Spatiotemporal Convergence of Crime and Vehicle Crash Hot Spots: Additional Consideration for Policing Places

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Abstract
Policing strategies that seek to simultaneously combat crime and vehicle crashes operate under the assumption that these two problems have a corollary relationship; an assumption that has received scant empirical attention and is the focus of the present study. Data were geocoded vehicle crash, violent crime, and property crime totals across Indianapolis census blocks over a 36-month period (2011-2013). Time series negative binomial regression and local indicators of spatial autocorrelation analyses were employed. Results indicate that both violent and property crime are significantly related to vehicle crash counts, both overall and during the temporal confines of patrol tours. Relationship strength was modest. Spatiotemporal analysis of crime and crash data can identify places for police intervention and improved scholarly evaluation.

Keywords
Crime-and-place, Vehicle crashes, Spatiotemporal clustering, Problem-solving, Police intervention

Citation
Carter, J. G., & Piza, E. L. (2017). Spatiotemporal convergence of crime and vehicle crash hotspots: Additional consideration for policing places. *Crime & Delinquency*. Online First. https://doi.org/10.1177/0011128717714793

This is the author's manuscript of the article published in final edited form as:

Carter, J. G., & Piza, E. L. (2017). Spatiotemporal Convergence of Crime and Vehicle Crash Hotspots: Additional Consideration for Policing Places. Crime & Delinquency, 0011128717714793. https://doi.org/10.1177/0011128717714793

Introduction

Evidence supporting the concentration of crime in micro-places (Weisburd, 2015) and hotspots policing (Braga, Papachristos, & Hureau, 2014) has demonstrated a promising path forward for policing strategies in urban areas. Though this growing body of research has largely focused on crime, scholars have also concluded that disorder concentrates in small geographies (Braga &Bond, 2008; Yang, 2010) and is distinctly different than crime (Gau &Pratt, 2010). Disorder can manifest through a range of problem behaviors and have implications for effective policing strategies to reduce crime (Sampson & Raudenbush, 1999). A particular problem behavior that has received increased empirical attention is motor vehicle traffic crashes, with scholars arguing that the increased understanding of this behavior has important policy implications for public safety (Kuo *et al*., 2013). Despite such an importance, the scholarly attention to the spatiotemporal distribution of different problem behaviors and outcomes remains relatively scant compared to crime and "...it is crucial for future research, not just for place-based research, to scrutinize the meanings and effects between various types of problem behavior" (Yang, 2007, p. 149).

There exists no single, testable theory of crime and crashes, particular regarding their co-location within micro-places. Rather, a number of studies across disparate literatures lends strong support for an anticipated relationship between these two problems police face on a daily basis, as well as promise for police to impact these problems. Moreover, a number of policing strategies that seek to simulteanously impact crime and vehicle crashes operate under the assumption that the two share a corollary relationship; an assumption that has received little empirical attention and is the focus of the present study. The research to be reviewed reveals three salient themes. First, there is logic and value in extending hotspots policing and crime and place studies to include a more expansive view of harms to society and problems facing police. Second, traffic deviance is not random, but has a root cause resulting from aggressive behavior and low self-control. Third, there appears to be consistent correlation between criminality, disorder, deviance, and traffic violations. Thus, a further understanding of traffic related problems and crime may lend additional insights to better comprehend criminal behavior, focused deterrence, and crime prevention strategies. As Corsaro *et al*. (2012, p. 512) note: “That the police are largely responsible for addressing both sets of problems [crime and crashes] creates research opportunities for academics who are routinely involved with policing. They should do more to take advantage of this set of circumstances. Judging from the current literature, however, it appears that the criminal justice interest in vehicle crashes, when it occurs, is largely accidental.”

The present study examines the spatiotemporal relationship between crime and vehicle crashes in Indianapolis, Indiana census blocks from 2011-2013. Specifically we draw upon individual- and macro-level criminological frameworks to explain the anticipated relationship between crime and crashes. Using Geographic Information Systems (GIS), we measure monthly vehicle crash, violent crime, and property crime totals across Indianapolis census blocks over the 36-month study period. Time series negative binomial regression models measured the level to which violent crime and property crime levels correlate with traffic crashes. Findings suggest that police seeking to simultaneously address crime and vehicle crashes should first identify micro-level units in the jurisdiction that stand to benefit most from such an intervention and lend promise for the inclusion of vehicle crash data in spatiotemporal modeling to improve evaluations of placed-based criminology and effective problem-oriented policing strategies.

Spatiotemporal Concentration of Crime and Vehicle Crashes

An anticipated relationship between spatiotemporal patterns of crime and vehicle crashes is supported by theories of criminal behavior and environmental criminology. Gottfredson and Hirschi's (1990, p. 90) general theory of crime asserts low levels of self-control bespeak criminal and deviant behaviors; many of which "…are trivial and mundane affairs that result in little loss and little gain." Arneklev *et al*. (1993, p. 227) extend the general theory of crime to what they refer to as imprudent behaviors wherein "Low self-control is also responsible for differential rates of various irresponsible acts." Similar to criminality, imprudent behaviors are the result of immediate gratification and a lack of regard for long-term consequences and aid in the explanation of a range of deviant behaviors. Such behaviors have also been shown to manifest in the form of traffic safety violations (Smith & King, 2013). Low self-control has been linked to drunk driving (Kean, Maxim & Teavan, 1993) and a lack of seatbelt use (Vaughn, Salas-Wright & Piquero, 2012). Additionally, criminality and risk-seeking predict risky driving behaviors such as speeding (Brace *et al*., 2001), reckless driving (Junger, West, & Timman, 2001), crashes (Giacopassi & Forde, 2000), and texting while driving (Quisenberry, 2015).

From an environmental criminology perspective, risk heterogeneity occupies a central space in research on neighborhoods and crime and deviance. Shaw and McKay's (1942) theory of social disorganization argues that negative community characteristics lead to the disruption of social organization. This creates a situation in which both formal and informal social networks, which promote the ability to solve common problems, are not created or maintained within the community (Sampson & Groves, 1989). As a result, social disorganization disrupts the social order to an extent that weakens collective efficacy, defined as the "willingness [of residents] to intervene for the common good" (Sampson *et al*., 1997, p. 919). Communities with low collective efficacy have little ability to maintain effective social controls over residents, creating a situation ripe for crime and deviance. Thus, community characteristics that create social disorganization are likely to cultivate environments where people have higher disregard for laws and social norms.

Though research incorporating traffic related offenses in place-based studies of crime and deviance are scant, there exists evidence to suggest traffic offenses concentrate in place similar to crime. Consistent with social disorganization, Cottrill and Thakuriah (2010) found vehicle crashes significantly clustered in Chicago's low-income and racially heterogeneous census tracts. In their examination of motor vehicle fatalities, Cubbin, LeClere, and Smith (2000) concluded that residents of neighborhoods with lower socioeconomic status and higher proportions of poor households headed by women are at higher risk. Using five years of aggregate crime and vehicle crash data to model improved police response times, Kuo *et al*. (2013) found that vehicle crashes clustered in the same census tracts as crime. Though the authors could not examine spatiotemporal distributions of crime and crashes in their study, they hypothesized that if such events are in fact concentrated in space and time that this approach could yield substantive reductions in police response time to handle varying calls for service. Evidence supporting the intersection of criminality and poor driving behaviors lends credence to the notion that areas with high concentrations of crime may be the same places with high concentrations of vehicle crashes. Put simply, given crime concentrates in place (Weisburd, 2015), it is reasonable to assume that such places may also experience higher rates of vehicle crashes that result from imprudent driving behaviors. This spatial convergence of the two primary enforcement activities of law enforcement (crime and traffic) lends promise for policing strategies, crime prevention, and the reduction of social harm.

