ALCOHOL OUTLETS AND CHILD MALTREATMENT: MODERATING EFFECT OF ACCESSIBILITY TO COMMUNITY PREVENTION AND TREATMENT RESOURCES

By

CORY MICHAEL MORTON

A Dissertation submitted to the Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Graduate Program in Social Work

written under the direction of

N. Andrew Peterson, PhD

and approved by

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New Brunswick, NJ

October 2012

ABSTRACT OF THE DISSERTATION

Alcohol Outlets and Child Maltreatment: Moderating Effect of Accessibility to Community Prevention and Treatment Resources

By CORY MICHAEL MORTON

Dissertation Director:

N. Andrew Peterson, Ph.D.

This study considered the unique impact neighborhoods have in influencing rates of child maltreatment and a specific primary prevention strategy that may be identified in the built environment. Over the past 30 years, researchers have identified specific elements of a neighborhood's structure that impact child maltreatment. The emphasis of these studies has been the identification of socioeconomic risk factors that are associated with higher rates of child maltreatment in communities. More recently, there has been growing recognition that the distribution of alcohol outlets is related to child maltreatment. Researchers have shown that those areas with higher density of alcohol outlets also tend to have corresponding higher rates of child maltreatment. No study to date, however, has tested the effects of protective factors that might attenuate the negative influence of socioeconomics and alcohol outlet density on child maltreatment rates. Recognizing that substance abuse has long been a major contributor to all forms of child maltreatment, this study extends prior research by testing both risk and protective features of neighborhoods' built environments that may be either risk or protective factors for child maltreatment. This study contributes to the literature by testing the moderating effect of one potential protective factor, the density of substance abuse prevention and treatment facilities in a community, on the relationship between alcohol outlet density and rates of child maltreatment. Using a cross-sectional design, the study utilized data from the New Jersey Department of Children and Families' Bergen County child maltreatment reports, New Jersey Division of Alcoholic Beverage Control listing of alcohol-selling retailers, New Jersey Division of Addiction Services listing of licensed substance abuse providers, Bergen County Center for Alcohol and Drug Resources' listing of substance abuse prevention and treatment facilities, and the United States Census. Findings indicate child maltreatment rates are higher in impoverished and unstable neighborhoods and those with greater alcohol outlet density. Additionally, neighborhoods with easily accessed substance abuse prevention and treatment facilities had lower rates of child maltreatment. The study findings highlight the relevance of applying primary prevention approaches and multi-sector collaboration to reduce child maltreatment.

Acknowledgements

I would like to extend fond thanks to all the members of my dissertation committee. First and foremost, I would like to thank my dissertation chair and faculty mentor, Dr. N. Andrew Peterson, for his unflappable patience and encouragement to complete this dissertation and for graciously including me on many research projects that have enabled me to intertwine the two main topics of this dissertation. Dr. Cassandra Simmel for guidance in this and other projects, including her tireless efforts to secure an internship for me with New Jersey's Department of Children and Families to get a behind the curtain view of state administered child welfare information systems. Dr. Raymond Sanchez-Mayers, who was coincidentally auditing the first course I was taking in Geographic Information Systems, for supporting and taking interest in my on-going spatial development. Dr. Richard L. Edwards for taking time from his extremely busy schedule as Dean of the School of Social Work at Rutgers and then as Interim Vice President for Academic Affairs to not only provide guidance for this dissertation but to impart useful professional wisdom and actively network his students to social work institutions around the globe. Dr. Claudia Coulton whose work got me interested in applying spatial reasoning to child maltreatment prevention for agreeing to participate on this committee and providing helpful guidance in its realization.

I would like to extend thanks and gratitude to Dr. Allison Blake, Commissioner of the New Jersey Department of Children and Families, for supporting my research interests when I was a research assistant at the Institute for Families and for facilitating the acquisition of the child maltreatment data used in this dissertation.

I would like to thank Dr. Allison Zippay, Director of the Doctoral Program at Rutgers' School of Social Work, for her dedication to the students she supports and shepherds through the process of obtaining a doctorate in Social Work.

I would also like to thank my parents, Mike and Kay Morton, for their love and support through my 24 years of schooling. It doesn't end here.

Lastly, I would like to thank Dr. Kelly Morton for facilitating my absence on weekends to complete the analysis and writing of this dissertation and she and my daughter Willa for being joyful and irresistibly-lovable people to come home to after hours spent in the confines of libraries across New Jersey and Manhattan.

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Introduction

Preventing child maltreatment continues to pose a difficult problem for researchers and practitioners. Research and interventions that identify and address risk and protective factors for child maltreatment may result in not only reduced harm to children, but also less financial costs that are incurred once a child enters the child welfare system. Since the enactment of the Child Abuse Prevention and Treatment Act (CAPTA) of 1974 formalized the need to coordinate prevention efforts nationwide, child welfare professionals and policy makers have applied a variety of strategies to keep children free of harm. Beginning with public awareness campaigns and mandatory reporting requirements for child maltreatment, prevention efforts have evolved from a focus on reducing harm to children once they come to the attention of child protection agencies to include a range of services that emphasize preventing child maltreatment before it occurs.

These strategies fall under one of three levels: primary (initiatives aimed at the general population), secondary (initiatives for at-risk groups), or tertiary (initiatives meant to prevent maltreatment from re-occurring). Regardless of the focus, these prevention efforts have generally been limited to a focus on family or individual (i.e. parent) level interventions aimed at improving parent-child interactions, educating families, increasing formal and informal family support, or improving family home environments through home visitation (Daro & Donnelly, 2002; Stagner & Lansing, 2009). Although these approaches may be successful for individual families, there has been little empirical support for the success of these family- and individual-level interventions in reducing overall rates of child maltreatment (reviewed in Reynolds, Mathieson & Toptizes, 2009). These approaches are limited in that they ignore the environment of parent-child relations and how these factors may influence child maltreatment. In fact, the typical prevention strategy in the area of child maltreatment could be seen as reactive instead of proactive through its identification of at-risk families, reacting to circumstances rather than changing their determinants (Jack & Gill, 2010). These strategies focus on the consequences of living in a socially disordered or economically disadvantaged community rather than building the community in a way that supports child well-being.

Focusing prevention efforts at the family level may also be limited because any achieved change with an individual family fails to address the rate at which new children and families enter the at-risk category. Conversely, efforts rooted at the community-level focus on the population as a whole and seek to permanently alter the environment, rooting out the structural determinants of behavior and altering that structure to promote pro-social behavior (Yacoubian, 2007). This study considers how primary prevention strategies can be specifically targeted to features of a neighborhood's built environment to reduce rates of child maltreatment. The built environment refers to the structure of a community in terms of the spatial distribution of road networks, retail activities, and the overall infrastructure of an area.

Neighborhoods play a unique role in influencing rates of child maltreatment and specific primary prevention features may be identified in their built environment. Over the past 30 years, there has been growing recognition that neighborhood structure impacts child maltreatment, particularly through socioeconomic factors (Coulton, Crampton, Irwin, Spilsbury & Korbin 2007). Additionally, a neighborhood's substance use environment, as evidenced by the density and distribution of alcohol-retailing outlets, has been linked to increased rates of child maltreatment (Freisthler, Merritt & LaScala, 2006). These findings suggest changes in the structure of neighborhoods may change rates of child maltreatment, although there has been no investigation that seeks to identify features of a neighborhood's built environment that protect against child maltreatment. This study seeks to test one feature of a neighborhood's built environment hypothesized to protect against child maltreatment and specifically targets substance abuse, a perennial problem in child welfare.

Background

Defining Child Maltreatment

The federal government established broad definitions of child maltreatment in the CAPTA (1974) legislation, which has been reauthorized several times, most recently in the Keeping Children and Families Safe Act (KCFSA) of 2003. The definition contains two parts and broadly defines child maltreatment as "any recent act or failure to act on the part of a parent or caretaker which results in death, serious physical or emotional harm, sexual abuse or exploitation or an act or failure to act which presents an imminent risk of serious harm" (USDHHS, 2008, p.2). Child maltreatment is then broken down into the different forms it may take including physical abuse, emotional abuse, sexual abuse, neglect, or abandonment. Child maltreatment that involves abuse (i.e., physically, sexually, emotionally, or psychologically inflicting harm on a child) is considered a violation of commission. The parent or caregiver has actively done something, whether intentional or not, to inflict damage to the child. Neglect, on the other hand, is a violation of omission where the parent has failed to provide for the child's basic needs in some way whether it be physical/environmental, medical, or educational (USDHHS, 2008). These actions can be a failure to provide adequate food in the home, to provide medical care when needed, or to ensure a child attends school regularly.

Measuring Child Maltreatment Incidence and Prevalence

Measuring the incidence and prevalence of child maltreatment in the United States is difficult as many incidents of child abuse or neglect are never reported and definitions of abuse and neglect are inconsistent across states (Fallon, Trocme, Fluke, MacLaurin, Tonmyr & Yuan, 2010). Several strategies have been employed to measure or estimate the prevalence of child maltreatment in the U. S. including analysis of administrative data; nationally representative, self-report surveys of children and families; and surveys of child welfare and mental health professionals. The following estimates present the different findings of these three types of prevalence or incidence measures.

The National Longitudinal Study of Adolescent Health (Add Health) is a nationally representative, longitudinal survey of children and adolescents conducted over three waves: 1994-1995, 1996, and 2001-2002. Retrospective prevalence rates were established using the 10,828 respondents who participated in all three waves of the Add Health study, whose ages ranged from 17-26 (Hussey, Chang & Kotch, 2006). It is important to note participants were not necessarily involved with child welfare services and the sampling frame was intended to capture the general population of children and adolescents in the U. S. In a series of questions, participants were asked to recall whether they experienced abuse or neglect by the time they were in the 6th grade, and the youth were directed to indicate the frequency of occurrence where the options were: never, once, twice, three or more times. Findings from the study of Add Health data revealed the following prevalence rates by type of abuse or neglect when using the most liberal criteria (maltreatment event occurred at least one time before 6th grade): supervisory neglect (child left alone without adult supervision), 41.5%; physical assault, 28.4%; physical neglect (caregiver did not meet child’s basic needs), 11.8%; contact sexual abuse, 4.5% (Hussey, Chang & Kotch, 2006). Using the more stringent measure of the event occurring 3 or more times, the prevalence rates drop considerably, supervisory neglect becomes 19.1%; physical assault 14.2%, and physical neglect 5.0% (Hussey, Chang & Kotch, 2006).

The Fourth National Incidence Study of Child Abuse and Neglect (NIS-4) surveys community professionals and includes children who have come to the attention of Child Protection Services (CPS) as well as those that have not (Sedlak, Mattenburg, Basena, Petta, McPherson, Greene & Li, 2010). NIS-4 uses a multi-stage sampling procedure to establish a nationally representative sample of professionals that would regularly come in contact with children and families and thus be sentinels for the identification of child maltreatment. The sampling procedure included 122 counties in the U. S. stratified by region, level of urbanization, crime rates, number of single, female-headed households, and rates of CPS case substantiation. From the sampled counties, the NIS-4 identified local sentinel agencies including 126 CPS agencies and 1,524 professional agencies including law enforcement, juvenile justice, public health, public housing, hospitals, runaway shelters, domestic violence shelters, day care centers, schools and other social service and health agencies. The NIS-4 used retrospective data from CPS agencies and prospective data from 11,321 individuals sampled through the sentinel agencies. These reports were combined and unduplicated to construct national estimates of child abuse and neglect. According to NIS-4, from 2005-2006, 1.25 million children experienced some form of child maltreatment, translating to 1 out of 58 children in the United States. Additionally, the NIS-4 established maltreatment rates for the different categories of child abuse and neglect where 4.4 children out of 1000 were physically abused; 1.8/1000 were sexually abused; 2.0/1000 were emotionally abused; 4.0/1000 physically neglected; 2.6/1000 emotionally neglected; and 4.9/1000 educationally neglected (Sedlak, *et al.*, 2010).

Lastly, the National Child Abuse and Neglect Data System (NCANDS) collects and analyzes data voluntarily submitted by public CPS agencies to the federal government in response to the CAPTA/KCFSA legislation. NCANDS reports on an annual basis how many children have been reported as victims of child maltreatment and what the case decision was for each report (U.S. Department of Health and Human Services, 2010). In 2008, CPS agencies received 3.3 million reports of child abuse and neglect involving nearly 6 million children and of those, 1.5 million were investigated by CPS and 772,000 were found to be victims of child abuse or neglect (USDHHS, 2010). Among those children categorized as victims of child maltreatment in 2008, 71% experienced some form of neglect, 16.1% were physically abused, 9.1 percent were sexually abused, 7.3% were psychologically maltreated and 2.2% were medically neglected (USDHHS, 2010). Taken together, these numbers show a large number of children are experiencing some form of child maltreatment.

Child maltreatment incidence and prevalence rates are difficult to establish as different forms of surveillance yield different estimates. The official reports of child maltreatment collected by child welfare agencies show the lowest incidence rates while estimates from nationally representative surveys of children and child service professionals estimate child maltreatment impacts a broad range of children in the U. S. (Hussey, Chang & Kotch, 2006; Sedlak, *et al.*, 2010; USDHHS, 2010). These estimates may be hard to compare as their methodology is so divergent (e.g., NCANDS uses administrative data while the NIS-4 uses surveys with a broad range of professionals), but the constructed incidence rates of maltreatment are fairly different. NIS-4 established child maltreatment as occurring to 17.1 per 1000 children in the U. S. while NCANDS establishes a rate of 10.3 per 1000. While there is not a consensus on incidence or prevalence rates of child maltreatment, there is agreement that the actual extent of child abuse and neglect is unknown (Fallon, *et al.*, 2010). This is because incidence and prevalence studies are limited by what is known to the community, what is kept hidden cannot be measured.

Regardless of these limitations and the differences in methodology, child maltreatment continues to be a serious issue that calls for new strategies to be employed in its prevention. After dramatic reductions in the rates of child maltreatment rates from 1993 until 2004, they have remained relatively stable since then, with only a 2% reduction in child victimization rates from 2004-2008 (Finkelhor & Jones, 2006; USDHHS, 2008). This stagnation in the child maltreatment rate suggests that family- and individual-level interventions could benefit from supportive strategies to prevent child maltreatment. Interventions that focus on the family could benefit from implementing environmental change to build communities in a way that encourages positive choices and promotes child well-being. Research has increasingly shown the importance of neighborhoods in influencing child maltreatment and environmental change efforts could be targeted at an issue long linked to child maltreatment, substance abuse (Coulton, et al., 2007; Freisthler, Merritt & LaScala, 2006).

Child Maltreatment Correlates

Substance Abuse and Child Maltreatment

Parental substance abuse has long been recognized as a problem inextricably linked with child maltreatment, it is estimated that 40-80% of all children who come to the attention of child welfare agencies are living in homes with a substance abusing parent (Banks & Boehm, 2001; Besinger, Garland, Litrownik & Landsverk, 1999; Young, Boles & Otero, 2007). Of those substance abusing parents, alcohol has been identified as the overwhelming primary problem (Young, Boles & Otero, 2007). Children who come to the attention of child welfare agencies because of parental alcohol or drug use are more likely to have their case substantiated than those without parental substance abuse issues, indicating a greater severity of abuse or neglect and greater costs incurred by the child welfare agencies as they work with families (Sun, Shillington, Hohman & Jones, 2001). These children are also more likely to come to the attention of child welfare agencies at a younger age, making early intervention and prevention efforts important (Semidei, Radel, Nolan, 2001).

Substance abuse treatment has also been identified as problematic for clients of the child welfare system (Rockhill, Green & Newton-Curtis, 2008). There are problems both in the availability of and access to substance abuse treatment. While estimates place substance abuse as one of the top issues in child welfare, child welfare agencies are only able to provide substance abuse treatment services to one-third of this population with the others waiting for up to twelve months for treatment (Banks & Boehm, 2001; Karoll & Poertner, 2003). In the context of reduced timeframes for achieving permanency, the ability to access treatment is of paramount concern. Additionally, community substance abuse services are often not organized in a way to ensure child welfare client participation due to inaccessibility (e.g. not convenient to public transportation) (Semidi, Radel & Nolan, 2001). Jacobson (2004) referred to this problem as the travel burden, or the difficulty experienced when neighborhood geography places an extreme distance between one's home locale and the treatment service. If it is difficult to access services, individuals may be less likely to engage with service providers to start treatment for substance abuse problems or continue in treatment when the travel burden outstrips an individual's tolerance for the search costs incurred.

Accessibility to treatment is important in child welfare services because when substance abuse treatment is successful, the permanency outcomes are generally positive. Green, Rockhill, and Furrer (2006, 2007) found that among women with children in foster care because of maternal substance abuse, those who completed substance abuse treatment programs had children who spent less time in foster care and were more likely to be reunified with their families. Ease of access to substance abuse treatment has also been associated with completion of a substance abuse treatment episode. Marsh, D'Aunno and Smith (2000) found mothers who were provided transportation to treatment were more likely to refrain from substance use than those who had more difficulty accessing treatment due to structural and logistical constraints. Reducing the logistical barriers to treatment is especially important for child welfare clients who may be limited by poverty in terms of their mobility and reliance on public systems of transportation (Rockhill, Green & Newton-Curtis, 2008). While this research takes a tertiary prevention focus, interventions that make substance abuse treatment more accessible to families may also serve to prevent child maltreatment before it occurs. As accessibility to treatment has been cited within child welfare services as an important predictor of treatment success, the ability to increase access to substance abuse prevention facilities in the community may serve to decrease substance abuse as a co-morbid factor in child maltreatment episodes.

Neighborhood Effects on Child Maltreatment

Over the last 30 years there has been growing recognition that particular neighborhood characteristics may be considered risk factors for child maltreatment. The ability to track rates of child maltreatment at a community or neighborhood level has been a relatively recent phenomenon as efforts to systematically report the occurrence of maltreatment began in earnest after the CAPTA legislation in the 1970's. The combination of federally-mandated child maltreatment data collection and theoretical advances allowed researchers to begin to recognize maltreatment as a community problem both in terms of its prevalence and its origin (Zuravin, 1989; Zuravin & Taylor, 1987). This recognition followed closely Bronfenbrenner's (1979) seminal publication outlining the precepts of the ecological model and challenging researchers to re-conceptualize how they approached and thought about social problems. The focus on ecological determinants of child maltreatment was also a response to the criticism of viewing child maltreatment as an individual-level or dyadic pathology alone (Gelles, 1973).

James Garbarino (1976) first investigated the ecological correlates of child maltreatment by investigating the child maltreatment rates in New York State's 62 counties and found a lack of economic and educational resources were strongly related to increased county-level rates of child maltreatment. From there, findings generally supported the assertion that socioeconomic factors in the environment (unemployment rate, poverty rate, income) are determinants of child and family interactions, including rates of child maltreatment (Deccio, Horner & Wilson, 1994; Garbarino & Crouter, 1978; Garbarino & Kostelny, 1992; Molnar, Buka, Brennan, Holton & Earls, 2003; Spearly & Lauderdale, 1983; Young & Gately, 1988; Zuravin, 1986; Zuravin & Taylor, 1987). While these early investigations showed support for the new ecological thinking in child maltreatment research, they suffered from the fact that measurement of the constructs was inconsistent and presentation of significant findings was inadequate. How researchers defined a neighborhood included aggregations at the county, metropolitan statistical area, zip code, city, and census tract level, and statistical significance was often not reported for findings, making interpretation difficult (reviewed in Zuravin, 1989).

