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County-Level Socioeconomic and Crime Risk Factors for Substantiated Child Abuse and Neglect

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Abstract

Rates of substantiated child abuse and neglect vary significantly across counties. Despite strong cross-sectional support for links between social-contextual characteristics and abuse and neglect, few longitudinal studies have tested relations between these risk factors and substantiated rates of abuse/neglect. The goal of this study was to identify county-level socioeconomic and crime factors associated with substantiated abuse/neglect rates over 13 years (2004–2016). Annual county-level data for Tennessee, obtained from the KIDS COUNT Data Center, included rates of substantiated child abuse and neglect, children's race and ethnicity, births to unmarried women, teen birth rate, children in families receiving Supplemental Nutrition Assistance Program (SNAP) benefits, and children in families receiving Temporary Assistance for Needy Families. Annual county-level crime report data, obtained from the Tennessee Incident Based Reporting System, included sexual offenses, non-sexual assaults, stalking incidents, thefts, property damage, and drug-related offenses. Bayesian spatio-temporal models indicated that substantiated child abuse and neglect rates were independently and positively associated with teen birth rates, percentages of births to unmarried mothers, drug-related offenses, and percentages of children receiving SNAP benefits. In contrast, substantiated child abuse and neglect rates were negatively associated with percentages of African-American youth. The findings highlighted distinct demographic, socioeconomic, and crime factors associated with substantiated child abuse and neglect rates and have the potential to enhance identification of high-risk counties that could benefit from targeted abuse and neglect prevention efforts.

Keywords

child; abuse; neglect; crime; Bayesian spatio-temporal; county

Introduction

Rates of substantiated child abuse and neglect change over time and place, and their effects ripple through neighborhoods, counties, and states (Fang, Brown, Florence, & Mercy, 2012; Fromm, 2001; Smith, Kay, & Womack, 2017). Variations in the extent of substantiated child abuse and neglect across geographic areas may be attributed to characteristics of the residents, qualities of neighborhoods, or to the policies and practices of local child welfare agencies (Maguire-Jack, 2014). Social-ecological models of child maltreatment emphasize the importance of contextual risk and protective factors and the need for prevention efforts targeting multiple levels (Belsky, 1980; Krug, Mercy, Dahlberg, & Zwi, 2002). A variety of neighborhood factors are associated with increased risk for substantiated child maltreatment, including economic hardship and violence (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Ernst, 2000; Freisthler, Gruenewald, Rerner, Lery, & Needell, 2007; Freisthler, Merritt, & LaScala, 2006). At the same time, greater proximity to social services (Morton, 2013) and child care (Klein, 2011) is linked with lower risk for substantiated maltreatment. Taken together, these studies highlight socioeconomic, crime, and demographic factors associated with substantiated child abuse and neglect across different geographic entities.

Identifying risk factors for substantiated child maltreatment at the county- and state-level could help to inform community-based programs and policies about the “person-centered” and “place-centered” characteristics that contribute to risk and responses to referrals (Freisthler et al., 2006). For example, maltreatment is more likely to be substantiated in counties with greater service accessibility (Font & Maguire-Jack, 2015); child removal rates are lower in states with higher percentages of African Americans (Russell & Macgill, 2015); and maltreatment disparities for African-American and Hispanic children are especially pronounced in counties with greater poverty disparities (Maguire-Jack, Lanier, Johnson-Motoyama, Welch, & Dineen, 2015). County-level factors, including poverty, unemployment, and percentage of households receiving public assistance, are also associated with the likelihood of intervention decisions made by child protective services (CPS; McCallum & Cheng, 2016). Thus, although rates of substantiated child abuse and neglect may be preferable to unverified indices such as allegations, they are susceptible to individual-, family-, and community-level factors that influence whether and where maltreatment will be detected as well as how CPS will respond. Despite this limitation, community-based programs targeting “place-centered” risk factors for substantiated child abuse and neglect serve an important complementary role to family-focused interventions because “environmental forces can overwhelm even well-intended parents” (Daro & Dodge, 2009).

Socioeconomic Indicators

Theoretical models of child maltreatment posit that neighborhood disadvantage is a distal risk factor for child maltreatment (Coulton et al., 2007). To date, the most reliable and robust community-level correlates of substantiated child abuse and neglect are socioeconomic indicators. Higher substantiated maltreatment rates are generally associated with impoverishment and economic hardship (Coulton et al., 2007; Freisthler et al., 2006), which includes indicators of poverty, unemployment, family income, education level, and single

parenthood (Deccio, Horner, & Wilson, 1994; Merritt, 2009; Smith et al., 2017). For example, for counties across Pennsylvania, both unemployment and mortgage foreclosure rates were positively associated with substantiated maltreatment reports (Frioux et al., 2014). Greater percentages of female-headed households are also associated with higher substantiated maltreatment rates (Freisthler, 2004; Freisthler, Midanik, & Gruenewald, 2004; Young & Gately, 1988), although race and ethnicity may moderate this association. The relation between substantiated child maltreatment rates and percentage of female-headed households is negative in predominantly African-American communities and positive in predominantly Hispanic communities (Garbarino & Kostelny, 1992). Teen pregnancy and single parenthood also increase risk for substantiated child maltreatment (Lounds, Borkowski, & Whitman, 2006).

