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Built environment and Property Crime in Seattle, 1998–2000: A Bayesian Analysis

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Abstract

The past decade has seen a rapid growth in the use of a spatial perspective in studies of crime. In part this growth has been driven by the availability of georeferenced data, and the tools to analyze and visualize them: geographic information systems (GIS), spatial analysis, and spatial statistics. In this paper we use exploratory spatial data analysis (ESDA) tools and Bayesian models to help better understand the spatial patterning and predictors of property crime in Seattle, Washington for 1998–2000, including a focus on built environment variables. We present results for aggregate property crime data as well as models for specific property crime types: residential burglary, nonresidential burglary, theft, auto theft, and arson. ESDA confirms the presence of spatial clustering of property crime and we seek to explain these patterns using spatial Poisson models implemented in WinBUGS. Our results indicate that built environment variables were significant predictors of property crime, especially the presence of a highway on auto theft and burglary.

Keywords

Property Crime; Exploratory Spatial Data Analysis; Bayesian Poisson Models; Seattle

1 Introduction

The mapping of crime and crime-related outcomes has an important place in the early history of cartography (Robinson, 1982; Andresen, 2007), and there have been many contributions to the geographical study of crime (Brantingham and Brantingham, 1991; Harries, 1974, 1980; Rengert, 1996). But particularly in the past decade there has been a re-emergence of an explicitly spatial analytical perspective. In part this re-emergence has been driven by the increased availability of geo-referenced data, and by the tools to analyze and visualize them: geographic information systems (GIS), spatial analysis, and spatial statistics (Chainey and Ratcliffe, 2005; Goldsmith et al, 2000; Hirschfield and Bowers, 2001). Spatial data are special and must be treated differently if analysts are to avoid the pitfalls of ignoring possible spatial autocorrelation (Cressie, 1991; O'Sullivan and Unwin, 2002).

Indeed, Cressie (1991) argued that classical, non-spatial data analysis should be regarded as a special case of spatial data analysis. While still not common, explicitly spatial methods have been used in studies of homicide at the tract level (Cohen and Tita, 1999), at the county level (Messner et al, 1999; Baller et al, 2001), and (in non-US research) at police district levels within São Paulo, Brazil (Ceccato et al, 2007). In this paper we use both exploratory spatial data analysis (ESDA) and Bayesian methods – specifically, spatial Poisson models – to better understand the patterning and predictors of property crime at the census tract level for Seattle, Washington using data from 1998–2000.

Areas differ in their rates of crime, with most places having few crimes and a few places accounting for a disproportionately large number of crimes. For example, in their analysis of calls to the Minneapolis police, Sherman et al (1989) found that all of the robberies were reported at 2.2% of the addresses in the city and all of the auto thefts at 2.7% of the places. More recently, Weisburd et al (2004) found that about 5% of places (facing street blocks) in Seattle accounted for about 50% of crime incidents, that the number of incidents was relatively stable over time, and that changes in crime trajectories in a few places accounted for overall city trends in crime. Similarly, Griffiths and Chavez (2004) found that 6% of the census tracts in Chicago accounted for 25% of homicides and thus could largely explain homicide trends over a 16 year period. For the most part, explanations for this “hot spot” activity have centered on factors about these places, such as the presence of bars, convenience stores, and bus stops (Roncek and Bell, 1981; Roncek and Maier, 1991).

Areas with similar characteristics tend to cluster together—a phenomenon that suggests spatially-based dependencies. There are three types of explanations for why offenses committed at one place are likely to be related to offenses committed in other places. First, spillover, is a measurement issue and relates to the division of areas into units of analysis. The more arbitrary the division, the more spatially related the areas are, in that arbitrary boundaries are likely to divide places that have similar characteristics and are functionally connected. However, even areas divided by official boundaries are likely to be related, because geographic boundaries are not necessarily the same as social boundaries. For example, although a census tract boundary might place houses on opposite sides of a street in different tracts, a burglar would be oblivious to the boundary (Morenoff et al, 2001). Second, spatial dependence in crime can result from structural similarities in different areas. Cohen and Tita (1999) adapted the notion of hierarchical diffusion to suggest that shared influences might explain why unrelated crack cocaine markets could develop in different cities or different parts of the same city. In their analysis of homicides in Pittsburgh, Cohen and Tita found support for the notion that areas of the city that had similar influences leading to violent youth gangs and new crack markets also had similarly high levels of homicides. Third, spatial dependence of crime can result from direct mechanisms, called contagious diffusion, by which activity in one area affects activity in another. In the case of crime, the direct mechanism could be offenders who travel from one neighborhood to other, generally nearby neighborhoods, in that offenders tend to act disproportionately near their homes and where their routine activities take them (Brantingham and Brantingham, 1993; Morenoff et al, 2001; Smith et al, 2000). For example, drug-related burglaries are likely to be spatially dependent because offenders commit crimes near their homes, near some other anchor point (e.g., a drug sales area), along familiar sites and paths, and near where they have successfully committed crimes before (Rengert, 1996).

This notion of contagious diffusion should better describe property crimes than violent crimes because property offenders are more likely to travel, and thus more likely to commit crimes in adjacent areas rather than the same area (White, 1932). For example, in his analysis of crimes in public housing in Cleveland, Pyle (1976) found that 61% of those arrested for violent crimes (homicide, rape, assault, robbery) lived in the same census tract

as the crime location, compared to 48% of those arrested for property crimes (burglary, larceny, auto theft). Rhodes and Conly (1981) suggested that property offenses are more likely to be planned instrumental activities, in which the offender travels to sites that have attractive targets, whereas violent offenses are more likely to be spontaneous and affective (but cf., Tedeschi and Felson, 1994). Thus, offenders would be more likely to travel to commit property than violent crimes, and it is this travel that would be one mechanism of contagious diffusion linking spatial areas.