With the advent of more sophisticated statistical techniques and the development of geographic information systems, more recent work has been able to use smaller levels of geographic aggregation that more validly approximate neighborhood boundaries and model the relationships therein. The way that researchers have operationalized and measured neighborhood and the indicators used to represent structural factors has also been more consistent. This has allowed for a more nuanced specification of socioeconomic and structural risk factors for child maltreatment. This research has established clear linkages between high rates of poverty, residential instability, child care burden, and drug and alcohol availability to higher rates of child maltreatment (Coulton, et al., 2007).

Poverty. Impoverished neighborhoods have been consistently linked with high rates of child maltreatment (Coulton, Korbin & Su, 1999; Drake and Pandey, 1996; Freisthler, 2004; Paulsen, 2003). Rather than use economic indicators of poverty alone, researchers have utilized a variety of U. S. Census indicators to proxy not only the economic dimension of poverty but the structural and demographic as well. Using indicators from the U. S. Census, Coulton and her colleagues utilized principal components analysis to reveal the underlying dimensions of poverty in neighborhoods, finding percent single, female-headed households, percent living below the poverty line, percent unemployed, number of vacant housing units, 5 year population loss, and percent African American combined to represent an impoverished neighborhood. The researchers computed factor scores and related them to neighborhood-level rates of child maltreatment. They found an overall strong relationship between child maltreatment and poverty, and further analysis showed that poverty was an important predictor in both predominately African American and predominately European American neighborhoods (Coulton, Korbin, Su & Chow, 1995; Coulton, Korbin & Su, 1999; Korbin, Coulton, Chard, Platt-Houston & Su, 1998). Similarly, Freisthler, Bruce and Needel (2007) found neighborhood level measures of poverty were positively related to child maltreatment substantiation rates for African American, Hispanic, and white children.

Impoverished neighborhoods impact child maltreatment rates not only across different racial or ethnic profiles, but across child maltreatment types as well (Drake & Pandey, 1996; Freisthler, Midanik & Gruenewald, 2004). Using percentage of families living in poverty, Drake and Pandey (1996) found correlations between sexual abuse, physical abuse and child neglect. Freisthler, Midanik & Gruenewald (2004) found percentages of poverty to be related to child physical abuse and percentages of female-headed households, poverty, and unemployment to be related with child neglect. Living in poverty and its attendant consequences is a consistent predictor of all types of child maltreatment regardless of one's racial or ethnic group. Indeed, poverty has consistently been the best predictor of a family's chances for child welfare system involvement (Coulton, et al., 2007; Freisthler, Merritt & LaScala, 2006).

Residential instability. Researchers have also investigated the relationship between neighborhood residential instability and rates of child maltreatment. Stable neighborhoods are operationalized as those where residents have a long tenure, housing units are fully/mostly occupied and there is less movement in and out of the area. The relationship to rates of child maltreatment here has been weaker and less consistent for residential instability than that for impoverishment. Investigations have found mixed effects when using residential instability to predict overall higher rates of child maltreatment. Ernst (2001) found residential instability to be a positive, significant predictor when investigating an affluent county in Maryland, but Freisthler, et al. (2004) and Coulton, Korbin and Su (1999) did not find a relationship for neighborhoods in California and Ohio, respectively.

One possible explanation for these inconsistent findings may involve the racial background of neighborhood residents. Korbin, *et al.* (1998) found residential instability, which was operationalized as a factor score of the percentages of people who moved in the last five years, household tenure of less than 10 years, and households that moved in the last year, to be positively related to child maltreatment rates, but only in predominately European American neighborhoods, while Freisthler, Bruce and Needel (2007) found the percentage of residents who moved in the last 5 years to be negatively correlated to substantiation rates for African American children. In contrast to poverty, residential instability seems to be operating differently across racial groups and has not been a consistent predictor of child maltreatment rates.

Child care burden. Child care burden is defined as the “amount of adult supervision and resources that may be available for children in the community” (Coulton, et al., 1995, p. 1270). When children outnumber adults in areas and there is a lack of natural support networks (i.e. elderly residents), that child care burden may become stressful for parents. Child care burden suggests a breakdown in the structure of helping networks in a neighborhood where parents have few choices for help when it comes to caregiving as well as possible reservations about children being able to play freely in the neighborhood. If there are no neighborhood sentinels in the form of adult or elderly residents who can act as de facto guardians for the children in a neighborhood, the result is an increase in stress as parents and children are either in constant contact, children are left alone more frequently without adequate adult supervision, or parents must travel outside their community to obtain competent child care, incurring both financial and human costs.

Coulton and her colleagues operationalized child care burden by using a factor score representing the indicators of percent elderly, ratio of children to adults, and the ratio of males to females. Using this approach, child care burden was found to be positively related to overall rates of child maltreatment (Coulton, *et al.*, 1995; Coulton, Korbin & Su, 1999). When investigating child maltreatment reports separated by race, only predominately European American neighborhoods and substantiation rates for white children were found to have a positive relationship to child care burden (Freisthler, Bruce & Needel, 2007; Korbin, *et al.*, 1998). Child care burden has been less consistent in predicting rates of child maltreatment, suggesting it may operate differently for different forms of child maltreatment and among ethnic and racial groups.

Drug and alcohol availability. The substance use environment of a neighborhood has important consequences for rates of child maltreatment as well. Freisthler and her colleagues have conducted a series of studies on neighborhoods within 3 California counties to explore how the alcohol and drug availability, operationalized as the density of alcohol retailers and drug arrests in a neighborhood, was linked with increased rates of child maltreatment. For overall rates of child maltreatment, there was a positive relationship to the density of bars and drug crimes in neighborhoods (Freisthler, Needel & Gruenewald, 2005). Adding an additional bar per 1000 people in the population was found to increase rates of child maltreatment by 2.2 children per 1000 (Freisthler, 2004). When child maltreatment rates were examined by race, the number of off-premises (i.e. liquor stores) outlets per 1000 population had a positive relationship with the substantiation rates for African American children (Freisthler, Bruce & Needel, 2007).

Findings from these studies also show a differential effect for three kinds of alcohol outlets: bars, restaurants, and off-premises outlets (i.e. liquor stores) on child abuse and neglect. Off-premises outlet density was found to be positively related to rates of child physical abuse while density of bars was found to be positively related to rates of child neglect (Freisthler, Midanik & Gruenewald, 2004). This differential effect can be seen as operating in the following way: in neighborhoods with higher off-premises outlet density, the substance user is more likely to consume the alcohol in the home and thus be in physical proximity to the child victim, resulting in a greater likelihood of physical abuse. For neighborhoods with higher densities of bars, the substance user is more likely to consume the alcohol away from home and thus leave the child victim at home without supervision (Freisthler, Midanik & Gruenewald, 2004).

Neighborhood Effects on Child Maltreatment: Concluding Remarks

The above results have shown clear linkages between socioeconomic factors and features of a neighborhood's built environment as being related to child maltreatment. Higher poverty, fractured and unstable neighborhoods, an environment that places a burden on caregivers in terms of diminished social networks, and neighborhoods inundated with unhealthy retail all serve to influence greater rates of child maltreatment (Coulton, *et al.*, 1995; Ernst, 2001; Freisthler, 2004; Molnar, *et al.*, 2003; Paulsen, 2003). This research has been able to define with some consistency structural risk factors for child maltreatment. There is a need for replication of these studies, as the most rigorous designs have been limited to two regions of the country, the Western and Midwestern United States. Investigations in different regions of the country may illuminate what predictors are constant and what is variable according to region. What has not been considered is the identification of structural features of neighborhoods that are protective factors against higher rates of child maltreatment.

This study tested a hypothesized protective factor in the built environment of neighborhoods, the density of prevention and treatment facilities, henceforth referred to as prevention accessibility. Primary prevention in child maltreatment calls for targeted investment of limited resources. Substance abuse and child maltreatment are inextricably linked and the ability to intervene in ways that reduce rates of substance abuse will have benefits for child welfare services as well. In the last 20 years, researchers have just begun to establish the way in which particular features of a neighborhood's built environment are linked to increased rates of child maltreatment. The work on substance use environments has only been completed in California and more work is needed to establish the validity of these findings across different regions in the U.S. No work to date has looked at the potentially moderating mechanism that neighborhood access to substance abuse prevention and treatment activities plays in reducing rates of child maltreatment.

Theoretical Framework and Key Constructs

A foundation in the social-ecological framework is necessary when conducting child maltreatment prevention research as the focus must extend beyond the parent-child dyad, recognizing the unique impact community has on individual behavior. Over time, thinking about the etiology of child maltreatment developed from centering on individual-level conceptions of pathology to ecologically-bounded definitions of how the relationships and transactions individuals forge with their environment impact child maltreatment (Coulton, *et al.*, 2007; Gelles, 1973). Although child maltreatment was first viewed as a pathology of an individual (only deviant people abuse their children) and then as a pathology in the parent-child relationship (pattern of deviant relational styles leads to child maltreatment), the fully realized thinking on child maltreatment defines the behavior as merely a "point along a more general continuum of caregiver-child relations" (Garbarino, 1977, p.722). This perspective views child maltreatment as only quantitatively different from non-abusive situations, in that child maltreatment occurs when a confluence of factors converge to produce the behavior and not when a qualitatively different individual acts independently of societal norms (Garbarino, 1977). This is not to say that the individuals lack agency, only that individual-level descriptions of this behavior lack explanatory power and child maltreatment should be viewed in context of the broader society. The degree to which an individual's ecology or in this context, neighborhood structure, is supportive protect against degradations in social norms. When individuals are surrounded by stressful or unhealthy environments, the parent-child relationship is disrupted in a negative way, often resulting in some form of child maltreatment (Garbarino, 1976). Recognizing that communities and neighborhoods affect individuals and work to shape behavior, prevention research should seek out those features of the environment linked to child maltreatment, both risk and protective factors. Interventions could then be developed to promote healthy family functioning while reducing child maltreatment by focusing on the development of communities that promote child well-being.

In this study, routine activities theory and facets of economic theory (i.e. opportunity costs) are used as the explanatory frameworks of behavior in the context of one's ecology. Routine activities theory was developed by Lawrence Cohen and Marcus Felson (1979) and states a violation (child maltreatment) occurs only when the following three variables converge: a motivated offender (adult), a suitable target (child), and no effective guardian. The most salient point of routine activity theory is that an opportunity must exist before a violation can occur. In terms of an individual's daily activities, the routines an individual engages in present opportunities where violations are likely to occur. The focus then is on the act of violation, or event, and not on the offender's motivation (Anderson, Gilliland & Veneziano, 2009). The capacity of a motivated offender to commit a violation against a suitable target is also influenced by the organization of the community where the violation occurs (Cohen & Felson, 1979). The built environment (i.e. the spatial distribution of roads or retail) serves to make the commission of violations more likely by motivating offenders in terms of making certain choices easier (i.e. the availability of alcohol).

Cohen and Felson (1979) based their framework on violations that occur outside of the family context (i.e. murder, robbery committed by strangers) based on trends at the time showing Americans after World War II spent more time outside of the home and thus would come into contact with offenders away from where they lived or offenses would occur in their home while they were absent. However, this is also applicable to violations that occur within the family unit (Freisthler, Midanik & Gruenewald, 2004). It is important to note that at the time routine activity theory was being developed there was a possible neglect of child maltreatment/family violence because incidence and prevalence rates of these violations were not well established. In fact, it was not until 1974 that the call was given to establish national estimates of child maltreatment (Daro & Donnelly, 2002). The application of the theory to violations that occur within the family unit use the same elements as investigations into violations outside of the family unit.

Routine activity theory has been applied by mainly criminology researchers in relation to a range of victimization crimes including larceny, deviant sexual behavior, assaults, and property crimes as well as patterns of substance abuse (Anderson & Hughes, 2009; Burrow & Apel, 2008; Ekendahl, 2006; Jackson, Gilliland & Veneziano, 2006; Mustaine & Tewksbury, 1998). Spano and Freilich (2009), in a review of the conceptualization of routine activity theory call for applications that focus on violation against children as most of the work has been concentrated on adult-to-adult crime.

It is theorized that neighborhoods with higher density of alcohol outlets can facilitate motivated offenders by making it easier to obtain substances; furthermore, depending on the type of alcohol outlet that predominates a neighborhood, different offenses may occur. If a neighborhood has greater availability of off-premises outlets (i.e. liquor stores), then the substance user is more likely to come in physical contact with the suitable target (child) making acts of commission like physical abuse more likely. If, however, a neighborhood has greater availability of on-premises (i.e. bars) alcohol outlets, substance users are more likely to drink out of the home and stay out of the home for longer periods of time which may result in acts of omission like child neglect. Here the suitable target does not have to come in contact with the offender, the motivation to leave the home to drink, leaving the child without proper guardianship, is enough to influence an offense. Neighborhoods with higher densities of alcohol outlets are hypothesized to motivate offenders, making child maltreatment more likely. On the other hand, there are features of the built environment that may act to limit motivated offenders.

The presence of substance abuse prevention and treatment facilities in a neighborhood may work to limit motivated offenders by making access to treatment more convenient. In economic theory, reducing the search costs associated with utilizing a service increases its likelihood of use (Clarke, 1998). This is especially true in the case of services aimed at improving mental health as greater distance between the consumer and the facility reduces the chances of receiving treatment (Shannon, Bashshur & Lovett, 1986). Search or opportunity costs can be conceptualized as the time and effort it takes to access some product. Here, individuals living in neighborhoods with easy access to substance abuse prevention and treatment facilities are more likely to utilize their services while those who reside in treatment deserts are less likely to access treatment for substance abuse due to increased search cost. Reducing search costs for treatment accordingly reduces the number of motivated offenders in a neighborhood, and, in turn may reduce rates of child maltreatment. This idea has not been tested in relation to the primary prevention of child maltreatment; however, it has been shown that increased accessibility to substance abuse treatment services predicts family reunification and in turn could be considered a tertiary prevention strategy (Green, Rockhill, & Furrer, 2007).

The routine activities approach does not consider what motivations are present when a violation is committed and treats individuals as merely objects in space which is appropriate here as the methods do not consider an individual’s potential for child abuse or neglect, only the environmental conditions that influence higher rates of child maltreatment (Clarke & Felson, 1992). Rather, this study represents an investigation of how the spatial environment is affecting violations of commission or omission and how changes made in any one of the three necessary ingredients for a violation to occur: motivated offender, suitable target, or effective guardian makes it less likely for the violation to take place.

In this study, neighborhoods with high densities of alcohol outlets are hypothesized to increase the number of motivated offenders by either removing adults from the home thus leading to higher instances of child neglect or by having adults come back into the home to drink, leading to higher rates of physical abuse. The differential nature of child abuse versus child neglect calls for the conceptualization of different motivated offenders. For child abuse, physical contact is a precondition and thus parents must be in the home for it to occur. Therefore, it is hypothesized that greater densities of off-premises outlets increase the likelihood of child maltreatment occurring by placing the motivated offender in direct contact with the suitable target. On the other hand, child neglect requires the absence of care giving and here it is conceptualized as the physical absence of the parent. Neighborhoods with greater densities of on-premises outlets motivate the offender to be physically removed from the home, leading to greater instances of child neglect. What has not been considered in the literature is the identification of features of the built environment that act as protective factors against child maltreatment. These neighborhood features act to reduce the number of motivated offenders and this effect is thought to act across the different types of child maltreatment.

Neighborhoods with higher densities of prevention and treatment facilities (i.e., organizations engaged in prevention activities and licensed substance abuse treatment facilities) may act to reduce the number of motivated offenders by providing easy access to treatment and providing environmental cues to discourage alcohol abuse. When treatment is easily obtained and the presence of community prevention organizations acts to discourage drinking, the number of offenders is then reduced regardless of the density or distribution of alcohol outlets. Substance abuse treatment facilities are hypothesized to have a moderating effect on the relationship between alcohol outlets and child maltreatment by impacting and even disrupting the relationship between alcohol outlet density and the incidence of child maltreatment in neighborhoods where prevention and treatment facilities are present.

Finally, the theoretical framework must account for the fact that high rates of child maltreatment have been consistently located in impoverished neighborhoods as well as the fact that alcohol outlets are more likely to be located in these areas (Coulton, et al., 2007; Freisthler, Merritt & LaScala, 2006; Gorman, Speer, Gruenewald & Labouvie, 2001). Poor neighborhoods are structured in a way that concentrates disadvantage, leading to a lack of social control allowing for not only negative outcomes in terms of interpersonal violence but also the inundation of addictive retail that is not welcome in more affluent areas (Popova, Giesbrecht, Bekmuradov & Patra, 2009). This disadvantage has been characterized by the sociodemographic profile of an area where “race, family structure, and resource deprivation are ecologically knotted at the neighborhood level” (Sampson, 2008, p. 201). Disentangling that knot has been a difficult task for researchers and the question often arises whether a certain type of person is more likely to live in an impoverished area or whether community structure actually influences individual behavior. It may be that alcohol outlets are merely co-located in communities with historical problems of interpersonal violence because it is easier for retailers to open outlets where there is no organized community response to restrict the flood of addictive retail. The relationship between child maltreatment and alcohol availability could then be spurious as the character of poor neighborhoods alone may bear the responsibility for both. It becomes important to account for this explicitly through including indicators of community structure, namely the sociodemographic profile of neighborhoods, as control variables.

As applied to routine activities theory, the erosion of social control in impoverished neighborhoods and influx of retail outlets promoting poor choices leads to those who live in impoverished areas with more access to and daily contact with harmful substances. This study espouses the idea that community structure does play a role in influencing individual behavior. Here, that role is hypothesized to operate through the built environment of neighborhoods where individuals are motivated to commit child maltreatment violations because of the wide availability of alcohol and the alcohol environment directly affecting substance use (Gruenewald, Holder, Treno, 2003).

Research Questions

1. Is the neighborhood-level density of alcohol outlets associated with rates of child maltreatment, controlling for socioeconomic and demographic factors?
2. Is there a differential effect for the types of alcohol outlets [on-premises (i.e. bars) vs. off-premises (i.e. liquor stores)] on two types of child maltreatment: child neglect and physical abuse?
3. Does accessibility to neighborhood substance abuse prevention and treatment facilities moderate the relationship between alcohol outlet density and rates of child maltreatment?

Hypotheses

1. Higher levels of alcohol outlet density will be related with higher rates child maltreatment, controlling for socioeconomic and demographic factors.
2. Higher density of on-premises alcohol outlets will be related with higher rates of child maltreatment with the primary abuse category of child neglect, controlling for socioeconomic and demographic factors.
3. Higher density of off-premises alcohol outlets will be related with higher rates of child maltreatment with the primary abuse category of child physical abuse, controlling for socioeconomic and demographic factors.
4. A neighborhood's substance abuse prevention and treatment facility density will moderate the relationship between alcohol outlet density and child maltreatment. Easier access to substance abuse prevention and treatment facilities will change the relationship between alcohol outlet density and rates

of child maltreatment, controlling for socioeconomic and demographic factors. In areas with a high density of alcohol outlets, child maltreatment rates will be lower when there is easy access to substance abuse prevention and treatment facilities.

