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Crime-general and crime-specific spatial patterns: A multivariate spatial analysis of four crime types at the small-area scale

Matthew Quick ^a

Guangquan Li ^b

Ian Brunton-Smith ^c

^a School of Planning, University of Waterloo, Waterloo, Canada

^b Department of Mathematics, Physics and Electrical Engineering, Northumbria University, Newcastle-upon-Tyne, United Kingdom

^c Department of Sociology, University of Surrey, Guildford, United Kingdom

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Crime-general and crime-specific spatial patterns: A multivariate spatial analysis of four crime types at the small-area scale

Purpose: To examine if, and how, spatial crime patterns are explained by one or more underlying crime-general patterns.

Methods: A set of Bayesian multivariate spatial models are applied to analyze burglary, robbery, vehicle crime, and violent crime at the small-area scale. The residual variability of each crime type is partitioned into shared and type-specific components after controlling for the effects of population density, deprivation, residential instability, and ethnic heterogeneity. Shared components account for the correlations between crime types and identify the crime-general patterns shared amongst multiple crimes.

Results: Two shared components are estimated to capture the crime-general pattern for all four crime types and the crime-general pattern for theft-related crimes (burglary, robbery, and vehicle crime). Robbery and violent crime exhibit the strongest positive associations with deprivation, instability, and ethnic heterogeneity. Shared components explain the largest proportions of variability for all crime types. Burglary, robbery, and vehicle crime each exhibit type-specific patterns that diverge from the crime-general patterns.

Conclusions: Crime-general patterns are important for understanding the spatial patterning of many crime types at the small-area scale. Multivariate spatial models provide a framework to

directly quantify the correlation structures between crimes and reveal the underlying crime-general patterns shared amongst multiple crime types.

Keywords: spatial pattern, crime-general, correlation, multivariate, Bayesian model, shared component

1. Introduction

Many crime types exhibit similar spatial patterns, are associated with the same set of risk factors, and are interpreted using the same ecological theories (Schmid, 1960; Wikstrom and Dolmen, 1990; Anselin et al., 2000; Ceccato et al., 2002; Schreck et al., 2009; Brantingham and Brantingham, 2010; Andresen, 2011; Chamberlain and Hipp, 2015). For example, social disorganization theory has been widely used to explain the neighbourhood-level spatial patterning of crime and, correspondingly, structural characteristics including socioeconomic disadvantage, residential instability, and ethnic heterogeneity have been found to be associated with crime categories, such as total crime, violent crime, and property crime, as well as specific violent and non-violent crime types (Warner and Pierce, 1993; Peterson and Krivo, 1996; Hipp, 2007; Hirschfield and Bowers, 1997). Despite the theoretical and empirical similarities between the geographical distributions of many crime types at the neighbourhood or small-area scale, little research has investigated the degree to which the spatial patterns of individual crime types are explained by one or more underlying crime-general patterns (Weisburd et al., 1993; Brantingham, 2016). Crime-general spatial patterns arise from geographically-situated processes and characteristics associated with multiple crime types and can be contrasted with crime-specific patterns, or the unique spatial patterns that arise from the processes and characteristics associated with only a single type of crime. One reason for the lack of research exploring crime-general patterns is that conventional quantitative methods analyze a single crime type (or a single dependent variable) and cannot directly model the geographical correlation structures between two or more crime types.

This paper applies a Bayesian multivariate spatial modeling approach to analyze the spatial patterns of burglary, robbery, vehicle crime, and violent crime at the small-area scale in

Greater London, United Kingdom. Multivariate models provide a formal statistical framework for modeling, summarizing, and visualizing the correlation structures between multiple dependent variables (Wang and Wall, 2003). For crime types with similar theoretical explanations, multivariate models allow for the total area-specific risk of each crime type to be explained by multiple data-generating processes, including shared components, which capture the underlying crime-general patterns shared amongst two or more crime types, and type-specific components, which capture the divergent spatial patterns for each crime (Knorr-Held and Best, 2001; Tzala and Best, 2008). Conceptually, shared components represent geographically-varying latent processes that are simultaneously associated with two or more crime types and type-specific components represent latent processes associated with only one type.

This paper illustrates the first application of a multivariate spatial modeling approach to more than two crime types at the small-area scale. In this study, the best fitting model estimates two shared components that capture the spatial pattern shared amongst all four crimes (burglary, robbery, vehicle crime, and violent crime) and the spatial pattern shared amongst the theft-related crime types (burglary, robbery, and vehicle crime) after controlling for the effects of population density, deprivation, residential instability, and ethnic heterogeneity. The shared components are found to explain the largest proportions of residual variability for all crime types. For theoretical inference, this study highlights the importance of unobserved crime-general processes for understanding the spatial patterning of burglary, robbery, vehicle crime, and violent crime, and provides insight into where crime-general and/or crime-specific processes shape the local composition of crime. For crime prevention policy, visualizing and differentiating the shared and type-specific spatial patterns helps to understand where the risks of multiple crime types are correlated and clustered, and where interventions should target crime-general or crime-

specific processes (Weisburd et al., 1993). In the following sections of this paper, the theories used to explain the spatial patterning of multiple crime types are reviewed, a set of hypotheses regarding crime-general and crime-specific spatial patterns are proposed, the Bayesian multivariate spatial modeling approach is detailed, and the crime-general and crime-specific patterns exhibited by burglary, robbery, vehicle crime, and violent crime in Greater London are visualized and discussed.

2. Theoretical perspectives on correlated spatial crime patterns

Little existing research has investigated how crime composition, or the mix of two or more crime types, varies within and between small-area units (Schreck et al., 2009; Brantingham, 2016).

This may reflect, in part, the historical orientation of geographical analyses towards identifying determinants of specific types for law enforcement applications, rather than exploring if and how ecological crime theories are generalizable across crime types (Weisburd et al., 1993). However, the intra-urban spatial patterns of many crime types have been shown to be positively correlated at the small-area scale (Schmid, 1960; Andresen and Malleson, 2011) and many crime types have been explained using the same set of ecological theories, including social disorganization, routine activity, and crime pattern theories (Roncek and Maier, 1991; Andresen, 2006; Kinney et al., 2008).

Social disorganization theory hypothesizes that the high levels of crime found in some neighbourhoods result from limited informal social control (Shaw and McKay, 1942). In more disorganized communities, residents are less capable of realizing common values and mobilizing to control delinquent behaviour, leading to increased crime (Sampson and Groves, 1989). While social disorganization theory was originally proposed to explain the residential locations of

young offenders, contemporary research has found that neighbourhoods with high disorganization, as operationalized by socioeconomic disadvantage, residential instability, and ethnic heterogeneity, often have high rates of total crime offenses, violent crime offenses, and property crime offenses, as well as specific offense types including robbery, burglary, and motor vehicle theft (Sampson and Groves, 1989; Peterson and Krivo, 1996; Smith et al., 2000; Morenoff et al., 2001; Hipp, 2007; Schreck et al., 2009; Chamberlain and Hipp, 2015).

Extending social disorganization theory with a focus on how cultural contexts influence crime, differential opportunity theory proposes that the strength of social ties between residents interacts with structural characteristics to influence both the frequency of crime and the composition of crime types within neighbourhoods, specifically distinguishing the processes associated with violent and non-violent crimes (Cloward and Ohlin, 1960). In socially disorganized neighbourhoods with weak social ties, conflict subcultures may lead to higher risks of violent crime as there are fewer opportunities to learn the skills required for property crime offending. In contrast, in disorganized neighbourhoods with dense ties and interconnected social networks, criminal subcultures emerge, property crime skills are more effectively transferred between residents, and higher property crime rates are anticipated. Supporting differential opportunity theory, Schreck et al. (2009) found that neighbourhoods with weaker network ties had greater ratios of violent crimes to property crimes after accounting for variables representing social disorganization.

Shifting focus from neighbourhood social or cultural processes to the locations of crime opportunities within the urban environment, routine activity theory hypothesizes that crime offenses result from the convergence of motivated offenders, suitable targets, and a lack of capable guardianship in space and time (Cohen and Felson, 1979). Crime pattern theory situates

the tenets of the routine activity theory in the urban environment, focusing on the ways in which locations attract motivated or opportunistic offenders (Brantingham and Brantingham, 2010). Like social disorganization theory, routine activity and crime pattern theories have been applied to interpret the spatial patterns of many crime types, including aggregated crime categories (e.g., property crime, violent crime, and predatory crime) and specific crime types, such as assault, residential and street robbery, burglary, motor vehicle theft, and break and enter (Sherman et al., 1989; Kinney et al., 2008; Roncek and Maier, 1991). While past research using routine activity and crime pattern theories has found that related crime types often exhibit similar patterns at the small-area scale (e.g., vandalism, vehicle crime, and burglary at the basomrade scale in Stockholm, Sweden (Ceccato et al., 2002), and vehicle crime, robbery, and violent crime at the census dissemination area scale in Vancouver, Canada (Andresen, 2011)), these perspectives also recognize that the spatial patterns of some crime types may be driven by the location of type-specific targets. For example, motor vehicle thefts and burglaries may be strongly correlated in many small-areas because neighbourhoods with high concentrations of residences are likely to have high concentrations of vehicles, but these crime types may have weaker correlations in areas with a high concentration of only one target type.