The Convergence of Crime, Traffic, and Places as a Policing Strategy

Over the past decade police executives recognized the need to maximize resource efficiency in light of lean budgets and increases in operational costs and demands for service (Wilson & Heinonen, 2012). Though crime control often receives the bulk of police expenditures as crime is viewed to be a more pressing public safety concern than traffic enforcement (Gascon & Foglesong, 2010), the role and value of police as enforcers of traffic safety has been articulated as an area for potential resource efficiency gains (NHTSA, 2014). The Strategic and Tactical Approaches to Traffic Safety (STATS) urged for the use of data-driven models to allocate enforcement resources and develop strategies for traffic enforcement to reduce overall criminal activity (Weiss, 2013).

With the recognition that police may obtain crime control, traffic safety, and resource benefits by leveraging advancements in data analyses and a focus on places, the NHTSA, Bureau of Justice Assistance (BJA), and National Institute of Justice (NIJ) co-produced the strategy currently known as Data-Driven Approaches to Crime and Traffic Safety (DDACTS). This approach combines community- and problem-oriented policing strategies with a reliance on data analysis to inform police decision making (Wilson, 2010). Put simply, DDACTS aims to utilize the analysis of crime and traffic data to guide the deployment of police resources while maximizing reductions in crime, disorder, and traffic safety. These desired outcomes are achieved through the identification of areas with the highest concentrations of crime and traffic crashes followed by high-visibility traffic enforcement in these areas (Hardy, 2010). To date, DDACTS has been piloted in a number of cities with initial evidence suggesting a focus on aggressive traffic enforcement may yield promising reductions in violent crime hot spots; however evaluations remain sparse and suffer from a high degree of implementation fidelity (McClure *et al*., 2014).

Beyond DDACTS, the focus on traffic offenses as a component to reduce crime and disorder has garnered considerable attention. For example, problem-oriented policing is focused on "a recurring set of related harmful events in a community that members of the public expect the police to address" (Clarke & Eck, 2014, p. 14). To this end, the Center for Problem-Oriented Policing (2016) has published seven guides specifically aimed at a variety of traffic issues. Municipal governments have also begun to dedicate resources targeting traffic crashes directly as a public safety issue, such as the Vision Zero program in New York City[1], which was designed after similar programs throughout Europe (Johansson, 2008).

There also exists a strong body of evidence between increased traffic-related enforcement, or directed patrols, and reductions in criminal behaviors such as robbery (Kubrin *et al*., 2010; Sampson & Cohen, 1988), gun carrying and violent crime (McGarrell *et al*., 2001; Sherman & Rogan, 1995), property crimes (Schnelle *et al*., 1977), and overall deviant behavior (Sherman & Weisburd, 1995). Cohen and Ludwig (2003) contend these reductions from directed patrols and focus on traffic offenses are a result of increased police presence in target areas. Such effects were echoed by Ratcliffe *et al*. (2011) in their randomized control trial of Philadelphia hotspots wherein they asserted that offenders were deterred through an increased likelihood of apprehension from increased police presence in hotspots. The effectiveness of visible traffic enforcement on crime has been observed in a number of additional studies (Stuster, Sheehan, & Morford, 1997; Weiss & Freels, 1996) and lends support for police to focus patrols on areas that experience significantly higher rates of vehicle crashes.

Lastly, recent research has urged police and policing scholars to focus on societal harm (Sherman *et al*., 2016). In his development of a harm policing index, Ratcliffe (2015) contends that data beyond crime and disorder should be considered for the deployment of police resources to maximize police efforts to improve communities. In his operationalization of the harm index, Ratcliffe (2015, p. 172) specifically notes that "Given the commitment many agencies make to road safety, it would appear prudent to include a measure of traffic accidents within a harm matrix for most police agencies with responsibility for a geographic area." Along with incidents of traffic accidents, Ratcliffe (2015) included measures of part one crime, part two crime, and investigative stops to measure harm within Philadelphia police districts from 2004-2013. He observed that in some police districts traffic accidents comprised a greater contribution to the harm index than any other measure, including total part two crimes. Moreover, the findings suggested that police emphasis on part one crimes had a diffusion of benefits effect on traffic accidents in districts that experienced higher rates of traffic accidents. Indeed, multiple lines of research across hotspots policing, directed patrols, DDACTS, harm reduction, and focused deterrence suggests additional crime and disorder benefits may be achievable through the inclusion of vehicle crashes in spatiotemporal modeling to inform the allocation of scarce police resources.

Methods

City of Study: Indianapolis, Indiana

Indianapolis, Indiana is the largest city in the state, the state capital, and a consolidated city-county municipality.[2] In 2013, Indianapolis had a population of 843,393 persons with a population density of 2,129 persons per square mile. The majority of citizens are White (59%) with much smaller proportions of ethnic minorities (28% Black, 9% Hispanic, and 2% Asian). Median household income was $41,361, with 20 percent living below the poverty line (as compared to 15.4 percent statewide), and 24 percent of the population had a bachelor's degree or higher (U.S. Census Bureau, 2016). The city's roadway system is comprised of a combination of rural roads and large thoroughfares connecting business, education, and recreational areas. Five interstate highways along with six U.S. and four Indiana highways converge in the city. Unlike other large metropolitan cities in the U.S., Indianapolis lacks notable public transportation alternatives leaving citizens to rely more heavily upon personal means of transportation.

Data

Data used in the current study were collected from a variety of sources. Crime data were provided electronically from the Indianapolis Metropolitan Police Department (IMPD) for the period from January 2011 through December 2013. Crime incidents were classified according to the Federal Bureau of Investigation's Uniform Crime Report definitions. For the current study, the research team aggregated individual crime types into two categories: Violent Crime (aggravated assault, homicide/manslaughter, rape, and robbery) and Property Crime (burglary, larceny theft, and motor vehicle theft).[3] Vehicle crash data were obtained from the Indiana State Police's Automated Reporting Information Exchange System (ARIES). The ARIES program provides Indiana police officers a user-friendly method of completing and submitting electronic crash reports accurately and efficiently. These reports then become part of the statewide database of Indiana motor vehicle collisions maintained by the Indiana State Police.[4] Both crime and vehicle crash incidents were provided in spreadsheet format, capturing information on the date and time of occurrence, incident type, and location. XY coordinates were provided for each incident, which the research team used to create GIS shapefiles of crime and vehicle crash incidents. Geocoding rates were quite high, with hit rates over 99 percent in each instance. XY coordinates were available for over 99 percent of incidents for each crime type, which exceeds the minimum hit rate of 85 percent advocated by Ratcliffe (2004). While theory suggests, and our analyses assume, vehicle crashes are largely the result of disregard for traffic laws and norms, we recognize that vehicle crashes may occur for other reasons (such as road conditions or pedestrian actions). Analysis of the data confirm that 95.1% of all traffic crashes included in the data are the result of a traffic violation.