Research Methodology

Data for this study were drawn from five sources: (a) 2003 New Jersey Department of Children and Families (DCF) Bergen County child maltreatment report data, (b) 2003 New Jersey Division of Alcoholic Beverage Control (ABC) listing of alcohol-selling retailers, (c) New Jersey Division of Addiction Services (DAS) listing of licensed substance abuse providers active in 2003, (d) Bergen County Center for Alcohol and Drug Resources' (CADR) listing of substance abuse prevention and treatment facilities active in 2003, and (e) the 2000 United States Census. The DCF data provide information for all substantiated instances of child maltreatment; this reflects the information gathered when a child maltreatment report was phoned into the New Jersey CPS hotline. Information is recorded on primary type of abuse: physical abuse, neglect, or sexual abuse and the reporters give an address as to where the child maltreatment incident occurred. The ABC listing of alcohol retailers contains information about what type of license each retailer holds, either on-premises or off-premises, as well as the address where the alcohol outlet is located. The DAS and CADR data combine to create a listing of all licensed substance abuse treatment facilities and substance abuse prevention facilities in Bergen County, New Jersey and contains the address where the facility is located. Finally, the Census data were used to create demographic and socioeconomic profiles of the neighborhoods in Bergen County, New Jersey.

Bergen County, NJ was chosen as the site of this investigation for two reasons. First, Bergen County has a strong substance abuse prevention presence in the form of the CADR which has kept a record of the prevention and treatment activities within its borders through a treatment resource guide which was necessary for creating an index of the availability of those services. Secondly, Bergen County is a large, densely populated area with a mix of urban and suburban neighborhoods and a racially diverse population. It is also the most populous county in the state of New Jersey with nearly 900,000 residents and over 200,000 families counted in the 2000 Census.

The address for each substantiated child maltreatment report, alcohol outlet and substance abuse treatment or prevention facility was geocoded using ArcMap 10.0 (ESRI, 2010). Geocoding is a process used to place an address within the spatial plane where each location is assigned latitude and longitude coordinates based on their location in the network of streets. Once addresses are geocoded, they can be matched to U.S. Census-defined neighborhoods, combined with the socioeconomic and demographic profile of a neighborhood, and exported to a statistical package for analysis.

Unit of Measurement

This study sought to investigate neighborhood effects on child maltreatment with neighborhood as the unit of analysis. The construct of neighborhood has been differentially operationalized in the literature from administrative units to resident-defined boundaries; however, within the neighborhood effects literature, the most commonly relied on measures of neighborhood boundaries are based on U. S. Census administrative units (Messer, 2007; Nicotera, 2007; Sampson, Morenoff, Gannon-Rowley, 2002). The decision to use administrative units to define neighborhoods is largely a function of convenience as the availability of sociodemographic data are most often packaged at some pre-determined level of aggregation due to privacy concerns or the sheer size of the dataset if released at the individual-level (Reynolds, 1998). Using Census data is advantageous because the information is readily available and provide a good picture of the structure of neighborhood. The information is best used for structural indicators of neighborhoods, but the information is limited in that resident perception of neighborhood boundaries is often different from the boundaries established by the U. S. Census Bureau (Coulton, Korbin, Chan & Su, 2001; Leventhal & Brooks-Gunn, 2000; Nicotera, 2007; Spielman & Yoo, 2009). The levels of U. S. Census aggregation of concern for this analysis include the block group, tract, and zip code, listed in ascending order according to size. Block groups have anywhere from 300-3000 residents with the average number of residents being 1500 and are nested within census tracts, which have anywhere from 1500 to 8000 residents with the average number of residents being 3000 (US Census Bureau, 2002). Outside of this enumeration hierarchy are zip codes which are larger than both the block group and tract in land and population size but do not have formal, census-established population criteria (Lery, 2008; US Census Bureau, 2002).

The level of aggregation is important as the size of each type of neighborhood boundary directly affects both the reliability and validity of any statistical estimates. This issue is known as the modifiable areal unit problem (MAUP) and is the problem encountered when neighborhood boundaries are arbitrarily established leading to changes in statistical conclusions as one modifies the scale or shape of neighborhood boundaries (Aron, McCrowel, Moon, Yamnamo, Roark, Simmons, Tatanashvili & Drake, 2010; Foster & Hipp, 2011; Flowerdew, Manley & Sabel, 2008; Zhang, 2005). There are essentially two areas of concern with the MAUP, referred to as the zone problem and the scale problem. The zone problem deals with the fact that administrative units of neighborhoods do not represent neighborhoods very well as compared to the way residents perceive and define neighborhood boundaries (Coulton, Cook & Irwin, 2004; Lery, 2009, 2008; Leventhal & Brooks-Gunn, 2000; Nicotera, 2007; Spielman & Yoo, 2009). The arbitrariness of these administrative boundaries leads to spillover effects as residents' sphere of influence often crosses administrative neighborhood boundaries which leads to dependence among the units of measurement, violating the assumptions of most statistical tests (Lery, 2008). The scale problem refers to the issues that arise due to the differences in size among neighborhood boundary choices. When the level of aggregation is small (i.e. block group), reliability may be an issue if measuring rare events as the occurrence may be too rare to produce stable statistical estimates (Aron, et al., 2010). The strength of small units of analysis lies in the ability of neighborhood proxy areas to be relatively homogenous in terms of demographic and socioeconomic variables. If the level of aggregation is large (i.e. zip code) the units may be too heterogeneous to validly proxy a neighborhood. The goal is to use neighborhood boundaries that are reasonably homogenous while at the same time providing enough variability for the estimation of statistical models (Lery, 2009).

In spatial analysis, smaller units of analysis have generally shown to be better units of analysis when estimating the relationship between predictor and criterion variables. Studies investigating the relationship between alcohol outlet density and violent crime have shown smaller units of analysis (i.e. Census tracts and Census block groups) are more appropriate than larger units (i.e. Counties), showing more consistency across locales and among different analyses (Gorman, Speer, Gruenewald & Labouvie, 2001; Scribner, Cohen, Kaplan & Allen, 1999; Speer, Gorman, Labouvie & Ontkush, 1998). However, one study investigating the role of spatial scale in linking neighborhood structure and foster care entry risk found no major differences in strength of association between levels of aggregation including zip code, census tract, and census block group (Lery, 2008, 2009). It has been widely assumed; however, that using larger units of analysis (zip code, county) may bias statistical estimates, leading to an overestimation of relationships (Soobader, LeClere, Hadden & Maury, 2001). Using smaller units of analysis has been shown to be a more stringent measure, producing weaker effects, so if an effect is still present at a smaller unit of analysis, there can be more confidence in its validity (Garner & Raudenbush, 1991, p. 256). Emerging research in the area of child maltreatment has shown zip codes to produce reliable estimates of the relationship between poverty and child maltreatment as well as foster care entry risk (Aron, et al., 2010; Lery, 2008, 2009). These are important findings as the availability of data at the zip code level is more widespread and easier to use (i.e. the data are "prêt-a-porter" and do not require geocoding to render usable).

Attention to the specification of neighborhood boundaries is important as changes affect the composition of one's sample and the resulting relationships between predictor and criterion variables (Foster & Hipp, 2011). As neighborhood boundaries change, the sociodemographic composition changes as well, directly affecting the underlying structure of an area as aggregation changes. Furthermore, this issue has not been widely investigated in the area of child maltreatment and especially in terms of the relationship between neighborhood alcohol availability, substance abuse treatment and prevention activity, and child maltreatment. This study investigated the role of scale in neighborhood boundaries by comparing three levels of geographic aggregation in Bergen County, NJ: block group (N=791), tract (N= 163) and zip code (N=75).

Measures

The dependent variable for this analysis was the rate of substantiated child maltreatment reports per 1,000 children for each level of aggregation. From the DCF data, substantiated child maltreatment reports were separated based on the primary child maltreatment type and this analysis concentrated on overall child maltreatment, child neglect and physical abuse.

The independent variables consisted of measures of alcohol outlet density, substance abuse treatment facility density, and measures of community socioeconomics and demographics. Research that has investigated the relationship between alcohol outlet density and community violence or drinking behavior has measured density in a range of ways including population based, roadway based, and network distance measures (Gruenewald & Johnson, 2010; Freisthler, 2005; Schonlau, Scribner, Farley, Theall, Bluthethal, Scott & Cohen, 2008; Weitzman, Folkman, Folkman, Wechsler, 2003). Population based measures operationalize alcohol availability as the number of retailers per some number of residents for an area akin to a rate calculation (i.e. 3.6 outlets per 1000 residents) (Freisthler, Midanik & Grunewald, 2004; Scribner, MacKinnon & Dwyer, 1994); roadway based measures operationalize alcohol availability based on how frequently retailers are encountered in the street network of a community (i.e. 2.4 outlets per mile of roadway) (Gruenewald & Johnson, 2010); network density operationalizes alcohol availability as the distance from an individual's residence to the nearest retailer or the number of retailers contained in a walkable buffer around one's home (i.e. number of outlets with a .5 mile radius) (Schonlau, et al., 2008). While there exists a large variation in the measurement of alcohol outlet density there is not a consensus about which measure is most appropriate and no explicit comparisons have been made between the different density measures.

This study compared different measures of alcohol outlet density and prevention accessibility in order to ascertain which measure produced the best model fit and was most appropriate for each area under consideration. The density and accessibility measures included the number of outlets/facilities per 10km of roadway, the number of outlets/facilities per square mile, and the distance in miles from each neighborhood's center point to the nearest outlet/facility. Roadway and land area-based measures were favored here over population based measures. In areas with a dense population, like Bergen County, these measures may be more appropriate. Consider the following example: if there is an alcohol outlet on the first floor of a large, mixed-use building with 1000 residents, one assumes that all residents have equal access to the outlet. Using a population density measure would produce a small density value describing the residents' access to alcohol as relatively low; however, the roadway, distance, and land-based measures should produce a higher density statistic, indicating easier access to alcohol. To examine model fit, the Akaike Information Criterion (AIC) was used to judge which density/accessibility measure fit the data best. A reduction in the AIC value of 3 indicated better model fit (Burnham & Anderson, 2004; Fotheringham, Brunsdon & Charlton, 2002).

Finally, the measures of community disorganization found to be significant in other studies on neighborhood effects on child maltreatment and population characteristics unique to Bergen County, NJ were used as control variables (Coulton, *et al.*, 1995; Freisthler, 2004). These were taken from the 2000 U.S. Census and include: poverty rate, unemployment rate, percent vacant housing units, percent of people who moved from 1995-2000, percent of single female-headed households, child to adult ratio, male to female ratio, percent of population over 65 years of age, percent African American, percent Latino/Hispanic, percent Asian, percent immigrant population at each level of aggregation. The preceding control variables were chosen for one of two reasons: 1. They fit with previously established socioeconomic correlates to rates of child maltreatment discussed earlier along three axes: Poverty (poverty rate, unemployment rate, percent African American); Residential Instability (percent vacant housing units, percent of people who moved from 1995-2000); Child Care Burden (percent of single female-headed households, child to adult ratio, male to female ratio, percent of population over 65 years of age) and 2. The variables made up a significant portion of the Bergen County, NJ population and were therefore important in defining community structure (percent Asian, percent immigrant population). Bergen County has some of the highest concentrations of Korean Americans in the United States, of the top 10 municipalities in the U.S. in terms of percentage Korean American, 8 of them are located in Bergen County, accordingly, there are high percentages of immigrants in these areas

(Shorter, 2005). The preceding population demographics and measures of community disorganization were subjected to Principal Components Analysis with varimax rotation and the factor scores for the underlying structure were used in the regression equation. This method follows other work in the area of neighborhood effects on rates of child maltreatment (Coulton, *et al.*, 1995; Korbin, *et al.*, 1998; Ernst, 2001).

Analytic Strategy

The analytic strategy used Ordinary Least Squares (OLS) or Geographically Weighted Regression (GWR) to assess the relationship between predictor and criterion variables. This technique is most appropriate when considering data that is spatially ordered as one must address spatial autocorrelation. The problem of spatial autocorrelation "corresponds to what was once called the first law of geography: everything is related to everything else, but near things are more related than distant things" (Lee & Wong, 2001, p.78-79). For this analysis, it may be that not only are independent observations highly correlated (multicollinearity), but also observations can be influenced by their proximity in a spatial plane violating the assumption in regression that observations are independent. So, measures from neighborhoods that share a boundary may be highly correlated, introducing measurement error into the statistical test employed as relationships vary as a result of space (Cahill & Mulligan, 2007; Graif & Sampson, 2009). Failing to account for spatial autocorrelation in the statistical model can lead to both Type I and Type II errors. In a model with significant positive autocorrelation (adjacent neighborhoods are similar), Type I error is more likely and in a model with significant negative spatial autocorrelation (adjacent neighborhoods are dissimilar), Type II error is more likely (Freisthler, Lery, Gruenewald & Chow, 2006).

To assess the presence of significant spatial autocorrelation that would bias statistical estimates, a two-step process was conducted. First, the dependent variables were investigated to determine the level and statistical significance of spatial autocorrelation. This process produced the Moran's Index (Moran's I) statistic which is interpreted like a correlation coefficient: values range from -1 to 1 indicating neighboring areas are either perfectly dissimilar (negative spatial autocorrelation) or perfectly similar (positive spatial autocorrelation). Second, it is possible that the array of independent variables can explain away the spatial autocorrelation of the dependent variable, if present (Charlton & Fotheringham, 2009; Freisthler, Bruce & Needel, 2007; Griffith, 1988). Here, the residuals from the OLS regression model were analyzed and, again, Moran's I was assessed for significant findings. If the Moran value was significant in both accounts, spatial autocorrelation was controlled for in subsequent analysis. A significant Moran value indicated the need to move beyond the OLS analysis into analyses that control for a neighborhood's contiguity with other neighborhoods and the possibility of influence across boundaries. Analyses using spatial models to examine relationships use GWR, a form of Generalized Least Squares regression, to control for spatial autocorrelation (Fotheringham & Rogerson, 2009; Freisthler, 2004; Freisthler, Bruce & Needel, 2007; Freisthler, Needel & Gruenewald, 2005).

The regression analysis was conducted using the following steps: an OLS model was performed using ArcGIS 10 then both the values of the dependent variable and the residuals from the OLS analysis were subjected to spatial autocorrelational analysis to assess whether or not the units of observation were correlated with one another merely due to their proximity. A significant Moran's Index indicates that the residuals from an OLS model are spatially dependent, positive values indicate clustering of units while negative values indicate a dispersed pattern. Finding a significant Moran's I calls for the use of GWR to control for spatial dependence. A non-significant Moran's I indicates that the OLS model is sufficient for statistical estimates.

Another concern is the small area analysis problem (hetereoskedasticity) where areas with exceedingly small populations are given the same weight in the regression equation as areas with large populations. An area with a total population of 15 children who all happen to have substantiated child maltreatment reports would have a child maltreatment rate of 100 percent, if those same 15 children lived in an area with a total child population of 100, the rate would only be 15 percent. The sensitivity of rate calculation to population size therefore has to be controlled. To control for this, each unit of observation was weighted by the square root of the child population for that area (Freisthler, 2004; Freisthler, Needel & Gruenewald, 2005). Lastly, the analysis was sensitive to the problem of multicollinearity, the fact that many of the socioeconomic controls in the regression equation were highly correlated. To correct for this, data reduction strategies were employed to reduce the number of variables using principle components analysis. This follows previous research in the area of child maltreatment neighborhood effects research and allows for the identification of the underlying factor structure of the data (Coulton, *et al*, 1995; Ernst, 2001; Korbin, *et al.,* 1998). This study used ArcGIS 10 and SPSS (PASW) 19.0 to test the relationship between predictor and criterion variables, controlling for spatial autocorrelation, where present, and hetereoskedasticity.

The moderating effect of substance abuse prevention and treatment accessibility was tested following Baron and Kenney's (1986) conceptualization. Moderation is said to occur in the following way: one variable (X) influences a second variable (Y), in this case the density of alcohol outlets (X) and rates of child maltreatment (Y). Introducing a third variable (Z) that serves as a moderator, in this case prevention accessibility, changes the nature of the relationship between X and Y, by either reducing it to non-significance, amplifying the effect, or weakening the effect (Baron & Kenny, 1986; Coulton & Chow, 1993; Frazier, Tix & Baron, 2004; Magill, 2010). The moderator acts through its interaction with the predictor variable X in influencing the relationship to Y (see Figure 1.). The moderator model was tested through computing an interaction term that was entered in the regression equation, here the product of the alcohol outlet density measures and the prevention accessibility measure. Hierarchical regression was employed to lend support to the moderator model by examining the significance of the R^2 and F change in the model as the following sets of variables were stepped in: the sociodemographic controls, alcohol outlet density, substance abuse prevention accessibility, and the interaction between alcohol outlet density and prevention accessibility. Moderation is supported if each step in the hierarchical regression is significant. When a significant moderation effect was found to exist, post hoc examinations of the relationship between alcohol outlet density and child maltreatment were compared at different levels of prevention accessibility. To aid in interpretation, post hoc analyses of covariance (ANCOVA) were performed to illustrate the relationship between alcohol outlet density and child maltreatment at different levels of the prevention accessibility, controlling for the sociodemographic profile of neighborhoods. This follows public health research investigating moderator effects (Peterson, Lowe, Peterson, & Janz, 2006; Lachman & Weaver, 1998). In this study, it was hypothesized that mean child maltreatment rates in areas with high alcohol outlet density would be decreased by easily accessed community substance abuse prevention and treatment facilities.

The final analysis took the following steps for each level of aggregation (census block group, census tract, zip code):

1. Reduced the set of socioeconomic controls using PCA.
2. Weighted each unit of administrative area by the square root of its child population.
3. Conducted OLS regression with PCA factor scores, alcohol outlet accessibility/density, and treatment and prevention accessibility on rates of child maltreatment, neglect, and physical abuse, separately.
4. If alcohol outlet accessibility/density and the measure of substance abuse treatment and prevention facility accessibility/density were found significant, an interaction term of alcohol x prevention was stepped into the regression equation.
5. Tested for spatial autocorrelation using the Moran’s Index for the dependent variable values and the residuals of OLS regression.

6. If Moran's Index was significant, repeated steps 2 and 3 using GWR.
7. If a significant moderation effect was found, post hoc evaluations were conducted by using ANCOVA of the child maltreatment variables at different levels of the alcohol and prevention variables.

