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Narcotics arrest data as a predictor of violent crime in Dallas, Texas.

Abstract

The Dallas Police Department (DPD) has the goal of reducing violent crime by targeting guns, gangs, and drugs. The limited resources available to the DPD require strategic planning to maximize the effect of patrol officers. The DPD currently targets violent crime (murder, rape, robbery-individual, robbery-business and aggravated assault) by analyzing criminal offense reports. This crime model is reactive rather than a proactive, intelligence-driven policing model. The DPD needs a statistical tool to predict high crime areas prior to the offenses occurring. This research will develop a geographically weighted regression (GWR) model that uses drug arrest data to determine risk for violent crimes at the block-face level. The GWR tool will assist the DPD in determining where to deploy additional resources to prevent violent gun crimes.

***Keywords**: crime control, Dallas Police Department, geographic weighted regression, narcotics trafficking , violent crime*

Introduction

The Dallas Police Department (DPD) has the goal of reducing crime by targeting criminal activity involving guns, gangs, and drugs. The limited resources available to the DPD require strategic planning to maximize the effect of patrol officers. The DPD currently targets violent crime (murder, rape, robbery-individual, robbery-business and aggravated assault) by analyzing criminal offense reports. This crime model is reactive rather than a proactive, intelligence-driven policing model. In fact, the DPD executives and middle-managers often refer to this method as "chasing dots" (crime incidents) on a map (Dallas Police COMPSTAT Meeting 2006).

The DPD has good reason to be concerned about violent crime. During the last decade, the DPD has reported higher violent crimes per capita under the FBI's Uniform Crime Reporting program than other major cities (Eiserer 2008). While individual comparisons of crime rates between cities are often misleading and disingenuous, they do occur (Federal Bureau of Investigation 2007; LaFluer and Eiserer 2007). These crime stories make the front page of newspapers, resulting in immense pressure from politicians and citizens' groups to reduce crime rates (Seidman and Couzens 1974). In his inauguration speech, Mayor Tom Leppert declared the goal of removing Dallas from "the list" of cities with the highest crime rates (Eiserer 2007). While the arrest of the perpetrators of these offenses remains a high priority for the DPD, the prevention of these offenses is of greater impact on the crime rate. An arrest does

not negate the offense, and thus has no effect on the crime rate other than temporarily preventing the arrestee from committing more offenses.

The strategy of DPD has been to identify hotspots based on police beat and reporting areas (RAs) analysis, and then to deploy resources to those locations. While offense location is useful for deployment, crime management requires more detailed analysis of underlying causes and crime risk levels (Craglia, Haining and Wiles 2000). Police officers, from beat cops to the highest executives, have shown to lack a fundamental understanding of crime hotspots and an inability to properly identify hotspots (Ratcliffe and McCullagh 1999; Willis et al 2007). Their perceptions of high crime areas do not match reality.

The DPD uses police beat and police RAs to analyze crime by aggregating data collected as point events to these larger areal units. DPD introduces the modifiable areal unit problem (MAUP) into its analysis because statistic and model parameters are dependent upon geographic resolution. The MAUP is a major problem in aggregate data analysis. The MAUP refers to the reduction of variability and error caused by aggregating data at varying spatial units (Dark and Bram, 2007). Predicting large area values based on small area data is not accurate and vice versa. Temporal and spatial scales have similar results when data is aggregated. The DPD collects its crime data as discrete address points. The proper scale for analyzing these points is discrete points, which is how the data is collected. The data is also collected as discrete temporal events. The aggregation of temporal events has similar effects on the analysis of the data (Ratcliffe and McCullagh 1998). Trend identification is also dependent

upon temporal accuracy. Averaging the events to a specific point in time is no more accurate than using random times for unknown events.