Research Questions and Contributions

Our research focuses on modeling Part I property crime at the census tract level for Seattle, Washington in 1998–2000; where Part I crimes are the more serious crimes and are so designated by the Federal Bureau of Investigations Uniform Crime Reports for known offenses and arrests. Our analysis opens with an exploration of whether there is spatial dependency in property crime and whether the relationship is different across property crime types. We use ESDA methods, specifically the global Moran's I statistic and spatial correlograms.

Several related questions emerge from ESDA. For example, can any observed spatial variation be explained by census and land-use variables? Is there a specific mechanism that can explain how property crime might diffuse across census tract boundaries? The models reported in this paper are based on count data; property crime data follow a Poisson distribution rather than a normal distribution (Osgood 2000). We apply Bayesian Poisson models to property crime count data to test whether similarities in census and land-use variables explain the patterning of crime and we consider whether a specific mechanism for diffusion—bus ridership—might exist that can explain the patterning of property crime. While we do not wish to impose any particular theory in our framework we use variables that draw on both social disorganization theory (Shaw and McKay, 1942) and routine activity theory (Cohen and Felson, 1979).

We believe our paper improves on prior research both methodologically and substantively. First, in our ESDA we examined five different types of property crime in order to determine whether spatial effects vary by type of crime. Moreover, although there have been some studies that have examined multiple types of crimes (e.g., Rhodes and Conly, 1981; Weisburd et al, 2004), few studies have tested whether ecological variables have consistent effects across crime types or how spatial structure accounts for the variation. Second, we draw on GIS-derived data and measures for the built and social environment, and on an emerging area in the social and health sciences, the use of Bayesian spatial modeling techniques (Withers, 2002). Third, as we describe in more detail below, we have used a more reliable measure of a busy place than prior studies. Specifically, we tested whether bus ridership (each bus stop weighted by the number of people who get on or off at the stop) as a possible mechanism through which spatial effects may be operating.

Our analysis is based on census tracts, an advantage because it enabled us to integrate crime and land-use data with census information relating to urban social and demographic variables. We assumed census tracts reflect neighborhoods, consistent with most research on the contextual effects of neighborhoods (Leventhal and Brooks-Gunn, 2000), a reasonable assumption because the Census Bureau creates census tracts to be as homogeneous as possible in terms of sociodemographic characteristics (Wooldredge, 2007). Further, because tract boundaries generally involve the type of built environment and physical features (e.g., expressways, major surface streets, rivers and other topographic features) that residents themselves use to define neighborhoods (Duncan and Aber, 1997). Moreover, Coulton et al (2001) found that while perceptions of neighborhood boundaries do not always match tract boundaries, perceived neighborhood areas are similar in size to

census tracts and, in a study of re-arrest for domestic violence in Cincinnati, Wooldredge (2002) found that the use of two geographic aggregations of contextual data – official definitions of neighborhoods and census tracts – generated similar substantive findings. A primary disadvantage of tract-level analyses is that some crime is a local phenomenon. That is, some crime hot spots tend to be small geographically bounded areas of perhaps a few blocks. Thus, for some types of crime the appropriate analytical procedure would involve one or more blocks (Walsh and Taylor, 2007).

2 Study Site and Data

Seattle covers an area of about 84 square miles (about 4% of King County), and over the past 30 years its population (563,374 in 2000) has remained relatively stable (Weisburd et al, 2004). The Seattle Police Department has excellent records (Seattle Police Department, 2007), and its data have long been used by researchers (Schmid, 1960a; 1960b). It is important to note that for the purposes of analysis we consider Seattle to be a closed system and we ignore edge effects (i.e., the effects of adjacent areas outside the city limits). We used U.S. Census 2000 census tract boundaries ($n = 121$ census tracts).

We obtained census tract-level Uniform Crime Report (UCR) data from the Seattle Police Department for the time period between 1998 and 2000. We used three years of data to create average counts and average rates, in order to obtain more stable estimates of crime. Crime rate (per 100,000 residents) data are used only in ESDA, while the dependent variables of interest in the Bayesian Poisson models are crime counts. While we have both spatial and non-spatial model results for five Part I property crimes (residential burglary, nonresidential burglary, theft, auto theft, and arson) and a composite total property crime (sum of the five crimes) respectively, space limits what can be included (comparative non-spatial results are available in an online supplement). Thus, our results focus on salient findings vis-à-vis the built environment, specifically land-use variables, as predictors of different property crimes in the Bayesian Poisson models.

To the crime data we added census tract level data from the 2000 U.S. Census, using Summary File 3, data on land-use, urban social dynamics, and a third class of variable associated with a vector of transmission, notably bus ridership. Table 1 includes the descriptive statistics on our outcome measures and predictors, and it includes, where relevant, the Moran's I (see supplemental on-line material for the correlation matrices between crime and predictor variables – Table S1–S3). The following paragraphs briefly describe the data sources and the calibration of measures, and provide the theoretical justification for variables used in our analysis.

Measures of Land-use

The presence or absence of particular land-uses, the mix of land-uses, and the presence or absence of resources and risks within a neighborhood have long been of interest to criminologists (Roncek, 1981; Stark, 1987). Built environment factors are of particular interest if they facilitate bringing perpetrators and victims of crime together in busy places (Rountree et al, 1994). While prior studies have examined the effect of bars and schools on crime, we include additional built environment or land-use variables: hotels, hospitals, highways, railroads, and parks.