Power Analysis

Power analysis is an integral part of statistical analysis as it details the probability of correctly rejecting the hull hypothesis in consideration of one's research design parameters (Pagano, 2007). A priori or prospective power analyses are helpful when designing a study as they give an indication of how large one's sample size should be in order to validly detect relationships between predictor and criterion variables. A priori power analysis was conducted using G*Power3, a stand-alone program used to calculate necessary sample size based on one's statistical test (Faul, Erdfelder, Lang & Buchner, 2007). Power here was set at .90 (error probability of 1-β) for a random effects linear regression model with 6 predictor variables. To obtain this level of power, a sample size of at least 157 is necessary. Based on these parameters, this study has adequate statistical power to correctly reject the null hypothesis only if census block groups (N=811) or tracts (N=163) were used for the unit of analysis. The use of zip codes (N=81) resulted in low statistical power and unstable estimates.

Finally, when working with event data in an environmental context such as this, it is common to have frequency distributions with high degrees of positive skew, as the unit of analysis frequently has a count of zero (i.e. no occurrences of child maltreatment in a particular census block). For example, the distributions of the dependent variables were not normal and had a high positive skew. In order to account for the skewness of the data, the values were transformed in the regression equation using a Box-Cox transformation. This transformation is a power transformation, raising each observation to some power in order to achieve normality (Osborne, 2010). Box Cox transformations are different from other power-family transformations (e.g., log, square root transformations) in that, rather than picking an arbitrary value to use as the power to raise all values by, one is presented with a range of power transformations in order to choose the value that best normalizes the data (Allison, Gorman & Kucera, 1995). These values are known as lambda (λ) and the value of λ that best normalized the data was chosen as the transformation power which eliminated skew.

Results

Sensitivity Analyses

The set of socioeconomic controls, alcohol outlet density, and prevention accessibility were tested at each level of aggregation to ascertain whether one performed better than the others in terms of the stability or strength of the statistical estimates. Results for each level of aggregation are presented in the Appendix in Appendix Tables A1-A27. There were no major discrepancies between the different levels of aggregation, and results from the census tract are presented here to follow prior research in this area and as a mid-point for the three levels tested (Freisthler, Bruce & Needel, 2007; Freisthler, Midanik & Gruenewald, 2004; Ernst, 2001; Coulton, *et al.*, 1995).

Additional sensitivity analyses were performed in terms of choosing an alcohol outlet density measure. The AIC value was used to make the determination of best model fit. The alcohol outlet density measure that produced the lowest AIC value is presented here. The AIC values for each model are presented in the Appendix Tables A1-A27.

Descriptive Statistics

Descriptive statistics for each variable included in the analysis are presented in Table 1. These descriptive statistics are provided in the table at the each level of aggregation: census block group, census tract, and zip code. Here, I report the values for the census tract level of aggregation.

Child maltreatment. The mean overall child maltreatment rate for Bergen County, NJ was 3.97/1000 which is a bit higher than the child maltreatment rate of

3.9/1000 for New Jersey in 2003 (USDHHS, 2009). Figure 2 illustrates the spatial distribution along the 163 Census tracts in Bergen County of the tract-level maltreatment rate. These rates were broken into quartile groups for illustration purposes. The mean physical abuse rate was 2.55/1000 and mean child neglect rate was 1.23/1000. The spatial distribution for neglect and physical abuse is depicted in Figures 3 and 4, respectively. These three variables: child maltreatment rate, neglect rate, and physical abuse rate are the three criterion variables for this study and all carry an extreme positive skew with child maltreatment at 2.92, neglect at 2.85, and physical abuse at 2.87. In order to correct for this skew, a Box Cox transformation was applied to the variables achieving the following improvement in skew and normalizing the data: child maltreatment skew=.157 where λ=.10, neglect skew=.008 where λ=-2.0, and physical abuse skew=.487 where λ=.10. These transformed variables were then used as criterion variables in the regression equations.

Alcohol outlets. The mean alcohol outlet density for all types of alcohol outlets was 2.46 per 10km of roadway. Broken down by type of license, off-premises outlets had .62 per 10km of roadway and on-premises outlets had 1.84 per 10km of roadway. The spatial distribution of outlet density measured at the Census tract level is presented in Figure 5 (all outlets), Figure 6 (off-premises) and Figure 7 (on-premises). The mean number of alcohol outlets per square mile at the census tract level was 7.68 per sq. mile for all types, 2.03 per sq. mile for off-premises outlets, and 5.64 per sq. mile for on-premises outlets. The mean distance in miles from the center of each census tract to its nearest alcohol outlet was .31 miles for all types, .51 miles for off-premises outlets, and .34 miles for on-premises outlets.

Substance abuse treatment and prevention facilities. Community substance abuse prevention and treatment facilities had a mean density of .03 per 10km of roadway. The mean number of facilities per square mile at the census tract level was .09 and the mean distance was 1.39 miles to the nearest facility from each tract's center point. Two measures of prevention accessibility, number per 10km and number per square mile, did not have enough variability to be used in the regression equation, for both measures less than 5% of the census tracts had a value greater than 0. For this reason, the distance from each census tract's center point to the nearest treatment and prevention facility was used in the regression equation and the spatial distribution of prevention accessibility is presented in Figure 8. The distance from the center of each census tract in miles was divided into quartiles for illustration purposes.

Principal Components Analysis

Principal Components Analysis (PCA) with varimax rotation was conducted on the set of socioeconomic variables as a data reduction strategy to protect against the issue of multicollinearity. Results from the PCA at the census tract level are presented in Table 2[1].

At the census tract level (N=163), PCA revealed three underlying factors: Impoverishment/Residential Instability/Child Care Burden, Predominately African

[1] PCA results at the census block group and zip code levels of aggregation are presented in Appendix Tables A28 and A29.

American, and Young Male. These three factors explained 69% of the variance in the set of socioeconomic variables. Seven variables loaded onto the first factor, Impoverishment/Residential Instability/Child Care Burden: poverty rate, immigrant population, 5-year residential movement, percent Latino/Hispanic, percent single female-headed households, vacant housing units, child to adult ratio. Here, disadvantage seems concentrated in certain areas with the economic indicator of poverty status combining with residential movement and vacant housing to suggest capital disinvestment. Additionally, ethnic minorities and single female-headed households loaded onto this factor showing again the demographic correlates of concentrated poverty. The second factor at the census tract level, Predominately African American was characterized by high percentages of African American residents, high unemployment rate, and areas with low percentages of Asian residents. It is also important to note that single, female-headed households loaded fairly strongly here as well (.603 communality). The second factor hints at economic disadvantage as well, but is differentiated from the first by being predominately African American and having a very low immigrant population. Lastly, two variables loaded onto the third factor, Young and Male, where census tracts were characterized by low percentages of residents over 65 years of age and a high male to female ratio.

Effect of Alcohol Outlet Density and Substance Abuse Prevention Accessibility on Child Maltreatment Rates

Alcohol outlet density was used as an independent variable in an OLS regression model with overall child maltreatment rates as the dependent variable and the factor scores from the PCA used as control variables. Three measures of alcohol accessibility were compared for model fit, alcohol outlet density per 10km of roadway, number of alcohol outlets per square mile, and the distance in miles from the center point of each neighborhood unit to the nearest alcohol outlet or prevention facility. The alcohol outlet density measure with the best model fit as measured by the AIC is presented here.

At the census tract level of aggregation, alcohol outlet density measured as the number of outlets per 10km of roadway had the best model fit as evidenced by the lowest AIC value of 334.31 (see Appendix Tables A1-A27 for results for each density measure). Table 3 presents the OLS results for overall rates of child maltreatment. Impoverishment/Residential Instability/Child Care Burden, Predominately African American, Young and Male, the number of alcohol outlets per 10km of roadway, and prevention accessibility were all significantly positively related to rates of child maltreatment. The results of a hierarchical regression to support the moderator model for the interaction of alcohol outlet density and substance abuse treatment and prevention accessibility is seen in Table 4. R^2 and F change statistics were significant when the interaction term was stepped into the regression equation. While first order spatial autocorrelation was positive and significant (MI=.220, p<.001), the set of independent variables explained away the significant autocorrelation in the regression model where the Moran's I for the residuals from the OLS were negative and non-significant (MI=-.057, p=.279).

Post hoc tests of the moderator effect using ANCOVA were performed to further explore the interaction effect. For the post hoc analysis, alcohol outlet density was recoded into three equal groups: low, medium, and high density. Similarly, prevention accessibility was recoded into short, medium, and long distance categories. As in the regression analysis, the factor scores from the principal components analysis were used as controls/covariates. Figure 9 illustrates the post hoc analysis. In areas with low prevention accessibility (longer distance to nearest prevention and treatment facility), a significant difference in mean child maltreatment rates was found between tracts with low and high alcohol outlet density. In areas with the highest alcohol outlet density, child maltreatment rates were greatest in areas with long distance to prevention and treatment facilities.

Effect of Alcohol Outlet and Substance Abuse Prevention Accessibility on Child Neglect Rates

Alcohol outlet density/accessibility was used as an independent variable in an OLS regression model with rates of child neglect as the dependent variable and the factor scores from the PCA used as control variables. Three measures of alcohol accessibility were compared for model fit, alcohol outlet density per 10km of roadway, number of alcohol outlets per square mile, and the distance in miles from the center point of each neighborhood unit to the nearest alcohol outlet or prevention facility.

For rates of child neglect, on-premises alcohol outlet density measured as the number of on-premises outlets per 10km of roadway had the best model fit as evidenced by the lowest AIC value of -65.45 (see Appendix Tables A1-A27 for OLS results for each density measure). Table 5 presents the results for rates of child neglect. Impoverishment/Residential Instability/Child Care Burden, Predominately African

American, the number of on-premises alcohol outlets per 10km of roadway, and the distance to the nearest substance abuse prevention or treatment facility were significantly positively related to rates of child neglect. . The results of a hierarchical regression to support the moderator model for the interaction of alcohol outlet density and substance abuse treatment and prevention accessibility is seen in Table 6. R^2 and F change statistics were significant when the interaction term was stepped into the regression equation While first order spatial autocorrelation was positive and significant (MI=.11, $p<.05$), the set of independent variables explained away the significant autocorrelation in the regression model where the Moran's I for the residuals from the OLS were negative and non-significant (MI=.004, p=.843). The R^2 value indicates that the set of variables explain 19 percent of the variation in neighborhood rates of child neglect.

Post hoc tests of the moderator effect using ANCOVA were performed to examine the relationship between on-premises alcohol outlet density and child maltreatment for residents with low, medium, and high distances to the nearest substance abuse prevention and treatment facility. For the post hoc analysis, alcohol outlet density was recoded into three equal groups: low, medium, and high density. Similarly, prevention accessibility was recoded into short, medium, and high distance categories. As in the regression analysis, the factor scores from the principal components analysis were used as controls/covariates. Figure 10 illustrates the post hoc analysis. Rates of child neglect differed significantly for the different categories of prevention accessibility. In areas with low prevention accessibility (longer distance to nearest prevention and treatment facility), a significant difference in mean child neglect rates was found between tracts with low and high alcohol outlet density. In areas with low alcohol outlet density, child neglect rates were greater in communities with the lowest accessibility to substance abuse prevention and treatment facilities while areas with the easiest prevention accessibility had the lowest neglect rates. In areas with high alcohol outlet density, neglect rates were greatest in areas with the longest distance to the nearest substance abuse prevention and treatment facilities.

Effect of Alcohol Outlet and Substance Abuse Prevention Accessibility on Physical Abuse Rates

Alcohol outlet density/accessibility was used as an independent variable in an OLS regression model with physical abuse rates as the dependent variable and the factor scores from the PCA used as control variables. Three measures of alcohol accessibility were compared for model fit, alcohol outlet density per 10km of roadway, number of alcohol outlets per square mile, and the distance in miles from the center point of each neighborhood unit to the nearest alcohol outlet or prevention facility.

At the census tract level of aggregation, alcohol outlet accessibility measured as the number of off-premises alcohol outlets per square mile had the best model fit as evidenced by the lowest AIC value of 293.39 (see Appendix Tables A1-A27 for results for each density measure). Table 5 presents the results for rates of physical abuse. Impoverishment/Residential Instability/Child Care Burden, Predominately African American, and Young and male were all significantly positively related to rates of physical abuse. The number of alcohol outlets per square mile and the distance to the nearest substance abuse prevention or treatment facility were significantly negatively related to rates of physical abuse (i.e., *greater* numbers of outlets per square mile were related to *lower* rates of physical abuse and *greater* distance to substance abuse prevention and treatment facilities were related to *lower* rates of physical abuse). While first order spatial autocorrelation was positive and significant (MI=.19, p<.001), the set of independent variables explained away the significant autocorrelation in the regression model where the Moran's I for the residuals from the OLS were negative and non-significant (MI=-.-.028, *p*=.662), ruling out spatial dependence. The R^2 value indicates that the set of variables explain 36 percent of the variation in neighborhood rates of child neglect.

Discussion

This study utilized secondary data to test the relationship between an area's socioeconomics, access to alcohol, and community substance abuse treatment and prevention facilities to rates of child maltreatment, neglect, and physical abuse. Additionally, the study questioned whether the presence of community substance abuse treatment and prevention facilities attenuated the relationship between alcohol access and child maltreatment, child neglect, and physical abuse. Furthermore, the study sought to compare different conceptualizations of how alcohol accessibility is measured at a neighborhood level. Finally, the role of spatial scale was investigated and how different levels of aggregation, census block group, census tract, and zip code, impact the statistical estimates and conclusions.

Summary of Findings

Principal Components Analysis. The results from the principal components analysis confirm that local conditions dictate the underlying factor structure and analyses using this approach should be sensitive to the community factors that make an area unique. For instance, no other study on the relationship between neighborhood level demographics, socioeconomics, and rates of child maltreatment has used the percentages of Asians in their analysis. The fact that Bergen County has the highest concentration of Korean Americans in the country necessitated this variable being included in the PCA. The factor structure changed slightly at each level of aggregation and the results deviate markedly from other studies in this area that have mainly found socioeconomic variables to load onto three factors related to increased rates of child maltreatment:

Impoverishment, Residential Instability, and Child Care Burden (Coulton, et al., 2007; Ernst, 2001). The results for Bergen County did not conform to this particular three factor structure. At the census tract level, variables previously found to load separately onto the three factors first identified by Coulton and her colleagues, mostly loaded together onto one factor which represented economic disadvantage, residential instability and an environment where children may outweigh and overburden caregivers. The second factor at the tract level suggests neighborhoods that are predominately African American with a large amount of unemployed workers. It is interesting that contrary to prior work, high percentages of African American residents were not grouped with high levels of poverty. These results do suggest neighborhoods that are divided along racial and ethnic heritage lines. The third factor at the census tract level was characterized by neighborhoods that were young and had high ratios of males to females. Bergen County holds some peculiarities as compared to the geographic areas explored previously in this area (Coulton, et al., 2007; Ernst, 2001).

The results from the PCA analysis underscore the importance of spatial scale when defining neighborhoods. Each level of aggregation had its own peculiarities and the determination of the factor structure seems influenced by the size and scope of the spatial scale. While each level of aggregation had at least one factor that could be considered indicative of economic disadvantage, the level of aggregation influenced the racial and ethnic composition of what was considered connected to an impoverished neighborhood. Spatial scale also played a role in determining factor structure; at the census block group level there were 4 underlying factors while the census tract and zip code levels only had 3 underlying factors. As one moves from a coarse level of aggregation, like the zip code, to a fine level of aggregation, like the census block group, variation increases as reflected by the increased number of underlying factors and the fact that the percent of variance explained decreased from 73% at the zip code, to 69% at the census tract, to 63% at the census block group. Future investigations may benefit from exploratory factor analysis (EFA) rather than theory-based principal components analysis. EFA may allow for the exact specification of a neighborhood's sociodemographic profile which may be more useful for local child welfare professionals. There exists a tension between the desire for global estimates of population level indicators associated with child maltreatment and the ability to forecast locally what types of population change would assuage rates of child maltreatment. While these do not necessarily have to be in opposition, the results here show how local factors influence the PCA in a way that runs counter to others' work in this area.

Sensitivity analyses. One goal of this study was to investigate different measures of alcohol accessibility and whether any one measure produced better model fit as applied to child maltreatment. The AIC was used as the measure of goodness of fit. Smaller AIC values indicate a better fit of the data. When comparing models a reduction in the AIC value by 3 is generally considered a satisfactory improvement in model fit (Fotheringham, Brundson & Charlton, 2002). Comparisons between the measures of alcohol outlet density/accessibility have not been addressed to date in the research literature. Most have used a population-based measure to indicate accessibility, but that was eschewed here in favor of measures based on the physical environment and access as defined by physical availability. The tobacco outlet literature does provide a guide; however, as comparisons have been made between the density measure of number of outlets per 10km of roadway and the number of outlets per square mile with the authors finding important differences between the two in terms of their fit and performance, showing outlets per square mile fit the data best for an investigation in the state of Iowa (Sanchez Mayers, Wiggins, Fulghum & Peterson, 2011). The measures of alcohol accessibility here were the number of outlets per 10km of roadway, the number of outlets per square mile, and the distance from a neighborhood's center point and the nearest alcohol outlet. These three were compared at each level of aggregation to discern what measure best fit the data.

Results from the sensitivity analyses indicated no overall best measure of alcohol accessibility, but rather a change in terms of what fits the data best as the spatial scale changes. Land area here seems to dictate which measure is most appropriate. For the largest level of aggregation, the zip code, alcohol outlets per square mile performed best, while for the smaller units, census block group and tract, alcohol outlets per 10km of roadway performed best. However, it is important to note that none of the models achieved the -3 AIC change set as the criteria for a definitive better model fit (Charlton & Fotheringham, 2009). More work should be done in this area and accessibility indices could take into account public transportation and roadway features that serve to inhibit or induce access to alcohol.

Sociodemographics and child maltreatment. Overall, the strongest predictors of increased rates of child maltreatment, neglect, and physical abuse were impoverishment along with a concatenation of racial and ethnic minorities and measures of poverty or residential instability. This confirms what prior work in this area has found (Coulton, et al, 2007; Freisthler, Merritt & LaScala, 2006). Results here show, at the census tract level, predominately African American neighborhoods were the strongest predictor of increased rates of overall child maltreatment and child neglect rates which mirrors much of the literature on the disproportionate involvement of African American families with the child welfare system and poor outcomes in terms of child morbidity and mortality (Drake, Jolley, Lanier, Fluke, Barth & Jonson-Reid, 2011; Fluke, Yuan, Hedderson & Curtis, 2003; Morton, Ocasio & Simmel, 2011; U.S. Department of Health and Human Services, 2011). These neighborhoods also had high rates of unemployment and high percentages of single, female-headed households.

Neighborhoods characterized by poverty, residential instability, and child care burden were the second strongest predictor of increased rates of overall child maltreatment and neglect and the strongest predictor of increased rates of physical abuse. Again, this finding is confirmed by prior research; living in poverty and its attendant consequences is a consistent predictor of all types of child maltreatment (Coulton, et al, 2007; Freisthler, Merritt & LaScala, 2006). Lastly, neighborhoods characterized by a great number of male and younger residents was connected with increased overall rates of child maltreatment, but was a stronger predictor for increased rates of physical abuse. This is a novel finding in terms of the neighborhoods effects literature, but it does find support elsewhere. Some studies have found perpetrators of severe physical abuse to be predominately male (Naidoo, 2000; Ricci, Giantris, Merriam, Hodge & Doyle, 2003).