Many major police departments have a tendency to perform superficial crime analysis (Willis et al 2007; O'shea and Nichols 2003). While they know the "when and where" of crime, they lack a profound understanding of the "how and why" of crime. Police departments also lack a fundamental knowledge of crime mapping and lack skill in analyzing the effectiveness of police practices for long-term viability. This is not to say that police departments cannot make crime maps, but rather the maps they do make are less likely to be accurate representations of the spatial processes of crime. Less than half of major police departments use any statistical tools (mean, mode, standard deviation, regression, or cluster analysis) other than counting (O'shea and Nichols 2003). Crime analysts continue to focus on tactical analysis and ignore, or spend very little time on, identifying the long-term, root causes of crime. The DPD is no different than other major police departments in these respects. The DPD analysis is mainly focused on police beats and RAs with highest percentage change between two time periods or highest raw count of offenses (Dallas Police Department Compstat Briefs 2006). The DPD continues to make decisions on the top 10 crime beats in the city without performing any sort of non-parametric analysis of those counts. Using a raw count of crime on beats does nothing to determine appropriate deployment strategies. The various aerial units, police beats, create problems as relative risk and differences in place average out

(Craglia, Haining and Wiles 2000). The DPD needs a statistical tool for predicting high crime areas prior to the offenses occurring.

This research will focus on developing a geographically weighted regression (GWR) tool that uses drug arrest data to determine risk for violent crimes at the block-face level. The GWR tool will assist the DPD in determining where to deploy additional resources to prevent violent gun crime. A block-face level analysis of crime will allow for a higher degree of accuracy in determining high risk locations.

Background

There are many theories to explain the cause of crime. While it is not the purpose of this paper to present an overview of criminological theory, a brief explanation of significant theories will be presented to provide the appropriate frame of reference for this research.

Social disorganization theory and routine activity theory explain crime as an event where risk is dependent on place. Social disorganization is defined as a process by which "traditions of delinquency are transmitted through successive generations of the same zone in the same way language, roles, and attitudes are transmitted" (Shaw and McKay 1942). Social disorganization is manifested in neighborhoods by residential instability, poverty and racial/ethnic heterogeneity. Residential instability refers to a mobile population that does not stay in one location for long periods of time. By contrast, residential stability often takes the form of home ownership, where residents have a vested interest in the long-term success of

the neighborhood. Poverty, not a cause of crime in itself, leaves a neighborhood devoid of resources to deal with common problems. Poverty also influences housing options and leads to clusters of poverty (Craglia, Haining and Wiles 2000). “People in poor areas are not burgled because they are poor, but because they live close to burglars.” Racial and ethnic heterogeneity create isolated populations who view the differences in language, culture, and customs as insurmountable obstacles to success.

Routine activity theory relates crime to everyday activities. According to routine activity theory, crime occurs at the intersection of three factors: a suitable target, a motivate offender and a suitable place (Andersen 2000). For example, “routine activity theory is about the increased potential of criminal victimization as a result of any person’s activities . . . ” Place managers act as intermediaries at places to prevent criminal activity (Mazerolle, Kadleck and Roehl 1998). The capable guardian, which protects the suitable target, can be a person or a process. Processes, such as well-manicured lawns, maintained buildings or well-lit areas, are manifestations of a capable guardian, even though that person is not visible. Motivated offenders have handlers, which act as intermediaries for criminal behavior. The presence of these intermediaries may not guarantee a lack of crime, but decrease in the risk of crime.

Social disorganization and routine activity theory have been expanded to include concepts such as social cohesion and collective efficacy. Collective efficacy is the willingness of community members to act on other’s behalf to achieve collective goals (Sampson 2004).

Collective efficacy relates to the neighborhood identity and has an influence on crime and disorder (Eck and Watrell 1999). Collective efficacy has a positive correlation with low levels of crime and disorder, even when controlled for socioeconomic factors (Sampson and Radenbush 2001). Reducing disorder lowers crime indirectly by increasing social cohesion. In some instances, "the density of local organizations and voluntary associations predicts high levels of collective efficacy" (Sampson 2004). Local knowledge of crime problems, in real-time, can result in the mobilization of local resources that have a more powerful impact on crime than police action alone. Additionally, neighborhoods with high risk for crime due to socioeconomic factors may not manifest those crime problems due to high collective efficacy.