Routine activity and crime pattern theories both assume that criminal acts result from rational decision-making and that each crime type has a distinct set of choice-structuring properties, or opportunities, costs, and benefits (Cornish and Clarke, 1987). Crime types with similar choice-structuring properties may be substitutable and correlated both within and between small-areas, as offenders may respond to generalized, rather than crime-specific, environmental cues (Hakim et al., 1984; Brantingham, 2016). Environmental cues provide information about the behaviour that is appropriate in a given context and, as applied to rational

offender decision-making, influence the attractiveness of a location for criminal behaviour (MacDonald and Gifford, 1989; Brantingham and Brantingham, 1993). For example, both burglary and vehicle theft are motivated by economic gain and, providing that the would-be offender does not specialize in one crime type, it is possible that these crime types are substitutable based on situational characteristics – such as the availability of specific target types – or environmental cues representing barriers to crime – such as the presence of a fence or a garage – or environmental cues representing the presence (or lack) of capable guardianship – such as visual indicators that a dwelling is occupied (MacDonald and Gifford, 1989). Likewise, despite robbery offences involving violence, an intended burglary or vehicle crime may be recorded by police as a robbery due to an unanticipated violent confrontation between offender and victim. While there are distinctions between crime types and choice-structuring properties at the incident-level, when crime data are aggregated by location and type, and are analyzed at the neighbourhood or small-area scale, the spatial patterns of crime types with similar choice-structuring properties may be correlated and share an underlying crime-general pattern.

2.3 Separating crime-general and crime-specific patterns

Summarizing ecological crime theories and past empirical research, a set of hypotheses regarding the crime-general and crime-specific spatial patterns of burglary, robbery, vehicle crime, and violent crime are proposed. Conceptually, we consider the total area-specific risk of each crime type to be associated with multiple data-generating processes, some of which are crime-general and some of which are crime-specific. Consider, for example, two types of theft crime distributed across a set of areas with similar levels of informal social control (social disorganization theory) but with varying concentrations of type-specific and geographically-

fixed crime targets (routine activity theory). In areas where there are equivalent concentrations of targets for both crime types, the risk of both crimes may be proportional to their association with informal social control (i.e., the proportion of risk due to the concentration of targets is the same for both crime types). In areas where the type-specific targets for only one crime type dominate, however, the number of opportunities and the number of offenses for the crime type with many targets will be greater than for the crime with few targets, even after accounting for the effects of informal social control on each type.

Hypothesis 1 (H1): Burglary, robbery, vehicle crime, and violent crime will share a crime-general pattern. We anticipate that this crime general-pattern will be evident after accounting for small-area structural characteristics because social, economic, and demographic census data do not entirely capture the social processes hypothesized by social disorganization theory.

Hypothesis 2 (H2): The crime types with similar choice-structuring properties and/or with correlated targets, as outlined by routine activity and crime pattern theories, will share a crime-general spatial pattern. This applies to the crime types involving theft (Hypothesis 2A (H2A): burglary, robbery, and vehicle crimes) and the crime types involving violence (Hypothesis 2B (H2B): robbery and violent crime). The crime-general patterns shared amongst subsets of the four crime types will be distinct from the crime-general pattern shared amongst all four crime types.

Hypothesis 3 (H3): Violent crime will exhibit a type-specific pattern that is different from the crime-general patterns. This hypothesis is anticipated by differential opportunity theory, which

contends that violent crimes are more common than non-violent crimes in socially disorganized areas with weak social ties (Schreck et al., 2009).

Hypothesis 4 (H4): Burglary, robbery, and vehicle crime will each exhibit crime-specific patterns that are distinguishable from the crime-general patterns and the type-specific pattern for violent crime. Each of these three crime types involves theft, has specific target types, and often involves geographically-fixed targets, such as buildings, dwellings, and parked vehicles (Hipp, 2016).

3. Methods for analyzing multiple crime patterns

Existing studies that explore the spatial patterns of multiple crime types have adopted four methodological approaches: cluster detection methods, the spatial point pattern test, regression analyses, and multivariate modeling of two crimes (i.e., with two dependent variables). Cluster detection methods are used to identify crime hotspots, or groups of areas or points that have high levels of crime and that exhibit positive spatial autocorrelation relative to a null hypothesis of no spatial autocorrelation (Anselin et al., 2000). To investigate the patterning of multiple crime types, past studies have separately identified clusters for each crime type and compared the locations of clusters (e.g., local Moran's I was used by Cohen and Tita (1999), Andresen (2011), and Bowers (2014)). For example, Weisburd et al. (1993) identify hotspots by choosing groups of addresses with high reported crime counts and analyze the pairwise correlations between fourteen crime types at these locations, finding that some crime types with similar choice-structuring properties were positively correlated, such as robbery and theft, and robbery and burglary. Haberman (2017) also investigates the composition of crime types at clusters,

separately identifying hotspots for eleven crime types and counting the number of intersections classified as a cluster for more than one type. Importantly, inferences regarding the correlations between crime types in hotspot analyses are based on only a subset of the available data (i.e., hotspot locations), and because cluster detection methods are univariate, hotspot analyses are not capable of analyzing covariates or quantifying the correlation structures between multiple dependent variables.

The spatial point pattern test quantifies the similarity of two geographically-referenced point datasets. This method iteratively samples a subset of points from one dataset (i.e., one crime type), establishes confidence intervals based on the sampled data, and calculates the percent of small-areas for which the second dataset (i.e., the non-sampled second crime type) falls within confidence intervals from the sampled dataset (Andresen, 2009). The spatial point pattern test has been applied to compare patterns of two crime types, showing that some crime types, including burglary and robbery, exhibit similar spatial patterns at the small-area scale (Andresen and Linning, 2012). Like cluster detection methods, the spatial point pattern test quantifies the degree to which one pattern is different from another (treating an existing crime pattern as the null hypothesis) but does not accommodate covariates or comparisons between more than two crime types.

Past studies analyzing multiple crime types via regression models typically compare the statistical significance and/or magnitude of coefficients from separate regression models fit to each crime type (e.g., Roncek and Maier (1991) and Hipp (2007)). Regression models have also been used to quantify the relationship between two crime types (Bowers, 2014) and the relationships between neighbourhood characteristics and a ratio of violent to nonviolent crimes (Schreck et al., 2009). While similar coefficient magnitudes for two or more crime types suggest

that they follow a similar spatial pattern based on observed explanatory variables, past applications of regression models overlook the potential correlation structures amongst model residuals, or the latent covariates not analyzed. To investigate the similarity of spatial crime patterns after controlling for explanatory factors, Ceccato et al. (2002) visualize the area-specific residuals from spatial regression models and find that the modelled crime risks for vandalism, residential burglary, and theft of/from cars were underestimated in low-income areas. This is conceptually similar to the multivariate modeling approach used in this paper, but whereas Ceccato et al. (2002) infers the correlations between crime types via map visualization, we directly model the correlation structures between multiple crime types.

In the aforementioned approaches, the correlations between crime types are inferred based on comparing the results of separate univariate analyses (i.e., for a single crime type or dependent variable). Multivariate modeling approaches, in contrast, analyze two or more dependent variables and directly estimate one or more model parameters that reveal and/or explain the correlation structures between dependent variables. One study has applied a multivariate model to two crime types. Liu and Zhu (2017) analyze burglary and non-motor vehicle thefts in a Bayesian spatial model featuring a multivariate conditional autoregressive (MVCAR) prior distribution. The MVCAR quantifies the strength of correlation between multiple spatially autocorrelated patterns (Besag et al., 1991; Gelfand and Vounatsou, 2003), and while the MVCAR prior is mathematically similar to the shared component models used in this research (MacNab, 2010; see Section 5), it assumes a single correlation structure for all crime types and cannot identify multiple correlation structures or spatial patterns shared amongst different subgroups of two or more crime types.

4. Study region and data

Greater London is the largest metropolitan region in England and is composed of the City of London and thirty-two surrounding boroughs. The geographic unit of analysis for this research was the lower super output area (LSOA). LSOAs are constructed by grouping together socially homogenous households (based on tenure and social status), have populations between one thousand and three thousand residents, and have been used to approximate the spatial boundary of neighbourhoods in past research (Sutherland et al., 2013; Malleson and Andresen, 2016).

