9 (1.5)
Total crime rate (/100,000 pop.)	7,103 (2,978)	6,944 (2,823)	6,840 (2,596)	6,837 (2,387)	6,563 (2,263)	6,112 (2,173)	5,950 (2,151)	5,925 (2,158)	6,163 (2,177)

Note. Summary statistics for overall child maltreatment, sexual abuse, physical abuse, and neglect are presented as the average number of substantiated cases across all populated zip codes in Davidson County, Tennessee ($N = 31$); pop. = population.

Table 2.

Comparison of spatio-temporal regression Bayesian models for overall child maltreatment, child sexual abuse, child physical abuse, and child neglect. Posterior mean, standard deviation (SD) and 95% credible interval (CrI) of all parameters

	Overall child maltreatment			Child sexual abuse			Physical abuse			Neglect		
	Mean	**SD**	**95% CrI**	**Mean**	**SD**	**95% CrI**	**Mean**	**SD**	**95% CrI**	**Mean**	**SD**	**95% CrI**
Intercept	−.658	.229	−1.108, −.191	−.738	.238	−1.212, −.264	−.934	.254	−1.410, −.425	−1.141	.278	−1.645, −.556
% families in poverty	.016*	.010	−.003, .035	.018*	.011	−.016, .040	.034**	.013	.009, .058	.031**	.014	.003, .058
Unemployment rate	.001	.006	−.012, .013	.002	.009	−.016, .020	.007	.011	−.014, .031	.023*	.013	−.002, .051
% vacant housing	.016*	.013	−.008, .043	.025*	.016	−.005, .057	.006	.020	−.014, .045	.033*	.022	−.010, .076
Total crime rate	.002**	.001	.000, .005	.002*	.001	.000, .005	.003*	.002	−.001, .006	.001	.002	−.002, .004
σ_θ	.185	.032	.127, .253	.162	.038	.092, .240	.184	.059	.004, .309	.331	.052	.294, .441
σ_ϕ	.309	.079	.162, .466	.205	.085	.039, .375	.189	.111	.016, .438	.524	.124	.272, .763
σ_α	.037	.030	.001, .111	.053	.045	.003, .164	.066	.055	.002, .204	.224	.108	.043, .473
ρ	.947	.021	.899, .979	.945	.032	.871, .987	.940	.042	.837, .992	.838	.054	.723, .930

* Posterior probability of being under or over zero > .80

** Posterior probability of being under or over zero > .95

Abbreviations: SD, standard deviation; CrI, credible interval; σ_θ, standard deviation unstructured term; σ_ϕ, standard deviation spatially structured term; σ_α standard mean deviation of the risk; ρ, temporal correlation.