Boundaries of census blocks were obtained from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) database. TIGER products are spatial extracts from the Census Bureau's data files, which correspond to common statistical reporting units for the decennial census. Census blocks were selected as the unit of analysis in recognition of insights from the crime-and-place literature. While neighborhood level studies have traditionally incorporated larger geographies, such as census tracts, contemporary crime-and-place scholars have largely adopted a "smaller is better" approach in designating units of analysis (Oberwittler & Wikstrom, 2009). Smaller units minimize within group heterogeneity, avoiding the incorrect assumption that patterns observed across larger units apply equally to the mosaic of smaller units of which it is comprised (Johnson *et al*., 2009:172), a problem commonly referred to as the Ecological Fallacy (Robinson, 1950). Therefore, we decided that the census block was the most appropriate spatial unit at which to measure the concentration of vehicle crashes and crime.

Sociodemographic data was collected from the American Community Survey (ACS). For each of the three years included in the study, five-year estimates of sociodemographic data of interest were extracted from the ACS.[5] We operationalized two variables commonly incorporated as measures of social disorganization. The first was concentrated disadvantage, a standardized index composed of the percentage of residents receiving public assistance, the percentage of families living below the poverty line, the percentage of female-headed households with children under the age of 18, and the percentage of unemployed residents (Morenoff *et al*., 2001; Sampson *et al*., 1997).[6] These measures, both collectively and individually, have been strongly linked to heightened levels of crime in prior research (Pratt & Cullen, 2005; Hipp & Wickes, 2016). The second social disorganization measure was racial heterogeneity, the probability of members of different ethnicities living in the same neighborhood, with high probabilities suggesting the co-existence of conflicting and competing values regarding the appropriateness of illicit conduct (Berg *et al.*, 2012, p. 412).

Research on social disorganization suggests that racial heterogeneity is an important predictor of crime under the assumption that areas with highly heterogeneous racial compositions are less cohesive and exhibit lower levels of social control (Bursik & Grasmick, 1993; Sampson & Grove, 1989). While percentage of minority residents has traditionally been used as an indicator of social disorganization, Williams (1984) demonstrated that crime and percentage of minority residents exhibited an inverted-U shape relationship, rather than linear. Thus, high levels of minority residents can actually stabilize an area once minorities become the dominate group at that place (Weisburd *et al*., 2012). Given that this is different than the linear relationship observed between crime and the other social disadvantage variables, we decided to account for racial heterogeneity via its own measure[7]. This follows the approach of recent crime-and-place studies (Berg *et al*., 2012; Nobles *et al*., 2016; Piza *et al*., 2016; Weisburd *et al*., 2012). Both concentrated disadvantage and racial heterogeneity were collected at the block group level, the lowest level of aggregation at which these data are available. For the analysis, each block was assigned the social disorganization and racial heterogeneity values of its surrounding block group.

Analytical Approach

For each month over the study period, counts of violent crime, property crime, and vehicle crash incidents were spatially joined to the 15,747 Indianapolis blocks within a GIS. To allow for longitudinal models, we converted the dataset into panel format by which an observation was created for each spatial unit across each of the 36 time periods. This resulted in a total of 566,892 observations (36 months X 15,747 blocks). Chi-square goodness of fit tests conducted after exploratory Poisson regression models confirmed that vehicle crashes were distributed as a negative binomial process (Pearson X^2 = 260,863.30; p=0.00). Hence, all analyses incorporated time series negative binomial regression models.

Models were conducted for four distinct time periods. To measure the general relationship between vehicle crashes and crime, all incidents were included in the first model. The three subsequent models incorporated crash and crime incidents occurring during each of the IMPD's patrol shifts: A tour (6am to 2pm), B tour (2 pm to 10pm), and C tour (10pm to 6am). The tour-specific models more directly inform police allocation strategies by measuring the overlap of vehicle crashes and crime during each phase of officer deployment. These models allow for the possibility that simultaneously targeting vehicle crashes and crime may be a more prudent strategy during certain times of the day than others.

The dependent variable was the count of vehicle crashes. The main independent variables of interest were standardized (i.e. z-score) violent crime and property crime levels. Standardized measures were used to account for the differing levels of violent and property crime. Statistically significant, positive relationships between the crime measures and vehicle crashes would suggest that hot spots of vehicle crashes and crime occupy the same micro-geography in Indianapolis. Six variables were included as controls. Concentrated disadvantage and racial heterogeneity controlled for observed levels of social disorganization in the surrounding block group. To address observed levels of spatial autocorrelation in the dependent variable, a spatial lag variable was included. The spatial lag was created in the GeoDa spatial analysis software (Anselin *et al.*, 2005).[8] We also included a temporal lag of the vehicle crash count (t -1) to account for the fact that prior levels of vehicle crashes may be predictors of current levels, a phenomena commonly observed with crime (Braga *et al.*, 2012; Sampson *et al.*, 1997). To account for linear trends in vehicle crashes, we included the sequential order of each month (January 2011=1, February 2011=2, and so on) while the number of days in each month were included to control for the differing month lengths in the study period.

Results

Table 1 displays descriptive statistics of all model covariates. Descriptive statistics are provided for the overall study period as well as the A, B, and C tour temporal periods. Figure 1 displays maps of the distributions of vehicle crash, violent crime, and property crime incidents across blocks in Indianapolis. In each case, blocks with incident counts greater than 2.5 standard deviations from the mean are dispersed throughout the city. Visual inspection of the map suggests that, for each incident type, high incident blocks tend to concentrate in the eastern and northwestern portions of the city. The northern and southern portions of Indianapolis contain a number of high vehicle crash and property crime blocks, while a cluster of high violence blocks appears in the city center. The correlation between these incident types is further diagnosed through the time series negative binomial regression models.

{Insert Table 1. about here}

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Findings of the negative binomial regression models are presented as Incidence Rate Ratios (IRR), which can be interpreted as the rate at which the dependent variable is observed, with a value of one as the baseline. An IRR of 0.90 suggests that, controlling for other independent variables, a one-unit increase in the variable is associated with a 10 percent decrease in the rate at which the dependent variable occurs while an IRR of 1.10 suggests a 10 percent increase in the rate at which the dependent variable occurs (Braga & Bond, 2008, p. 590). Table 2 displays the findings of the main model. Both the standardized violent crime and property crime rates achieved statistical significance, exhibiting positive relationships with vehicle crashes. However, the strength of the relationship is modest, with one-unit increases in the standardized violent crime and property crime levels associated with one percent and two percent increases in the vehicle crash count, respectively. The concentrated disadvantage index was significantly related to vehicle crashes, with every one-unit increase in the index associated with a four percent increase in vehicle crash counts. Racial heterogeneity did not achieve statistical significance.

{Insert Table 2. about here}

Table 3 displays the findings of the A, B, and C patrol tour models. During A tour, each one-unit increase in the standardized property crime level was associated with a one percent increase in vehicle crash counts while violent crime did not achieve statistical significance. Similar to the main model, concentrated disadvantage was significantly and positively related to vehicle crash counts while racial heterogeneity did not achieve statistical significance. During B tour, both violent crime and property crime were significantly related to vehicle crashes, with one-unit increases in each associated with a one percent increase in the dependent variable. Similar findings were observed for the social disorganization variables, with every one-unit increase in concentrated disadvantage associated with a four percent increase in vehicle crashes and racial heterogeneity failing to achieve statistical significance. Findings were largely replicated in the C tour model, with violent crime, property crime, and concentrated disadvantage each exhibiting statistically significant, positive relationships with vehicle crashes. As in the other models, racial heterogeneity failed to achieve statistical significance.