Economic hardship and food insecurity are associated with greater likelihood of CPS involvement (Yang, 2015). Social safety net programs could lower risk for child abuse and neglect by increasing financial and food security. The Temporary Assistance for Needy Families (TANF) program provides financial support to families, encourages job preparation, and requires parents to obtain child care in order to find employment. The Supplemental Nutritional Assistance Program (SNAP) provides cash benefits to low-income households that only can be used to purchase food. By strengthening household financial and food security, the TANF and SNAP programs could reduce risk for parent-to-child physical aggression by lowering parental stress and depression (Stith et al., 2009), parental neglect by ensuring that children's basic needs are met, and abuse by non-family members by improving access to child care. These reductions in maltreatment risk would be reflected in lower likelihood of CPS involvement, lower rates of substantiated abuse and neglect, and fewer children removed from their homes.

Programs such as TANF and SNAP typically serve a more vulnerable segment of the population: families with young children who participate in these programs report higher rates of prior exposure to maltreatment, adult interpersonal violence, and community violence (Sun et al., 2016, 2016b). Importantly, there is evidence suggesting that TANF and SNAP benefits decrease family poverty and food insecurity (Jolliffe, Gundersen, Tiehen, & Winicki, 2005; Nord & Prell, 2011; Ratcliffe, McKernan, & Zhang, 2011), reduce the likelihood of CPS involvement (Cancian, Yang, & Slack, 2013; Fein & Lee, 2003), and lower risk of substantiated child abuse and neglect (Lee & Mackey-Bilaver, 2007) over time.

Understanding how social-contextual factors contribute to maltreatment risk requires attention to both spatial and temporal dimensions (Gracia et al., 2017) because cross-sectional and longitudinal findings may differ substantially and offer unique directions for practice and policy. For example, at any point in time, spending on maltreatment prevention services could be associated with *higher* rates of substantiated abuse and neglect because services target neighborhoods with higher rates of maltreatment and may also improve detection of maltreatment. However, greater spending on prevention services should predict *decreases* in rates of substantiated abuse and neglect over time if the services are effective in reducing abuse and neglect. The present study sought to address one critical gap in this literature that has not been examined with longitudinal data: the extent to which TANF and

SNAP receipt are associated with risk for substantiated abuse and neglect over and above per capita income, crime rates, and demographic composition.

Community Violence

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 variance in risk for substantiated child abuse and neglect above and beyond indicators of economic disadvantage. Social disorganization theory has been applied to improve our understanding of how community characteristics may influence neighborhood crime rates (Shaw & McKay, 1942), including violent criminal offenses (Gracia, Lopez-Quilez, Marco, Lladosa, & Lila, 2014; Sampson, Raudenbush, & Earls, 1997), sexual offenses (Tewksbury, Mustaine, & Covington, 2010), drug-related offenses (Furr-Holden et al., 2011), and thefts (Sampson, 1987). The same theoretical framework also may help explain changes in rates of substantiated child abuse and neglect over time (Mustaine, Tewksbury, Huff-Corzine, Corzine, & Marshall, 2014). Both direct and indirect exposure to violence in the community are associated with higher rates of child abuse and neglect (Coulton et al., 2007; Stith et al., 2009). The mechanisms responsible for this association may include shared distal (e.g., poverty, unemployment) and proximal (e.g., family stress, parenting) risk factors as well as self-selection of high-risk families into communities with higher crime rates. Increased social isolation has also been proposed as a potential mechanism linking crime to maltreatment (Cicchetti & Lynch, 1993; Institute of Medicine and National Research Council, 2014). Higher perceived levels of violence in the community are associated with lower participation in community activities (McIntyre, 1967), social isolation (Belsky, 1993; Coohey, 1995) and higher maltreatment rates (Lynch & Cicchetti, 1998). Objective indicators of community violence (i.e., domestic violence, aggravated assaults, murders, drug crimes) are associated with greater risk for child neglect (Kim, 2004) and predict risk for substantiated maltreatment over and above poverty (Daley et al., 2016). Although prior research has demonstrated a link between community violence and maltreatment, two critical questions remain: (1) Are changes in crime rates associated with changes in substantiated child abuse and neglect rates over time? and (2) What types of criminal activities are most salient as risk markers for substantiated maltreatment?

