

THE GEOGRAPHY OF DRUG MARKET ACTIVITIES AND CHILD MALTREATMENT

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Abstract

Objective. The purpose of this study is to begin to understand how the drug market activities place children at risk for being abused or neglect by examining both the temporal and spatial patterns of drug market activities over time.

Methods. Data were collected for 95 Census tracts in Sacramento, California over seven years ($n = 665$). The study examined the relationship between child maltreatment (as measured by referrals, substantiations, and foster care entries) and drug possessions and drug sales. Data were analyzed using Bayesian space-time models.

Results. Referrals for child maltreatment investigations were less likely to occur in places where current drug market activity (as measured by drug possessions and drug sales) were present. However, drug sales and past year local and spatially lagged drugs sales were positively related to referrals. After the investigative phase (i.e., referrals) Census tracts with more drug possessions and drug sales had higher numbers of substantiations and those tracts with more possessions also had more entries into foster care.

Conclusions. The temporal delay between drug sales and child maltreatment referrals may: (1) indicate that the surveillance systems designed to protect children may not be very responsive to changing neighborhood conditions or (2) be indicative of the time it takes for drug sales to reach their users and for the detrimental effects of the drug use to appear. Drug activity is likely factored into the overall risk to children by child welfare caseworkers as evidenced by significantly higher substantiations and foster care entries in these areas.

In 2007, about 2.1 million children lived in with at least one parent who abused or was dependent on illegal drugs (Substance Abuse and Mental Health Services Administration, 2009). Parents who were identified as drug dependent or drug abusers were 2.9 times more likely to physically abuse their children and 10.4 times more likely to neglect their child than matched controls (Kelleher et al., 1994). Furthermore, Deren (1986) found that of children who died due to abuse or neglect 25% had a mother who was a drug addict. Parental drug use has been identified as a major factor related to child neglect, particularly when the perpetrator is a biological parent (Sedlak et al, 2010). Taken together these facts suggest that a substantial number of children are at risk for child abuse and neglect by drug abusing parents. Child abuse and neglect and child maltreatment will be used interchangeably in this paper and refer to actions by a parent or caregiver that result in harm, the potential for harm, or threat of harm either through commission or omission and includes physical abuse, sexual abuse, and neglect of children (U.S. Department of Health and Human Services, 2010).

Additionally, there is limited evidence that the some aspects of drug market activity may be positively related to rates of child maltreatment (Albert and Barth, 1996; Freisthler et al., 2005b; Freisthler and Weiss, 2008). Drug market activities are defined here as any of the activities that support drug markets, including manufacturing, selling, purchasing, and use. Drug possession incidents in Census block groups were related to higher rates of substantiated reports of child maltreatment controlling for other Census-based indicators of social disorganization (Freisther et al., 2005b). However, drug sale incidents were not related to child maltreatment in the same study (Freisthler et al., 2005b). These authors suggested that drug possession may be a proxy for overall levels of drug use in the neighborhood. Thus the relationship between drug possessions and child maltreatment may be indicative of overall drug problems.

Increases in drug arrests at the county level were related to increases of referrals to Child Protective Services (CPS) from 1998 – 2001 (Freisthler and Weiss, 2008). Albert and Barth (1996) also found that drug arrests for women were positively related to rates of maltreatment in urban and rural counties but found no relationship between drug arrests and maltreatment in suburban counties. The relationship between drug arrests, whether for the entire population or just women, was used as an indicator of parents who are unable to care for their children, either because of problems with drug abuse or because they are in jail (called caretaker incapacity, a form of child neglect). However, missing from these studies is a specific understanding of how spatial aspects of drug market activities may affect maltreatment across neighborhood areas. Further, these two studies were conducted at the county level, making it difficult to follow the small-scale rise and fall of drug markets that may affect neighborhoods.

The locations of drug markets themselves are largely immeasurable. Arrests for drug crimes are imperfect indicators of drug market activity. This is largely due to their illicit nature and their ability to disband in one area and reform in another similar area quickly when caught by law enforcement or their safety is otherwise compromised (LaScala et al., 2005). Although enforcement data by police on locations of drug crimes (through incident reports) is a better indicator as it does not rely solely on an arrest being made, these data are still subject to police knowledge of the location of these events (Klinger and Bridges, 1997).