This could be an important finding in terms of needs assessment and program development to reduce the risk of physical abuse.

Alcohol access and child maltreatment. I hypothesized that neighborhoods with greater alcohol outlet densities would have correspondingly high rates of child maltreatment. Controlling for socioeconomic and demographic factors, this was found to be true. Those areas inundated with alcohol outlets of any kind had higher rates of overall child maltreatment. Secondly, I hypothesized there would be a differential effect on child neglect and child physical abuse based on the type of alcohol outlet that predominated an area. For neighborhoods with a higher density of on-premises alcohol outlets, I hypothesized a relationship to higher rates of child neglect. For neighborhoods with a higher density of off-premises alcohol outlets I hypothesized a relationship to higher rates child physical abuse. These were partially confirmed. For child neglect, it was found that rates of child neglect were significantly related to on-premises outlets only. Physical abuse was significantly related to off-premises outlets, but, surprisingly, the direction of the relationship for off-premises outlets was contrary to what was hypothesized. Neighborhoods with greater densities of off-premises outlets actually had lower rates of physical abuse. These findings are contrary to prior research for off-premises alcohol outlets but agree with prior work with on-premises alcohol outlets (Freisthler, Midanik & Gruenewald, 2004).

The counterintuitive findings for on-premises outlets may be related to how New Jersey licenses its alcohol retailers. Previous studies have been able to separate on-premises alcohol outlets into two main types: bars or restaurants. This research found higher rates of physical abuse to be linked to greater densities of bars only (Freisthler, Needel & Gruenewald, 2005). In New Jersey, the licenses are grouped by consumption (on-premises) and distribution (off-premises) only without making a distinction for bars versus restaurants in the consumption category. Neighborhoods with a preponderance of restaurants that serve alcohol are generally of a different character than those with a preponderance of bars. In the study referenced above, restaurants greatly outnumbered bars with a mean of 6.33 per 1000 residents in the former and .40 per 1000 in the latter. For this study, it could be that restaurants are outnumbering bars to a degree that masks any effect the presence of bars may bear on a neighborhood. It is also important to note that some of the on-premises outlets have a package provision, meaning patrons may purchase alcohol to take with them from the bar or restaurant. This is a small percentage of the overall on-premises outlets, roughly 9%, but future work in New Jersey could investigate this special category of on-premises outlets.

Substance abuse prevention and treatment facility access, alcohol density and child maltreatment. I hypothesized that access to community substance abuse prevention and treatment facilities would moderate the relationship between alcohol outlet density/accessibility and rates of child maltreatment. Specifically, the relationship between alcohol outlet density and child maltreatment would be a stronger among neighborhoods with less access to prevention and treatment facilities. Conversely, there would be a weak relationship between alcohol outlet density and child maltreatment among neighborhoods with greater access to prevention and treatment facilities. I tested this moderation effect for rates of overall child maltreatment, neglect, and physical abuse.

For overall child maltreatment, a moderation effect was found. Not only was a greater distance to the nearest substance abuse prevention and treatment resource related to higher rates of child maltreatment, but the interaction between alcohol outlet density and prevention and treatment access was significant as well. Neighborhoods with the greatest distance to prevention and treatment facilities and the highest alcohol outlet density had the highest rates of child maltreatment as well. Interestingly, neighborhoods with what was defined as medium access to prevention and treatment had the lowest rates of child maltreatment. This finding and may be indicative of desirable neighborhoods being those that are not too close to commercial activity but not too far from it either to seem remote or cut off from community resources.

Lower rates of child neglect were associated with easier access to community substance abuse prevention and treatment as well. Here a moderation effect was also found between the density of on-premises alcohol outlet density and prevention and treatment access was significant. Again, neighborhoods with the longest distance to prevention and treatment had higher rates of child maltreatment in both low and high areas of alcohol outlet density.

Limitations

This study is limited by its reliance on secondary data as well as its cross-sectional design. The child maltreatment indicators used were substantiated reports of child abuse and neglect. As such, they may not be indicative of what the true rates of child maltreatment are in the areas under investigation, they only include those families who were reported to CPS. Measuring child maltreatment has always been difficult and researchers are developing innovative ways to couple different sources of administrative data to compute child maltreatment rates that do not rely exclusively on CPS reports, retrospective surveys, or community sentinels. Recent work has combined child maltreatment reports with child fatality data to develop indices of child maltreatment (Putnam-Hornstein, 2011). Future research should continue to explore ways to present rates of child maltreatment that attempt to account for its hidden nature.

This study treated all alcohol retailers the same in that I considered risk to be distributed equally among the set of outlets. It may be that there are alcohol outlets in a neighborhood that are considered especially problematic in terms of crime or property damage occurring in and around them, compared to outlets that have little or no collateral damage associated with their location. Future research could identify problem alcohol outlets by connecting rates of alcohol-related crime occurring in close proximity and investigating whether a difference exists between good and bad outlets in terms of their relationship to child maltreatment.

This study relied on the physical location of alcohol retailers and substance abuse prevention and treatment facilities to make assumptions about the possible behavior of the individuals who reside nearby. The indicators of alcohol and prevention availability do not necessarily mean residents are purchasing and abusing alcohol, accessing the services of substance abuse professionals, or receiving prevention messaging. Future work could utilize multi-level modeling that couples survey data on individual drinking behavior and service use with community indicators of child maltreatment, alcohol access, and access to substance abuse prevention facilities. Research that can link individual behavior to increased access to either alcohol or prevention facilities will help close the gap in linking these attributes of the built environment to rates of child maltreatment. The inability to determine causality is also a limitation of this study. It is impossible to know whether drinking behavior was influenced by the easy access to alcohol or if those with alcohol problems are drawn to live in areas with easy access to alcohol. Accordingly, it is not known whether increased child maltreatment rates were caused by increased alcohol accessibility, conducting time-series designs that track the changing alcohol retail environment along with changes in rates of child maltreatment would be necessary to add weight to any causality argument.

Implications for Theory and Practice

The results from this study support a primary prevention approach to reducing child maltreatment through environmentally-focused interventions. This study adds to the existing literature confirming the importance of neighborhood structure in influencing rates of child maltreatment, abuse, and neglect. This is not only limited to the socioeconomic and demographic profile of an area, but also the study adds to evidence of the importance of the built environment, both for risk and protection. One concern here was the distribution of alcohol retail in a community and its relationship to increased rates of child maltreatment. The routine activities framework was partly supported here for child maltreatment and child neglect. For neglect, it could be possible that the neighborhood is structured is a way that makes it very easy to leave one’s home and drink, and in this study, neighborhoods with many on-premises alcohol outlets had correspondingly high rates of child neglect. Prevention strategies could investigate the possibility of limiting alcohol licenses in areas that are already saturated with alcohol retailers as a way to reduce the harms associated with alcohol abuse. Restricting the number or density of alcohol retail licenses is seen as a promising area and others have made the call to target alcohol outlet density as an environmentally-focused prevention goal (Campbell, *et al.*, 2007).

Additionally, the significant findings for substance abuse prevention and treatment facility access and the significant moderation effects also support a primary prevention approach in terms of democratizing access to substance abuse treatment. This may be an important protective factor against child maltreatment. Areas with easier access to prevention and treatment not only had lower rates of child maltreatment but also impacted the relationship between alcohol outlet density and overall child maltreatment and neglect. This type of strategy would not focus on those at risk of committing child abuse or those who had already become involved with the child welfare system. Rather, increasing access to substance abuse prevention and treatment targets the population as a whole to see change across systems. Primary prevention and especially environmentally-focused prevention are not familiar waters for the child welfare field. Its focus has traditionally been on providing services to families and not on organizing communities in a way that benefits child well-being. The ability to shift some resources from providing services to investing in communities in a way that builds capacity would take considerable partnership between governmental departments in terms of linking resources between health and human services, child welfare, mental health and addiction services, and alcoholic beverage control.

The last half century has seen great success using public health approaches to prevention in the fields of tobacco control and motor vehicle safety. The strategies employed in these prevention efforts may be modeled to child maltreatment prevention as there are direct analogues between them. Martin, Green, and Gielen (2007) argue for using the lessons from tobacco control and automobile injury control to inform child maltreatment prevention based on four similarities between the three areas: all involve a complex pattern of behaviors occurring outside the sight of health professionals and are resistant to individual level intervention; the time and effort spent to change the behaviors via individual level intervention is not equal to the compensation practitioners receive; all of the behaviors have environmental and behavioral antecedents that can be identified as intervention points; all three can leverage strong public support in terms of child protection (p.207). Some of the lessons learned from tobacco and automobile injury control that are particularly salient to this study are the need to "investigate varied…conceptual frameworks to identify new opportunities for effective intervention" and the "use of a multi-disciplinary, multi-sector approach" to prevention (Martin, Green, & Gielen, 2007, p. 215-217).

The routine activities conceptual framework offers a perspective that has rarely been applied to child maltreatment prevention. Results from this study evidence a linkage between a neighborhood's built environment and rates of child maltreatment, there was a connection between areas inundated with unhealthy retail and child maltreatment as well as accessibility to substance abuse prevention and treatment facilities. These findings suggest the physical layout of a community may impact behavior through the facilitation of drinking on one hand and prevention messaging or treatment on the other. The daily routines individuals engage in are impacted by what they encounter on the way and the built environment plays a part in helping or hindering choices one makes. Child maltreatment prevention work would benefit from thinking and research that supports the physical change of communities to support child well-being. In this study, easy access to prevention and treatment facilities in a neighborhood was connected to lower rates of child maltreatment even in the face of high densities of potentially addictive retail outlets. The ability to democratize substance abuse prevention and treatment would have people more likely to encounter prevention messaging in a community or engage more successfully in treatment.

Substance abuse and child maltreatment have long been recognized as two sides of a coin in the child welfare system, substance abuse is a major risk factor for system involvement and the successful completion of substance abuse treatment is frequently a required element in any consideration of a child's reunification with their parents (Karoll & Poertner, 2003; Young, Boles & Otero, 2007). Substance abuse treatment is important both before and after child maltreatment occurs as a primary and tertiary prevention strategy—primary, in that wide access to treatment is more likely to connect with families that would be at risk for child maltreatment and tertiary in the traditional sense of providing families with services after maltreatment has occurred. There exists a need for multi-disciplinary, multi-sector approaches to child maltreatment prevention that couples child welfare work with substance abuse prevention. This would require alliances between departments of family and children's services and substance abuse services at the governmental level and child welfare agencies and substance abuse prevention and treatment agencies at the local level. This is not a new idea. At the federal level, the United States Department of Health and Human Services created the National Center on Substance Abuse and Child Welfare (NCSACW) with funding from the Substance Abuse and Mental Health Services Administration's Center for Substance Abuse Treatment and the Administration on Children, Youth and Families, Children's Bureau's Office on Child Abuse and Neglect (USDHHS, n.d.). This initiative is meant to support state-level collaborations between systems of substance abuse services, child welfare, and family courts by providing technical assistance and disseminating knowledge on collaborative efforts. While this is a noble effort and a crucial first step in cross-systems collaboration, only about a quarter of states are involved with the NCASCW so far.

While the NCASCW takes on an approach that looks to increase the availability and quality of substance abuse and child welfare services, there are other opportunities for multi-sector approaches to child maltreatment prevention. Findings from this study indicated neighborhoods with high densities of alcohol outlets had correspondingly high rates of child maltreatment. Rather than focus on ensuring substance abuse prevention and treatment resources are widely available, prevention efforts could investigate making access to alcohol less available. Child welfare agencies could lend their support to existing substance abuse prevention efforts that use environmental strategies to prevent alcohol abuse. There has been very promising work in the reduction of excessive drinking through policy changes aimed at zoning and land use regulations to limit the physical availability of alcohol, in fact, these strategies are some of the most effective interventions for problem drinking (Sparks, Jernigan & Mosher, 2011). These strategies have limited the total number of retail licenses for alcohol, limited the days and hours alcohol is sold or increased the price of alcohol through taxation. Child welfare agencies could lend considerable support to substance abuse prevention agencies in terms of leveraging support for this type of policy change. Connecting the prevention of excessive drinking to the prevention of child abuse could open policy windows to limit the density of alcohol retailers in ways that substance abuse prevention agencies working alone could not.

The results from this study add to the evidence that access to services is an important determining factor in their use. For child welfare clients, reducing the logistical barriers to substance abuse treatment has been shown to increase the likelihood of positive permanency outcomes (Rockhill, Green & Newton-Curtis, 2008; Marsh, D'Aunno & Smith, 2000). Attention should be paid to the location of human service facilities as both a functional benefit and an ethical imperative. Impoverished communities are often over-looked and segregated from resources such as substance abuse prevention and treatment (Massey, 2004), locational strategies for these facilities should consider how to best diffuse the network of locations to reach communities in need. Community assessments should utilize GIS in order to locate areas considered treatment deserts and those historically segregated from quality services due to economic or racial attributes and engage community leaders in planning any extensions of service.

Directions for Future Research

Future research considering structural risk and protective factors for child maltreatment would be aided by the use of time-series designs to track the changing rates of child maltreatment as well as the alcohol retail environment and substance abuse prevention and treatment milieu. This would aid in the ability to make more definitive statements about the nature of the relationship between rates of child maltreatment and access to alcohol or prevention and treatment. The ability to combine CPS reports and substantiations of child maltreatment with other administrative databases that proxy child maltreatment (i.e., child fatality data) and survey data measuring child maltreatment potential could add further nuance to defining neighborhood rates of child abuse and neglect.

This study tested one protective factor found in a neighborhood, but there are others that could be investigated as well. A host of resources could be identified as supporting child well-being including available, safe play space, neighborhood civic organizations, churches, and other structural features of neighborhoods that function as barriers to child maltreatment and extend beyond the demographic and economic indicators of quality. Identifying the structural features of neighborhoods that protect against child maltreatment helps in the investigation of within-group differences for impoverished areas and may help shed light on ways to organize communities to build well-being beyond economics (Korbin, *et al.*, 1998). The ability to think creatively about what is a risk or protective factor for child maltreatment may broaden the potential for both investment and intervention strategies that seek to build strong communities.

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Tables

Table 1. Descriptive statistics of predictor and criterion variables for Bergen County, NJ

	Census Block Group (N=811)		Census Tract (N=163)		Zip Code (N=81)	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Child Maltreatment[1]						
Overall child maltreatment rate	4.25	7.50	3.97	4.06	4.07	8.26
Physical abuse rate	2.67	4.65	2.55	2.45	1.36	2.92
Child neglect rate	1.39	4.47	1.23	2.05	2.49	5.43
Socioeconomic Variables						
% in poverty	5.18	5.30	4.78	3.29	5.77	4.63
% unemployed	4.08	3.38	3.92	1.96	4.46	2.63
% vacant housing units	2.34	2.48	2.45	1.38	2.59	1.34
% 5 year residential movement	37.01	12.63	36.62	8.62	36.54	7.33
% single female-headed households	5.77	5.20	5.38	3.28	6.02	4.20
Child to adult ratio	.30	.11	.31	.07	.31	.07
Male to female ratio	.90	.22	.89	.06	.90	.05
% population over 65	15.33	6.29	15.09	3.50	14.39	3.34
% African American	4.70	1.17	4.67	10.92	4.71	10.23
% Asian	10.55	1.09	10.46	8.58	9.35	7.52
% Latino/Hispanic	10.67	1.05	10.01	8.56	13.42	14.85
% immigrant population	25.56	1.41	24.52	11.96	24.22	11.25
Alcohol Outlet Density[2]	.67	1.07	2.46	2.80	4.80	8.83
Off-premises outlet	.17	.41	.62	.77	.83	1.00

On-Premises outlet	.50	.85	1.84	2.27	3.97	8.66
Alcohol Outlets per square mile[3]	11.94	21.94	7.68	9.58	6.05	8.45
Off-premises outlet	3.19	8.42	2.03	2.87	1.49	2.28
On-premises outlet	8.75	17.13	5.64	7.46	4.56	6.62
Miles to nearest Alcohol Outlet[4]	.28	.22	.31	.28	.48	.62
Off-premises Outlet	.46	.35	.51	.41	.74	.77
On-premises Outlet	.30	.23	.34	.29	.53	.72
Substance Abuse Prevention						
Density[2]	.03	.20	.03	.14	.11	.30
Per square mile[3]	.45	2.81	.09	.45	.19	.56
Miles to nearest[4]	1.33	.88	1.39	.90	.52	.72

[1]Measured as number of substantiated incidents per 1000 children
[2]Measured as number of outlets per 10km of roadway
[3]Average number of outlets per square mile
[4]Distance in miles from centerpoint of each administrative boundary to nearest outlet

Table 2. Principal Components Analysis of socioeconomic variables at the census tract

Variable	Factor 1 Poverty, Residential Instability, Child Care Burden	Factor 2 Predominately African American	Factor 3 Young and Male
% immigrant population	**.905**	.075	.075
% poverty	**.828**	.218	.128
% 5-year residential movement	**.816**	.093	.208
Child to adult ratio	**-.714**	.009	.411
% Latino/Hispanic	**.709**	.384	.301
% single female headed households	**.625**	**.603**	.171
% vacant housing units	**.608**	.133	-.024
% African American	.215	**.767**	-.070
% Asian	.477	**-.643**	-.026
% unemployment	.558	**.581**	.164
% over 65 years of age	.012	-.227	**-.843**
Male to female ratio	.183	-.164	**.751**

Note: N=163. These 3 factors explained 69% of the variance in the set of variables.

Table 3. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities.

	Variables	Dependent variable: overall child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.059		-.057	
Socioeconomics		B	se	B	se
	Factor 1: Impoverishment, residential instability, child care burden	.288***	.010	.294***	.010
	Factor 2: Predominately African American	.383***	.009	.376***	.009
	Factor 3: Young male	.070***	.009	.067***	.009
Alcohol density					
	Outlet density per 10km	.022***		.022***	.007
Prevention and treatment access					
	Prevention and treatment distance	.020*	.010	.093***	.013
Interaction					
	Prevention and treatment density x alcohol outlet density			-.026***	.003

Model 1 R^2=.41, Model 2 R^2=.41
Model 1 AIC=336.16, Model 2 AIC=337.83
*p<.05, **p<.01, ***p<.001

Table 4. Hierarchical regression analysis of overall child maltreatment rates on socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities, and alcohol x prevention interaction term

Variables	Dependent variable: child maltreatment rate per 1000 children		
	R^2 change	*F* change	d.f.
Socioeconomic Controls	.402	1264.79***	3,160
Alcohol	.004	37.76***	4,159
Prevention	.000	3.94*	5,158
Alcohol x Prevention	.008	79.92***	6,157
Total equation			
R^2	.41		
Adjusted R^2	.41		

*p<.05, **p<.01, ***p<.001

Table 5. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities.