Racial and Ethnic Composition

Theoretical models propose that racial and ethnic minority families are disproportionately affected by child maltreatment due, in part, to higher exposure to risk factors than non-minority families (Barth, Miller, Green, & Joy, 2001). Empirical support for the association between maltreatment risk and racial/ethnic composition of communities, however, have been mixed. Whereas some studies have found higher substantiated maltreatment risk in communities with greater percentages of racial minorities (Freisthler, Bruce, & Needell, 2007), others have not (Freisthler, 2004). Similarly, some studies have found that higher percentages of Hispanic or Latino residents are associated with lower rates of substantiated abuse and neglect (Lee & Mackey-Bilaver, 2007), whereas others have found that percentage of Hispanic residents was positively associated with substantiated maltreatment rates (Freisthler, 2004). Aggregating demographic data across counties could contribute to inconsistent findings by obscuring meaningful variation within and between smaller

geographic units such as neighborhoods (Aron et al., 2010). A recent study examining both state- and county-level correlates of maltreatment for 42 states found higher maltreatment report rates in counties with greater percentages of White children and in counties with lower percentages of Latino children after controlling for county-level demographic, socioeconomic, and service-related factors (Smith et al., 2017). Whether a similar protective effect of racial/ethnic composition against substantiated maltreatment is observed over time, controlling for the effects of socioeconomic risk factors, will be investigated in the present longitudinal study.

Present Study

Prior research on risk factors for child abuse and neglect rates across neighborhoods, block groups, zip codes, census tracts, counties, and states has been limited by cross-sectional designs that preclude inference regarding temporal precedence (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014; Smith et al., 2017). The present study addressed this critical gap in our understanding by examining how change in risk factors over time and place were associated with change in rates of substantiated child abuse and neglect using annual data from 2004–2016 for the state of Tennessee. One of the few studies to assess relations between neighborhood contextual factors and risk for substantiated maltreatment over time found that lower property values and greater policing activity were associated with higher maltreatment risk over a 12-year period; the authors of this study emphasized that failing to model ‘time’ (i.e., account for change in risk factors and rates of abuse and neglect over time) could lead to misinterpretations of risk estimates because fluctuations in risk would be obscured by data aggregation (Gracia, Lopez-Quilez, Marco, & Lila, 2017).

The predictors assessed in the present study were selected because they could inform debates regarding the role of sociodemographic factors in risk for substantiated child abuse and neglect (e.g., racial composition) or because they represent potentially malleable risk factors that could be inform targeted prevention programs (e.g., criminal offenses). Based on prior work examining the role of economic hardship, we hypothesized that lower per capita income, higher teen birth rate, and higher percentages of births to unmarried mothers would be associated with higher rates of substantiated child abuse and neglect. Second, we hypothesized that the percentage of children receiving TANF and SNAP benefits would be negatively associated with rates of substantiated child abuse and neglect on the basis that families receiving this assistance may experience less financial stress and hardship. Third, we hypothesized that crime rates, including assault, sexual offenses, stalking, theft, property damage, and drug-related offenses, would be positively associated with rates of substantiated abuse and neglect. Based on the aforementioned mixed findings regarding the relations between racial and ethnic composition and maltreatment (Freisthler, 2004; Freisthler et al., 2007), we did not anticipate that change in rates of substantiated abuse or neglect would be associated with percentages of individuals who identify as African American or Hispanic. Finally, to overcome interpretive challenges resulting from high correlations among demographic, socioeconomic, service- and crime-related risk factors (Smith et al., 2017), we tested their unique associations with child abuse and neglect rates after controlling for the other factors. A Bayesian spatio-temporal approach was adopted to account for spatial and temporal dependencies in the data structure. By revealing the county-level factors that

influence risk for child abuse and neglect over time and identifying counties with increasing relative risk, this analytic approach can help to identify where and how to target community prevention efforts.