On the other hand, the effects of drug markets (e.g., child maltreatment) are much more visible and easily studied. Yet knowing specifically how drug markets affect these problems remains elusive as these problems are often not seen until after the markets themselves have been disbanded. Thus understanding the timing of when drug markets appear and subsequent development of problems, such as child maltreatment, can provide important information in the

prevention of these problems. Do social problems, like child abuse, occur contemporaneously with the development of drug markets or are the effects of these markets seen after some time? Further, do drug market activities only affect problems in the areas in which they occur or are the effects spatially diffuse? For example, the characteristics of adjacent neighborhoods (e.g., drug activity) may affect child maltreatment in a local area (i.e., spatial lags). The spatial dynamics of drug market activities have not yet been studied with regards to child maltreatment.

Some of these spatial aspects of visible drug sales have been studied with respect to drug use and other social problems. For example, visible drug sales were not related to drug use within the same area, but drug sales that occurred in adjacent areas were related to local drug use (Freisthler et al., 2005a). Thus individuals may purchase drugs near their home, but not necessarily within the same neighborhood in which they live (i.e., one or two “neighborhoods” away). However, drug crimes both within Census tracts and in adjacent Census tracts were positively related to assaults in Texas (Gorman et al., 2005) and drug sales were related to assaults over time in California (Banerjee et al., 2008).

The spatial aspects of visible drug markets support a theory developed by Eck (1995) which purports that drug markets operate through two primary structures: social networks and routine activities. A social network drug market is one that is primarily invisible where contacts for drug sales are made through friends and friends of friends. This helps to ensure that the drug seller maximizes control of the market in order to increase the level of safety. These markets are likely to be more geographically diffuse as they rely more on relationships between people than on a specific place. Contrast this type of market with a routine activity drug market that is purposely positioned in a place where individuals who want drugs are likely to look in order to

purchase drugs. This often includes environments that are high traffic areas with multiple access routes thus making them more visible to both potential customers but also to law enforcement.

Given these theoretical perspectives, it is not surprising that current research suggests highly visible drug markets (i.e. routine activity markets) serve a different role than less visible drug markets. Overall, visible drugs markets have been demonstrated to be geographically clustered with distinct rise and fall patterns over time (Gruenewald et al., 2010; Petronis and Anthony, 2003; Weisburd and Mazerolle, 2000). The presence of visible drug markets brings increased traffic from outsiders and concentration of illicit activities in the neighborhood of origin. As a result, the presence of visible drug markets is likely to have a distinct ecological impact upon the residents in the neighborhood of origin. Based on routine activities theory, it is plausible that increased drug visibility within specific neighborhoods lends itself to more problems such as child maltreatment and further erosion of the social infrastructure that originally drew visible markets to an area. However, if one mechanism by which drug activity affects maltreatment is through drug use, it would be more likely that drug market activity may not be related to child maltreatment in the same area but in adjacent areas as the drugs are spread from their source (the sellers) to the customers.

The current study takes the first step in better understanding how the geography of drug markets affects child maltreatment over time. The purpose of this study is to begin the process of understanding how the drug market activities place children at risk for being abused or neglected by examining both the temporal and spatial patterns of drug market activities over a seven year time period. The research questions for this study are: (1) Is there a relationship between drug market activities and official reports of child maltreatment? (2) Are drug sales and drug possession in adjacent neighborhoods related to official reports of child maltreatment? and (3)

Are past year sales and possession in local and adjacent neighborhoods related to child maltreatment?

Methods

Study Design. Data were collected for 95 Census tracts in Sacramento, California over seven years (2002 – 2008). An ecological panel design was used to analyze the data with a final sample size of 665 spatial units (95 Census tracts * 7 years). Census tracts were chosen as the geographic unit of analysis as they approximately represent neighborhood areas. On average Census tracts have approximately 4000 residents and 1500 households (US Census Bureau, 1994).

Measures. The dependent variable, child maltreatment, was measured using official data on referrals for investigations by Child Protective Services, substantiated reports, and entries into foster care. These three measures can be loosely considered as a continuum of harm due to child maltreatment. A referral for a child maltreatment investigation is usually initiated by a professional (i.e. medical doctor, teacher), family member, neighbor or friend if abuse or neglect is suspected. If the Child Protective Services worker who investigates the case believes there is enough evidence to show the maltreatment occurred, the referral is substantiated (Simpson et al., 2000). If the allegation of maltreatment was deemed severe enough or if the child was considered to be at continued risk for immediate harm the investigating worker can remove the child from the home and place him or her into foster care. As such, these three outcomes are nested within each other. The number of substantiations is a function of the number and type of referrals of allegations needing investigation and the number of children who enter foster care is a function of the types and severity of substantiated cases.