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.004		.003	
Socioeconomics		B	se	B	se
	Factor 1: Impoverishment, residential instability, child care burden	.044***	.003	.044 ***	.003
	Factor 2: Predominately African American	.075***	.003	.074***	.003
	Factor 3: Young male	.001	.003	.001	.003
Alcohol access					
	On-Premises density per 10km	.004***	.002	.008***	.002
	Off-premises density per 10km	-.004	.004		
Prevention and treatment access					
	Prevention accessibility	.024***	.003	.030***	.004
Interaction					
	Prevention and treatment density x on premises outlet density			-.003***	.001

Model 1 R^2=.19, Model 2 R^2=.19; Model 1 AIC=-65.45, Model 2 AIC=-65.49; *p<.05, p<.01, ***p<.001

Table 6. Hierarchical regression analysis of child neglect rates on socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities, and alcohol x prevention interaction term

Variables	Dependent variable: child neglect rate per 1000		
	R^2 change	*F* change	d.f.
Socioeconomic Controls	.179	409.496***	3,160
Alcohol	.002	7.007**	5,158
Prevention	.010	67.655***	6,157
Alcohol x Prevention	.002	6.524**	7,156
Total equation			
R^2	.19		
Adjusted R^2	.19		

*p<.05, **p<.01, ***p<.001

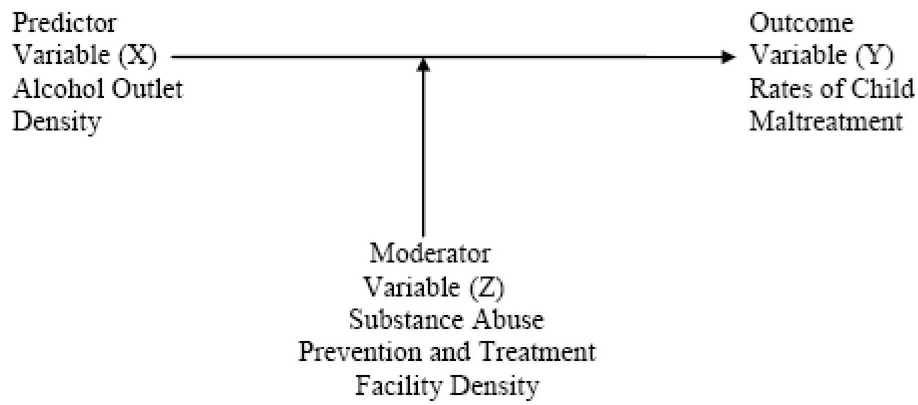
Table 7. OLS regression model of overall physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities.

	Variables	Dependent variable: physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.028		-.028	
Socioeconomics		B	Se	B	se
	Factor 1: impoverishment, residential instability, child care burden	.299***	.009	.301***	.009
	Factor 2: predominately African American	.290***	.008	.288***	.008
	Factor 3: young male	.101***	.008	.102***	.008
Alcohol access					
	On-Premises density per square mile	.001	.001		
	Off-premises density per square mile	-.011	.004	.013**	.006
Prevention and treatment access					
	Prevention accessibility	-.019***	.009	.008	.010
Interaction					
	Prevention and treatment density x off premises outlet density			-.010***	.002

Model 1 R^2=.19, Model 2 R^2=.19; Model 1 AIC=-65.45, Model 2 AIC=-65.49; **p*<.05, ***p*<.01, ****p*<.000

Figures

Figure 1. Diagram of hypothesized moderator effect.[2]



[2] Adapted from Frazier, Tix and Baron, 2004

Figure 2. Spatial distribution for Bergen County child maltreatment rate.

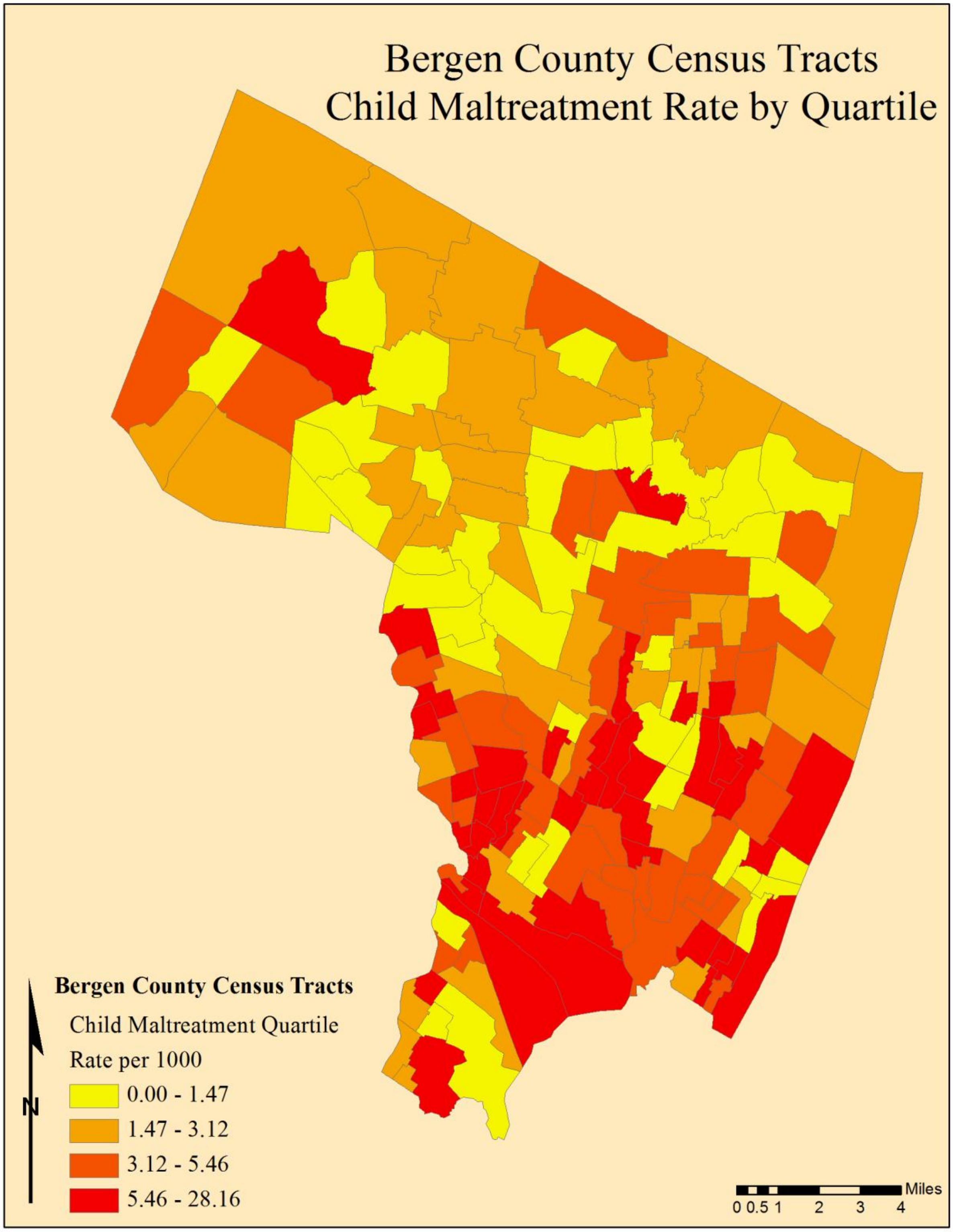


Figure 3. Spatial distribution of Bergen County physical abuse rate

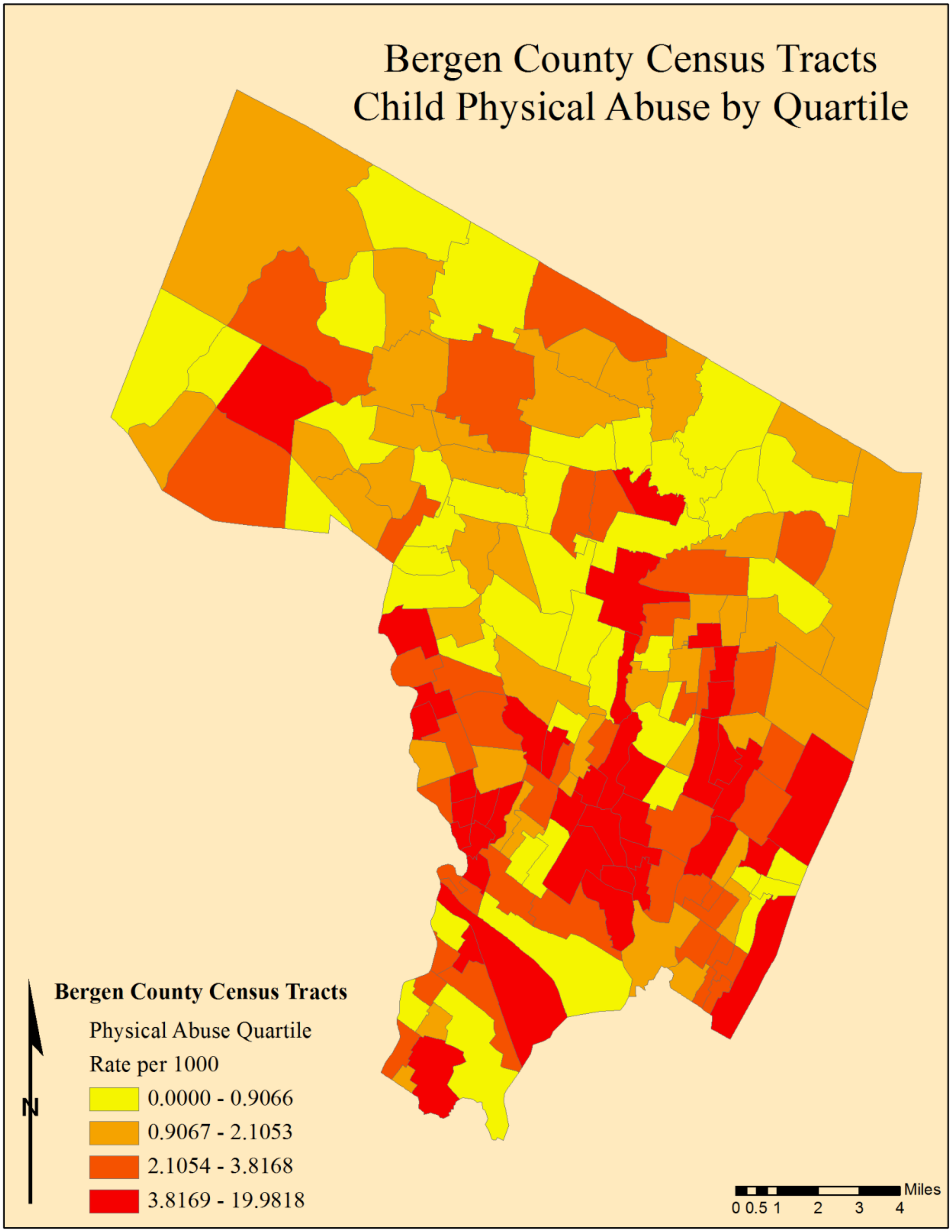


Figure 4. Spatial distribution of Bergen County child neglect rate

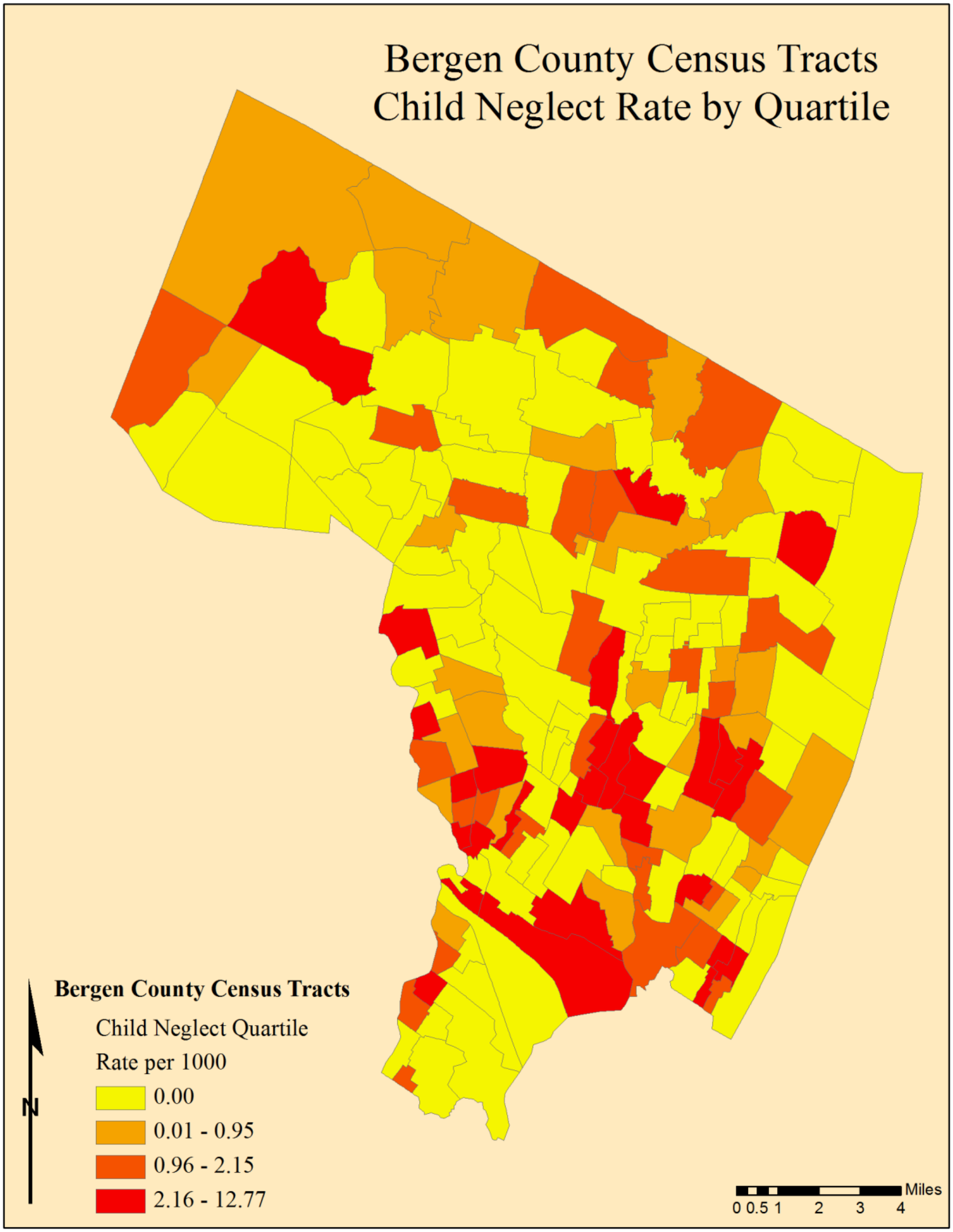


Figure 5. Spatial distribution of alcohol outlet density measured as number of outlets per 10km of roadway

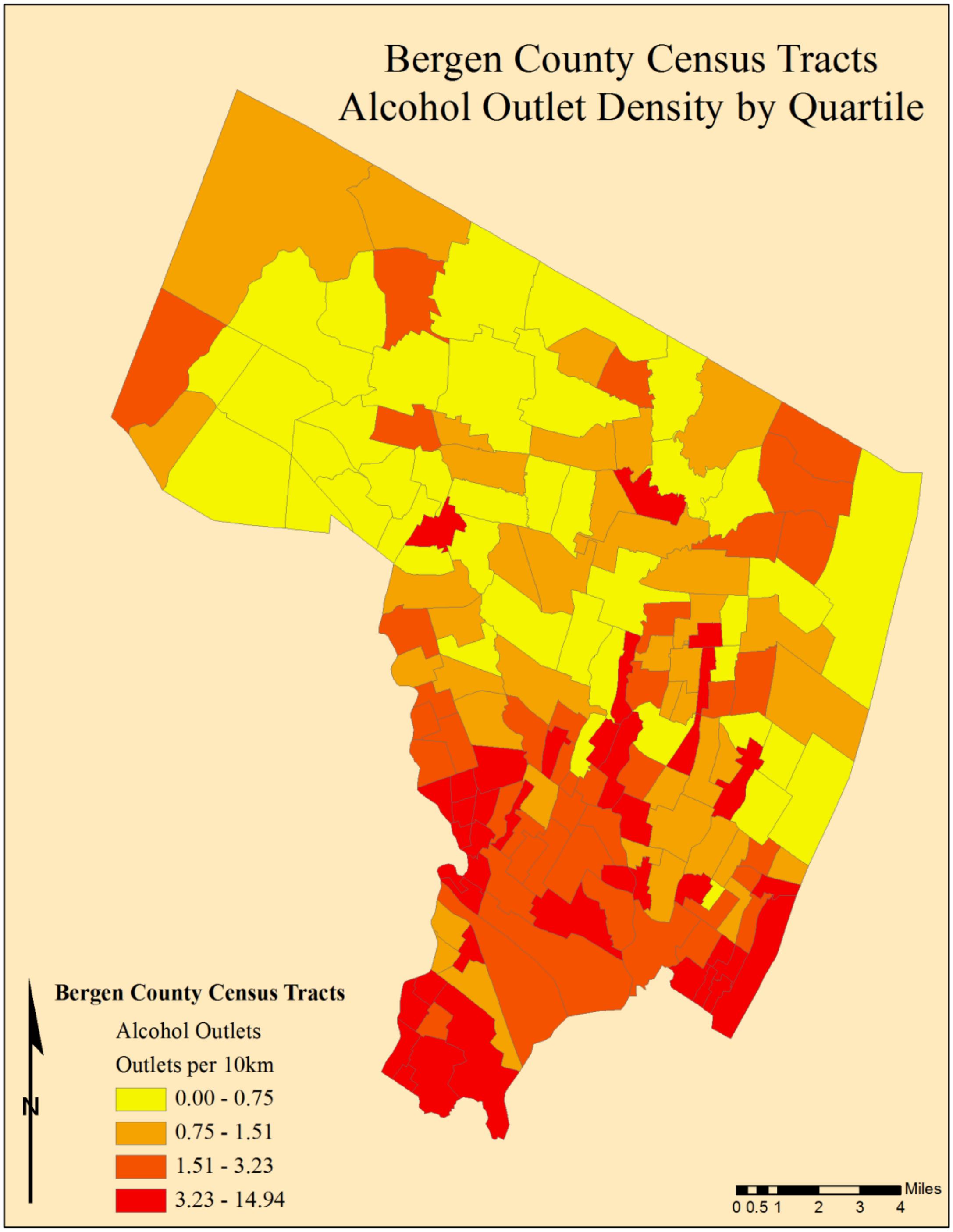


Figure 6. Spatial distribution of off-premises alcohol outlet density measured as number of outlets per 10km of roadway