Method

Data Sources

This study was conducted over a 13-year period (2004 to 2016) using annual summary statistics for Tennessee counties ($n = 95$). Study procedures were approved by the Meharry Medical College institutional review board. Maltreatment rates and demographic and socioeconomic data were obtained from the KIDS COUNT Data Center and provided by the Tennessee Commission on Children and Youth (www.datacenter.kidscount.org). We examined rates of substantiated child abuse and neglect (per 1,000 youth), percentage of the population under 18-years-old identifying as African American, percentage of the population under 18-years-old identifying as Hispanic, mean per capita income, teen birth rate (live births per 1,000 females ages 15–17), percentage of births to unmarried mothers, percentage of the population under 18-years-old whose families received financial support through TANF, and percentage of the population under age 18 whose families were receiving federally-funded food coupons through SNAP. Substantiated rates of abuse and neglect 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 Tennessee Bureau of Investigation's Incident Based Reporting System (www.crimeinsight.tbi.tn.gov). These variables, all reported per 100,000 population, include the following criminal offense subtypes: assaults, sexual offenses, stalking incidents, thefts, property damage, and drug-related offenses. Assaults included any of the following: murder, negligent manslaughter, negligent vehicular manslaughter, aggravated assault, simple assault, kidnapping/abduction, involuntary servitude, intimidation, and animal cruelty. Sexual offenses included any of the following: forcible rape, forcible fondling, forcible sodomy, statutory rape, sexual assault with an object, pornography/obscene material, and prostitution. Stalking incidents included stalking and violations of orders of protection. Thefts included any of the following: burglary, robbery, bribery, embezzlement, counterfeiting/forgery, extortion/blackmail, fraud, and thefts (all types). Property damage included arson and destruction/damage/vandalism of property. Drug-related offenses included drug/narcotic violations and drug/narcotic equipment violations.

Data Analytic Strategy

A Bayesian spatio-temporal approach offers important advantages over the frequentist approach due to its 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 counties) in

the data. A conditionally independent Poisson distribution was used to model the number of substantiated child abuse and neglect cases in the state of Tennessee:

$$y_{it} | \eta_{it} \sim \text{Po}(E_{it} \exp(\eta_{it})), \quad i = 1, \dots, 95, t = 1, \dots, 13$$

where y_{it} is the number of minors with substantiated child maltreatment reports, η_{it} defines the log relative risk for every county and year, and E_{it} is the expected number of cases of substantiated abuse and neglect in proportion to the population under 18-years-old in each county and year.

Separate models were used to assess the relation of demographic, socioeconomic, and crime variables to substantiated child abuse and neglect over time; a full model including all variables was also tested. Two Bayesian spatio-temporal regression approaches were used to assess the spatio-temporal distribution of child maltreatment risk. The first model incorporated a linear temporal trend parameter (Lawson, Brown, & Vidal Rodeiro, 2003). In this model, the log relative risk was defined as follows:

$$\eta_{it} = \beta_0 + X_{it}\beta + \phi_i + \theta_i + \gamma t + \delta_{it}$$

where β_0 is the intercept, X_{it} defines the vector of predictors, β is the vector of regression coefficients, ϕ_i and θ_i represent the spatially structured and unstructured effects, respectively, γ is a fixed linear time trend for t years, and δ_{it} defines a random spatio-temporal interaction.

Second, we conducted an autoregressive model to explore non-linear temporal structures (Martínez-Beneito, López-Quílez, & Botella-Rocamora, 2008). In contrast to the linear model that assumes a general increase or decrease in risk over the entire study period, the autoregressive model is more flexible 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 county for a given year based on prior risk estimates for that county (i.e., temporal dependence) and risk estimates for neighboring counties in that year (i.e., spatial dependence) as well as in previous years (i.e., spatio-temporal dependence; Martínez-Beneito et al., 2008). Prior research has 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). The log relative risk was defined as follows:

$$\begin{aligned} \eta_{i1} &= \beta_0 + X_{i1}\beta + \alpha_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1}) \\ \eta_{it} &= \beta_0 + \beta X_{it} + \alpha_t + \rho \cdot (\eta_{i(t-1)} - \beta_0 - \alpha_{t-1}) + \phi_{it} + \theta_{it} \end{aligned}$$

where η_{i1} is the log relative risk for the first study period (2004), and η_{it} is the log relative risk for the following years. α_t is the mean deviation of the risk in the year t , ρ defines the

temporal correlation among years, and ϕ_{it} and θ_{it} refer to the structured and unstructured spatial random effects, respectively.

Following the Bayesian approach, we assigned prior distributions for the parameters. β parameters were specified as vague Gaussian distributions, except β_0 , which was specified as an improper uniform distribution. A normal distribution $N(0, \sigma^2)$ was used for the unstructured effects (θ and α) and a conditional spatial autoregressive (CAR) model (Besag, York, & Mollié, 1991) was used for the structured effect (ϕ). Using Markov Chain Monte Carlo (MCMC) techniques, 100,000 iterations were generated, and the first 10,000 were discarded as burn in period. The convergence diagnosis $\hat{R}$ (Gelman, Carlin, Stern, & Rubin, 1990) and a visual inspection of the chains were used to check the convergence of the models; $\hat{R}$ was close to 1.0 for all parameters and plots showed good convergence behavior. The Deviance Information Criterion (DIC) was used as a measure of model fit (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002): smaller DIC values are preferred and differences greater than 10 between models are considered substantial. For example, a smaller DIC for the autoregressive model compared to the linear model would indicate that a non-linear pattern of changes in risk over time is a better fit to the data than a linear trend. Modeling was conducted using the software R and the WinBUGS package.