The cumulative findings suggest a statistically significant, positive relationship between both property crime and violent crime and vehicle crashes. Despite the achieved significance, IRR values suggest a low effect size in each instance. The strongest relationships were observed in the C tour model. During this time frame (10pm to 6am) one-unit increases in violent crime and property crime were each associated with a three percent increase in vehicle crashes. To put this in perspective, blocks with violent crime and property crime levels three standard deviations or greater above the mean exhibited vehicle crash level increases of at least nine percent, an arguably modest total. This suggests that the tactic of simultaneously targeting crime and vehicle crashes should be reserved only for the blocks in Indianapolis experiencing the highest levels of activity. Furthermore, clusters of high-activity blocks should be distinguished from high activity blocks that are more evenly dispersed throughout space. Clusters would make better target areas by allowing police to target numerous high risk areas without having to dedicate a substantial amount of additional patrol resources.

To identify high-activity blocks, we conducted a Local Indicators of Spatial Autocorrelation (LISA) analysis (Anselin, 1995) in the ArcGIS 10.2 software package.[9] LISA improves upon traditional hotspot identification tools by identifying clusters of places with values similar in magnitude, as well as spatial outliers. In particular, LISA can distinguish between statistically significant clusters of high values surrounding by high values (HH), low values surrounding by low values (LL), high values surrounded by low values (HL), and low values surrounded by high values (LH) (Kennedy *et al.*, 2011:356).[10] Such information can be beneficial for police deployment because it allows for easy identification of areas that should be prioritized for intervention, as well as those that should perhaps receive a smaller allocation of available resources (Kennedy *et al.*, 2011).

Figure 2 displays the results of a LISA analysis of cumulative violent crime, property crime, and vehicle crash levels throughout Indianapolis blocks. Given the different frequency of occurrence for these incident types, counts of violent crime, property crime, and vehicle crashes were first standardized within each block. The standardized scores were then summed to create an overall activity index. The LISA analysis was conducted on this index. As displayed in Figure 2, clusters of statistically significant HH clusters appear throughout the city. Nearly as prevalent are HL outliers: high activity blocks surrounded by low activity blocks. The LISA analysis also found LL clusters and LH outliers, though they were rarely observed. This information can inform police deployment decisions by identifying clusters of HH blocks as target areas. Such an approach can also be used to evaluate progress and re-allocate resources over time. For example, police can select a small subset of HH clusters for intervention, only adding additional target areas when the results of a LISA analysis confirm that risk has reduced in these areas. In a similar vein, police can monitor HL clusters to track whether observed crime and traffic problems expand to new areas (i.e. the HL clusters turn into HH clusters) or if a spatial diffusion of benefits occurs (i.e. HL clusters turn into LL clusters or lose statistical significance).

Discussion and Conclusions

There exists a strong collective knowledgebase that suggests police can enhance their operational focus through the inclusion of traffic crashes into spatiotemporal decision making. Traffic violations are considered to be indices of disorder, social incivility, and disregard for social norms (Giacopassi & Forde, 2000). Traffic crashes reflect a greater set of problems that plague communities and require proactive and preventative strategies in an order to reduce community exposure to harm (Corsaro *et al*., 2012). Moreover, there is promising evidence to support the use of hotspots policing (Braga *et al*., 2014) and directed patrols (McGarrell *et al*., 2001; Sampson & Cohen, 1988) to reduce crime and disorder in problem places. Police are expected to be responsive to these community problems and broader set of service tasks (Ratcliffe, 2015) amidst stagnant or decreasing budgets (Cook, 2015). The inclusion of vehicle crash and crime data into spatiotemporal models lends promise to further inform the complex task of policing problem places and maximizing resource allocations.

To our knowledge, this study is the first examine vehicle crash and crime data using spatiotemporal modeling. In sum, our findings suggest a positive and statistically significant relationship between both property crime and violent crime and vehicle crashes. Though effect sizes are modest at best, with the strongest relationship indicating a one-unit increase in violent crime and property crime associated with a three percent increase in vehicle crashes, the findings support the logic that crime and vehicle crash hotspots may prove worthy of directed police patrols and aggressive traffic enforcement. We do not contend that crime and vehicle crashes are similar problems that can be remedied by the same policing strategy, however the literature reviewed demonstrates increased police activity can indeed impact both problems. For example, a study of 171 cities in the U.S. concluded that robbery was reduced while police conducted proactive drinking and driving activities (Sampson & Cohen, 1988). Evidence supporting hotspots policing lends promise that such an approach may generate crime deterrence through an increased perception of apprehension (Braga *et al*., 2014; Ratcliffe, *et al*., 2011). Moreover, Sorg (2016) concluded that hotspots import crime; that is, people travel to hotspots to commit crime. An emphasis on traffic enforcement in areas that experience high rates of crime and crashes may deter would-be offenders from driving to criminal places – a notion supported by the diffusion of benefits observed in a number of hot spots policing studies (Telep *et al*., 2014).

Deploying focused police patrols to traffic problem areas has been shown to have positive impacts on traffic disorder, such as reductions in speeding (Ryeng, 2012), traffic fatalities (DeAngelo & Hansen, 2014), and vehicle crashes (Newstead, Cameron, & Legget, 2001). A directed patrol strategy could also take the form of Data-Driven Approaches to Crime and Safety (DDACTS). Initial findings suggest DDACTS can reduce both crime and vehicle crashes (Bryant, Collins, & White, 2015; Rydberg, McGarrell, & Norris, 2014). Despite these promising results, there is scant literature that evaluates the deterrent effects for both crime and vehicle crashes in hot spots and should be a focal point of future research. Furthermore, the contemporary expectation is that police should aim to improve public safety and reduce harm in the communities they serve. As such, the inclusion of vehicle crashes into spatiotemporal modeling would enable police to develop and deliver more harm-focused strategies within areas of the city that do not experience equivalent levels of crime.

Though increased traffic enforcement has been shown to have crime reducing benefits while simultaneously avoiding adverse outcomes among community members experiencing increased police activity (Chermak, McGarrell, & Weiss, 2001), a decision to employ aggressive traffic enforcement to reduce vehicle crashes and crime presents the same community challenge police face with hotspots policing; primarily concerns of police-community relations and police legitimacy (Kochel, 2011; Weisburd *et al*., 2011). A policing strategy that focuses on traffic enforcement in crash-crime hotspots may magnify the risk of reducing police legitimacy and community relations through perceptions of racial profiling and excessive police activity in communities that tend to be largely inhabited by minorities (Kochel, 2011). Despite evidence that those living in hotspots do not perceive increased activity to reflect poorly on the police (Haberman *et al*., 2016), the reality is that aggressive enforcement tactics, especially those grounded in vehicle strops, would require police to consider efforts to promote the strategy with the community receiving the targeted intervention. This is especially important in light of the findings of a recent field experiment finding that residents exposed to directed police patrols reported reductions in perceptions of procedural justice and trust in police as compared to residents in areas assigned to problem-solving or control conditions (Kochel & Weisburd, 2017).