Bars are dangerous places that often contribute to the crime rates in surrounding areas (Gruenewald et al, 2006; Peterson et al, 2000). We used the 1999 U.S. West Seattle telephone directory to create a listing of the names and addresses of bars, taverns, and pubs in the City of Seattle. These addresses were geocoded and then aggregated to create a count variable for each census tract.

Schools, hotels, and hospitals bring both potential offenders and victims to an area, and thus could be a mechanism for linking areas (see with reference to schools, Roncek and Lobosco, 1983; Roncek, 2000). We obtained publicly available listings of public secondary schools, hotels, and hospitals for Seattle, which were address matched and aggregated to census tracts. Secondary schools, hotels, and hospitals were coded as 0 for absent and 1 for present.

Using derived and publicly available shapefiles, we created three dummy variables that captured the absence (coded 0) or presence (coded 1) within a census tract of a highway, a railroad, and a park. Highways are important because they provide easy access for outsiders to and from an area. For example, burglars are likely to commit offenses near highway exits (Rengert and Wasilchick, 1985). Highways also reduce guardianship because they break up neighborhoods. The presence of a railroad in an area is an indicator of industrial use and like highways can serve as a barrier between neighborhoods. Public places like parks can also influence crime rates (Sherman et al, 1989).

Following the Chicago School's ecological model, we used GIS to derive a variable that measured the distance from the central city (Shaw and McKay, 1942; Smith et al, 2000). This variable is generally related to social status, as distance from downtown is related to who lives where. For each tract, the distance from downtown was defined as the number of kilometers between the centroid of the central downtown tract and the centroid of that tract.

Measures of Urban Social Structure

Following Sampson and colleagues (Morenoff and Sampson 1997; Sampson et al, 1999) and prior research in criminology, we used 2000 census variables to create three scales to describe urban social structure. Regardless of the rotation method used in the formation of these scales, the variables for each scale loaded on single factors using either principal components or alpha-scoring factor analysis (Sampson et al, 1999). First, a concentrated disadvantage scale described the conditions of economic disadvantage in racially segregated neighborhoods (Massey and Denton, 1993; Wilson, 1987). We defined this scale based on the percentage of individuals below the poverty line, percentage receiving public assistance, percentage unemployed, percentage of households that are female-headed with children, and percentage black. Second, we used a concentrated affluence scale to describe economically privileged neighborhoods (Sampson et al, 1999). This scale was defined by the percentage of families that have incomes of more than \$75,000, percentage of workers in managerial and professional positions, and the percentage of adults with at least a Bachelors degree. Third, concentrated immigration was defined by the percentage of persons foreign born, the percentage linguistically isolated, and the percentage Asian. Percentage Hispanic was used by Sampson and colleagues in constructing concentrated immigration scales in their work on Chicago but in the case of Seattle, and following Kaukinen and Fulcher (2006) in a study based in Toronto, it is more appropriate to use percentage Asian. In 2000 the U.S. Census reported that the foreign-born represent 16.9 percent of the Seattle population, the majority originating from Asia (the three largest countries of origin are the Philippines, Vietnam and China and nine of the top 14 countries of origin are in Asia). European origin accounts for 16% of the total foreign-born in Seattle, with Latin America supplying 13% and Africa 7%. Compared to other U.S. cities Seattle has a relatively low proportion of African Americans and Hispanics.

Both social disorganization and routine activity theory research suggest that neighborhood instability is important. Thus, we employed measures of residential mobility and percent renters to create an index of neighborhood instability. The index of neighborhood instability was calculated by summing equally weighted z-scores and dividing by two (Sampson et al, 1999).

Vector of Transmission

We included bus ridership as a predictor because public transportation is a specific means by which people move across census boundaries, and thus could be a mechanism for contagious diffusion of crime. The work on bus stops parallels research on rapid transit stations (Block and Davis, 1996; Block and Block, 2000) and the role of movement generators (Taylor and Harrell, 1996). About 17% of residents in Seattle use public transportation to commute to work (U.S. Bureau of the Census, 2005). We obtained files of the Seattle area bus stops from the King County Department of Transportation, Metro Transit Division. The Metro bus stop database included information about each stop's operation dates, whether it was free or a pay stop, and the ridership (number of people who got on and off at that stop per day). Bus stops were present in every census tract (the Seattle Crime and Victimization Study reported that 97% of the population lived within three blocks of a bus stop). In order to determine which areas were truly "busy places," we defined the bus ridership variable as the number of bus stops per census tract weighted by average daily ridership.

Other Demographic Variables

The remaining variables, taken from the U.S. Census and related to measures of urban structure, all have a known association with property crime counts. The first is total population. To yield unbiased estimates in a Poisson model we treat total population as the offset variable; that is, this variable represents the number of people at risk of being victims. The two other demographic variables are the percent male in the population and percent of population between the ages of 18–25. Age and gender are generally the most robust individual-level risk factors associated with perpetrators and victims of crime, including property crime (Steffensmeier et al, 1989; Steffensmeier and Streifel, 1991; South and Messner, 2000).

3 ESDA

Moran's I and Spatial Correlograms

Spatial autocorrelation measures the similarity between observations for a given variable as a function of spatial distance (Odland, 1988). For continuous variables, such as crime rate, the Moran's I coefficient is a commonly used measure, typically calculated for first-order spatial autocorrelations (i.e., the adjacent areas), of deviation from spatial randomness.