Results

Visually inspecting mean rates of child abuse/neglect across Tennessee counties during the study period reveals a peak in 2005 (14.9 substantiated cases per 1,000 youth) and a trough in 2016 (5.9 substantiated cases per 1,000 youth). A correlation matrix including county means for variables aggregated across the entire study period is presented in Table 1. Medium-to-large correlations among aggregated means of demographic, socioeconomic, and crime variables highlight the difficulty of parsing relations between abuse/neglect rates and individual predictors and support testing a full model including all predictors.

The temporal effect of risk for substantiated child abuse and neglect for each study year revealed a pattern of quadratic change (Figure 1): a linear decrease from 2004 to 2008 was followed by a non-linear increase from 2008 to 2016. The relative risk of substantiated child abuse and neglect in each county in four study years (i.e., 2004, 2008, 2012 and 2016) is mapped in Figure 2. A value of '1' reflects average risk; hence, a value of 1.5 would indicate an increase in risk of 50%. Counties with higher (> 1) relative risks tended to be located in the center of the state in 2004, 2012, and 2016, and in the eastern part of the state in 2008.

Socioeconomic Indicators

Results of Bayesian spatio-temporal models are presented in Table 2. Variables with a greater-than-95% posterior probability of being different from zero were considered significant. Findings were interpreted for the autoregressive model, which showed a substantial improvement in fit (DIC = 9,409) over the linear time model (DIC = 18,055) and indicated that changes in maltreatment risk were non-linear. Higher risk for child abuse and neglect was associated with higher teen birth rate, higher percentage of births to unmarried mothers, and lower percentage of youth in families receiving TANF benefits. Contrary to

expectation, the percentage of youth in families receiving SNAP benefits was *positively* associated with risk for child abuse and neglect. In addition, per capita income was not associated with child maltreatment risk.

Community Violence

Findings were interpreted for the autoregressive model, which showed a substantial improvement in fit (DIC = 9,416) over the linear time model (DIC = 18,027). Higher risk for child abuse and neglect was associated with higher rates of property damage and drug-related offenses. Contrary to expectation, risk for child abuse and neglect was not associated with rates of assault, sexual offenses, stalking, or theft.

Racial and Ethnic Composition

The DIC for the autoregressive model with demographic variables (DIC = 9,414) indicated a substantial improvement in fit over the linear time model (DIC = 18,221); hence, findings are only interpreted for the autoregressive model. Neither percentage of youth identifying as Hispanic nor percentage of youth identifying as African American was associated with risk for child abuse and neglect in the demographic model.

Full Model

A full model including all demographic, socioeconomic, and crime variables was assessed to determine their unique association with risk for child abuse and neglect. Once again, findings were interpreted for the autoregressive model, which showed an improvement in fit (DIC = 9,407) over the linear time model (DIC = 17,824). Results were largely consistent with previous models: higher risk for child abuse and neglect was associated with higher teen birth rates, higher percentages of births to unmarried mothers, higher percentages of youth in families receiving SNAP benefits, and with higher rates of drug-related offenses. In addition, higher percentage of youth identifying as African American was associated with lower risk for child abuse and neglect.

Discussion

Child maltreatment is a major public health concern in the U.S. (U.S. Department of Health and Human Services, 2016) and its true prevalence is likely to be underestimated by official maltreatment reports (Finkelhor, Turner, Shattuck, & Hamby, 2013). Nevertheless, variation in rates of substantiated child abuse and neglect across geographic areas has been leveraged to better understand social-contextual risk factors (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014), which could facilitate efforts to improve risk detection, enhance multilevel prevention strategies targeting families and communities, and inform child welfare practice (Daro & Dodge, 2009; Molnar, Beatriz, & Beardslee, 2016). Unfortunately, variations in risk for substantiated maltreatment over time have been largely ignored by studies examining person- and place-centered risk factors (Freisthler et al., 2006). The present study sought to address this critical gap in the literature using a Bayesian approach to assess spatio-temporal associations between theoretically-driven predictors and substantiated rates of abuse/neglect from 2004 to 2016 across the state of Tennessee.