A large body of research on the relationship between narcotics and violent crime exists. It is not the focus of this research to validate any causal links, but rather to explore spatial relationships between the two events. The possession and sale of narcotics has to occur in an area where drug markets will be tolerated (McCord and Ratcliffe 2007). The findings indicate that "socially disorganized areas are believed to be business-friendly environments for drug markets because they are prone to contain sufficient numbers of drug users in their population, while also lacking the resources or social efficacy to prevent the establishment of the illegal trade". McCord and Ratcliffe explored the correlation between land-use features and social disorganization as they related to drug market emergence in Philadelphia, PA. They concluded that social disorganization isn't sufficient to explain drug markets, as some low-income neighborhoods are lacking drug markets, even though all other indicators might be present. It is

possible that drug dealers are drawn to general social degeneration rather than specific features. Place managers and capable guardians may prevent the emergence of drug markets. However, place managers can only influence disorder when they act collectively with other members of the neighborhood (Mazerolle, Kadleck, and Roehl 1998). A place manager who calls 9-1-1 or attempts to intervene as an individual does not have any greater success at restoring order than police action alone.

Drug arrest data have been discounted as a measurement of drug activity in a neighborhood by some researchers. These researchers believe that police patrol high crime areas more frequently. The resulting drug arrests are viewed as biased by unequal application of police resources. Despite this assumption, a positive correlation between drug activity and violent crime was found to exist (Martinez, Rosenfeld and Mares, 2008). Martinez, et al, examined drug overdoses as a measure of drug activity in a neighborhood using deaths from cocaine and heroin. They assumed that marijuana markets would have no relationship with violent crime, due to the calming effect of marijuana.

Researchers have begun to question the basic assumption that arrest data is biased by police action and not an indicator of drug activity in a neighborhood. By comparing arrest data with community surveys, drug arrests were an indicator of drug market activity in a neighborhood (Warner and Cromer, 2003). Additionally, researchers comparing drug activity, violent crime and alcohol availability found that drug activity had the strongest correlation to

violent crime, more so than alcohol availability (Gorman, Zhu and Horel, 2005). Additional research has examined the spatial relationships between alcohol availability, drug activity and violent crime. Using a geographically weighted regression tool, the researchers were able to predict violent crime within 1% (Wheeler and Waller, 2008). This research will not include alcohol availability due to alcohol not being universally available in all parts of Dallas.

Resignato attempted to explore the effects of narcotics on violent crime. Narcotics driven crime was explained by three potential causes: psychopharmacological, economic compulsion and the black market effect (Resignato, 2000). The psychopharmacological effect is simply the alteration of neurochemistry which might lead a person to commit violent acts. The economic compulsion is crime driven by the cost of an increasingly expensive drug habit. The black market effect is the violent crime associated with the prohibition of narcotics and their distribution. Resignato's research, though compelling, aggregated data to metropolitan statistical areas. The aggregation of the data impedes the analysis by comparing areas with little to no drug activity and violent crime to areas with very high drug activity and violent crime rates. In this case, aggregation reduces variability and error, making the outcomes less meaningful than block face analysis. Resignato found that of the three potential factors behind narcotics driven crime, the Black Market effect had the greatest impact.

Street-level drug activity, disorder and serious crime cluster within specific places (Weisburd and Mazerolle 2000). Weisburd and Mazerolle suggest that a crime-specific targeting strategy is more useful than generic hot-spot analysis, and is a more refined approach to

resource allocation. A diffusion of police benefit to other crime problems is expected within drug market locations.

Methodology

Data collected for this research will include crime reports made by the DPD for the UCR categories of murder, rape, robbery-individual, robbery-business and aggravated assault. The offense reports will be further filtered by selecting only those offenses involving firearms. The UCR offense description includes whether the offense involved a firearm. Drug arrest data will come from arrest reports made by the DPD. These reports are also classified by UCR offense. The reports will be filtered by those classified as “Narcotics & Drugs” arrests. These will include possession of controlled substances, possession of marijuana, dangerous drugs and possession of drug paraphernalia. The arrests will include drugs such as cocaine (both powder and rock), heroin, marijuana, PCP, and prescription drugs.

The GWR model will be used to identify locations with a higher risk of crime by self-selecting areas with low social efficacy. Demographic data, such as that available through the U.S. Census Bureau, can be useful to identify areas with capacity for low social efficacy. However, the areal resolution for U.S. Census data is very low.