4.1. Crime counts in Greater London

Reported crime data for 2015 for the City of London Police and the Metropolitan Police Service were retrieved from <https://data.police.uk/>. These data have been shown to provide an accurate picture of crime risk for LSOAs (Tompson et al., 2015). Four crime types were analyzed: burglary, robbery, vehicle crime, and violent crime (Table 1). Burglaries were defined as entering a dwelling or non-dwelling with the intent of theft, robberies as theft with force or threat of force, vehicle crimes as theft of or from a vehicle, and violent crimes included common assaults and offences involving bodily harm (Tompson et al., 2015; The Home Office, 2016). Note that this crime dataset does not include information for specific subtypes of burglary, robbery, vehicle crime, or violent crime. While Greater London is geographically contiguous and crime data were retrieved from one source, it is possible that reporting and classification differences between the two police agencies, and the relatively lower residential population density in the City of London (mean of 883 residents per km² compared to a mean of 10,170 per km² for the region), may influence the results of this study. Results were not changed by

excluding LSOAs in the City of London, likely because the City of London covers less than one percent of the total number of areas analyzed.

Table 1. Descriptive statistics for crime counts and explanatory variables.

Crime types	Total count	Mean	Std. Dev.	Min.	Max.
Burglary	70,209	14.52	9.72	0	173
Robbery	21,371	4.42	6.96	0	175
Vehicle crime	82,076	16.98	11.91	0	166
Violent crime	190,798	39.46	39.94	0	950
Explanatory variables					
Population density (per km ²)	NA	10,170	3,252.23	123	90,950
Deprivation	NA	7.53	2.57	1.63	17.33
Residential instability	NA	15.13	7.00	3.79	63.85
Ethnic heterogeneity	NA	0.56	0.21	0.04	0.96

Figure 1 maps the spatial patterns of burglary, robbery, vehicle crime, and violent crime counts. For all crime types, areas with high counts were located in and around Inner London, and areas with low counts were located to the southwest, southeast, and northwest. Robbery and violent crime appear to have similar spatial patterns, with high counts located in north and central Greater London, however violent crime had an additional group of LSOAs with high counts in the west of the study region. High counts of both burglary and vehicle crime were located along the north side of the Thames River in the east and along the northern boundary of Greater London. Detailed maps of crime counts in Inner London and in the City of London are

shown in Appendix 1. Positive pairwise correlations between the small-area counts of all crime types support the visual similarities of spatial crime patterns (Appendix 2). The crime types involving violence, violent crime and robbery, were the most strongly correlated (Kendall's $\tau_B = 0.48$), while the weakest positive correlations were between violent crime and nonviolent crime types, specifically burglary ($\tau_B = 0.27$) and vehicle crime ($\tau_B = 0.29$). Most LSOAs had a mix of multiple crime types (Appendix 3).

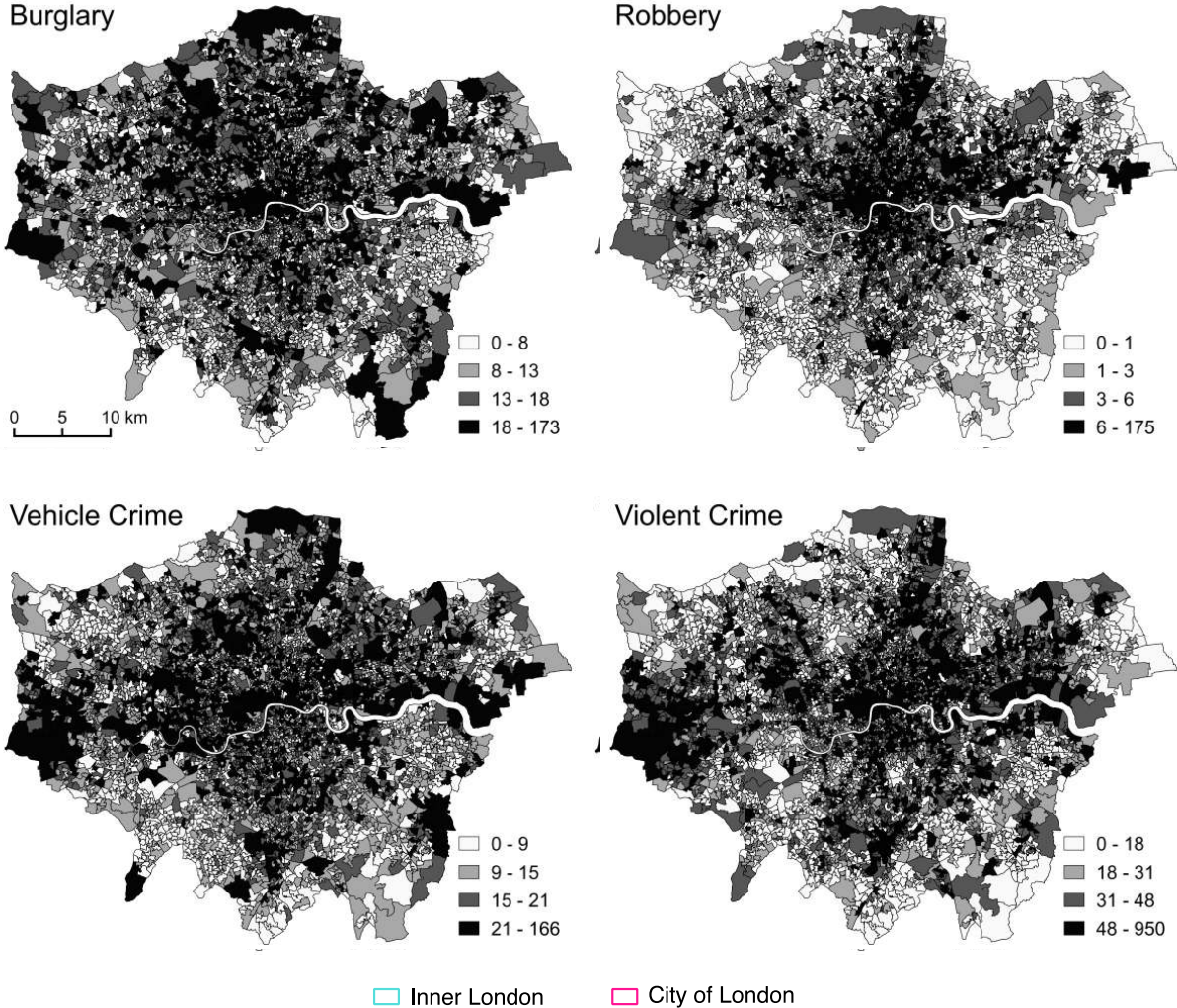


Figure 1. Quantile maps of burglary, robbery, vehicle crime, and violent crime counts. Each map class includes one-quarter of all LSOAs in Greater London.

4.2. Explanatory variables

Four variables were chosen to explain the spatial patterns of all crime types: population density, deprivation, residential instability, and ethnic heterogeneity (Table 1). These variables are commonly used to operationalize social disorganization and have been found to be associated with burglary, robbery, vehicle crime, and violent crime at a variety of small-area scales (Shaw and McKay, 1942; Sampson and Groves, 1989; Morenoff et al., 2001; Hooghe et al., 2011; Sutherland et al., 2013; Chamberlain and Hipp, 2015). Population density was operationalized as the number of usual residents per square kilometre and data were retrieved for 2015 from the Office for National Statistics¹. Population density was included as an explanatory variable and the relationship between population density and each crime type was directly quantified. This was because the population for these four crime types is not well-defined. Also, treating residential population as a population at risk (i.e., when constructing crime rates for models requiring continuous data or when constructing log-offsets for models requiring count data) may not be appropriate in Greater London, where crime has been shown to cluster in areas with smaller residential populations, such as the city centre (Wikstrom and Dolmen, 1990; Malleson and Andresen, 2016). Deprivation was derived from the index of multiple deprivation by removing the crime indicator and re-calculating according to the original weights for education,

¹ Usual residents include people who were in the United Kingdom (UK) on census day, people who had been in the UK for 12 months or more prior to census day, and people with a permanent address in the UK but who were outside of the UK on census day for a period of less than 12 months.

health, housing, income, and living environment dimensions (Department for Communities and Local Government, 2015). Residential instability and ethnic heterogeneity data were retrieved from the 2011 Census of England and Wales. Residential instability was operationalized as the percent of residents who did not live at the same address in the year prior and ethnic heterogeneity was operationalized as the index of ethnic heterogeneity², where values range between zero (low heterogeneity) and one (high heterogeneity).

5. Bayesian multivariate spatial modeling

Let O_{ik} denote observed crime counts for small-area i ($= 1, \dots, 4835$) and type k ($= 1, \dots, 4$) where O_{i1} represents area-specific counts of burglary, and O_{i2} , O_{i3} , and O_{i4} represent area-specific counts of robbery, vehicle crime, and violent crime, respectively. Conditioning on the underlying crime risk μ_{ik} , O_{ik} 's are modelled as independent Poisson random variables. The Poisson model is often used in Bayesian spatial modeling of small-area count data (Richardson et al., 2004; Haining et al., 2009). A Bayesian modeling approach was employed because it allows for the estimation of hierarchical generalized linear mixed models with structured random effects that would be otherwise intractable via frequentist methods (Breslow and Clayton, 1993). The multivariate models used to analyze the four crime types are described below.