Measures of spatial autocorrelation like Moran's I can be calculated to measure relations among more distant areas by re-defining the weights matrix, w , for pairs of locations separated by greater distances or spatial lags (2, 3 ... n). $I(k)$ is Moran's I , where k is the number of spatial lags between a set of paired geographical units (e.g., tracts). A spatial correlogram is a plot of $I(k)$ against the number of spatial lags, k for $k = 1, 2, \dots, n$, which can facilitate evaluation of the behavior of autocorrelation as a function of spatial or lag distance (Cliff et al, 1975). The profile of the spatial correlogram can be informative. Four general profiles can exist. First, a positive autocorrelation for small values of k and negative spatial autocorrelation at the higher values of k is indicative of a linear gradient at macro-scales. A second profile occurs when autocorrelation is found only at the smallest values of k indicating that attribute values are independent among more distant pairs of areas and that any explanation for the spatial association would involve processes that operate at a localized scale (Odland, 1988). A third profile occurs when no Moran's $I(k)$ coefficients are significant, indicating that there is no spatial pattern. And, a fourth pattern occurs when autocorrelation is found at both the small and high values of k but where intermediate values of k are not significant. This pattern has been observed in epidemics and is indicative of a hierarchical diffusion process rather than a contagion process (see Cliff et al, 1975).

In Figure 1 we show the spatial correlograms for total property crimes and the five specific property crime types. A queen contiguity matrix was used in calculating the Moran's I for all spatial lags. For total property crimes, the Moran I indicates significant spatial lags at $k=1$ and $k=2$ and non-significant values at higher k . That is, the profile most closely follows the second pattern identified above, indicating localized processes. In general, this same pattern of localized spatial effect is true for all other property crime types, although some showed significant effects at longer lags (i.e., non-residential burglary). The average number of significant Moran's I values in the crime-specific correlograms was 2.4. Compared to nonresidential burglary and arson (their Moran's I are significant when $k=3$), theft, auto theft, and residential burglary demonstrated more localized spatial patterning (significant at $k=2$ but not at higher k). It should be noted that because over 65 percent of property crimes are theft the respective spatial correlograms are similar.

4 Bayesian Spatial Models

The Moran's I and spatial correlograms indicated the presence of spatial autocorrelation in our outcome variables (and for predictor variables, see Table 1). The presence of spatial autocorrelation introduces redundancy affecting the calculation of confidence intervals and significance tests in regression-based techniques. An explicitly spatial modeling approach should account for spatial autocorrelation.

With this general understanding of the nature of the spatial relationship of property crime in Seattle for 1998–2000, we turned to the questions of whether this spatial patterning could be explained by census and land-use variables, and whether remaining spatial effects could be explained, at least in part, by some mechanism of diffusion. That is, we wanted to explore whether census tracts shared the same kinds of conditions that lead to property crime (hierarchical diffusion) controlling for land-use and urban structure. In addition, we wanted to explore whether the spatial relationships could have been the result of “vectors of transmission” (Baller et al, 2001) by which crime was transmitted across census boundaries (contagious diffusion), specifically focusing on a possible vector associated with public transportation, which in Seattle is primarily buses. To answer these questions we used Bayesian spatial Poisson regression modeling in WinBugs (Lunn et al, 2000, Law and Haining, 2004).

We compared two statistical models: generalized linear models (Poisson regression) and spatial Poisson linear models. Both relate the random distribution of the dependent variable (crime counts) to the linear combination of the explanatory covariates (X) through the logarithm link function (Christensen and Waagepetersen, 2002; Griffith and Haining, 2006). The Poisson model is

$$Y = \text{Poisson}(\mu) \\ \log(\mu) = \log(E) + BX$$

where μ is the expected count of property crime events, E is the population at risk and by definition has a regression parameter of 1. B is the vector of estimated parameters. This generalized linear model does not consider spatial structure. As discussed previously, “spatial is special” and hence we use the spatial Poisson model with convolution priors (Mollie 1996) as below:

$$Y = \text{Poisson}(\mu) \\ \log(\mu) = \log(E) + BX + h + w$$

where h is the first set of random effects for which we assume a normal prior, and w represents the spatial random effects assigned an intrinsic conditional autoregressive prior (Besag et al., 1991). The intrinsic conditional distribution of w_i given other locations w_{-i} is

$$w_i|w_{-i} \sim N\left(\frac{\sum_{j \sim i} w_j}{n_i}, \frac{1}{n_i \tau_c}\right)$$

where τ_c is the precision parameter, $j \sim i$ denotes tract j is a neighbor of tract i , and n_i is the total number of neighbors of tract i (a first-order queen contiguity matrix). The coefficients ($\beta_1, \dots, \beta_p$) should be interpreted exponentially. For instance, holding other factors equal, one unit of change in x_{il} will lead to the $(e^{\beta_l} - 1)$ percent (multiplied by 100) increase or decrease in property crime. This spatial model divides the random effect for each area into spatially structured and unstructured components and allows us to calculate the contribution of each. The unstructured random effect could capture over-dispersion in this spatial Poisson model. We calculated the proportion of the variability in the random effects that resulted from spatial structure (α) as below:

$$\alpha = \frac{sd(w)}{sd(w) + sd(h)}$$

where, $sd(w)$ and $sd(h)$ represent the marginal standard deviation of spatial and non-spatial random effects, respectively. Hence, $1 - \alpha$ is the proportion due to the unstructured component.

In setting up our models we followed a conventional approach to specifying the priors (Thomas et al., 2004). The intercept is specified as a uniform distribution and other model parameters with a Gaussian distribution having a mean 0 and a variance 100,000. The large variance here indicates that the range of the simulated values is wide (similar model specifications can be found elsewhere; Clayton and Kaldor (1987), Breslow and Clayton (1993), Yang et al (2009)). Regarding the prior on the precision of the spatial error distribution, we specified a Gamma distribution with a shape parameter, $Kappa$, 2 and a scale parameter, $Theta$, 2000; both common specifications in a spatial model.