These data were obtained from the Center for Social Services at the University of California, Berkeley University of California (http://cssr.berkeley.edu/ucb_childwelfare/) which is contracted by the California Department of Social Services to maintain and archive all the data on child maltreatment allegations for the state of California. Data were obtained from two different databases: the referral database (referral and substantiation data) and the foster care database (entry into foster care data). Data were provided in aggregate form as counts of referrals, substantiations, and foster care entries at the Census tract level. Geocoding rates were 91.5% for referrals, 94.0% for substantiations, and 88.9% for foster care entries.

For this study, only entries into foster care that lasted for 5 or more days were used. In addition, the data are unduplicated counts of children in the system with referrals, substantiations, and foster care entries. For children who received more than one referral or had more than one allegation type (e.g., physical abuse and neglect), the allegation for the most severe type of maltreatment is used. This ensures that the rate of maltreatment refers to population rates. In the analyses, referrals are indexed by the total child population for each Census tract, substantiations are indexed by the total number of referrals, and foster care entries are indexed by the number of substantiated reports to model this continuum. On average, there are 93 referrals for investigations of child maltreatment, 26 of those are substantiated, and about 11 children enter foster care per Census tract.

---INSERT TABLE 1 ABOUT HERE---

Data for the independent variables came from the Sacramento Police Department and were used to model the amount drug market activity in Census tracts for the years 2002 to 2008. In particular, this study utilized drug-defined crimes (i.e. violations of laws prohibiting the possession or sales of illegal drugs) from police incident data on drug possessions and drug sales

which provided information on the location of the event as well as the code designating the type of crime. Drug possession incidents included the following police codes: HS 109575, HS 11162.5A-B, HS 11350(A) -11350(B), HS 11357(A) to HS 11357(E), HS 11364, HS 11365(A), HS 11370.1, HS 11377(A), HS 11550(A), HS 11550(E), HS 11173-11173(A), VC 23222(B), PC 377, PC 381(A) -(B), PC 4573.5 to PC 4573.6, BP 4060, BP 4140, BP 4230, BP 4324(A), BP 4325, BP 4390(A), and BP 4390.1. Drug sales incidents included the following police codes: HS 11351 to HS 11351.5, HS 11353(A) to HS 11355, HS 11359 to HS 11360(A), HS 11361(B), HS 11366, HS 11368, HS 11370.2, HS 11375(A), HS 11378, HS 11380(A) to HS 11382, HS 11532(A), PC 626.85(A), BP 4059(A), BP 4149, and BP 4143. Geocoding rates for the drug incident data exceeded 99% for each year. Each Census tract has on average 33 drug possession incidents and 5 drug sale incidents.

As this study seeks to examine the current and lagged effects of drug market activity (see Figure 1), four covariates were created and included in each model: (1) the number of drug possessions or sales for the current year for each Census tract; (2) the number of past year drug possessions or sales (i.e., temporal lag T_{-1}); (3) the average number of drug possessions or drug sales in adjacent Census tracts (i.e., spatial lags S_{-1}); and (4) the average number of past year drug possessions in adjacent tracts (i.e., spatial-temporal lags $T_{-1}S_{-1}$). Since the geographic extent (e.g., area) remains the same throughout the seven years of the study, the number of possessions and sales are used rather than a density measure (number per area). This measure reflects the real increases and decreases in drug possessions or sales over the study period.

---INSERT FIGURE 1 ABOUT HERE---

Statistical Analysis. Bayesian conditionally autoregressive (CAR) space-time models are used to analyze the spatial and temporal effects of drug market activity on child maltreatment.

Bayesian analysis treats unknown information as random variables with probability distributions. In this case, the three outcome variables are treated as having Poisson distributions. Prior distributions are specified to describe the uncertainty surrounding unknowns before the data was observed. Inferences are derived using Bayes' rule to condition on the values of the observed data giving posterior densities of the unknowns. Computation is implemented using Monte Carlo Markov chain (MCMC) methods.