Our analyses suggest IMPD may be able to deter crime and vehicle crashes in geographic areas that experience significantly higher rates of each incident. Though reductions are likely to be marginal based on the incidence rate ratios observed, such reductions would be consistent with expected deterrence outcomes from problem-based (Weisburd *et al*., 2010) and hotspot policing (Braga *et al*., 2014; Ratcliffe *et al*., 2011) interventions. Despite a growing evidence-base focused on temporal and geospatial policing in criminology and criminal justice, examinations of vehicle crash and other traffic-related offenses remain sparse and underdeveloped. Much of the work in this area has been generated by scholars in urban public health policy and demonstrates substantive promise (Corsaro *et al*., 2012). For these reasons, and those we articulate below, it appears evident that criminologist should devote additional attention to this line of research.

Micro-places of crash and crime concentrations also provide opportunities to pursue robust evaluations of police interventions as these locations may provide field settings to employ rigorous evaluations methods, such as randomized control trials, that help to establish causality and improved internal validity. Data capturing traffic-related incidents can be paired with traditional crime and disorder measures to gauge program effectiveness, displacement, and diffusion of benefits. For example, results of our LISA analysis identify locations in Indianapolis where crime and crashes cluster at a statistically higher rate than contiguous areas. Such areas could be the focus of an intervention to assess intervention impact in the target area while capturing any potential displacement or diffusion in buffer areas. Furthermore, evaluations may include cost-benefit analyses given the availability of financial estimates related to vehicle crashes; an aspect of the hotspots policing research that Braga and his colleagues (2014) found to be severely lacking in their meta-analysis.

Relatedly, the identification of micro-places that experience significantly higher rates of vehicle crashes also creates opportunities to engage in problem-oriented policing strategies and subsequent evaluations. Significantly higher rates of crashes in micro-places may be the result of factors that can be improved upon through environmental design or modified traffic laws. Through a problem-oriented approach police could identify the nature of vehicle crashes (i.e., speeding crashes, vehicle-pedestrian crashes, or drunk-driving crashes) and develop solutions to mitigate these incidents. For example, an intersection may be poorly lit and vehicle operators do not see pedestrians walking or biking. Another example may be that surface streets around popular entertainment zones, such as bars, create traffic funnels where persons under the influence must navigate. Despite seven guides published by the Center for Problem-Oriented Policing to focus on problem-solving for traffic issues, a review of the literature reveals only a single study (Corsaro *et al.*, 2012) that evaluates this approach. This lack of scholarly evidence is consistent with Weisburd *et al.*'s (2010) systematic review of problem-oriented policing (POP) in which few evaluations of POP employed rigorous methods. Specifically, Weisburd *et al.* (2010, p. 164) note "We think it a major public policy failure that the government and the police have not invested greater effort and resources in identifying the POP approaches and tactics that work best to combat specific types of crime….a much larger number of studies is needed to draw strong generalizations regarding the possible effectiveness of POP…". Spatiotemporal modeling of crime and crash hotspots can identify small units of geography for POP experiments in the field that employ robust designs.

Notes

[1] For more information see: http://www1.nyc.gov/site/visionzero/index.page

[2] Though Marion County and Indianapolis share city-county boundaries, the cities of Beech Grove, Lawrence, Southport, and Speedway are independent cities also located within Marion County and fall outside of the Indianapolis Metropolitan Police Department's jurisdiction. Crime, crash, and control variable data for each of these four independent cities was not included in the present study.

[3] While collected as part of the UCR, arson was not provided to the research team because it is primarily addressed by the Indianapolis Fire Department, rather than IMPD. Therefore, arson was excluded from the study.

[4] Indiana motor vehicle collisions have a number of characteristics that are used to determine whether or not an incident requires completion and submission of an Indiana crash report. If the answer to each of the questions below is "yes", the incident meets the definition of a motor vehicle crash that requires a crash report: 1) Did the incident involve one or more motor vehicles?; 2) Of the motor vehicles involved, was at least one in motion?; 3) Did the incident originate on a traffic way?; 4) Did the incident occur on private property and, as specified in IC 9-26-2-4: (1) occurred on commercial or other private property that is open to the public; and (2) resulted in: (A) personal injury or death; or (B) property damage to an apparent extent greater than $1,000; 5) Was there at least one occurrence of injury or damage, which was not a direct result of a cataclysm (act of nature)?

[5] ACS estimates included the five-year periods of 2007-2011, 2008-2012, and 2009-2013 for the years 2011, 2012, and 2013, respectively.

[6] While prior measures of social disadvantage have also included percentage of black residents, racial composition was addressed via a separate variable, which is discussed shortly.

[7] Reliability coefficients (Cronbach's Alpha) for the social disadvantage index were almost identical with (.8431) and without race (.8457). Diagnostic models with social disorganization inclusive of race mirrored the findings presented. These additional results can be provided by the authors upon request.

[8] First order Queen Continuity was used in the creation of the spatial lag variable. Moran's I was 0.188 (p =0.001).

[9] Spatial relationships were operationalized via the inverse distance method, meaning nearby neighboring features had a larger influence on computation for a target feature than features that are far away. Distance between features were measured via Manhattan distance, which adds the difference between the X coordinates of two points (corresponding to the center of a block) to the difference between the Y coordinates of the two points. This approach is a better measurement of distance in urban settings, where traveling from one are to another rarely occurs in a straight line, but rather follows pre-determined networks such as roadways and sidewalks (Chainey and Ratcliffe, 2005; Rossmo, 2000).

[10] It should be noted that each high/low combination may not be observed in all instances.

References

Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographic Analysis,* 27, 93-115.

Anselin, L., Syabri, I., & Youngihn, K. (2005). GeoDa: An introduction to spatial analysis. *Geographic Analysis*, 38, 5-22.

Arneklev, B. J., Grasmick, H.S., Tittle, C. R., & Bursik, R. J. (1993). Low self-control and imprudent behavior. *Journal of Quantitative Criminology*, 9(3), 225-247.

Berg, M., Stewart, E., Brunson, R., & Simons, R. (2012). Neighborhood cultural heterogeneity and adolescent violence. *Journal of Quantitative Criminology*, 28, 411-435.

Brace, C., Scully, M., Clark, B., & Oxley, J. (2010). T*he Relationship Between Crime and Road Safety*. Accident Research Centre. Monash University. Report No. 284.

Braga, A. A., Papachristos, A. & Hureau, D. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Quarterly*, 31(4), 633-663.

Braga, A. & Bond, B. (2008). Policing crime and disorder hot spots. A randomized controlled trial. *Criminology*, 46(3), 577–607

Braga, A., Hureau, D., & Papachristos, A. (2012). An ex post facto evaluation framework for place-based police interventions. *Evaluation Review,* 35(6), 592–626.

Bryant, K. M., Collins, G. M., & White, M. D. (2015). *Shawnee, Kansas, Smart Policing Initiative: Reducing Crime and Automobile Collisions through Data-Driven Approaches to Crime and Traffic Safety*. Bureau of Justice Assistance. U.S. Department of Justice. Available at: http://www.smartpolicinginitiative.com/sites/all/files/Shawnee%20Site%20Spotlight%20 FINAL%202015.pdf

Bursik, R. & Grasmick, H. (1993). *Neighborhoods and crime: The dimensions of effective community control*. New York: Lexington Books.