To compare these models, Spiegelhalter and colleagues (2002) proposed the Deviance Information Criterion (DIC), which is a generalization of Akaike's Information Criterion (AIC). A DIC reduction of more than 10 between models indicates a better fit and more precise predictions. Generally a DIC reduction of between 5 and 10 is substantial enough to select the model with lower DIC, though a difference of less than 5 indicates that models are similar and it could be misleading to report only the model with the lowest DIC (Spiegelhalter et al, 2002; Lunn, 2000).

Spatial Poisson Model Results

In this section we present model results for total property crime and separately for five different types of property crimes. In models where we do not control for spatial errors most predictor variables were significant, and in the direction anticipated (non-spatial models are available in supplemental material, Table S4). Before we focus on the spatial model results, we emphasize that all spatial Poisson models outperform the ordinary Poisson models based on the improvement in the DIC. Following convention in Bayesian analysis our results tables include the posterior means and standard distributions of each covariate, the posterior

summaries. Spatial Poisson models are computationally demanding; approximately 100,000 iterations to achieve desirable MC standard error and convergence.

One contribution of this study is to untangle the relationships between land-use variables and various property crimes. Table 2 reports the spatial Poisson model results. Several important findings are summarized. First, the presence of a highway is associated with auto theft, non-residential burglary, theft, and total property crimes. Generally, other things equal, these property crime incidents are higher in the census tracts with highways than in those without highways, a difference ranging from 25 percent higher for auto theft ($\exp(0.224)-1$; Table 2.e) to 78 percent higher for non-residential burglary ($\exp(0.576)-1$; Table 2.d). Highway can be interpreted as facilitating easy access to and exit from crime scenes, especially for property crimes. In contrast to the presence of a highway, the presence of a railroad had little impact.

Second, the number of bars is positively associated with non-residential burglary, auto theft, arson, and theft (and total property crimes). The addition of one bar in a census tract increases the non-residential burglary approximately 20 percent, arson and auto theft increase by 10 percent, and theft increases by 13 percent. This finding reconfirms the relation between bars and property crime rates (Gruenewald et al, 2006; Peterson et al, 2000); although residential burglary is an exception. All of these associations hold even after controlling for other covariates.

Third, controlling for other covariates (including the percentage under 25 and percentage male), we find that arson is positively related to the presence of a school and that park presence increases theft crimes. In Seattle, those tracts with schools have 40% more arson crimes than those without. The total number of theft crimes increases 23% with the presence of a park in a census tract. Fourth, among the five property crimes, theft contributes most to the total property crimes (as noted above), and thus models of total property crimes and theft share similar results (e.g., significant land-use predictors). Without dividing property crimes into its five main constituent types, the analytic results for specific property crime types would be hidden (e.g., differences in their association with land-use variables).

Finally, using the spatial models with convolution priors, we are able to split the random effects into spatially and non-spatially structured effects. In Table 2.e, auto theft has the highest proportion of variation in the error terms due to spatial structure (α): over 80%. Similarly, almost 80% of the residual residential burglary crimes are due to spatially structure variation (Table 2.c). The spatial component plays a relative small role in nonresidential burglary and arson (both below 30%). These results match the correlograms where we found residential burglary and auto theft showed a more localized pattern than other property crimes. For all property crime types combined spatial structure accounts for almost 40% of the residual (Table 2.a).

With respect to bus ridership, studies suggested that public transportation is a mechanism of crime diffusion (Block and Block, 2000; Taylor and Harrel, 1996) and that robbery, violent crimes, and other street problems are positively associated with bus stops or rapid transit stations (Loukaitou-Sideris, 1999; Block and Davis, 1996). Not as much attention has been paid to property crimes. Our study advances the literature by providing evidence that aggregate property crimes are associated with public transportation. However, theft is the only property crime that positively correlates with bus ridership. An increase of one standard deviation in bus ridership (roughly 200 passengers per stop) results in an 18% increase in the total number of theft crimes. This association is independent of other possible confounders, such as, distance from downtown, percentage of young and male population, and the

presence of highway. Thus, bus ridership can be regarded as a potential source of theft victims and a means by which the criminals move across tracts.

In contrast to land-use variables and bus ridership, the demographic and urban dynamic variables have only a limited association with property crimes. Social affluence is negatively related to non-residential burglary, auto theft, and theft. A high disadvantage score is positively associated with more arson incidents. While social disorganization and routine activity theory suggest neighborhood instability and immigrant concentration are related to crimes, our analytic results do not provide evidence to support these arguments. A high percentage of the population between ages 18 and 24 was related to high residential burglary and theft crimes, although percentage of male population was not a significant predictor for property crimes.

5 Discussion

In this paper we used both ESDA and Bayesian statistical methods; the latter still rarely applied to studies of crime. As expected ESDA revealed a spatial structure to the distribution of property crimes and that spatial relationships vary by type of property crime. The queen's first-order Moran's I are all high, indicating significant spatial structure to underlying property crime patterns in Seattle. This result is consistent with prior research showing that, as compared to violent offenders, property offenders tend to commit crimes farther from their homes and across larger territorial domains. Among the property crimes, theft is the most localized crime.