The full model is as follows:

$$y_{ik} \sim \text{Poisson}(\theta_{ik})$$

$$\log(\theta_{ik}) = \log(e_{ik}) + \alpha + \beta_1 x_{ik} + \beta_2 x_{ik-1} + \beta_3 x_{i-1k} + \beta_4 x_{i-1k-1} + u_i + \beta * k + \delta_i * k$$

θ_{ik} = underlying risk of having a referral for investigation of a report of child maltreatment at Census tract i at time k (years 1 – 7) In subsequent models, this is the underlying risk for substantiations or foster care entries.

e_{ik} = the population at risk. For referrals this is the total child population in Census tract i at time k . For substantiations, this is the number of children referred for child maltreatment investigations and for foster care entries this is the number of children with substantiated reports.

α = intercept

$\beta_1 x_{ik}$ = local effects of drug possessions or sales

$\beta_2 x_{ik-1}$ = temporal lag of drug possessions or sales (T_{-1})

$\beta_3 x_{i-1k}$ = spatial lag of drug possession or sales (S_{-1})

$\beta_4 x_{i-1k-1}$ = temporal and spatial lag of drug possession or sales ($T_{-1}S_{-1}$)

u_i = is the spatial random effects (i.e., spatially correlated heterogeneity) for area i

$\beta * k$ = fixed linear time trend for k time periods

$\delta_i * k$ = random spatio-temporal interaction modeling a linear time trend correlated spatially over neighboring Census tracts.

The use of spatial random effects smooth estimates across neighboring areas through use of the CAR model. This assumes that adjacent Census tracts share similar characteristics (Cliff and Ord, 1973). Adjacencies were determined by those Census tracts that shared a boundary. A Census tract that just shared a vertex (i.e., a point) with another tract was not considered a neighbor.

The precision parameters controlling the degrees of spatial smoothing and the space-time interaction were modeled a priori with vague gamma prior distributions. A proper but vague normal prior was given to the time trend variable. By convention, the intercept is given a flat prior (Thomas et al., 2002). Vague (or non-informative) priors are used because there is very little prior information about the nature of the relationship between drug market activity and child maltreatment. Models were run separately for drug sales and drug possessions with each of the dependent variables (for a total of six models). For each model, there were 50,000 iterations of MCMC burn-in and the posterior estimates are based on an additional 50,000 iterations.

Results

The relative risks from the Bayesian models can be found in Table 2 (for possessions) and Table 3 (for sales). The credible interval of the relative risks for the main study variables can be found in Figure 2 (for possessions) and Figure 3 (for sales). While Bayesian models do not assess statistical significance in the classical sense credible intervals that do not cross one in Figures 2 and 3 can be considered to have underlying distributions different from one.

Tables 2 and 3 show that, on average, referrals for investigations of child maltreatment, the number of substantiations, and number of foster care entries has been decreasing over time as shown by the time trend variables. The positive spatial heterogeneity term shows that maltreatment is similar to areas that are adjacent to each other.

Drug possession incidents in current year local and spatially lagged (S_{-1}) areas are negatively related to referrals for investigations for child maltreatment. Neither past year local (T_{-1}) nor spatially lagged ($T_{-1}S_{-1}$) variables for drug possessions were related to the referrals. Once a referral is made, current year drug possession in local areas is positively related to substantiations. Given that an allegation has been substantiated, current year drug possessions were also positively related to foster care entries in local areas. In addition, possessions in past year spatially lagged ($T_{-1}S_{-1}$; i.e. adjacent) areas were negatively related to an allegation being substantiated and past year drug possessions were negatively related to entries into foster care.

---INSERT TABLE 2 AND FIGURE 2 ABOUT HERE---

Similar to drug possessions, current year local and adjacent (S_{-1}) drug sales were negatively related to Child Protective Services referrals. Last year drug sales, in both local (T_{-1}) and adjacent ($T_{-1}S_{-1}$) areas, were positively related to referrals. Drug sales in local areas were positively related to an allegation being substantiated after being referred for investigation. Once substantiated, drug sales in spatially lagged areas were positively related to foster care entries in local areas. Past year adjacent area ($T_{-1}S_{-1}$) drug sales were negatively related to both substantiations and foster care entries.

---INSERT TABLE 3 AND FIGURE 3 ABOUT HERE---

Discussion

Based on the results presented above, there appears to be a distinct spatial and temporal pattern of drug market activity and child maltreatment. Referrals for child maltreatment investigations are less likely to occur in places where current drug market activity (as measured by drug possessions and drug sales) are present. However, with the case of drug sales, past year local and spatially lagged drugs sales were positively related to referrals. In other words, the

more drug sales in Neighborhood B from Figure 1 or in neighborhoods adjacent to “B” (e.g., A, D, and E) last year, the more referrals for child maltreatment investigations there are in Neighborhood B this year.