Geospatial approaches have demonstrated cross-sectional associations between domestic assaults and child maltreatment (Barczyk, Duzinski, Rao & Lawson, 2016), longitudinal associations between policing activity and substantiated maltreatment rates (Gracia et al., 2017), and a predictive relation between crime rates (domestic violence, aggravated assaults, murders, drug crimes) and next-year substantiated child maltreatment (Daley et al., 2016). The present study provides a novel extension of social disorganization theory by showing that higher rates of drug-related offenses were associated with higher rates of substantiated child abuse and neglect, controlling for other criminal offense subtypes, socioeconomic, and demographic variables. These findings are consistent with prior work showing a positive association between drug-related arrests and referrals for investigations of child maltreatment (Freisthler & Weiss, 2008). The mechanisms that account for the association between drug-related offenses and substantiated child abuse/neglect remain unclear. Drug-related offenses may increase maltreatment risk by lowering perceptions of social control (Kim & Maguire-Jack, 2015; Sampson, Morenoff, & Gannon-Rowley, 2002). Alternately, unmeasured correlates of drug-related offenses such as higher concentrations of bars (Groff & Lockwood, 2014) or parental substance abuse may contribute to risk for substantiated maltreatment.

There is a fairly consistent association between percentages of single parent households and risk for substantiated maltreatment (Coulton et al., 2007). A study of single parents found that number of teen births was associated with higher risk for child neglect over and above race (Zuravin & Diblasio, 1992). Recent work has demonstrated that counties with higher rates of single parenthood also have higher rates of reported child abuse and neglect (Smith et al., 2017). The present study extends these findings by showing that higher teen birth rates and percentages of births to unmarried mothers were independently associated with higher risk for substantiated maltreatment over place and time. The transition to parenthood for adolescents may contribute to risk for maltreatment by disrupting attachments (Flaherty & Sadler, 2011), elevating family stress levels (Curenton, McWey, & Bolen, 2009), and increasing risk for parental depression (Gilson & Lancaster, 2008). In addition, teenage mothers may be more likely to engage in harsh parenting behaviors or other types of maltreatment due to lack of knowledge of child development (McCullough & Scherman, 1998).

Social safety net programs such as SNAP and TANF are likely to be related to less child abuse and neglect indirectly by increasing families' financial security, buffering against risk factors (e.g., family stress, parental depression, domestic violence), and enhancing protective factors such as social support and resilience (Cox, Kotch, & Everson, 2003; Ennis, Hobfoll, & Schroder, 2000; Gassman-Pines & Hill, 2013; McConnell, Breitzkreuz, & Savage, 2011; Orthner, Jones-Sanpei, & Williamson, 2004; Yeung, Linver, & Brooks-Gunn, 2002). Prior work has generally demonstrated a protective effect of economic security and social safety net policies on maltreatment risk. For example, a study of economic predictors of child maltreatment in two large metropolitan communities over a 30-month period found that increases in job loss preceded increases in reported child abuse (Steinberg, Catalano, & Dooley, 1981). Another study found that increases in earned income tax credit was associated with a large reduction in CPS involvement, with stronger effects observed for low-income, single-parent households (Berger, Font, Slack, & Waldfogel, 2017). Yet another

individual-level longitudinal study demonstrated lower rates of substantiated child abuse/neglect in Medicaid-eligible children participating in the food stamp program who were followed from birth to five years old (Lee & Mackey-Bilaver, 2007).

Surprisingly, the present study found that higher percentages of children receiving SNAP benefits were associated with *higher* rates of substantiated child abuse and neglect over space and time, controlling for demographic variables, other socioeconomic predictors, and crime rates. One interpretation for this counter-intuitive finding regarding SNAP participation is that Bayesian spatio-temporal models may be vulnerable to self-selection bias, whereby counties with higher maltreatment risk also would be more likely to participate in the SNAP program year after year (Nord & Golla, 2009). To assess the plausibly causal impact of social safety net programs such as SNAP and TANF on child abuse and neglect while accounting for selection bias may require the use of difference-in-differences (DD) approaches in conjunction with natural experiments, such as the temporary expansion of SNAP benefits and eligibility through the American Recovery and Reinvestment Act. Alternately, instrumental variables (IV) approaches could be used to examine the effect of policy variation between states on child abuse and neglect. These methods have been used to demonstrate the impact of paid family leave policies on decreases in hospital admissions for pediatric head trauma (a leading cause of fatal child maltreatment) (Klevens, Luo, Xu, Peterson, & Latzman, 2016), the impact of decreases in welfare generosity on increases in children's out-of-home placements (Wildeman & Fallesen, 2017), and the impact of more restrictive TANF policies on higher substantiated maltreatment cases and foster care placements (Ginther & Johnson-Motoyama, 2017). Future studies should apply DD and IV approaches to understand the impact of SNAP on child maltreatment risk.