Bayesian model results suggest that the spatial structure of property crime can be explained by census and land-use variables for some but not all types of property crime. Unique to our work is the inclusion of bus ridership as a potential vector of transmission between places for some types of property crime. The strong spatial patterning for property crimes, particularly theft, makes sense if we believe that a greater percentage of property crimes are committed by juveniles who, compared to adults, are more limited in their ability to travel to crime and therefore are likely to travel shorter distances (Rhodes and Conly, 1981). Based on recent national data in the Uniform Crime Reports, 25.6% of all larceny arrests are of individuals under age 18, and 7.4% are of individuals under age 15 (calculated from data in Table 38, Federal Bureau of Investigation, 2008). Because larceny-theft is the most common property crime, the pattern it shows should also be reflected in what happens regarding overall property crime. With regard to bus ridership as a possible vector of transmission, that is indeed the case. For the other property crimes, the effect is in the same direction, although not as strong or significant, a result that could be due in part to the fact that these crimes are less common than larceny-theft.

In this study we treated highways in the same way we treated railroads, that is, as barriers between neighborhoods. Because highways prevent residents from easily traveling to neighboring areas, major roads and highways typically serve as boundaries between census tracts. However, we should note that highways might also serve as vectors of transmission between areas (Rengert, 1985). Within Seattle, there are 15 ramps onto or off of Interstate 5, the primary north-south highway in the city. However, because most of these ramps have restrictions (e.g., only a northbound entrance and a southbound exit), the number of census tracts affected is relatively small and further testing of the presence of highways as possible vectors of transmission should be undertaken in other locations.

Although this research is limited by the fact that we used police records, and the necessary reliance that citizens would report the crime and police would record it, it has the strengths that we relied on both census and built environment variables.

In the field of geography, questions such as migration destination, shopping choice, and house selection have been addressed by more sophisticated statistical models, including spatial information processing, hierarchical decision making, and spatial cognition (Fotheringham et al, 2000, pp. 213–235). Offenders who commit multiple property crimes are likely to use hierarchical decision making. Whether the question is home selection or shopping choice, people generally evaluate clusters of alternatives and then evaluate particular alternatives from the selected cluster. For example, when buying a house, people typically choose a section of the city and then look at houses within that section. This idea of hierarchical decision making, which is analogous to Meier and Miethe's (1993) structural choice theory, suggests that for some crimes offenders first choose an area in which to commit a crime and then pick individual targets within that area.

In order to better understand spatial relationships and to examine potential vectors of transmission, however, it would be useful to make four improvements on our research. First, different size areas should be used, both smaller and larger than the census tract (Openshaw, 1984, Hipp, 2007). Second, there is a need to include more time points and to test specifically for change over time. Third, it would be important to extend the analysis to a study of violent crime, and specifically different violent crime types (in progress). Fourth, it would be important to have individual-level data such as unemployment, education, income, and car ownership and to embed this information in a hierarchical framework (Rountree et al, 1994). Several studies have found that crime hot spots explain a disproportionate amount of crime. Future research needs to determine the extent to which hot spots account for the effects found here and whether the procedure used here might be useful in determining whether these hot spots are related by vectors of transmission, such as public transportation (see Newton, 2007, Newton and Bowers, 2007). Such results would be useful both for theory development and for the deployment of police resources (e.g., Braga, 2001).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.
Spatial Correlograms for Total Part Property Crime and Five Specific Property Crimes*

Table 1

Descriptive statistics for outcome (crime) and predictor variables used in the models, including Moran's I values (where appropriate) (N= 121 census tracts) -- Note: crime rates per 100,000 residents)

	Min	Max	Mean	S.D.	Moran I	P-value
A: Outcome variables						
Counts						
Property Crime	100.00	6154.00	1068.59	813.76	0.375	0.001
Residential Burglary	0.00	310.00	103.84	59.22	0.371	0.001
Nonresidential Burglary	0.00	371.00	54.06	58.04	0.446	0.001
Theft	83.00	5196.00	698.98	643.36	0.373	0.001
Auto Theft	2.00	645.00	207.48	128.10	0.393	0.001
Arson	0.00	18.00	4.24	3.71	0.370	0.001
Rates						
Property Crime	58.00	1778.09	265.21	277.67	0.407	0.001
Residential Burglary	0.00	29.02	7.59	3.77	0.212	0.001
Nonresidential Burglary	0.00	63.85	5.02	8.45	0.355	0.001
Theft	12.45	500.43	59.10	71.70	0.414	0.001
Auto Theft	1.73	97.46	16.32	14.03	0.354	0.001
Arson	0.00	4.27	0.34	0.45	0.165	0.005
B: Predictor Variables						
Land-use						
Highway	0.00	1.00	0.43	0.49		
Rail Road	0.00	1.00	0.21	0.41		
Park	0.00	1.00	0.49	0.50		
School	0.00	1.00	0.20	0.40		
Hospital	0.00	1.00	0.08	0.27		
Hotel	0.00	1.00	0.16	0.37		
Distance from Downtown	0.00	13.77	6.87	3.50	0.923	0.001
Number of Bars	0.00	5.00	1.23	1.57	0.308	0.001
Urban Social Structure						
Concentrated Disadvantage	-0.98	3.59	0.00	1.00	0.580	0.001
Concentrated Affluence	-2.67	1.99	0.00	1.00	0.636	0.001

	Min	Max	Mean	S.D.	Moran I	P-value
Immigration	-0.88	5.18	0.00	1.00	0.632	0.001
Instability	-0.49	0.66	0.00	0.22	0.093	0.034
Vector of Diffusion						
Bus Ridership	5.04	1898.13	107.57	199.64	0.238	0.001
Other Demographic						
Total Population	384.00	10334.00	4617.32	1968.03	0.112	0.022
% Males	0.43	0.72	0.50	0.04	0.456	0.001
% 18-24	0.03	0.82	0.11	0.11	0.388	0.001

Table 2

Spatial model results: posterior means and standard distributions of each covariate, the posterior summaries, and error terms.