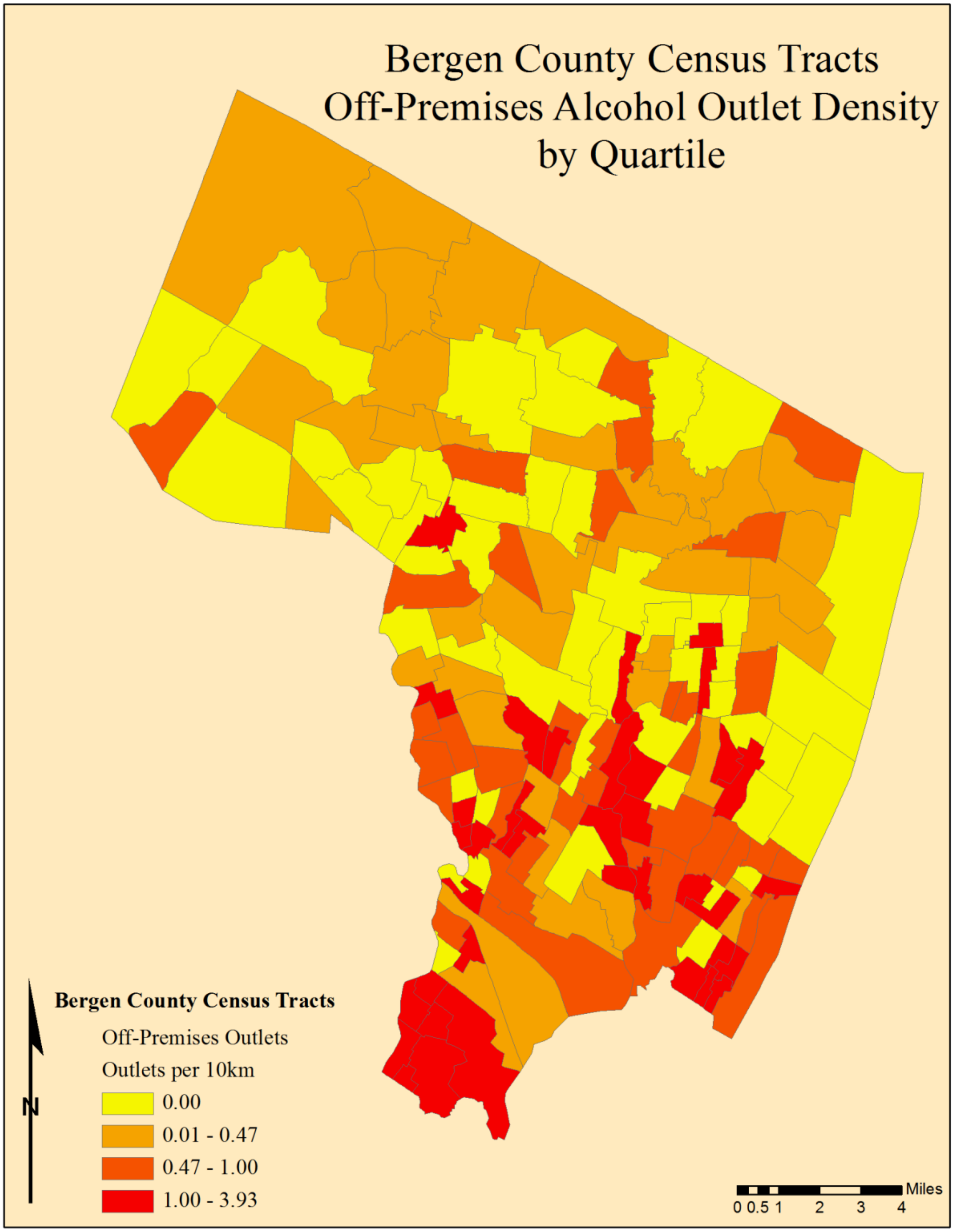


Figure 7. Spatial distribution of on-premises alcohol outlet density measured as number of outlets per 10km of roadway

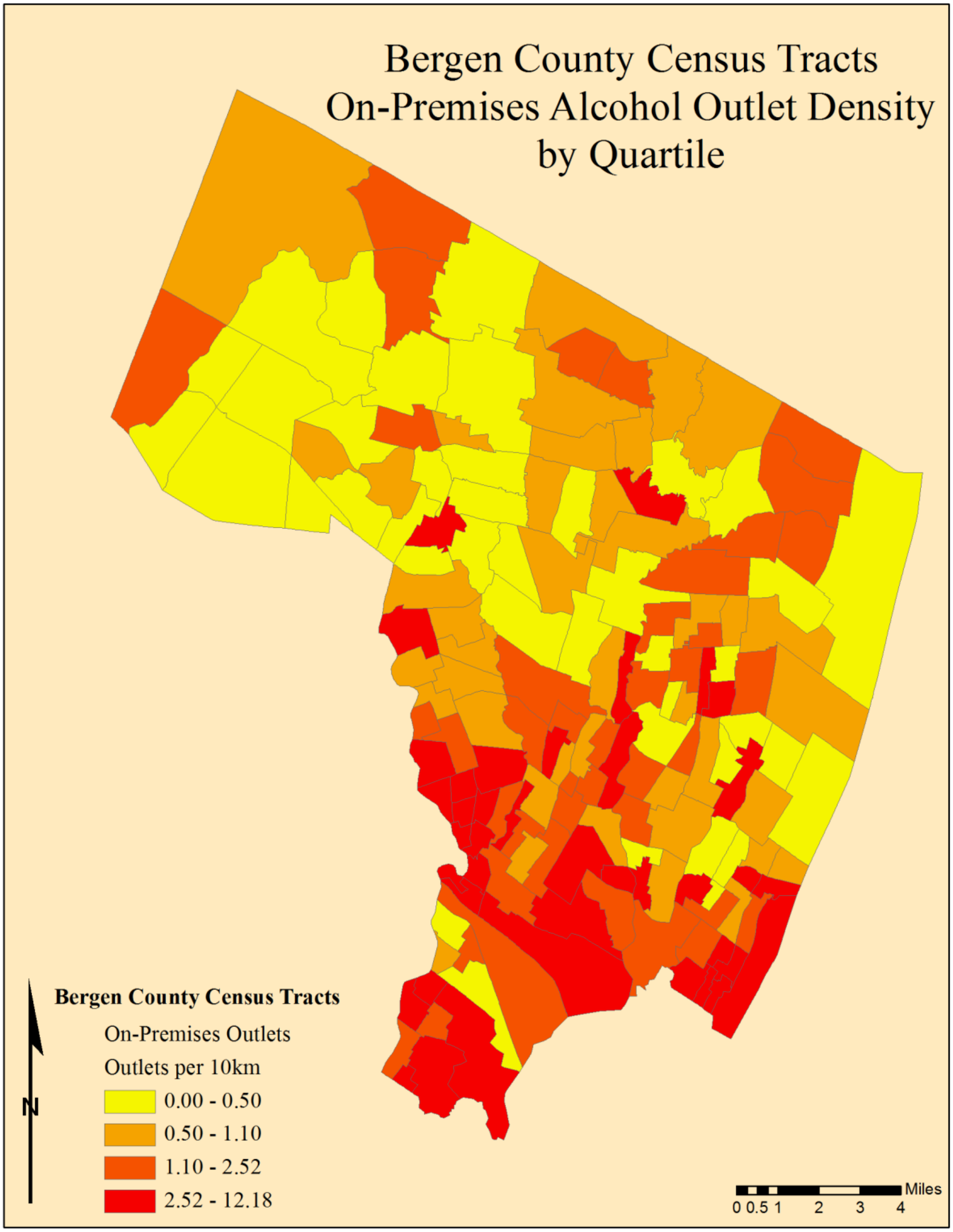


Figure 8. Spatial distribution of substance abuse prevention accessibility measured as the distance from the census tract's centroid to the nearest facility

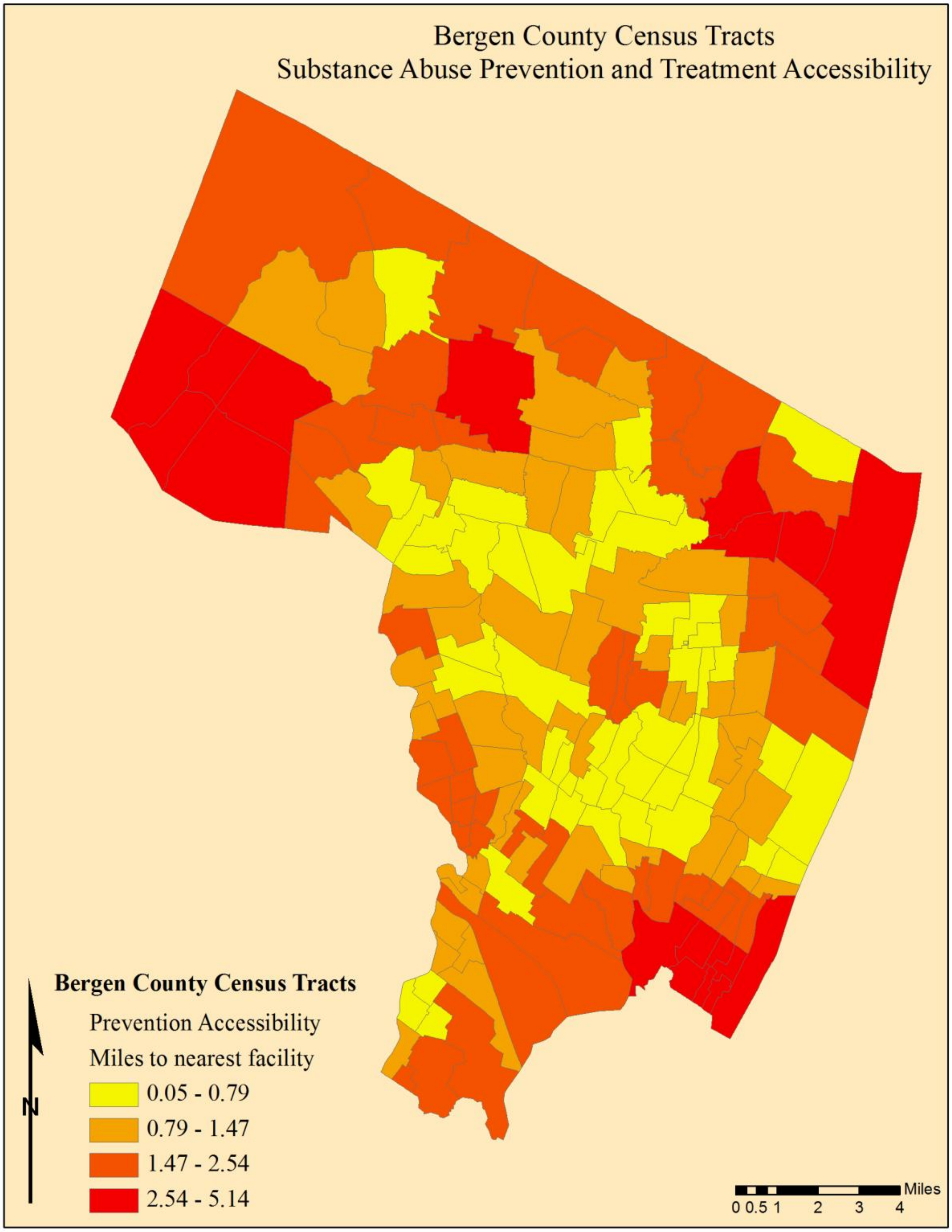


Figure 9. Interaction of Alcohol Outlet Density and Substance Abuse Prevention and Treatment Facility Accessibility on Rates of Child Maltreatment.

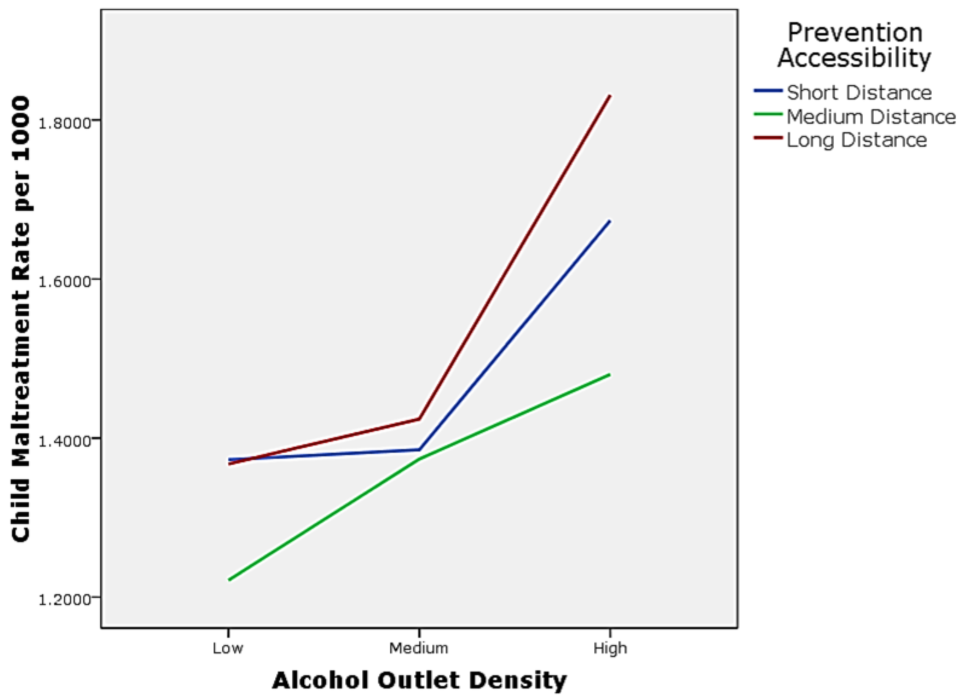
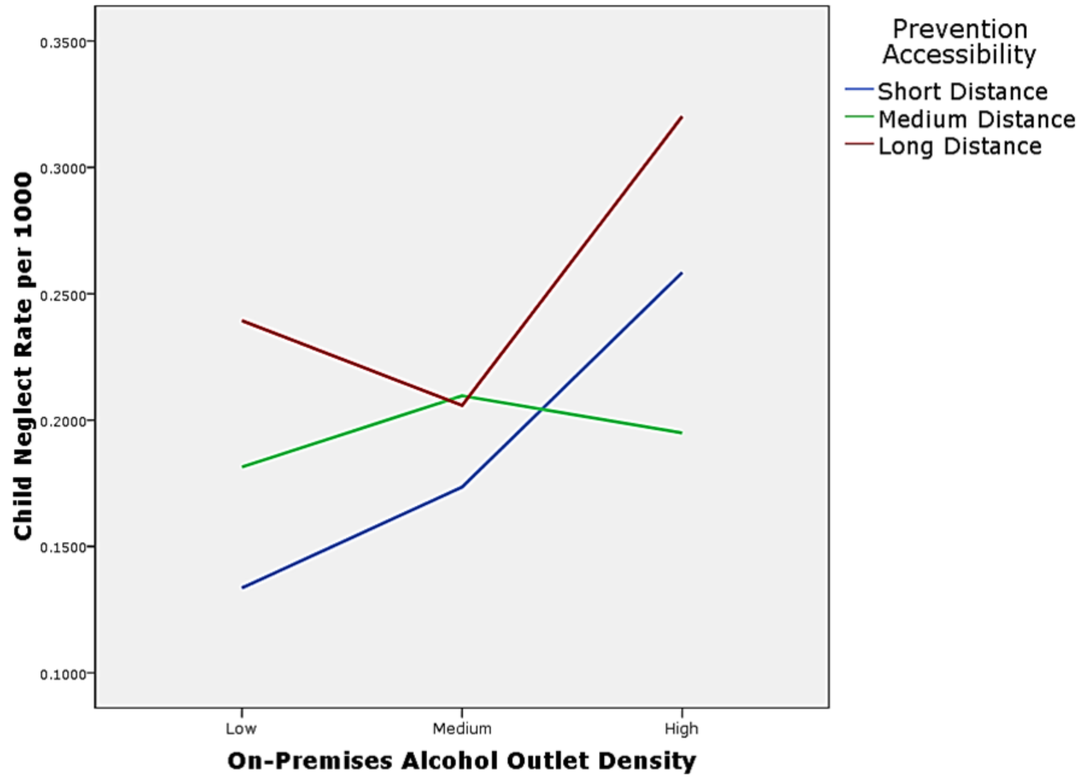


Figure 10. Interaction of On-premises Alcohol Outlet Density and Substance Abuse Prevention and Treatment Facility Accessibility on Rates of Child Neglect.



Appendix

Table A1. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: Outlet density per 10km of roadway

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.001		.001	
Socioeconomics		B	se	B	se
	Factor 1	.249***	.007	.250***	.009
	Factor 2	.067***	.007	.068***	.008
	Factor 3	.029***	.007	.029***	.008
	Factor 4	-.026***	.009	-.029**	.010
Alcohol density					
	Alcohol outlet density per 10km	.014*	.007	.057***	.007
Prevention and treatment access					
	Prevention accessibility	.031***	.007	.052	.010
Interaction					
	Prevention accessibility x off-premises per 10km			-.025***	.002

Model 1 R^2=.12, Model 2 R^2=.12
Model 1 AIC=1847.94, Model 2 AIC=1849.94; ****p*<.001, ***p*<.01, **p*<.05

Table A2. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: Distance to nearest outlet in miles

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.001		-.002	
Socioeconomics		B	se	B	se
	Factor 1	.260***	.007	.259***	.007
	Factor 2	.079***	.007	.079***	.007
	Factor 3	.038***	.007	.038***	.007
	Factor 4	-.022*	.009	-.022*	.009
Alcohol access					
	Alcohol outlet distance	.106**	.033	.039	.060
Prevention and treatment access					
	Prevention distance	.029***	.007	.018	.011
Interaction					
	Prevention accessibility x outlet distance			.038	.028

Model 1 R^2=.12, Model 2 R^2=.12; Model 1 AIC=1849.63, Model 2 AIC=1850.40; ***p<.001, **p<.01, *p<.05

Table A3. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: outlets per square mile

	Variables	Dependent variable: child maltreatment rate per 1,000 children	
		Model 1 Socioeconomics, alcohol, and prevention access	
	Spatial autocorrelation	.001	
Socioeconomics		B	se
	Factor 1	.256***	.007
	Factor 2	.073***	.007
	Factor 3	.032***	.007
	Factor 4	-.023**	.009
Alcohol access			
	Alcohol outlets per square mile	.000	.000
Prevention and treatment access			
	Prevention accessibility	.034***	.007

Model 1 R^2=.12
Model 1 AIC=1849.56
****p*<.001, ***p*<.01, **p*<.05

Table A4. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: number of outlets per 10km of roadway

	Variables	Dependent variable: child neglect rate per 1,000 children	
		Model 1 Socioeconomics, alcohol, and prevention access	
	Spatial autocorrelation	.011	
Socioeconomics		b	se
	Factor 1	.191***	.007
	Factor 2	.000	.007
	Factor 3	.006	.007
	Factor 4	-.040***	.009
Alcohol access			
	On-premises per 10km	.009	.033
	Off-premises per 10km	.010	
Prevention and treatment access			
	Prevention accessibility	.027***	.007

Model 1 R^2=.12; Model 1 AIC=1309.04; ****p*<.001, ***p*<.01, **p*<.05

Table A5. OLS regression model of overall child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: Distance to nearest outlet in miles

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.013		-.002	
Socioeconomics		B	Se	B	Se
	Factor 1	.187***	.005	.187***	.005
	Factor 2	-.003	.005	-.003	.005
	Factor 3	.003	.005	.003	.005
	Factor 4	-.040***	.006	-.040***	.006
Alcohol access					
	On-premises distance	.005	.027		
	Off-premises distance	-.063	.017	-.035	.026
Prevention and treatment access					
	Prevention accessibility	.031***	.005	.039***	.008
Interaction					
	Prevention accessibility x off premises outlet distance			-.015	.012