Model 1 analyzes the spatial pattern of each crime type independently and assumes no correlation structure between crime types. In Model 1, the small-area risk of each crime type

² The index of ethnic heterogeneity for area $i = 1 - \sum p_{id}^2$, where p_{id} is the proportion of residents of ethnicity d in area i relative to the total population in area i . Ten ethnicities ($d = 10$) were included in the index calculation (Table KS201UK: Office of National Statistics (2011)).

(μ_{ik}) is modeled (on the log scale) as the sum of type-specific intercepts (α_k), a set of type-specific spatially structured random effects (s_{ik}), and a set of type-specific unstructured random effects (e_{ik}). The type-specific intercepts capture the average risk of each crime type across Greater London. The two random effects terms, s_{ik} and e_{ik} , capture spatial autocorrelation and overdispersion of count data, respectively. The sum of s_{ik} and e_{ik} is known as the BYM structure after Besag et al. (1991) and, when mapped, these parameters represent the type-specific patterns of each crime. For example, areas with high values of $(s_{i1} + e_{i1})$ have high type-specific risk of burglary and areas with low values of $(s_{i2} + e_{i2})$ have low type-specific risk of robbery.

$$\log(\mu_{ik}) = \alpha_k + s_{ik} + e_{ik} \quad (1)$$

In Model 2, we separate the spatial pattern of each crime type into one shared component and four type-specific components. The shared component ($\lambda_k \cdot f_i$) models the geographical correlations between all crime types, where λ_k are four type-specific scaling parameters and f_i is a set of spatially structured random effects terms that are common to all four crime types. When mapped, f_i represents the crime-general pattern shared amongst all crime types. The scaling parameters allow each crime type to have a different risk gradient or loading on the crime-general pattern. For example, if the pattern of violent crime is close to the crime-general pattern shared amongst all crimes, the scaling parameter for violent crime (λ_4) will be positive and away from 0, but if it does not resemble the crime-general pattern of f_i , the scaling parameter will be close to 0 (Knorr-Held and Best, 2001). A crime-general pattern common to all crime types is theoretically supported by past research showing that social disorganization is generalizable to burglary, robbery, vehicle crime, and violent crime (see Section 2), and empirically supported by the positive pairwise correlations between all crime types in Greater London (Appendix 2). In addition to the one shared component, type-specific components s_{ik} and e_{ik} were included to

capture the crime-specific patterns that diverge from the crime-general pattern (Held et al., 2005; Tzala and Best, 2008).

$$\log(\mu_{ik}) = \alpha_k + (\lambda_k \cdot f_i) + s_{ik} + e_{ik} \quad (2)$$

Model 3 adds a second shared component to account for the crime-general pattern shared amongst burglary, robbery, and vehicle crime ($\gamma_{1:3} \cdot v_i$). This shared component was added based on the similar motivations and choice-structuring properties of theft-related crime types, with past research showing that theft crimes are substitutable in response to changes in deterrence policies (Hakim et al., 1984), the possibility that the target types for these crime types may be correlated within small-areas, and preliminary results from Model 2 showing that the type-specific spatial patterns of these crime types were similar. This shared component is the product of three unknown scaling parameters ($\gamma_{1:3}$) and a set of spatially structured random effects (v_i), where v_i represents the crime-general pattern shared amongst the theft-related crimes and where scaling parameters $\gamma_{1:3}$ quantify the relative associations between the three theft-related crimes and v_i . Note that the scaling parameter for violent crime (γ_4) was fixed to 0 so v_i is only shared by burglary, robbery, and vehicle crime.

$$\log(\mu_{ik}) = \alpha_k + (\lambda_k \cdot f_i) + (\gamma_{1:3} \cdot v_i) + s_{ik} + e_{ik} \quad (3)$$

In Model 4, we add regression coefficients (β_{nk} , with subscript n denoting the n^{th} explanatory variable) to estimate the associations between each crime type and population density, deprivation, residential instability, and ethnic heterogeneity. Compared to Model 3, which separates the total risk of each crime type into two shared components and four type-specific components, Model 4 separates the residual risk of each crime type into shared and type-specific components after controlling for observed covariates. For reference, shared components are analogous to regression coefficients insofar as they explain the spatial variability of all crime

types, however, whereas x_{ni} are observed data, both f_i and v_i are unobserved parameters that capture the residual crime-general patterns that arise from the geographical correlations amongst multiple crime types. Note that we tested an additional model with a shared component common to only robbery and violent crime, however this model did not converge. This suggests that the correlations between violent crime and robbery were entirely captured by the four explanatory variables and the crime-general pattern common to all crimes (see Section 7).

$$\log(\mu_{ik}) = \alpha_k + (\beta_{nk} \cdot x_{ni}) + (\lambda_k \cdot f_i) + (\gamma_{1,3} \cdot v_i) + s_{ik} + e_{ik} \quad (4)$$

To quantify the degree to which model parameters explain the overall variability of each crime type, variance partition coefficients (VPCs) were calculated for all parameters in Models 2, 3, and 4 (Goldstein et al., 2002). In Model 1, the variability of all crime types was entirely explained by the type-specific parameters. The VPC estimating the amount of variability explained by the crime-general pattern common to all crime types in Model 2, for example, is equal to the empirical variance of $(\lambda_k \cdot f_i)$ divided by the sum of the empirical variances of $(\lambda_k \cdot f_i)$ and $(s_{ik} + e_{ik})$. The VPCs for observed covariates in Model 4 were calculated as $\beta_{nk}^2 \cdot \text{var}(x_{ni})$ and were added to the denominators when calculating the VPC for all model parameters (Section 6; Appendix 4).

5.1. Prior distributions

In Bayesian modeling, all parameters are treated as random variables and assigned prior probability distributions. The improper uniform distribution was assigned for each of the type-specific intercepts (α_k) (Thomas et al., 2004). A vague normal distribution with a mean of zero and a variance of 1,000 was assigned to each regression coefficient (β 's). For the two shared components, the logarithm of each scaling parameter (i.e., $\log(\lambda_k)$ and $\log(\gamma_{1,3})$) was assigned a

normal distribution with a mean of zero and a variance of 0.17. This prior, which was the prior originally proposed for shared component modeling in disease mapping applications, has two assumptions (Knorr-Held and Best, 2001). First, all of the scaling parameters are assumed to be positive, implying that all four crime types are positively correlated. This is supported by exploratory analysis of this dataset (see Appendix 2). Second, this prior assumes that, before analyzing the data, each scaling parameter ranges between 0.2 and 5 with a 95% probability (Knorr-Held and Best, 2001; Held et al. 2005). We also considered two other values (0.2 and 0.5) for the prior variance, each corresponding to a prior distribution with weaker information than $Normal(0, 0.17)$. The results from analyses using these alternative priors were very similar to those presented here, meaning our findings were not sensitive to the prior choice. Following Held et al. (2005), a sum-to-zero constraint was imposed on $\log(\lambda_k)$ and $\log(\gamma_{1:3})$ (i.e., $\log(\lambda_1) + \log(\lambda_2) + \log(\lambda_3) + \log(\lambda_4) = 0$; $\log(\gamma_1) + \log(\gamma_2) + \log(\gamma_3) = 0$) to avoid the non-identifiability problem between the scaling parameters and the random effects terms f_i and v_i .

The type-specific unstructured random effects terms (e_{ik}) were independently assigned a normal distribution with a mean of zero and an unknown type-specific variance ($\sigma_{e_k}^2$). The spatially structured random effects terms in shared and type-specific components (f_i , v_i , and s_{ik}) were modeled via the intrinsic conditional autoregressive (ICAR) model. In the ICAR model, the conditional distribution of each f_i , v_i , and s_{ik} is a normal distribution with mean equal to the average of the f_i 's, v_i 's, and s_{ik} 's in neighbouring areas (Besag et al., 1991). Neighbourhood structure was defined via a first-order queen contiguity matrix, where two areas are neighbours if they share a common boundary, a common vertex, or both. The variances of common spatially structured random effects (σ_f^2 and σ_v^2) were set to one to guarantee a unique solution and the variances for type-specific spatially structured random effects ($\sigma_{s_k}^2$) were treated as unknown

(Tzala and Best, 2008). Note that, because the variances of f_i and v_i were set to one, the scaling parameters within each shared component are interpreted relative to each other (Held et al., 2005; Wang and Wall, 2003). For example, the influence of the crime-general pattern f_i on burglary relative to the influence of f_i on robbery is equal to λ_1 / λ_2 .

Hyperprior distributions were assigned to the variances of type-specific random effects terms s_{ik} and e_{ik} . A positive half Gaussian prior, $Normal_{+\infty}(0, 10)$, was assigned to the type-specific standard deviations σ_{s_k} and σ_{e_k} (Gelman, 2006). Similar results were obtained when an *Inverse Gamma*(0.5, 0.0005) or an *Inverse Gamma*(0.001, 0.001) prior distribution was assigned to the variances $\sigma_{s_k}^2$ and $\sigma_{e_k}^2$ (Kelsall and Wakefield, 1999).