Prior work on the association between race and ethnicity and rates of child abuse and neglect has yielded mixed findings (Freisthler, 2004; Freisthler et al., 2007). The present study found that counties with higher percentages of African-American youth were associated with *lower* rates of substantiated child abuse and neglect over time, but only when included in a model with socioeconomic and crime-rate variables. Similarly, a recent cross-sectional study utilizing data from 42 states (Smith et al., 2017) found that child maltreatment report rates were higher in counties with larger percentages of white youth; although the cultural or contextual factors that account for these relations are not well understood, it is notable that the association between race and maltreatment was evident even after controlling for a variety of socioeconomic indicators. These findings cannot be explained by theoretical models predicting *greater* maltreatment risk in racial and ethnic minorities due to disproportionate exposure to risk factors (Barth et al., 2001). Interestingly, in the present study, mean percentage of African-American youth was correlated with both potential risk and protective factors for substantiated child abuse and neglect. Counties with higher mean percentages of African-American youth had higher percentages of children receiving TANF benefits but also higher teen birth rates and percentages of births to unmarried mothers. Notably, mean percentage of African-American youth was correlated with lower mean rates of substantiated abuse and neglect despite being highly correlated with most criminal offense subtypes. Future studies should seek to identify familial (e.g., parenting, extended family support) and neighborhood (e.g., social cohesion, childcare assistance) factors that

may shield racial minorities from risk for substantiated child abuse and neglect (Garbarino & Sherman, 1980; Maguire-Jack & Negash, 2016; Maguire-Jack & Showalter, 2016).

Limitations of this study highlight directions for future research. First, the present findings may not extend to smaller spatial units such as neighborhoods, to other states, or to different time frames. Second, despite using Bayesian spatio-temporal models to examine associations between predictors and maltreatment outcomes over space and time, the present findings are correlational in nature and preclude causal inferences. For example, it remains unclear whether county-level contextual factors influence risk for substantiated child maltreatment or if families at elevated risk for maltreatment are forced by their circumstances to reside in counties with these characteristics (Freisthler et al., 2006). Third, analyses are limited to examining rates of substantiated child abuse and neglect and cannot account for incidents that were either unreported or reported but could not be substantiated by the child welfare system. Fourth, there was a strong and positive correlation between percentages of children in families receiving TANF and SNAP; their unique and potentially additive effects on risk for substantiated abuse and neglect should be tested using longitudinal data obtained from families.

The present findings have important implications for maltreatment prevention and future research on contextual risk and protective factors. Despite decreases in relative risk for substantiated child abuse and neglect in the state of Tennessee from 2004 to 2008, this study showed an overall pattern of *increasing* relative risk from 2008 to 2016. During this period of non-linear increases in relative risk, maps showed counties located in the central, far-eastern, and western parts of the state transitioning from decreasing to increasing risk. Future studies are needed to determine whether this period of increasing risk for substantiated maltreatment was triggered by the Great Recession. Moreover, counties with elevated relative risk for substantiated child abuse and neglect were clustered near each other. Bayesian spatio-temporal models can help to identify counties with rapidly increasing risk for substantiated child maltreatment in need of prevention services. Child maltreatment prevention efforts in the state of Tennessee may benefit most from a focus on reducing teen birth rates, births to unmarried mothers, and drug-related offense rates via a combination of school-based prevention services, community programs, law enforcement strategies, and policy initiatives (Daro & Dodge, 2009; Molnar et al., 2016; Morris et al., 2017).

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Figure 1.
Temporal effect for each year (2004–2016) for substantiated child abuse and neglect.

Figure 2.

Maps of relative risk of substantiated child abuse and neglect by county in four study years, 2004, 2008, 2012, and 2016 [a value of '1' reflects average risk; hence, a value of 1.5 would indicate an increase in risk of 50%].

Table 1
Bivariate Correlations Among Aggregated Child Abuse and Neglect, Demographic, Socioeconomic, and Crime Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Abuse/Neglect	--												
2. Hispanic	-.16	--											
3. African American	-.27**	.26*	--										
4. Per capita income	-.05	.20*	-.08	--									
5. Teen birth rate	.33**	.22*	.33**	.02	--								
6. Birth unmarried	.18	.05	.63***	-.07	.72***	--							
7. TANF	.05	-.05	.58***	-.24*	.57***	.71***	--						
8. SNAP	.44***	-.23*	.13	-.23*	.64***	.62***	.67***	--					
9. Assaults	-.05	.35***	.65***	.05	.37***	.48***	.36***	.02	--				
10. Sexual offenses	-.12	.46**	.53***	.07	.18	.25*	.22*	-.15	.81***	--			
11. Stalking	-.07	.22*	.39***	-.13	.14	.19	.09	-.04	.53***	.40***	--		
12. Thefts	.03	.36***	.42***	.14	.32**	.30**	.24*	-.04	.75***	.72***	.27**	--	
13. Property damage	.02	.26*	.63***	.04	.40***	.49***	.44***	.11	.91***	.76***	.44***	.82***	--
14. Drug offenses	.09	.11	.08	-.07	.16	-.01	.03	-.001	.31**	.32**	.14	.41***	.37***

 $p < .001$

**
 $p < .01$

*
 $p < .05$.