Model 1 R^2=.13, Model 2 R^2=.13; Model 1 AIC=1309.91, Model 2 AIC=1309.91; ****p*<.001, ***p*<.01, **p*<.05

Table A6. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: outlets per square mile

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.011		.012	
Socioeconomics		b	Se	b	Se
	Factor 1	.193***	.005	.192***	.005
	Factor 2	.002	.005	.001	.005
	Factor 3	.005	.005	.006	.005
	Factor 4	-.039***	.006	-.039***	.006
Alcohol access					
	On-premises per square mile	.001***	.000	-.001	.001
	Off-premises per square mile	-.001	.001		
Prevention and treatment access					
	Prevention accessibility	.027***	.005	.021***	.006
Interaction					
	Prevention accessibility x on premises per square mile			.001	.000

Model 1 R^2=.12, Model 2 R^2=.12; Model 1 AIC=1309.26, Model 2 AIC=1310.17, ****p*<.001, ***p*<.01, **p*<.05

Table A7. OLS regression model of physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: number of outlets per 10km of roadway

	Variables	Dependent variable: physical abuse rate per 1,000 children	
		Model 1 Socioeconomics, alcohol, and prevention access	
	Spatial autocorrelation	.013	
Socioeconomics		B	Se
	Factor 1	.318***	.010
	Factor 2	.102***	.010
	Factor 3	.044***	.010
	Factor 4	-.021	.012
Alcohol access			
	On-premises per 10km	.004	.013
	Off-premises per 10km	.066	.026
Prevention and treatment access			
	Prevention accessibility	-.019	.010

Model 1 R^2=.10
Model 1 AIC=2406.86
****p*<.001, ***p*<.01, **p*<.05

Table A8. OLS regression model of physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: Distance to nearest outlet in miles

	Variables	Dependent variable: physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.020		.020	
Socioeconomics		B	Se	B	Se
	Factor 1	.353***	.010	.349***	.010
	Factor 2	.135***	.010	.132***	.010
	Factor 3	.065***	.010	.062***	.010
	Factor 4	-.009	.012	-.011	.012
Alcohol access					
	On-premises distance	.094	.053		
	Off-premises distance	.201***	.034	.142***	.050
Prevention and treatment access					
	Prevention accessibility	-.032***	.010	-.056***	.016
Interaction					
	Prevention accessibility x off premises outlet distance			.051***	.023

Model 1 R^2=.13, Model 2 R^2=.13; Model 1 AIC=2405.25, Model 2 AIC=2407.22; ***p<.001, **p<.01, *p<.05

Table A9. OLS regression model of physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census block group. Alcohol variable: outlets per square mile

	Variables	Dependent variable: physical abuse rate per 1,000 children	
		Model 1 Socioeconomics, alcohol, and prevention access	
	Spatial autocorrelation	.013	
Socioeconomics		B	Se
	Factor 1	.334***	.010
	Factor 2	.119***	.010
	Factor 3	.052***	.010
	Factor 4	-.014	.012
Alcohol access			
	On-premises per square mile	-.002***	.001
	Off-premises distance per square mile	.000	.000
Prevention and treatment access			
	Prevention accessibility	-.011	.010

Model 1 R^2=.10
Model 1 AIC=2408.61
****p*<.001, ***p*<.01, **p*<.05

Table A10. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: outlets per 10km of roadway

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.059		-.057	
Socioeconomics		B	Se	B	Se
	Factor 1	.288***	.010	.294***	.010
	Factor 2	.376***	.009	.376***	.009
	Factor 3	.070***	.009	.067***	.009
Alcohol outlet density					
	Outlets per 10km	.022***	.004	.022	.007
Prevention and treatment access					
	Prevention accessibility	.020***	.010	.093***	.007
Interaction					
	Prevention accessibility x outlet density			-.026***	.003

Model 1 R^2=.41, Model 2 R^2=.41
Model 1 AIC=336.16, Model 2 AIC=337.83
****p*<.001, ***p*<.01, **p*<.05

Table A11. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: distance in miles to nearest outlet

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.062		-.065	
Socioeconomics		B	Se	B	Se
	Factor 1	.309***	.009	.310***	.009
	Factor 2	.392***	.008	.394***	.009
	Factor 3	.078***	.009	.076***	.009
Alcohol access					
	Outlet Distance	-.131***	.032	-.039	.070
Prevention and treatment access					
	Prevention accessibility	.051***	.010	.051***	.015
Interaction					
	Prevention accessibility x outlet distance			-.051	.035

Model 1 R^2=.40, Model 2 R^2=.40
Model 1 AIC=336.38, Model 2 AIC=338.36; ****p*<.001, ***p*<.01, **p*<.05

Table A12. OLS regression model of overall child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: alcohol outlets per square mile

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.060		-.059	
Socioeconomics		B	Se	B	Se
	Factor 1	.299***	.009	.296***	.010
	Factor 2	.386***	.008	.381***	.009
	Factor 3	.072***	.009	.072***	.009
Alcohol outlet density					
	Outlets per square mile	.004***	.032	.015***	.002
Prevention and treatment access					
	Prevention accessibility	.024***	.010	.071***	.012
Interaction					
	Prevention accessibility x outlet density			-.005***	.001

Model 1 R^2=.40, Model 2 R^2=.40
Model 1 AIC=336.38, Model 2 AIC=338.36; ****p*<.001, ***p*<.01, **p*<.05

Table A13. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: alcohol outlets per 10km of roadway

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.004		.003	
Socioeconomics		B	Se	B	Se
	Factor 1	.044***	.003	.044***	.003
	Factor 2	.075***	.003	.078***	.003
	Factor 3	.001	.004	.001	.003
Alcohol density					
	On-Premises outlets per 10km	.004**	.002	.008**	.002
	Off-Premises outlets per 10km	-.004	.004		
Prevention and treatment access					
	Prevention accessibility	.024***	.003	.030***	.004
Interaction					
	Prevention accessibility x outlet density			-.003**	.001

Model 1 R^2=.19, Model 2 R^2=.19; Model 1 AIC=-65.45, Model 2 AIC=-65.49; ***p<.001, **p<.01, *p<.05

Table A14. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: Distance to nearest alcohol outlet

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.006		.002	
Socioeconomics		B	Se	B	Se
	Factor 1	.046***	.003	.047***	.003
	Factor 2	.078***	.003	.082***	.003
	Factor 3	.003	.003	.003	.003
Alcohol access					
	Distance to nearest on-premises	-.071***	.011	-.009	.025
	Distance to nearest off-premises	.050***	.008	.141***	.016
Prevention and treatment access					
	Prevention accessibility	.024***	.003	.060***	.005
Interaction					
	Prevention accessibility x on-premises distance			-.039**	.013
	Prevention accessibility x off-premises distance			-.044***	.008

Model 1 R^2=.20, Model 2 R^2=.21; Model 1 AIC=-67.14, Model 2 AIC=-66.00; ****p*<.001, ***p*<.01, **p*<.05

Table A15. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: Outlets per square mile

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.008		-.004	
Socioeconomics		B	Se	B	Se
	Factor 1	.035***	.003	.035***	.003
	Factor 2	.071***	.003	.071***	.003
	Factor 3	.001	.003	.001	.003
Alcohol density					
	On-premises outlets per square mile	.003***	.000	.002	.001
	Off-premises outlets per square mile	.000	.003		
Prevention and treatment access					
	Prevention accessibility	.022**	.003	.018***	.004
Interaction					
	Prevention accessibility x on-premises per square mile			.001*	.000

Model 1 R^2=.20, Model 2 R^2=.20; Model 1 AIC=-66.32, Model 2 AIC=-66.81; ***p<.001, **p<.01, *p<.05

Table A16. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: Outlets per 10km of roadway

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention		Model 2 + Interaction effect	
	Spatial autocorrelation	-.027		-.029	
Socioeconomics		B	Se	B	Se
	Factor 1	.290***	.009	.292***	.009
	Factor 2	.288***	.008	.285***	.008
	Factor 3	.099***	.008	.099***	.008
Alcohol density					
	On-premises outlets per 10km	.017***	.004	.024**	.008
	Off-premises outlets per 10km	-.062***	.013	.009	.022
Prevention and treatment					
	Prevention accessibility	-.022**	.009	.013	.011
Interaction					
	Prevention accessibility x on-premises per 10km			-.003	.005
	Prevention accessibility x off-premises per 10km			-.037**	.012

Model 1 R^2=.36, Model 2 R^2=.37; Model 1 AIC=295.18, Model 2 AIC=294.29; ****p*<.001, ***p*<.01, **p*<.05

Table A17. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: Distance in miles to nearest outlet

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.028		-.029	
Socioeconomics		B	Se	B	Se
	Factor 1	.279***	.008	.285***	.008
	Factor 2	.289***	.008	.294***	.008
	Factor 3	.106***	.008	.116***	.008
Alcohol access					
	Distance to nearest on-premises outlet	-.245***	.034	-.256***	.034
	Distance to nearest off-premises outlet	.122***	.024	.122***	.024
Prevention and treatment					
	Prevention accessibility	-.023**	.009	-.037***	.009
Interaction					
	Prevention accessibility x on-premises distance			.101***	.015
	Prevention accessibility x off-premises distance			-.565***	.059

Model 1 R^2=.37, Model 2 R^2=.38; Model 1 AIC=293.39, Model 2 AIC=293.68; ***p<.001, **p<.01, *p<.05

Table A18. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the census tract. Alcohol variable: Outlets per square mile

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.028		-.028	
Socioeconomics		B	Se	B	Se
	Factor 1	.299***	.009	.301***	.009
	Factor 2	.290***	.008	.288***	.008
	Factor 3	.101***	.008	.102***	.008
Alcohol density					
	On-premises outlets per square mile	.001	.001		
	Off-premises outlets per square mile	-.011**	.004	.013*	.006
Prevention and treatment access					
	Prevention accessibility	-.019*	.009	.008	.010
Interaction					
	Prevention accessibility x off-premises per square mile			-.010***	.002

Model 1 R^2=.36, Model 2 R^2=.36Model 1 AIC=293.39, Model 2 AIC=293.39; ***p<.001, **p<.01, *p<.05

Table A19. OLS regression model of child maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per 10km

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.011		.016	
Socioeconomics		B	Se	B	Se
	Factor 1	-.144***	.013	-.145***	.013
	Factor 2	-.035	.023	-.031	.023
	Factor 3	.256	.012	.270	.013
Alcohol density					
	Alcohol outlets per 10km	.003**	.001	.005***	.001
Prevention and treatment access					
	Prevention accessibility	-.597***	.017	-.536***	.010
Interaction					
	Prevention accessibility x outlets per 10km			-.013**	.004

Model 1 R^2=.27, Model 2 R^2=.27
Model 1 AIC=222.17, Model 2 AIC=223.50
****p*<.001, ***p*<.01, **p*<.05

Table A20. OLS regression model of child physical maltreatment rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Distance to nearest outlet

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.018		.018	
Socioeconomics		B	Se	B	Se
	Factor 1	-.097***	.012	-.095***	.012
	Factor 2	.094***	.023	.094***	.023
	Factor 3	.169***	.012	.160***	.012
Alcohol access					
	Distance to nearest outlet	-.205***	.017	-.573***	.023
Prevention and treatment access					
	Prevention accessibility	-.620***	.017	-.573***	.023
Interaction					
	Prevention accessibility x distance to nearest outlet			-.155**	.048

Model 1 R^2=.25, Model 2 R^2=.25
Model 1 AIC=221.71, Model 2 AIC=224.39
****p*<.001, ***p*<.01, **p*<.05

Table A21. OLS regression model of child maltreatment abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per square mile

	Variables	Dependent variable: child maltreatment rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.038		.035	
Socioeconomics		B	Se	B	Se
	Factor 1	-.102***	.012	-.107***	.012
	Factor 2	-.005	.023	.004	.023
	Factor 3	.120***	.013	.114***	.014
Alcohol density					
	Outlets per square mile	.017***	.002	.015***	.002
Prevention and treatment access					
	Prevention accessibility	-.609***	.017	-.653***	.026
Interaction					
	Prevention accessibility x outlets per square mile			.005*	.002

Model 1 R^2=.24, Model 2 R^2=.24
Model 1 AIC=220.10, Model 2 AIC=221.29
****p*<.001, ***p*<.01, **p*<.05

Table A22. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per 10km

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.071		-.069	
Socioeconomics		B	Se	B	Se
	Factor 1	-.045***	.006	-.048***	.006
	Factor 2	.013	.011	.019	.011
	Factor 3	.094***	.007	.099***	.007
Alcohol density					
	On-premises outlets per 10km	.002**	.001	.003***	.001
	Off-premises outlets per 10km	.059***	.006	.049***	.008
Prevention and treatment					
	Prevention accessibility	-.221***	.008	-.204***	.014
Interaction					
	Prevention accessibility x on-premises outlets per 10 km			-.011***	.002
	Prevention accessibility x off-premises outlets per 10 km			.032**	.011

Model 1 R^2=.20, Model 2 R^2=.21; Model 1 AIC=106.03, Model 2 AIC=105.89;****p*<.001, ***p*<.01, **p*<.05

Table A23. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Distance to nearest outlet

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.079		-.078	
Socioeconomics		B	Se	B	Se
	Factor 1	-.013*	.006	-.018**	.006
	Factor 2	.071***	.012	.078***	.012
	Factor 3	.086***	.006	.081***	.006
Alcohol access					
	On-premises outlet distance	-.052***	.013	-.081***	.016
	Off-premises outlet distance	-.014	.011		
Prevention and treatment access					
	Prevention accessibility	-.233***	.009	-.192***	.012
Interaction					
	Prevention accessibility x on-premises outlet distance			.044	.039

Model 1 R^2=.17, Model 2 R^2=.17
Model 1 AIC=104.31, Model 2 AIC=106.31
****p*<.001, ***p*<.01, **p*<.05

Table A24. OLS regression model of child neglect rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per square mile

	Variables	Dependent variable: child neglect rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	-.078		-.078	
Socioeconomics		B	Se	B	Se
	Factor 1	-.011	.006	-.009	.006
	Factor 2	.032**	.011	.033**	.011
	Factor 3	.067***	.007	.073***	.007
Alcohol density					
	On-premises outlets per square mile	.000	.001		
	Off-premises outlets per square mile	.031***	.004	.041***	.007
Prevention and treatment access					
	Prevention accessibility	-.225***	.009	-.231***	.013
Interaction					
	Prevention accessibility x off-premises outlets per square mile			.041***	.007

Model 1 R^2=.18, Model 2 R^2=.18; Model 1 AIC=104.44, Model 2 AIC=102.44; ****p*<.001, ***p*<.01, **p*<.05

Table A25. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per 10km

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.066		.080	
Socioeconomics		B	Se	B	Se
	Factor 1	-.115***	.012	-.117***	.012
	Factor 2	-.146***	.022	-.140***	.022
	Factor 3	.158***	.012	.175***	.013
Alcohol density					
	On-premises outlets per 10km	.002	.001		
	Off-premises outlets per 10km	.093***	.011	.005***	.001
Prevention and treatment access					
	Prevention accessibility	-.503***	.016	-.403***	.026
Interaction					
	Prevention accessibility x off-premises outlets 10km			-.031	.020

Model 1 R^2=.24, Model 2 R^2=.25; Model 1 AIC=209.05, Model 2 AIC=210.52; ***p<.001, **p<.01, *p<.05

Table A26. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Distance to nearest outlet

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.076		.080	
Socioeconomics		B	Se	B	Se
	Factor 1	-.072***	.011	-.077***	.011
	Factor 2	-.006	.021	-.001	.022
	Factor 3	.132***	.011	.130***	.011
Alcohol access					
	On-premises outlet distance	.095***	.024	.063*	.030
	Off-premises outlet distance	-.238***	.021	-.201***	.027
Prevention and treatment access					
	Prevention accessibility	-.509***	.016	-.481***	.023
Interaction					
	Prevention accessibility x on-premises distance			.088	.072
	Prevention accessibility x off-premises distance			-.087*	.041

Model 1 R^2=.23, Model 2 R^2=.23
Model 1 AIC=208.29, Model 2 AIC=209.90; ****p*<.001, ***p*<.01, **p*<.05

Table A27. OLS regression model of child physical abuse rates, socioeconomic variables, alcohol access, and substance abuse prevention and treatment facilities at the zip code. Alcohol variable: Outlets per square mile

	Variables	Dependent variable: child physical abuse rate per 1,000 children			
		Model 1 Socioeconomics, alcohol, and prevention access		Model 2 + Interaction effect	
	Spatial autocorrelation	.062		.060	
Socioeconomics		B	Se	B	Se
	Factor 1	-.079***	.011	-.078***	.012
	Factor 2	-.093***	.021	-.093***	.022
	Factor 3	.088***	.012	.092***	.013
Alcohol density					
	On-premises outlets per square mile	.010***	.003	.012***	.003
	Off-premises outlets per square mile	.029***	.007	.020*	.009
Prevention and treatment					
	Prevention accessibility	-.519***	.016	-.521***	.025
Interaction					
	Prevention accessibility x on-premises per square mile			-.006	.005
	Prevention accessibility x off-premises per square mile			.025	.014

Model 1 R^2=.21, Model 2 R^2=.21; Model 1 AIC=209.49, Model 2 AIC=211.47;****p*<.001, ***p*<.01, **p*<.0

Table A28. Principal Components Analysis of socioeconomic variables at the census block group

	Factor 1	Factor 2	Factor 3	Factor 4
Variable				
% Latino/Hispanic	**.685**	.307	-.006	.100
% single, female-headed households	**.680**	.104	-.103	.320
% unemployed	**.663**	.082	.098	-.232
% African American	**.627**	-.116	-.061	-.023
% poverty	**.558**	.414	.185	.094
% immigrant population	.271	**.852**	.122	.004
% Asian	-.289	**.844**	-.093	-.061
% 5-year residential movement	.384	**.648**	.070	.253
% vacant housing units	.193	.255	.235	-.111
Child to adult ratio	-.118	-.223	**-.829**	-.158
% over 65 years of age	-.208	-.152	**.818**	-.187
Male to female ratio	.017	.019	-.030	**.924**

Note: N=811. These 4 factors explained 62% of the variance in the set of variables.

Table A29. Principal Components Analysis of socioeconomic variables at the zip code level

	Factor 1	Factor 2	Factor 3
Variable			
% in poverty	**.935**	.123	-.136
% unemployed	**.883**	.029	-.320
% Latino/Hispanic	**.872**	.165	-.232
% immigrant population	**.814**	.002	.438
% vacant housing units	**.743**	.018	.189
% African American	**.622**	-.056	-.438
% single, female-headed households	.080	**.870**	-.152
Male to female ratio	-.107	**.798**	-.010
% 5-year residential movement	.465	**.770**	.210
Child to adult ratio	.064	-.226	**-.752**
% Asian	.053	-.214	**.743**
% over 65 years of age	-.487	-.126	**.570**

Note: N=83. These 3 factors explained 73% of the variance in the set of variables.