The crimes and arrests will be geocoded based on the address in the report. Geocoding accuracy will be paramount to a successful GWR model. Therefore, events will be geocoded to

the parcel, when possible, and to the line segment when not possible. Roughly 99% of the offense and arrest data will geocode correctly (Dallas Police Department, 2008). The average nearest neighbor values for both offenses and arrests are typically less than 300 feet, or the average block length, which will minimize the impact of any geocoding errors. The data will not be aggregated to any areal units. Rather, the data will be analyzed as discrete points along a network. Aggregating the data to areal units will introduce error in the variability and central tendency for each areal unit.

The GWR model will use a rolling 365 day dataset of drug arrest data. The rolling year of data will include changes due to seasonality and policy changes from year to year. A dataset that is used to compare a month from a previous year to the current year does not allow for changes in policy that may have been implemented and slowly adopted. Short-term predictions from the GWR model may not be very useful. The crime rate for murder is approximately 0.56 murders per day for the entire City of Dallas (Dallas Police Department, 2008). A single day's prediction will not be useful for deployment strategy support. A 14-day or 30-day period of crime should be predicted in order for the deployment of police resources. A single-day prediction extrapolated to longer periods of time will have more meaning for decision makers and will still maintain a high degree of accuracy.

A nearest neighbor analysis (NNA) will be performed to determine the appropriate scale, to identify clusters of events and to the set limits of the GWR model. No distance limits are necessary for the GWR to work. However, the risk of crime is not equal across all locations.

A hot spot of narcotics arrests should stand out amongst other locations with high arrests and not be diminished due to comparisons with areas of no arrests. NNA distances may vary between crime and arrest classifications. The number of events and the size of the study area will change the NNA distances and the standardized nearest neighbor index (*R*). The NNA formula is expressed as:

$$R_0 = \sum_{i=1}^{n} d_i / n$$

where $\sum_{i=1}^{n} d_i$ is the average distance between point *i* and its nearest neighbor, and *n* is the number of points in the study area. The expected nearest neighbor distance R_e, based on a completely random spatial distribution of the points, can be expressed as:

$$R_e = \frac{1}{2\sqrt{\rho}} = \frac{1}{2\sqrt{n / A}}$$

where ρ is the density of *n* points in area *A*. The actual test statistic for the NNA will not be necessary to calculate. This research is not concerned with, nor does the prediction of crime events depend upon, the distribution pattern being either clustered or random. Locations that lack clustering will necessarily have a low risk of crime. Areas with a high level of clustering will conversely have a high risk of crime. Quantifying the level of clustering will not be necessary to accurately predict outcomes.

The NNA will be performed on each arrest event, providing a distance matrix for each narcotics arrest and crime location. The weighting of the GWR will be dependent upon each arrest point. This will allow for drug markets of varying sizes to be analyzed in the same manner, without introducing the MAUP into the model. The discrete points of arrest data will be aggregated by the geocoding process to street blocks, but the model need not consider that aggregation in the evaluation of crime risk. Each arrest point will have a value for R_0, where the distance is the average for the arrest and all crimes in the dataset.

The GWR model will perform a regression analysis based on the spatial proximity between each arrest point (*i)* and observations (violent crimes) at point *j.* Events near point *i* have a greater influence on the regression estimation than events which occur at greater distances from point *i*. The GWR equation can be expressed as:

$$y_i = b_{i0} + \sum_{j=1}^{p} b_{ij} x_{ij} + \varepsilon_i$$

where *b* represents the independent variables found in regression analysis, x_{ij} represents the distance to violent crime *j* at narcotics arrest location *i*, and the coefficient *p* is specific to narcotics arrest location *i* (Rogerson 2006). An inverse weight will be applied to observations of *j*, so that any values for *j* that are farther away from location *i* will have less influence on y_i. The equation for normal weighting is expressed as:

$$w_{ij} = e^{-\beta d_{ij}^2}$$

where d_{ij} is the distance from point *i* to observation *j* and β is the weight coefficient. To begin the GWR, the values for w_{ij} are calculated by assuming values for β. If β=0, then the formula becomes the ordinary least squares function. The nearest neighbor distance will be used to place limits on w_{ij}. The weighting equation will be modified to limit the influence of d_{ij} to values less than R_e. The limiting of d_{ij} would be accomplished by setting $w_{ij} = -1$ when $R_e < d_{ij}$. Where $R_e \geq d_{ij}$ limiting of d_{ij} would be accomplished by setting $w_{ij} = 1$. This modification would allow clusters of narcotics arrests to have more influence on the risk of violent crime. The crimes farther away from the narcotics arrests are less likely to be influenced by the presence of a drug market, and therefore, should have less influence in the model.