Center for Problem-Oriented Policing. (2016). *Problem-Specific Guides*. U.S. Department of Justice. Retrieved from http://www.popcenter.org/guides/

Chainey, S., & Ratcliffe, J. (2005). *GIS and crime mapping.* London: Wiley.

Clarke, R. V., & Eck, J. E. (2014). *Becoming a problem-solving crime analyst*. London. Willan.

Cohen, J., & Ludwig, J. (2003). Policing crime guns. In J. Ludwig and P. J. Cook (eds.), *Evaluating gun policy: Effects on crime and violence,* (pp. 217–239). Washington, DC: Brookings Institution Press.

Cook, P. J. (2015). Will the current crisis in police legitimacy increase crime? Research offers a way forward. *Psychological Science in the Public Interest,* 16(3), 71-74.

Corsaro, N. Gerard, D. W., Engel, R. S., & Eck, J. E. (2012). Not by accident: An analytical approach to traffic crash harm reduction. *Journal of Criminal Justice,* 40(6), 502-514.

Cottrill, C. D., & Thakuriah, P. (2010). Evaluating pedestrian crashes in areas with high low-income or minority populations. *Accident Analysis and Prevention,* 42(6), 1718-1728.

Cubbin, C., LeClere, F. B., & Smith, G. S. (2000). Socioeconomic status and injury mortality: Individual and neighborhood determinants. *Journal of Epidemiological Health*, 54(7), 517-524.

DeAngelo, G., & Hansen, B. (2014). Life and death in the fast lane: Police enforcement and traffic fatalities. *American Economic Journal: Economic Policy*, 6(2), 231-257.

Federal Bureau of Investigation. (2013). *Crime in the United States, 2013*. Uniform Crime Reporting. Washington, DC.

Gascon, G., & Foglesong, T. (2010). *Making Policing More Affordable: Managing Costs and Measuring Value in Policing*. New Perspectives in Policing. National Institute of Justice. Harvard Kennedy School. Retrieved from https://www.ncjrs.gov/pdffiles1/nij/231096.pdf

Gau, J. M., & Pratt, T. C. (2010). Revisiting broken windows theory: Examining the sources of the discriminant validity of perceived disorder and crime. *Journal of Criminal Justice,* 38(4), 758-766.

Giacopassi, D., & Forde, D. R. (2000). Broken windows, crumpled fenders, and crime. *Journal of Criminal Justice*, 28(5), 397-405.

Gottfredson, M. R., & Hirschi, T. (1990). *A General Theory of Crime*. Stanford University Press. Stanford, CA.

Haberman, C. P., Groff, E. R., Ratcliffe, J. H., & Sorg, E. T. (2016). Satisfaction with police in violent crime hot spots: Using community surveys as a guide for selecting hot spot policing tactics. *Crime and Delinquency*, 62(4), 525-557.

Hardy, E. (2010). Data-driven policing: How geographic analysis can reduce social harm. *Geography and Public Safety Bulletin*, 2(3), 1-2.

Hipp, J. & Wickes, R. (2016). Violence in urban neighborhoods: A longitudinal study of collective efficacy and violent crime. *Journal of Quantitative Criminology,* DOI 10.1007/s10940-016-9311-z, 1-26.

Johansson, R. (2008). Vision zero – implementing a policy for traffic safety. *Safety Science*, 47(6), 826-831.

Johnson, S., Bowers, K., Birks, D., & Pease, K. (2009) Predictive mapping of crime by ProMap: accuracy, units of analysis, and the environmental backcloth. In: Weisburd D, Bernasco W, Bruinsma G (eds) *Putting crime in its place: units of analysis in geographic criminology*. Springer, New York, 179–198.

Junger, M., West, R., & Tillman, R. (2001). Crime and risk behavior in traffic: an example of cross-situational consistency. *Journal of Research in Crime and Delinquency*, 38(4), 439-459.

Keane, C., Maxim, P. S., & Teevan, J. J. (1993). Drinking and driving, self-control, and gender: Testing a general theory of crime. *Journal of Research in Crime and Delinquency*, 30(1), 30-46.

Kennedy, L., Caplan, J., & Piza, E. (2011). Risk clusters, hotspots, and spatial intelligence: Risk terrain modeling as an algorithm for police resource allocation strategies. *Journal of Quantitative Criminology*, 27(3), 339-362.

Kochel, T. R. (2011). Constructing hot spots policing: Unexamined consequences for disadvantaged populations and for police legitimacy. *Criminal Justice Policy Review*, 22(3), 350-374.

Kochel, T., & Weisburd, D. (2017). Assessing community consequences of implementing hot spots policing in residential areas: Findings from a randomized field trial. *Journal of Experimental Criminology*, DOI: 10.1007/s11292-017-9283-5.

Kubrin, C. E., Messner, S. F., Deane, G., McGeever, K., & Stuckey, T. D. (2010). Proactive policing and robbery rates across U.S. cities. *Criminology*, 48(1), 57-97.

Kuo, P., Lord, D., & Walden, T. D. (2013). Using geographical information systems to organize police patrol routes effectively by grouping hotspots of crash and crime data. *Journal of Transport Geography*, 30, 138-148.

McGarrell, E. F., Chermak, S. M.,Weiss, A., & Wilson, J.M. (2001). Reducing firearms violence through directed patrol. *Criminology and Public Policy*, 1(1), 119-148.

McClure, D., Levy, J., La Vigne, N., & Hayeslip, D. (2014). *DDACTS Evaluability Assessment: Final Report on Individual and Cross-Site Findings*. Washington, DC: Urban Institute. Report No. 247889.

Morenoff, J., Sampson, R., & Raudenbush, S. (2001). Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence. *Criminology*, 39: 519-559.

National Highway Traffic Safety Administration [NHTSA]. (2014). *Data-Driven Approaches to Crime and Traffic Safety: Operational Guidelines*. Washington, DC.

Newstead, S. V., Cameron, M. H., & Legget, L. M. (2001). The crash reduction effectiveness of a network-wide traffic deployment system. *Accident Analysis and Prevention*, 33, 393-406.

Oberwittler, D., & Wikstrom, P. (2009) Why small is better: Advancing the study of the role of behavioral contexts in crime causation. In: Weisburd D, Bernasco W, Bruinsma G (eds) *Putting crime in its place: units of analysis in geographic criminology*. Springer, New York, 35–59.

Pratt, T. C., & Cullen, F. T. (2005) Assessing macro-level predictors and theories of crime: A meta-analysis. Crime and Justice, 32, 373–450.

Quisenberry, P. N. (2015). Testing and driving: Can it be explained by the general theory of crime? *American Journal of Criminal Justice*, 40(2), 303-316.

Ratcliffe, J. H. (2015). Towards an index for harm-focused policing. *Policing: A Journal of Policy and Practice*, 9(2), 164-182.

Ratcliffe, J. (2004). Geocoding rate and a first estimate of a minimum acceptable hit rate. International *Journal of Geographical Information Science*, 18: 61-72.

Ratcliffe, J. H., Taniguchi, T., Groff, E. R., & Wood, J. D. (2011). The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots. *Criminology*, 49(3), 795-832.

Robinson, W. (1950) Ecological correlations and the behavior of individuals. *American Sociological Review,* 15, 351-357.

Rossmo, D. (2000). *Geographic profiling.* Washington, DC: CRC Press.