(a) Total Part I Property							(b) Theft					
Variables	mean	sd	MC error	2.50%	median	97.5%	mean	sd	MC error	2.50%	median	97.50%
constant	-3.059	0.062	0.005	-3.178	-3.060	-2.939 *	-2.469	0.075	0.006	-2.637	-2.465	-2.333 *
Land-use												
Highway	0.308	0.088	0.007	0.138	0.310	0.477 *	0.303	0.095	0.008	0.138	0.297	0.512 *
Railroad	0.051	0.106	0.008	-0.157	0.050	0.263	-0.009	0.109	0.008	-0.211	-0.017	0.226
Park	0.157	0.075	0.005	0.011	0.161	0.297 *	0.210	0.093	0.007	0.025	0.210	0.401 *
School	0.121	0.092	0.006	-0.063	0.122	0.306	0.134	0.115	0.009	-0.086	0.133	0.344
Hospital	0.129	0.203	0.015	-0.257	0.127	0.530	0.206	0.247	0.020	-0.309	0.209	0.720
Hotel	-0.251	0.179	0.014	-0.599	-0.251	0.099	-0.217	0.178	0.015	-0.514	-0.247	0.138
Distance	-0.317	0.057	0.004	-0.428	-0.316	-0.208 *	-0.346	0.068	0.005	-0.474	-0.344	-0.215 *
Bar	0.112	0.028	0.002	0.056	0.111	0.162 *	0.119	0.033	0.003	0.050	0.119	0.178 *
Diffusion Vector												
Bus Ridership	0.130	0.045	0.004	0.048	0.126	0.222 *	0.165	0.055	0.005	0.062	0.169	0.265 *
Demographics												
% Males	0.040	0.048	0.003	-0.055	0.042	0.126	0.048	0.065	0.005	-0.091	0.052	0.163
% 18-24	0.098	0.049	0.003	-0.001	0.098	0.190	0.098	0.052	0.004	-0.010	0.099	0.199
Urban Structure												
Disadvantage	-0.008	0.069	0.005	-0.141	-0.007	0.127	-0.009	0.088	0.007	-0.166	-0.017	0.168
Affluence	-0.246	0.069	0.005	-0.407	-0.243	-0.111 *	-0.245	0.080	0.006	-0.411	-0.245	-0.102 *
Immigration	-0.109	0.062	0.005	-0.229	-0.111	0.019	-0.156	0.072	0.006	-0.275	-0.157	0.000 *
Instability	-0.018	0.213	0.014	-0.425	-0.018	0.411	0.018	0.260	0.020	-0.511	0.029	0.500
Error Terms ⁺												
sd.e	0.206	0.131	0.011	0.036	0.176	0.438	0.183	0.088	0.007	0.053	0.170	0.369
sd.h	0.323	0.099	0.008	0.076	0.370	0.419	0.397	0.045	0.003	0.282	0.412	0.450
Alpha (α)	0.374	0.226	0.019	0.082	0.321	0.849	0.306	0.124	0.010	0.108	0.292	0.561
DIC	1151,400						1229,900					