5.2. Model fitting

All models were fit via the Markov chain Monte Carlo (MCMC) algorithm in WinBUGS v.1.4.3. Population density, deprivation, and residential mobility were standardized in Model 4 to improve convergence. Two MCMC chains were run and model convergence was reached at 600,000 iterations (or 300,000 for each chain). Convergence was monitored by visual inspection of history plots and formally assessed via Brooks-Gelman-Rubin diagnostics (Brooks and Gelman, 1998). An additional 200,000 iterations (for each chain) were sampled for posterior inference, where every fortieth iteration was retained to reduce autocorrelation of the MCMC samples. A total of 610,000 iterations were used for posterior inference. The Monte Carlo errors for all model parameters were less than five percent of corresponding posterior standard deviations, indicating that the 610,000 iterations were sufficient to approximate the posterior distributions (Lunn et al., 2012). The Deviance Information Criterion (DIC) was used for model comparison. The DIC balances goodness of fit and model complexity, where goodness of fit is

assessed via the posterior mean deviance (\overline{D}) and model complexity is assessed via the effective number of parameters (ρ_D). The model with the smallest DIC value is considered to be the best fitting model (Spiegelhalter et al., 2002).

6. Results

Table 2 compares the four multivariate spatial models using the DIC. The DIC decreased from Model 1 to Model 2, providing evidence that burglary, robbery, vehicle crime, and violent crime are correlated and share an underlying crime-general pattern. Model fit also improved in Model 3 when adding a second shared component to capture the crime-general pattern shared amongst the three theft-related crimes. Model 4, which added four explanatory variables, had the smallest DIC, and was identified as the best fitting model. The WinBUGS code for Model 4 is shown in Appendix 5.

Table 2. Model comparison of the four multivariate spatial models using DIC.

Model	Description	\overline{D}	ρ_D	DIC
1	Type-specific patterns	100,344	14,119	114,463
2	Type-specific patterns, one crime-general pattern	100,387	11,881	112,268
3	Type-specific patterns, two crime-general patterns	100,150	12,078	112,228
4	Type-specific patterns, two crime-general patterns, explanatory variables	100,125	11,855	111,980

Results from Model 4 are shown in Table 3. The regression coefficients are shown as relative risks (i.e., $\exp(\beta_n)$), where a relative risk estimate greater than one indicates a positive

association with crime. Uncertainty of model parameters is indicated by the 95% credible interval (95% CI), or the interval that contains the true value of a parameter with 95% probability. Population density was found to be negatively associated with all crime types, which aligns with past research showing that areas with high crime often have low residential population densities in Greater London (Malleon and Andresen, 2016). Deprivation and residential instability were positively associated with all crime types, and ethnic heterogeneity was only positively associated with robbery and violent crime at 95% CI. Of the four crime types, robbery and violent crime had stronger positive relationships with deprivation, residential instability, and ethnic heterogeneity, supporting past research showing that the structural characteristics of social disorganization often have greater positive associations with crime types involving violence than with non-violent crimes (Warner and Rountree, 1997; Hipp 2007; Sutherland et al., 2013; Hirschfield and Bowers, 1997).

Table 3. Posterior medians and 95% CI's for parameters from Model 4.

	Burglary	Robbery	Vehicle crime	Violent crime
Intercept ($\exp(\alpha_k)$)	13.79 (12.31, 15.55)	1.53 (1.26, 1.89)	15.82 (14.04, 17.94)	15.34 (14.20, 17.04)
Population density (β_1)	0.80 (0.77, 0.82)	0.73 (0.70, 0.77)	0.76 (0.74, 0.79)	0.79 (0.77, 0.82)
Deprivation (β_2)	1.06 (1.02, 1.09)	1.41 (1.33, 1.49)	1.03 (0.99, 1.07)	1.40 (1.36, 1.45)
Residential instability (β_3)	1.15 (1.12, 1.18)	1.28 (1.22, 1.34)	1.09 (1.06, 1.12)	1.22 (1.18, 1.24)

Ethnic heterogeneity (β_4)	0.84 (0.68, 1.01)	2.29 (1.57, 3.22)	0.83 (0.67, 1.01)	3.27 (2.64, 3.78)
Scaling parameters				
All crimes (λ_k)	0.74 (0.71, 0.77)	1.48 (1.43, 1.52)	0.72 (0.70, 0.75)	1.26 (1.23, 1.29)
Theft-related crimes ($\gamma_{1:3}$)	0.87 (0.83, 0.91)	1.19 (1.14, 1.24)	0.96 (0.92, 1.00)	NA ^a
Empirical variances of random effects terms				
All crimes ($\lambda_k \cdot f_i$)	0.11 (0.09, 0.12)	0.41 (0.38, 0.45)	0.10 (0.08, 0.12)	0.30 (0.28, 0.32)
Theft crimes ($\gamma_{1:3} \cdot v_i$)	0.20 (0.17, 0.26)	0.38 (0.30, 0.49)	0.25 (0.20, 0.32)	NA
Type-specific ($s_{ik} + e_{ik}$)	0.08 (0.05, 0.10)	0.27 (0.21, 0.33)	0.13 (0.10, 0.16)	0.001 (0, 0.01)

^a $\gamma_4 = 0$.

The scaling parameters in both shared components were unambiguously greater than zero for all crime types, indicating that the crime types grouped together in each shared component were significantly associated with the corresponding crime-general patterns (Tzala and Best, 2008). For the shared component common to all four crimes, the scaling parameters were significantly greater for robbery and violent crime than for burglary and vehicle crime at 95% CI (Table 3). Accordingly, the crime-general pattern for all crime types had about two times the influence on robbery ($\lambda_2 / \lambda_3 = 1.48 / 0.72 = 2.06$ (95% CI: 1.95, 2.14)) and on violent crime (λ_4

$/\lambda_3 = 1.26 / 0.74 = 1.75$ (95% CI: 1.67, 1.82)) than on vehicle crime. The crime-general pattern for all crime types had about the same influence on both burglary and vehicle crime ($\lambda_1 / \lambda_3 = 0.74 / 0.72 = 1.03$ (95% CI: 0.98, 1.08))

The crime-general pattern for the three theft-related crimes had the strongest positive influence on robbery ($\gamma_2 = 1.19$) and the weakest positive influence on burglary ($\gamma_1 = 0.87$). Figure 2 maps the crime-general spatial patterns shared amongst all four crime types and amongst the three theft-related crime types. In general, areas with high risk due to the crime-general pattern for all crimes were located in central areas of Greater London whereas areas with high risk due to the crime-general pattern for theft-related crimes were located in the northern half of Greater London.

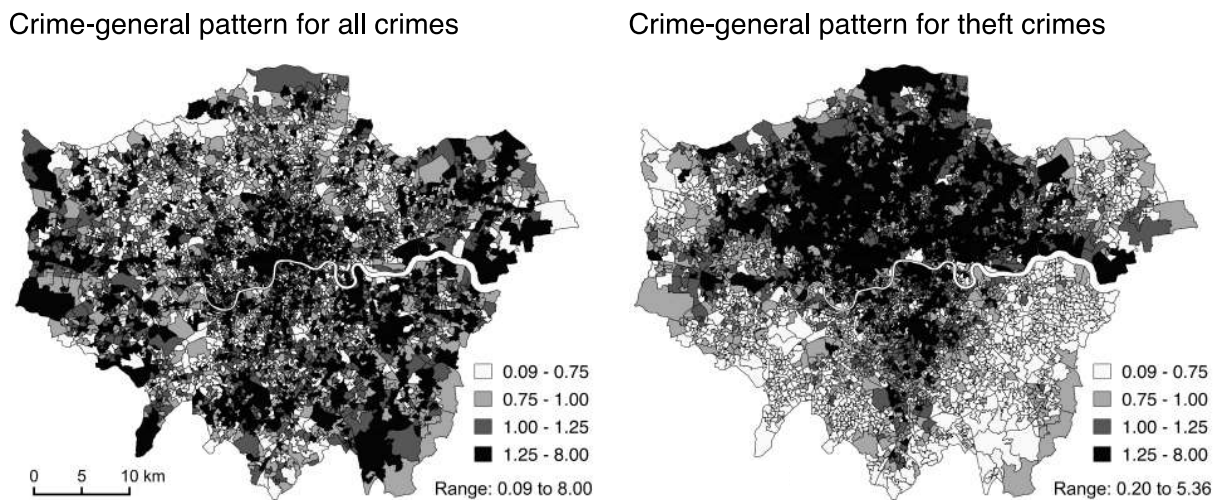


Figure 2. The crime-general pattern shared amongst all crime types ($\exp(f_i)$ from Model 4) and the crime-general pattern shared amongst the theft-related crime types ($\exp(v_i)$ from Model 4).