Rydberg, J., McGarrell, E. F., & Norris, A. (2014). *Flint DDACTS Pilot Evaluation*. Michigan Justice Statistics Center. School of Criminal Justice. Michigan State University. Available at: http://cj.msu.edu/assets/DDACTS-Report-ExecSummary_MSP_2012_BJ_CX_K036-FINAL.pdf

Ryeng, E. O. (2012). The effect of sanctions and police enforcement on drivers' choice of speed. *Accident Analysis and Prevention*, 45, 446-454.

Sampson, R. J., & Cohen, J. (1988). Deterrent effects of the police on crime: A replication and theoretical extension. *Law and Society Review*, 22(1), 163-189.

Sampson, R., & Groves, W. (1989). Community structure and crime: Testing social disorganization theory. *American Journal of Sociology*, 94(4), 774-802.

Sampson, R. J., & Raudenbush, S. W. (1999). Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology*, 105(3), 603-651.

Sampson, R., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277: 918-924.

Schnelle, J. F., Kirchner, R. E., Casey, J. D., Useleton, P. H., & McNees, M. P. (1977). Patrol evaluation research: A multiple-baseline analysis of saturation patrolling during day and night hours. *Journal of Applied Behavior Analysis*, 10(1), 33-40.

Shaw, C., & McKay, H. (1942). *Juvenile delinquency and urban areas*. University of Chicago Press: Chicago, IL.

Sherman, L., Neyroud, P. W., & Neyroud, E. (2016). The Cambridge crime harm index: Measuring total harm from crime based on sentencing guidelines. *Policing: A Journal of Policy and Practice*, 10(3), 171-183.

Sherman, L. W., & Rogan, D. P. (1995). The effects of gun seizures on gun violence: ‘Hot spots’ of patrol in Kansas City. *Justice Quarterly*, 12(4), 673-693.

Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime 'hot spots': A randomized, controlled trial. *Justice Quarterly*, 12(4), 625-648.

Smith, P., & King, R. D. (2013). From road rage to everyday automotive incivility: A routine activities approach to low-level deviance. *The Sociological Quarterly*, 54(3) 476-500.

Sorg, E. T. (2016). Classifying import and domestic hot spots of crime by offender home proximity. *Policing: A Journal of Policy and Practice*. Advanced Online Publication. DOI:10.1093/police/paw002.

Stuster, J., Sheehan, M., & Monford, G. (1997). *Contributions of Traffic Enforcement to the War on Crime: Case Study of the Grand Prairie, Texas Police Department*. Washington, D.C.: National Highway Traffic Safety Administration.

Telep, C. W., Weisburd, D., Gill, C. E., Vitter, Z., & Teichman, D. (2014). Displacement of crime and diffusion of crime control benefits in large-scale geographic areas: A systematic review. *Journal of Experimental Criminology*, 10(4), 515-548.

U.S. Census Bureau. (2016). *State and Country Quick Facts*. Retrieved from http://quickfacts.census.gov/qfd/states/18/1836003.html

Vaughn, M. G., Salas-Wright, C. P., & Piquero, A. R. (2012). Buck up: Non-seat belt use and antisocial behavior in the United States. *Annals of Epidemiology*, 22(12), 825-831.

Weiss, A. (2013). *Data-Driven Approaches to Crime and Traffic Safety (DDACTS): A Historical Overview*. Washington DC: NHSTA.

Weiss, A. & Freels, S. (1996). The effects of aggressive policing: The Dayton traffic enforcement experiment. *American Journal of Police*, 15(3), 45-64.

Weisburd, D. (2015). The law of crime concentration and the criminology of place. *Criminology*, 53(2), 133-157.

Weisburd, D., Hinkle, J. C., Famega, C., & Ready, J. (2011). The possible “backfire” effects of hot spots policing: An experimental assessment of impacts on legitimacy, fear and collective efficacy. *Journal of Experimental Criminology*, 7(4), 297-320.

Weisburd, D., Telep, C. W., Hinkle, J. C., & Eck, J. (2010). Is problem-oriented policing effect in reducing crime and disorder? Findings from a Campbell systematic review. *Criminology and Public Policy*, 9(1), 139-172.

Williams, K. (1984). Economic sources of homicide: Reestimating the effects of poverty and inequality. *American Sociological Review*, 49, 283-289.

Wilson, R. E. (2010). Place as the focal point: Developing a theory for the DDACTS model. *Geography and Public Safety Bulletin*, 2(3), 3-4.

Wilson, J. W., & Heinonen, J. A. (2012). Police workforce structures: Cohorts, the economy, and organizational performance. *Police Quarterly*, 15(3), 283-307.

Yang, S. M. (2010). Assessing the spatial-temporal relationship between disorder and violence. *Journal of Quantitative Criminology*, 26(1), 139-163.

Yang, S. M. (2007). *Causal or Merely Co-Existing: A Longitudinal Study of Disorder and Violence at Places*. Doctoral Dissertation. University of Maryland. College Park, MD.

Tables and Figures

Table 1. Descriptive Statistics

Dependent Variable			
Crashes	**Mean (Std. Dev.)**	**Min. (Max.)**	**3-Year Total**
Overall	0.11 (0.46)	0 (16)	62,115
A tour	0.04 (0.23)	0 (7)	22,477
B tour	0.06 (0.29)	0 (11)	31,308
C tour	0.01 (0.13)	0 (5)	8,330
Independent Variables			
Violent crime	**Mean (Std. Dev.)**	**Min. (Max.)**	**3-Year Total**
Overall	0.08 (0.38)	0 (21)	29,199
A tour	0.02 (0.16)	0 (13)	5,924
B tour	0.03 (0.22)	0 (20)	12,062
C tour	0.03 (0.20)	0 (14)	11,213
Violent crime (standardized)	**Mean (Std. Dev.)**	**Min. (Max.)**	
Overall	0 (1)	-0.27 (57.19)	
A tour	0 (1)	-0.15 (51.33)	
B tour	0 (1)	-0.20 (81.47)	
C tour	0 (1)	-0.19 (71.90)	
Property crime	**Mean (Std. Dev.)**	**Min. (Max.)**	**3-Year Total**
Overall	0.24 (0.87)	0 (93)	138,076
A tour	0.08 (0.35)	0 (21)	45,571
B tour	0.09 (0.52)	0 (91)	51,125
C tour	0.07 (0.33)	0 (52)	41,380
Property crime (standardized)	**Mean (Std. Dev.)**	**Min. (Max.)**	
Overall	0 (1)	-0.32 (85.84)	
A tour	0 (1)	-0.25 (55.28)	
B tour	0 (1)	-0.21 (104.87)	
C tour	0 (1)	-0.27 (96.67)	
Control Variables	**Mean (Std. Dev.)**	**Min. (Max.)**	
Area (sq. miles)	0.03 (0.07)	0.00 (2.00)	
Spatial lag	6.12 (9.16)	0 (184)	
Racial heterogeneity	0.06 (0.57)	-2.25 (1.60)	
Concentrated disadvantage	-0.28 (3.23)	-5.87 (10.19)	