The relationship of drug activity and child maltreatment changes once child welfare workers are involved. In this case, Census tracts with more drug possessions and drug sales have higher numbers of substantiations and those tracts with more possessions also have more entries into foster care. This suggests that during the investigative phase, caseworkers may uncover evidence of harm to a child that is either directly (e.g., drug use) or indirectly (e.g., unsafe environment) related to drug market activity.

The positive relationship between drug possession incidents and substantiated reports of child abuse and neglect corroborates findings from Freisthler and colleagues (2005b). However, the current study also finds a positive relationship between drug sales and child maltreatment unlike Freisthler and colleagues (2005b). This discrepancy may be due to the difference in how substantiations were denominated. Here substantiations are viewed as a subset of referrals, while the previous study examined this relationship at a population level with the total number of children in an area as the denominator. Similarly, if one assumes that drug arrests are an indicator of underlying drug activity, the findings from the current study confirm those by previous panel studies of child maltreatment (Albert and Barth, 1996; Freisthler and Weiss, 2008).

The negative relationship between drug activity and referrals may indicate that the individuals and professionals who report child maltreatment are not aware of current drug sales and possessions. However, the temporal delay between drug sales and child maltreatment referrals indicates that the surveillance systems designed to protect children may not be very

responsive to changing neighborhood conditions. Neighbors, teachers, family, and friends may be more aware of past year drug sales, especially if reports of the “drug busts” of law enforcement are widely circulated and may be more watchful for adverse effects of drug market activities. Similarly, potential reporters might feel a sense of safety about reporting individuals from already distressed or “known” drug areas as opposed to those where they just suspect drug activities might be occurring.

Another interpretation of these findings is that current drug market activity itself does not place children at risk for abuse and neglect. If drug possessions are actually a surrogate for drug use, the relationship seen here may actually be due to the underlying drug use behaviors of parents that are placing children at risk for maltreatment. The time lag found between drug sales and referrals for maltreatment investigations in Census tracts may be indicative of the time it takes for drug sales to reach their users and for the detrimental effects of the drug use to appear. Thus, the prevailing mechanism relating drug activity to child maltreatment may be through parental drug abuse.

Either interpretation of these findings (e.g., lag time of surveillance systems or the detrimental effects of drug use) suggests that child welfare workers do not have current information on where drug markets are affecting parenting behaviors. Yet, when they do investigate cases in areas with high numbers of drug possessions and drug sales, drug activity is likely factored into the overall risk to children, as evidenced by significantly higher substantiations and foster care entries in these areas.

Implications for Prevention. Understanding this relationship between the timing and location of drug market and its subsequent effects on child maltreatment may point to avenues for prevention efforts. Reducing the time delay between drug market development and referrals

for child maltreatment investigations may prevent some child maltreatment from occurring. Finally, these findings suggest some natural partnerships including increased collaboration between law enforcement and child welfare caseworkers. Police could provide child welfare caseworkers with locations of emerging drug markets as they investigate new drug cases in these areas. Further, information on emerging drug market locations would allow caseworkers or other child welfare professionals to target these areas for prevention programming so that subsequent maltreatment does not occur. Finally, publicizing drug activity in local areas or implementing public awareness campaigns encouraging individuals to report suspected child abuse and neglect in neighborhoods where drug market activities are occurring might further prevent maltreatment.

Limitations. Although this study provides insight in the role of drug market activities on child abuse and neglect, it does have limitations. As an ecological population-level study, inferences cannot be made about individual behaviors. Though one mechanism by which findings are explained is through parental drug use behaviors, without information specific to individuals these hypotheses are conjecture. Future work that examines ecological-level drug activity with individual-level drug use would allow testing of these theories. The findings seen here might be due to overall neighborhood structure that contributes to both child abuse and drug activity. Controlling for variables that measure these distressed aspects of neighborhoods would better illuminate the unique role of drug market activities on child maltreatment. Finally, the use of police incident data limits the understanding of the relationship of drug activity and maltreatment to primarily visible (or “routine activities”) drug markets. Examining these relationships for “social network” drug markets may provide additional insight that can better inform the development of prevention programs.