Figure 3 maps the type-specific patterns that diverge from the crime-general patterns. Burglary and violent crime show no clear type-specific pattern, however burglary had areas with moderately high and moderately low risk dispersed across Greater London whereas the type-

specific risk of violent crimes was small and essentially uniform across all areas (range between 0.98 and 1.03). This suggests that the four explanatory variables and the shared component common to all crimes captured almost all of the spatial variability of violent crime (also see Figure 4). In contrast, the type-specific patterns of robbery and vehicle crime were distinctly clustered. For robbery, high risk areas surrounded the city centre and low risk areas were located around the periphery of the study region. For vehicle crime, high risk areas were concentrated along the Thames River, particularly at the easternmost and westernmost boundaries of Greater London. Visually, areas with high type-specific burglary risk appear to overlap with areas with low type-specific vehicle crime risk.

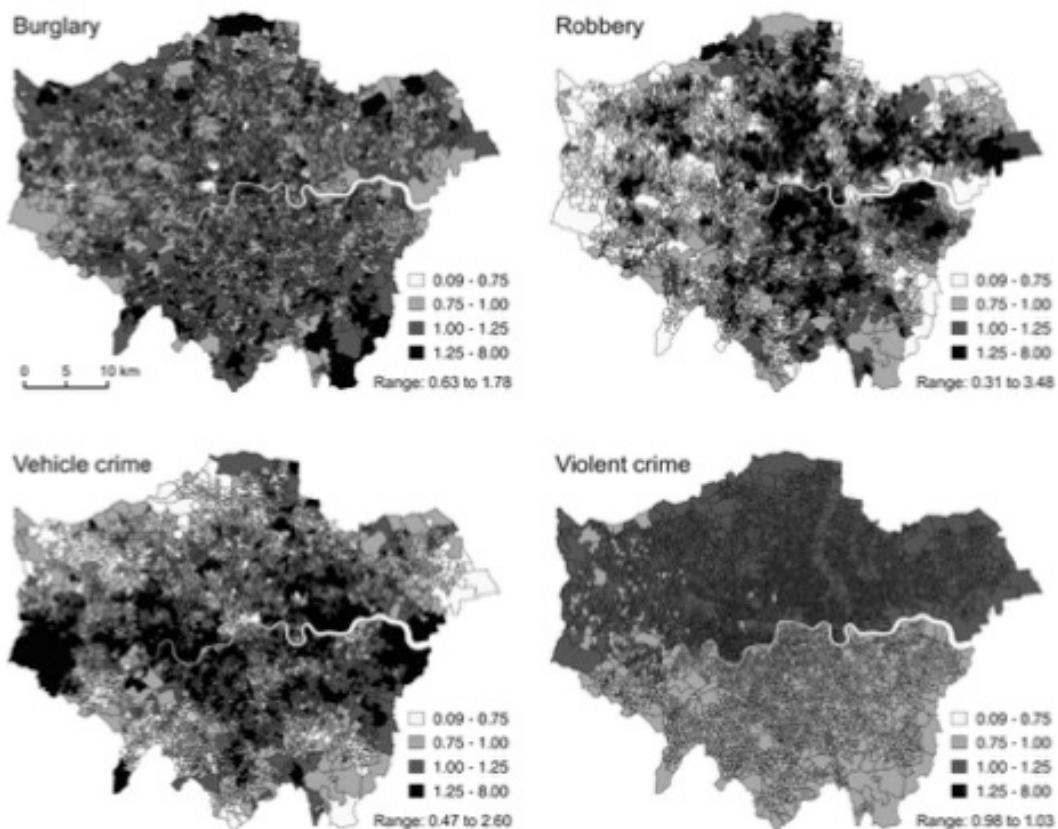


Figure 3. Type-specific spatial patterns of burglary, robbery, vehicle crime, and violent crime ($\exp(s_{ik} + e_{ik})$ from Model 4).

The VPCs for the shared components, type-specific components, and explanatory variables from Models 3 and 4 are visualized in Figure 4 (see Appendix 4 for posterior medians and uncertainty intervals). In Model 3, the shared component common to all crimes explained the largest proportions of variability for violent crime and robbery (99% and 50%, respectively), and the shared component for the theft-related crimes explained the largest proportions of vehicle crime and burglary (51% and 49%, respectively). This finding was consistent in Model 4 after accounting for explanatory variables; for violent crime and robbery, the largest proportions of variability were explained by the shared component common to all crimes (52% and 30%, respectively), and for burglary and vehicle crime, the largest proportions of variability were explained by the shared component common to theft-related crimes (45% and 44%, respectively). In total, the four covariates added in Model 4 explained about 48% of the variability of violent crime, but only between 13% and 21% percent of the variability of burglary, robbery, and vehicle crime. For robbery and violent crime, the variance explained by regression coefficients/explanatory variables in Model 4 was largely transferred from the shared components common to all crime types. Note that violent crime had almost no residual type-specific variability, confirming the lack of a type-specific violent crime pattern (Figure 3).

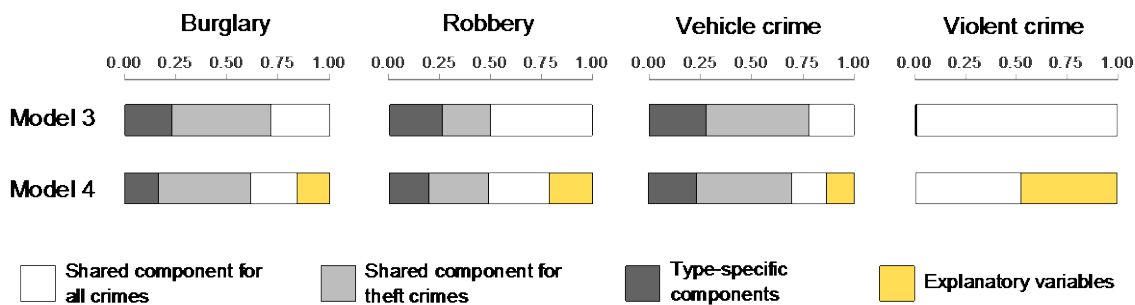


Figure 4. Variance partition coefficients from Model 3 and Model 4.

7. Discussion

This paper has examined if, and how, multiple crime types share underlying crime-general patterns through the application of a Bayesian multivariate spatial modeling approach. In this study, the best fitting model estimated two shared components that captured the crime-general pattern shared amongst burglary, robbery, vehicle crime, and violent crime, and the crime-general pattern shared amongst the three theft-related crimes (burglary, robbery, and vehicle crime). Because shared and type-specific components are estimated as random effects terms in a regression modeling framework, crime-general and crime-specific spatial patterns have specific interpretations as latent/unobserved covariates or processes associated with multiple crime type or only one crime type, respectively.

7.1. Interpreting crime-general and crime-specific patterns

Focusing first on the shared component common to all four crime types, the results of this research show that burglary, robbery, vehicle crime, and violent crime share an underlying crime-general spatial pattern. This supports H1, which contends that there are geographically-situated crime-general processes simultaneously associated with these four crime types after accounting for population density, residential instability, deprivation, and ethnic heterogeneity. In fact, the crime-general pattern common to all four crime types explained a larger proportion of variability of all crime types than all but one observed covariate (the relationship between deprivation and violent crime) (Figure 4; Appendix 4). This provides quantitative evidence that, in Greater London, the crime-general processes captured by the spatially structured shared component are relatively more important for understanding the overall spatial patterning of

crime, broadly defined, than the structural characteristics commonly used to operationalize social disorganization. One interpretation of this crime-general pattern is that it reflects dimensions of social disorganization not entirely represented via small-area structural characteristics, such as collective efficacy, the density of friendship networks amongst residents, or the level of social cohesion and trust between residents. Past research has shown that, in addition to structural characteristics, these features are important for understanding the social and cultural contexts of neighbourhoods with high levels of a range of crime types (Sampson and Groves, 1989; Sampson et al., 1997; Peterson and Krivo, 1996; Sutherland et al., 2013).

Focusing on the shared component for theft-related crimes, burglary, robbery, and vehicle crime were also found to be positively associated with a second underlying crime-general pattern. This supports H2A, which draws on the similarities in choice-structuring properties of theft crimes and the geographical correlations of theft targets to posit that there is a second distinct crime-general pattern shared by the three theft-related crimes. Based on the necessary elements for theft crimes as outlined by routine activity theory, specifically the convergence of motivated offenders, suitable targets, and a lack of capable guardianship, and the underlying economic motivation for the crime types involving theft, it is possible that the crime-general pattern for burglary, robbery, and vehicle crime is representative of environmental cues that concurrently influence the offense types involving theft (Cohen and Felson, 1979; Brantingham, 2016). In Greater London, for example, the crime-general pattern for burglary, robbery, and vehicle crime was highest in the adjacent boroughs of Westminster, Camden, and Haringey, where the average relative risk amongst LSOAs was more than fifty percent higher than average ($\exp(v_i) > 1.5$). These boroughs are close to the City of London, have relatively highly transient and dynamic populations (Malleon and Andresen, 2016), and have some of the highest levels of

income inequality in Greater London (Sutherland et al., 2013; Trust for London, 2018).