Table 2. Times Series Negative Binomial Regression Findings: Overall

Covariates	IRR	S.E.	z	*p.*
Independent Variables				
Violent crime (standardized)	1.01	0.00	3.53	0.00**
Property crime (standardized)	1.02	0.00	6.42	0.00**
Control Variables				
Concentrated disadvantage	1.04	0.00	10.24	0.00**
Racial heterogeneity	0.99	0.01	-1.15	0.25
Area (sq. miles)	2622.37	894.99	23.06	0.00**
Spatial lag	1.09	0.00	33.27	0.00**
Lagged crash count	1.09	0.00	22.17	0.00**
Days in month	1.05	0.01	9.38	0.00**
Month sequence	1.00	0.00	9.05	0.00**
Model				
Log likelihood	-140550.38			
Wald X^2	2779.52 (9)			

N=551,145; $^{**}p$<0.01

Table 3. Times Series Negative Binomial Regression Findings: Patrol Tours

			A TOUR	
Covariates	**IRR**	**S.E.**	**z**	***p.***
Independent Variables				
Violent crime (standardized)	1.01	0.00	1.36	0.17
Property crime (standardized)	1.01	0.00	3.93	0.00**
Control Variables				
Concentrated disadvantage	1.04	0.01	7.00	0.00**
Racial heterogeneity	1.02	0.02	1.07	0.29
Area (sq. miles)	2291.40	890.47	19.91	0.00**
Spatial lag	1.09	0.00	30.57	0.00**
Lagged crash count	1.11	0.01	9.29	0.00**
Days in month	1.05	0.01	5.23	0.00**
Month sequence	1.00	0.00	6.37	0.00**
Model				
Log likelihood	-71536.94			
Wald X^2	1709.95 (9)			
			B TOUR	
Covariates	**IRR**	**S.E.**	**z**	***p.***
Independent Variables				
Violent crime (standardized)	1.01	0.00	3.31	0.00**
Property crime (standardized)	1.01	0.00	4.53	0.00**
Control Variables				
Concentrated disadvantage	1.04	0.00	9.10	0.00**
Racial heterogeneity	0.98	0.01	-1.64	0.10
Area (sq. miles)	3220.07	1217.23	21.37	0.00**
Spatial lag	1.09	0.00	31.21	0.00**
Lagged crash count	1.12	0.01	15.03	0.00**
Days in month	1.06	0.01	7.06	0.00**
Month sequence	1.00	0.00	5.70	0.00**
Model				
Log likelihood	-89336.49			
Wald X^2	2072.66 (9)			
			C TOUR	
Covariates	**IRR**	**S.E.**	**z**	***p.***
Independent Variables				
Violent crime (standardized)	1.03	0.01	4.81	0.00**
Property crime (standardized)	1.03	0.01	5.15	0.00**
Control Variables				
Concentrated disadvantage	1.05	0.01	9.38	0.00**
Racial heterogeneity	0.99	0.24	-0.55	0.58
Area (sq. miles)	725.30	248.56	19.22	0.00**
Spatial lag	1.06	0.00	22.38	0.00**
Lagged crash count	1.12	0.04	3.26	0.00**
Days in month	1.06	0.02	3.73	0.00**
Month sequence	1.00	0.00	1.64	0.10
Model				
Log likelihood	-37475.37			
Wald X^2	1097.68 (9)			

N=551,145; ** $p<0.01$

Figure 1. Distribution of Crash, Violent Crime, and Property Crime Incidents across Census Blocks (2011-2013).

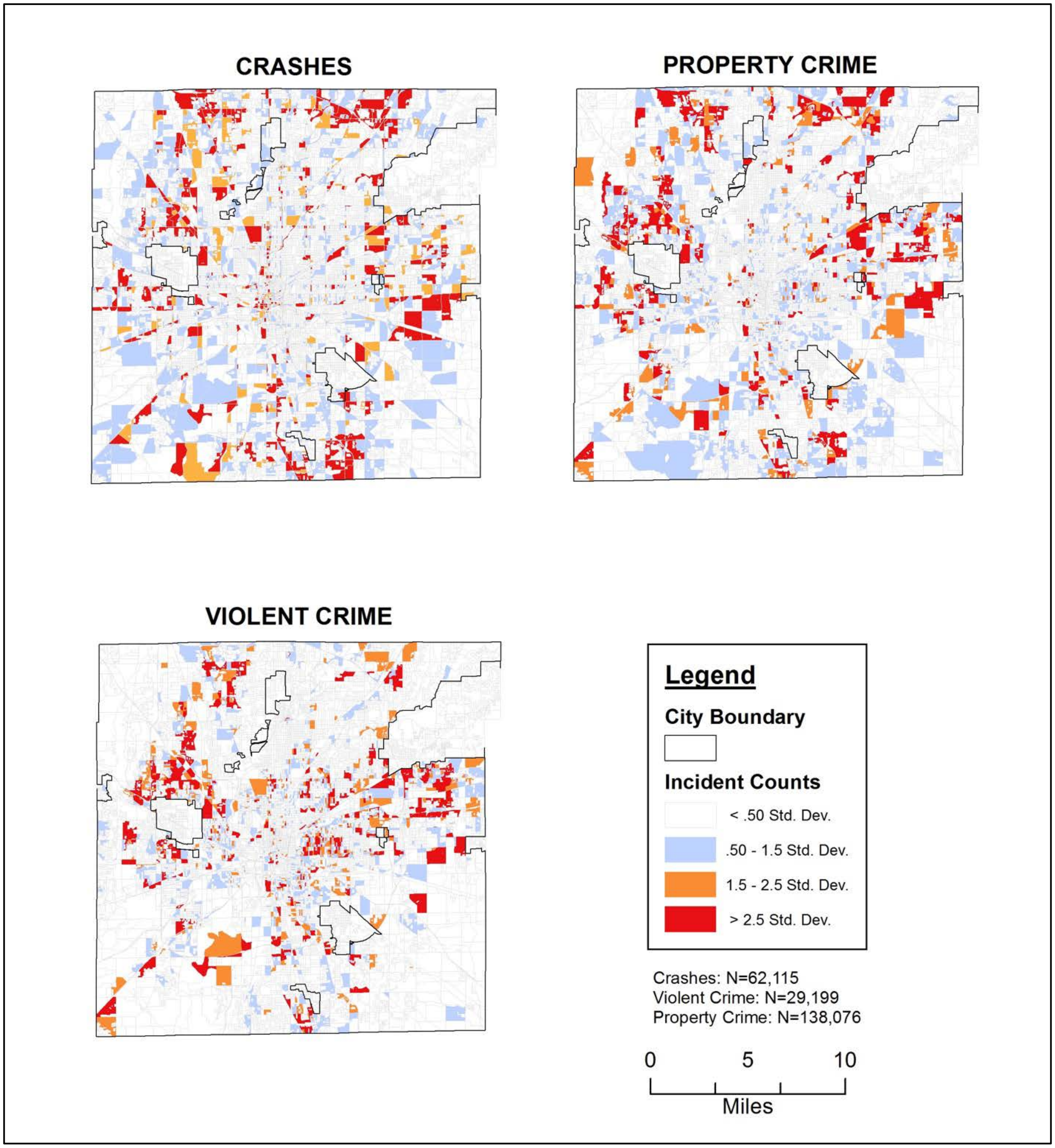

Figure 2. Local Indicators of Spatial Autocorrelation (L.I.S.A.) analysis for Cumulative Crash, Violent Crime, and Property Crime Hot Spots (2011-2013).