(c) Residential Burglary									
Variables	mean	sd	MC error	2.50%	median	97.50%	mean	sd	MC error
constant	-3.835	0.064	0.004	-3.964	-3.832	-3.716 *	-5.361	0.113	0.008
<u>Land-use</u>									
Highway	-0.028	0.089	0.004	-0.198	-0.028	0.156	0.576	0.139	0.009
Railroad	0.008	0.100	0.004	-0.194	0.009	0.205	0.329	0.161	0.009
Park	-0.043	0.067	0.003	-0.170	-0.042	0.087	0.038	0.127	0.008
School	-0.043	0.079	0.002	-0.189	-0.045	0.121	0.267	0.147	0.006
Hospital	-0.013	0.180	0.008	-0.358	-0.020	0.352	0.130	0.320	0.020
Hotel	-0.115	0.151	0.008	-0.421	-0.111	0.168	-0.401	0.270	0.020
Distance	-0.087	0.123	0.008	-0.359	-0.084	0.148	-0.551	0.094	0.007
Bar	0.012	0.028	0.001	-0.043	0.012	0.067	0.177	0.047	0.003
<u>Diffusion Vector</u>									
Bus Ridership	0.037	0.040	0.001	-0.041	0.037	0.116	0.114	0.061	0.004
<u>Demographics</u>									
% Males	0.004	0.053	0.002	-0.096	0.003	0.112	0.000	0.073	0.005
% 18-24	0.132	0.059	0.004	0.010	0.133	0.245 *	0.062	0.073	0.004
<u>Urban Structure</u>									
Disadvantage	-0.013	0.064	0.004	-0.139	-0.012	0.111	-0.004	0.112	0.008
Affluence	-0.066	0.078	0.005	-0.214	-0.068	0.099	-0.462	0.115	0.008
Immigration	-0.060	0.069	0.004	-0.194	-0.060	0.074	-0.159	0.099	0.007
Instability	0.096	0.209	0.010	-0.310	0.093	0.508	0.247	0.334	0.019
<u>Error Terms</u>									
sd.e	0.433	0.053	0.003	0.322	0.432	0.547	0.168	0.046	0.004
sd.h	0.116	0.066	0.005	0.024	0.105	0.270	0.582	0.027	0.001
Alpha (α)	0.794	0.106	0.008	0.550	0.808	0.949	0.222	0.046	0.004
DIC	999.742						887.100		
(d) Nonresidential Burglary									
Variables	mean	sd	MC error	2.50%	median	97.50%	mean	sd	MC error
constant	-3.835	0.064	0.004	-3.964	-3.832	-3.716 *	-5.361	0.113	0.008
<u>Land-use</u>									
Highway	-0.028	0.089	0.004	-0.198	-0.028	0.156	0.576	0.139	0.009
Railroad	0.008	0.100	0.004	-0.194	0.009	0.205	0.329	0.161	0.009
Park	-0.043	0.067	0.003	-0.170	-0.042	0.087	0.038	0.127	0.008
School	-0.043	0.079	0.002	-0.189	-0.045	0.121	0.267	0.147	0.006
Hospital	-0.013	0.180	0.008	-0.358	-0.020	0.352	0.130	0.320	0.020
Hotel	-0.115	0.151	0.008	-0.421	-0.111	0.168	-0.401	0.270	0.020
Distance	-0.087	0.123	0.008	-0.359	-0.084	0.148	-0.551	0.094	0.007
Bar	0.012	0.028	0.001	-0.043	0.012	0.067	0.177	0.047	0.003
<u>Diffusion Vector</u>									
Bus Ridership	0.037	0.040	0.001	-0.041	0.037	0.116	0.114	0.061	0.004
<u>Demographics</u>									
% Males	0.004	0.053	0.002	-0.096	0.003	0.112	0.000	0.073	0.005
% 18-24	0.132	0.059	0.004	0.010	0.133	0.245 *	0.062	0.073	0.004
<u>Urban Structure</u>									
Disadvantage	-0.013	0.064	0.004	-0.139	-0.012	0.111	-0.004	0.112	0.008
Affluence	-0.066	0.078	0.005	-0.214	-0.068	0.099	-0.462	0.115	0.008
Immigration	-0.060	0.069	0.004	-0.194	-0.060	0.074	-0.159	0.099	0.007
Instability	0.096	0.209	0.010	-0.310	0.093	0.508	0.247	0.334	0.019
<u>Error Terms</u>									
sd.e	0.433	0.053	0.003	0.322	0.432	0.547	0.168	0.046	0.004
sd.h	0.116	0.066	0.005	0.024	0.105	0.270	0.582	0.027	0.001
Alpha (α)	0.794	0.106	0.008	0.550	0.808	0.949	0.222	0.046	0.004
DIC	999.742						887.100		
(e) Auto Theft									
Variables	mean	sd	MC error	2.50%	median	97.50%	mean	sd	MC error
constant	-3.491	0.065	0.005	-3.614	-3.493	-3.362 *	-7.575	0.143	0.005
<u>Land-use</u>									
Highway	0.224	0.097	0.007	0.032	0.228	0.407 *	0.085	0.164	0.003
(f) Arson									
Variables	mean	sd	MC error	2.50%	median	97.50%	mean	sd	MC error
constant	-3.491	0.065	0.005	-3.614	-3.493	-3.362 *	-7.575	0.143	0.005
<u>Land-use</u>									
Highway	0.224	0.097	0.007	0.032	0.228	0.407 *	0.085	0.164	0.003

(f) Arson												
Variables	mean	sd	MC error	2.50%	median	97.50%	mean	sd	MC error	2.50%	median	97.50%
Railroad	-0.014	0.128	0.008	-0.255	-0.016	0.242	0.342	0.185	0.003	-0.020	0.342	0.707
Park	0.108	0.073	0.005	-0.029	0.104	0.263	0.186	0.151	0.003	-0.110	0.186	0.476
School	0.092	0.082	0.004	-0.067	0.091	0.255	0.355	0.178	0.003	0.009	0.353	0.708 *
Hospital	0.171	0.209	0.014	-0.230	0.167	0.609	0.504	0.374	0.010	-0.242	0.504	1.221
Hotel	-0.287	0.181	0.014	-0.652	-0.280	0.036	-0.621	0.322	0.008	-1.254	-0.622	0.003
Distance	-0.306	0.125	0.010	-0.522	-0.313	-0.048 *	-0.085	0.116	0.006	-0.305	-0.085	0.148
Bar	0.091	0.031	0.002	0.030	0.092	0.151 *	0.088	0.052	0.001	0.017	0.088	0.187 *
Diffusion Vector												
Bus Ridership	0.064	0.044	0.003	-0.024	0.065	0.149	0.105	0.071	0.002	-0.035	0.106	0.240
Demographics												
% Males	0.048	0.056	0.004	-0.056	0.048	0.160	0.082	0.088	0.002	-0.089	0.082	0.254
% 18-24	0.097	0.058	0.004	-0.017	0.100	0.208	0.077	0.085	0.002	-0.095	0.079	0.236
Urban Structure												
Disadvantage	-0.025	0.067	0.005	-0.151	-0.027	0.116	0.303	0.124	0.005	0.061	0.301	0.551 *
Affluence	-0.206	0.078	0.006	-0.359	-0.206	-0.048 *	-0.234	0.146	0.006	-0.535	-0.233	0.046
Immigration	-0.067	0.083	0.006	-0.221	-0.068	0.100	-0.148	0.115	0.004	-0.369	-0.149	0.079
Instability	-0.065	0.221	0.013	-0.473	-0.064	0.368	0.131	0.392	0.007	-0.650	0.135	0.898
Error Terms												
sd.e	0.470	0.042	0.003	0.377	0.470	0.557	0.203	0.083	0.007	0.040	0.259	0.277
sd.h	0.119	0.067	0.005	0.024	0.107	0.269	0.487	0.071	0.003	0.348	0.487	0.627
Alpha (α)	0.805	0.097	0.007	0.591	0.818	0.953	0.284	0.099	0.008	0.073	0.319	0.401
DIC	1082.600						536.100					

+ sd.e represents the marginal standard deviation of spatially structured effects; sd.h indicates the marginal standard deviation of non-spatially structured effects; alpha refers to the proportion of the variability in the error terms that is due to spatial structure.