Combined, these characteristics may be interpreted by offenders as environmental cues that reduce perceptions of capable guardianship (i.e., anonymity due to the transient and dynamic populations) and increase the attractiveness of theft targets (i.e., economically valuable material goods) for burglary, robbery, and vehicle crime (Brantingham and Brantingham; 1993; Chiu and Madden, 1998; Rice and Smith, 2002; Hipp, 2007).

A third shared component that included only robbery and violent crime was tested to investigate the presence of a crime-general pattern shared amongst the crimes involving violence (H2B). This shared component did not converge during modeling and, therefore, this study does not appear to support H2B insofar as this crime-general pattern is estimated using a shared component with spatially structured random effects terms. However, there were similarities between the patterns of robbery and violent crime, as both crime types had the strongest positive associations with deprivation, residential instability, and ethnic heterogeneity (Table 3), and both crime types had the largest amounts of variability explained by the crime-general pattern (or shared component) common to all crime types (Figure 4). This suggests that the correlations between the patterns of robbery and violent crime were entirely captured by the structural characteristics and the crime-general pattern for all crimes. Note that this finding does not preclude a crime-general pattern shared amongst multiple crime types involving violence under alternative model specifications (i.e., without structural characteristics or without a shared component common to all crimes) or when analyzing specific violent crime subtypes.

In addition to the crime-general patterns, this research identified crime-specific patterns for burglary, robbery, and vehicle crime, but did not identify a divergent crime-specific pattern for violent crime. While the lack of a type-specific violent crime pattern is inconsistent with H3,

it is possible that the joint effects of social ties and structural characteristics on violent crime, as outlined by differential opportunity theory (Schreck et al., 2009), are captured by the structural characteristics and the crime-general pattern common to all crime types. Alternatively, it is possible that, because the violent crime category includes a number of different subtypes and is the most frequent crime type analyzed (Table 1), violent crime dominates the crime-general pattern for all crimes such that it summarizes the type-specific pattern of violent crime as well as some of the matching elements of burglary, robbery, and vehicle crime.

Each of burglary, robbery, and vehicle crime exhibited type-specific patterns. This finding supports H4. These crime types had between 15% and 25% of their overall variabilities explained by type-specific components, supporting the hypothesis that these crime types would exhibit crime-specific patterns as they involve geographically-situated targets, such as dwellings, residents, or vehicles. Interestingly, burglary and vehicle crime appear to have opposing type-specific patterns; the type-specific patterns of these crimes were negatively correlated (Kendall's τ_B correlation between $(s_{i1} + e_{i1})$ and $(s_{i3} + e_{i3})$ was -0.36) and only two percent of areas in the top quintile of burglary risk were also in the top quintile for vehicle crime risk. One possible interpretation of this opposing pattern is that burglary and vehicle crime are substitutable insofar as the differences between these crime-specific patterns represent the differences in the availability of targets. For example, areas with high type-specific vehicle crime risk but low burglary risk located on the western and eastern boundaries of Greater London correspond to Heathrow Airport and London City Airport, both locations with high concentrations of vehicle crime targets but low concentrations of burglary targets (Figure 3).

7.2. Multivariate spatial modeling and policy applications

In general, past research exploring the spatial patterns of multiple crime types have separately identified hotspots for individual crime types and examined if hotspot locations overlap or if crime types are correlated between hotspot locations (Weisburd et al., 1993; Haberman, 2017). These approaches, however, make inferences from a subset of the available data (i.e., only hotspot locations) and assume that the small-area risks of each crime type are driven by a single unobserved data-generating process (i.e., separate models for each type with no covariates). In contrast, this multivariate modeling approach uses data from all areas to model the correlation structures between crime types and allows for the small-area risks of each crime type to be simultaneously generated from multiple observed and latent covariates, some of which are crime-general and some of which are crime-specific. Regardless of the theoretical interpretation of the shared and type-specific components and the associated crime-general and crime-specific patterns, this research shows that quantifying and investigating the residual structure of spatial crime patterns, and the correlation structures between crime types amongst area-specific residuals in particular, provides important insight into where, and why, crime-general and/or crime-specific processes shape the local composition of crime types.

Applied to crime prevention policy, the crime-general patterns estimated via shared components identify locations where crime prevention initiatives should be designed to address the underlying mechanisms associated with multiple crime types. For example, areas with high risk due to the crime-general pattern shared amongst all crime types may be best suited for interventions that aim to increase informal social control amongst neighbourhood residents, perhaps through initiating or funding community-based organizations (Schreck et al., 2009; Sharkey et al., 2017). It is possible that strengthening informal social control may reduce all types of crime, with particular effects on violent crime and robbery as these types had the largest

scaling parameters for this shared component (Table 3). Areas with high risk due to the crime-general pattern for theft-related crimes, on the other hand, may be best suited for initiatives focused on modifying the environmental cues associated with all types of theft crimes, perhaps through more prevalent police patrols to increase offender perceptions of guardianship, through urban design guidelines that establish a sense of territoriality amongst residents and improve natural surveillance of high theft areas, or through increasing awareness of theft crimes amongst local place managers, such as store employees or government staff (Eck and Weisburd, 1995; Groff, 2014). In contrast, implementing crime prevention initiatives designed for a specific crime type in areas with high risk due to the crime-general patterns may reduce the prevalence of a single crime but be ineffective at addressing the underlying mechanisms shared amongst multiple crimes.

7.3. Limitations and future research

One limitation of this study, and of most geographical research analyzing official crime data, is that each crime type includes a number of subtypes and that the differences between the intended and recorded crime types are not acknowledged (Brantingham, 2016). While data are not currently available for more detailed types at the small-area scale, it is possible that there may be interesting crime-general or crime-specific patterns not observed with the current data, such as for assault or homicide, for thefts and narcotics offenses, or for commercial or residential burglaries (Brantingham, 2016). Second, we interpret the two crime-general patterns using ecological theories applied in past literature, however little research has explored how crime composition varies at the small-area scale and no previous studies have applied shared component models to analyze crime data (Schreck et al., 2009). As such, we cannot

contextualize the results of this study based on other study regions, time periods, or crime types. Our proposed explanations and our multivariate modeling approach should be further tested on a range of different crime types, in different study regions, at different spatial scales (e.g., street segments and points), and using additional covariates (e.g., land use, collective efficacy) to refine understanding of the latent crime-general and crime-specific processes that are modeled via the shared and type-specific components. When analyzing more specific crime types or using more precise geographical units, future research should consider statistical models that accommodate zero-inflated count data and ensure that the scaling parameters and random effects terms within shared components are appropriately specified.

Future research should also look to extend this Bayesian shared component model to spatiotemporal contexts, where the space-time patterns of two or more crime types are separated into at least one shared spatial pattern and at least one shared time trend (Tzala and Best, 2008). Studies may look to quantify how the correlation structures between crime types become stronger or weaker in response to longer-term processes of neighbourhood change or shorter-term processes related to law enforcement interventions targeting one or more crime types in a set of locations. Researchers applying multivariate spatial models to spatiotemporal data, to higher resolution spatial or spatiotemporal data, or to more crime types should note that the models implemented in this paper will be computationally expensive (i.e., the MCMC methods used in this paper would take a very long time to converge), and alternative approaches to fitting multivariate models should be considered, such as Integrated Nested Laplace Approximation for Bayesian inference (Blangiardo et al., 2013). Furthermore, research should investigate how identifying and differentiating crime-general and crime-specific spatial patterns can be used to

inform and evaluate place-based crime prevention policies, for example analyzing the degree to which hotspot policing initiatives influence all or only a subset of crime types.