The GWR model will be performed several times using this weighting scheme and one that makes no allowance for R_e.

This research will differ from previous research by using a multi-level approach to assessing which drug arrest types are useful for predicting various violent crime categories. The GWR model will use different weighting schemes for the dataset in order to find the best possible accuracy. Every iteration of narcotic and crime type will be explored to discover any relationships that may exist.

Evaluation

The GWR model will be evaluated by predicting known outcomes using historical data. The predicted outcomes will then be compared with observed outcomes within the historical data. A statistical analysis will be conducted to determine how accurately the model has performed. A Monte Carlo simulation and a nearest neighbor analysis will then be conducted to determine if crime patterns have changed over periods of time (Metropolis and Ulam 1949; Ratcliffe 2005). The Monte Carlo simulation will use random values for the range of each variable to create a distribution of the sampling means. The simulation will provide a measure of the error in the predicted values.

The method developed by Ratcliffe to detect spatial pattern change over time periods uses nearest neighbor values between random points and the crime data to determine spatial changes. A random set of points will be generated using Hawth's Tools for ArcGIS (Brenner 2004). The distances between the random points and the two crime sets, one crime set of points before treatment and one crime set of points after, will be compared using a Spearman's rank correlation. The outcomes will determine if the crime pattern has shifted across spatial units within the two time periods. This method will be evaluated using ArcMap GIS 9.2 (ESRI 1995-2009). Hawth's Analysis Tools for ArcMap (Beyer 2004) will be used to calculate the nearest neighbor distances. The correct number of evaluation points is difficult to determine. Too many points will result in overlap and double counting of data, which would lead to an

even distribution of distances. Too few points may not provide enough cases, resulting in too much error and an inadequate evaluation of the outcome. For the purposes of this study, the police beats will be used as the evaluation points. A centroid for each of the 232 police beats should provide ample coverage of the entire City of Dallas.

The GWR will be assessed for its ability to predict each category of violent crime. The GWR model may be better at predicting certain offense types, but not others. The limitations of the GWR should be fully explored. This research will be used to determine which crime types are suited to a GWR analysis and which are not.

The GWR will be assessed for accuracy within temporal variations in the dataset. This research will be used to determine the minimum inputs required to maintain accuracy for each crime category. A GWR model may require a full year of data. However, the valid results may be achieved with 6 months of data or with 6 weeks of data. This research will also be used to determine the minimum amount of time needed to evaluate the effectiveness of a deployment.

Conclusion

This research will further our understanding of narcotics and their effects on violent crime. The limited resources available to law enforcement agencies make the intelligent and careful deployment of police resources essential to reducing violent crime. This research will provide decision makers at the Dallas Police Department with the tools necessary to make

careful and deliberate decisions about the deployment priorities for patrol resources. It is possible that narcotics arrest data will prove unsuited for predicting violent crime locations. This outcome will still provide value to understanding the relationship between narcotics and violent crime.

This research will address the spatial relationship between violent crime and drug markets in the urban setting. Previous research relied on aggregated data which reduced the importance of spatial relationships between events. This research will address the local nature of criminal activity and drug markets, which cannot be examined by aggregating data to larger areal units. The small-scale, block-face analysis of this research will further underline the value of using discrete point data to analyze localized processes. Multi-variate analysis benefits from the variability inherent in small-scale analysis.

This research will also assist the DPD with identifying areas that have factors for high crime, but have no manifestations of high crime. These areas should be studied further for intermediary factors of crime, such as social efficacy. The ability to identify these areas with lower crime rates may lead to the duplication of successful social programs in other areas with higher crime rates, thereby reducing the crime burden on police resources.

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