Conclusion. This study advances this understanding of drug market activities and child maltreatment in several important ways. First, the spatial aspects of drug market activity are explicitly modeled as effects both on local and adjacent areas for current and past years. Second, these relationships are studied over time and the timing of drug activity events and child maltreatment are considered through the use of temporal lags. Finally, this study considers the continuum of decisions points for children involved in the child welfare system to understand how and where the effects of drug market activity may be detected through professionals tasked with reporting suspected child maltreatment. The findings presented here are a beginning step in understanding how drug market activity affects child maltreatment and provides some insight in how these consequences might be mitigated through prevention programs, collaborations between law enforcement and the child welfare system, and the development of better surveillance efforts.

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Table 1: Descriptive Statistics for Child Maltreatment Outcomes, Drug Possessions, and Drug Sales

Variable Name	Mean	SD	Min	Max
Child Maltreatment Outcomes				
Referrals	98.31	89.78	0.00	475.00
Substantiations	26.12	26.86	0.00	145.00
Foster Care Entries	10.59	12.20	0.00	62.00
Drug Possessions				
Local Drug Possessions	32.99	45.92	0.00	376.00
Past Year Drug Possessions (T_{-1})	32.68	46.53	0.00	376.00
Adjacent Drug Possessions (S_{-1})	34.13	25.71	0.67	127.00
Past Year Adjacent Drug Possessions ($T_{-1}S_{-1}$)	33.71	26.13	0.67	127.00
Drug Sales				
Local Drug Sales	5.19	8.22	0.00	62.00
Past Year Drug Sales (T_{-1})	5.52	8.87	0.00	62.00
Adjacent Drug Sales (S_{-1})	5.33	4.59	0.00	22.00
Past Year Adjacent Drug Sales ($T_{-1}S_{-1}$)	5.64	4.93	0.00	23.20

Table 2: Relative Risk for Bayesian Space-Time Models of Child Maltreatment Referrals, Substantiations, and Foster Care Entries to Drug Possessions over 7 Years in 95 Census Tracts (n = 665)

Variable Name	<u>Referrals</u>	<u>Substantiations</u>	<u>Foster Care Entries</u>
	Relative Risk	Relative Risk	Relative Risk
Constant	0.1137 *	0.2315 *	0.3101 *
Local Drug Possessions	0.9985 *	1.0009 *	1.0024 *
Past Year Drug Possessions ($T_{.1}$)	0.9996	1.0003	0.9985 *
Adjacent Drug Possessions ($S_{.1}$)	0.9963 *	1.0012	1.0014
Past Year Adjacent Drug Possessions ($T_{.1}S_{.1}$)	1.0007	0.9981	0.9993
Spatial Heterogeneity	3.5859 *	1.0178 *	1.0358 *
Time Trend	0.9152 *	1.2511 *	1.4263 *
Space-Time Trend	1.1134 *	1.0378 *	1.0301 *

* indicates effects for which the Relative Risk excludes one for parameter estimate

Table 3: Relative Risk for Bayesian Space-Time Models of Child Maltreatment Referrals, Substantiations, and Foster Care Entries to Drug Sales over 7 Years in 95 Census Tracts (n = 665)

	<u>Referrals</u>	<u>Substantiations</u>	<u>Foster Care Entries</u>
Variable Name	Relative Risk	Relative Risk	Relative Risk
Constant	0.1024 *	0.2242 *	0.3286 *
Local Drug Sales	0.9962 *	1.0065 *	1.0021
Past Year Drug Sales (T_{-1})	1.0034 *	1.0000	0.9986
Adjacent Drug Sales (S_{-1})	0.9875 *	1.0052	1.0128 *
Past Year Adjacent Drug Sales ($T_{-1}S_{-1}$)	1.0057 *	0.9950	0.9869 *
Spatial Heterogeneity	0.9101 *	1.0211 *	1.0380 *
Time Trend	3.2871 *	1.2364 *	1.4371 *
Space-Time Trend	1.1108 *	1.0402 *	1.0315 *

* indicates effects for which the Relative Risk excludes one for parameter estimate

Figures

Figure 1: Visual Depiction of the Temporal and Spatial Relationships between Census Tracts

Figure 2: Bayesian Relative Risk and 95% Credible Interval Estimates for Models of Child Maltreatment Referrals, Substantiations, and Foster Care Entries to Drug Possessions

Figure 3: Bayesian Relative Risk and 95% Credible Interval Estimates for Models of Child Maltreatment Referrals, Substantiations, and Foster Care Entries to Drug Sales