Note. Birth unmarried = percentage of live births to unmarried mothers; TANF = temporary assistance to needy families; SNAP = supplemental nutritional assistance program.

Table 2

Results from Bayesian Spatiotemporal Models Testing County Characteristics Associated with Substantiated Child Abuse and Neglect

	Demographic Model <i>b</i> (SE)	Socioeconomic Model <i>b</i> (SE)	Crime Model <i>b</i> (SE)	Full Model <i>b</i> (SE)
Model 1: Linear time				
Intercept	-0.159 (0.052)	-0.309 (0.07)	-0.179 (0.06)	-0.597 (0.076)
γ (Linear time)	0.005 (0.002) *	0.012 (0.002) *	0.013 (0.001) *	0.006 (0.003) *
σ_θ	0.390 (0.083)	0.4235 (0.060)	0.453 (0.054)	0.429 (0.063)
σ_ϕ	0.488 (0.225)	0.277 (0.207)	0.251 (0.18)	0.345 (0.199)
σ_δ	0.086 (0.007)	0.082 (0.007)	0.080 (0.007)	0.083 (0.007)
Hispanic	0.063 (0.012) *			0.055 (0.015) *
African American	0.005 (0.004)			-0.002 (0.004)
Per capita income		0.001 (0.001)		0.001 (0.001)
Teen birth rate		0.006 (0.001) *		0.006 (0.001) *
Unmarried births		0.007 (0.001) *		0.007 (0.001) *
TANF		-0.020 (0.004) *		-0.010 (0.004) *
SNAP		0.0001 (0.001)		0.001 (0.001)
Crime				
Assault			-0.0002 (0.00002) *	-0.0002 (0.00002) *
Sexual offenses			0.0001 (0.0001)	-0.0002 (0.0001) *
Stalking			0.001 (0.000) *	0.001 (0.0002) *
Theft			0.0001 (0.0001) *	0.0001 (0.00001) *
Prop. Damage			0.0001 (0.00003) *	0.0001 (0.00003) *
Drug offenses			0.0001 (0.00002) *	0.0002 (0.00002) *
DIC	18,221.1	18,054.5	18,027.1	17,824.3
Model 2: Autoregressive				
Intercept	0.122 (0.049)	-0.865 (0.142)	-0.097 (0.059)	-0.993 (0.136)
σ_θ	0.237 (0.015)	0.230 (0.014)	0.232 (0.015)	0.234 (0.014)

	Demographic Model b (SE)	Socioeconomic Model b (SE)	Crime Model b (SE)	Full Model b (SE)
σ_ϕ	0.308 (0.036)	0.315 (0.033)	0.316 (0.037)	0.298 (0.035)
σ_α	0.105 (0.027)	0.097 (0.025)	0.108 (0.029)	0.095 (0.025)
ρ	0.751 (0.021)	0.689 (0.024)	0.749 (0.021)	0.672 (0.024)
Hispanic	-0.010 (0.014)			-0.004 (0.011)
African American	-0.003 (0.004)			-0.012 (0.004)*
Per capita income		-0.001 (0.003)		-0.001 (0.003)
Teen birth rate		0.004 (0.002)*		0.003 (0.001)*
Unmarried births		0.006 (0.002)*		0.007 (0.002)*
TANF		-0.029 (0.011)*		-0.018 (0.012)
SNAP		0.024 (0.003)*		0.021 (0.004)*
Crime				
Assault			-0.00004 (0.00004)	-0.00004 (0.00005)
Sexual offenses			0.0004 (0.0004)	0.0005 (0.0004)
Stalking			-0.00006 (0.0006)	-0.000003 (0.0006)
Theft			-0.00003 (0.00005)	0.00001 (0.00003)
Prop. Damage			0.00017 (0.00007)*	0.0001 (0.0001)
Drug offenses			0.00016 (0.00004)*	0.0001 (0.00004)*
DIC	9,414.3	9409.4	9,416.2	9406.5

Note. Teen birth rate = number of live births per 1000 females ages 15–17; unmarried births = percent of live births to women who are not married; TANF = percent of children receiving temporary assistance to needy families; SNAP = percent of children receiving supplemental nutrition assistance program benefits; prop. = property; γ = linear time trend; σ_θ = standard deviation spatially unstructured term; σ_θ = standard deviation spatially structured term; σ_λ = standard deviation spatiotemporal interaction; ρ = temporal correlation.

*The 95% credible intervals do not include zero.