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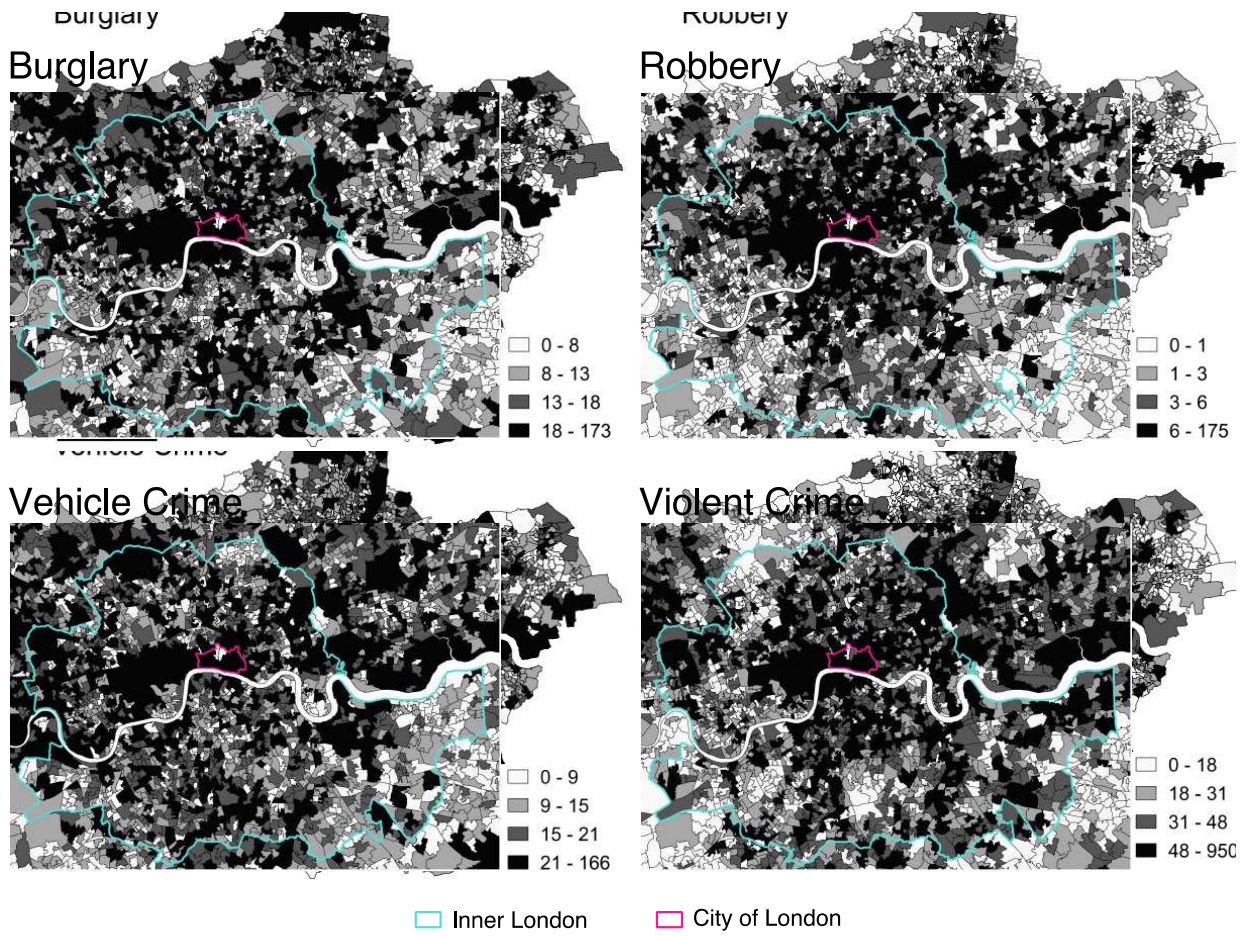
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Appendix 1: Crime counts in Inner London and in the City of London.



Appendix 2: Pairwise Kendall's τ_B correlation coefficients for LSOA crime counts.

	Burglary	Robbery	Vehicle crime	Violent crime
Burglary	--			
Robbery	0.30	--		
Vehicle crime	0.37	0.30	--	
Violent crime	0.27	0.48	0.29	--

Appendix 3: Crime type composition within LSOAs.

The composition of crime types within each LSOA was assessed via the Gibbs-Martin heterogeneity index (GMI). The GMI, which is also referred to as the Herfindahl concentration formula or Simpson's index of diversity, has been used in past research to measure crime type mix within small-area units (Haberman, 2017). The calculation for $GMI_i = 1 - \sum p_{ik}^2$, where p is the proportion of crime type k relative to the total count of the four crime types in small-area i . A GMI score of zero indicates that an area has only one crime type. With four crime types, the maximum possible value is 0.75 and occurs when the four types occur in equal proportions. Approximately 89% percent of LSOAs had GMI scores greater than 0.5, indicating that a majority of areas have a mix of two or more crime types (Figure A2).

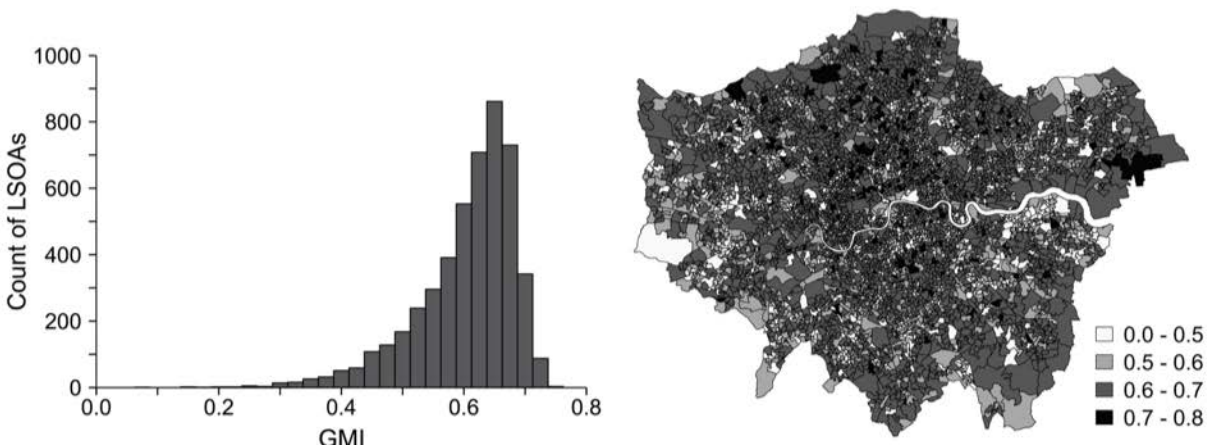


Figure A2. Histogram and map showing the mix of crime types in London.

Appendix 4: Posterior medians and 95% CI's of variance partition coefficients from Models 2, 3, and 4.

Model 2	Burglary	Robbery	Vehicle crime	Violent crime
$\lambda_k \cdot f_i$	0.54 (0.48, 0.59)	0.82 (0.72, 0.89)	0.45 (0.40, 0.52)	0.73 (0.68, 0.76)
$s_{ik} + e_{ik}$	0.46 (0.41, 0.52)	0.18 (0.12, 0.28)	0.55 (0.48, 0.60)	0.28 (0.24, 0.32)

Model 3	Burglary	Robbery	Vehicle crime	Violent crime
$\lambda_k \cdot f_i$	0.29 (0.22, 0.34)	0.50 (0.45, 0.54)	0.22 (0.16, 0.26)	0.99 (0.98, 1.00)
$\gamma_{1:3} \cdot v_i$	0.49 (0.43, 0.54)	0.24 (0.19, 0.29)	0.51 (0.46, 0.55)	NA
$s_{ik} + e_{ik}$	0.23 (0.17, 0.28)	0.26 (0.22, 0.30)	0.28 (0.23, 0.32)	0.003 (0, 0.005)

Model 4	Burglary	Robbery	Vehicle crime	Violent crime
$\lambda_k \cdot f_i$	0.22 (0.19, 0.25)	0.30 (0.26, 0.33)	0.17 (0.14, 0.20)	0.52 (0.50, 0.55)
$\gamma_{1:3} \cdot v_i$	0.45 (0.38, 0.50)	0.28 (0.23, 0.34)	0.44 (0.37, 0.50)	NA
$s_{ik} + e_{ik}$	0.16 (0.12, 0.19)	0.19 (0.16, 0.23)	0.23 (0.19, 0.27)	0.002 (0, 0.02)
$\beta_{1k} \cdot x_{1i}$	0.11 (0.08, 0.14)	0.07 (0.05, 0.09)	0.12 (0.10, 0.15)	0.10 (0.08, 0.12)
$\beta_{2k} \cdot x_{2i}$	0.006 (0, 0.02)	0.08 (0.06, 0.11)	0.001 (0, 0.01)	0.20 (0.16, 0.23)
$\beta_{3k} \cdot x_{3i}$	0.04 (0.03, 0.06)	0.04 (0.03, 0.06)	0.01 (0, 0.03)	0.07 (0.05, 0.08)
$\beta_{4k} \cdot x_{4i}$	0.003 (0, 0.02)	0.02 (0, 0.05)	0.002 (0, 0.02)	0.11 (0.08, 0.15)

Appendix 5: WinBUGS code for Model 4

```

model {
for (i in 1:N) {
for (k in 1:K) {
O[i,k] ~ dpois(mu[i,k])

### centering parameterization of log(mu[i,k])
log(mu[i,k]) <- log.mu[i,k]
log.mu[i,k] ~ dnorm(eta[i,k], tau.e[k])
eta[i,k] <- alpha[k] + (lambda[k] * f[i]) + (gamma[k] * v[i]) + s[k,i] + (b1[k] * popden[i]) + (b2[k] * dep[i]) + (b3[k] * ins[i]) + (b4[k] * ieh[i])
}}

### set weights for ICAR prior
for (j in 1:sumNumNeigh) { weights[j] <- 1 }

### shared component for all crimes
f[1:N] ~ car.normal(adj[], weights[], num[], 1) ### random effects for shared component
for (k in 1:4) {
loglambda[k] ~ dnorm(0, 5.9)
loglambda.c[k] <- loglambda[k] - loglambda.mean
lambda[k] <- exp(loglambda.c[k])
}
loglambda.mean <- mean(loglambda[1:4])

### shared component for three theft-related crimes
v[1:N] ~ car.normal(adj[], weights[], num[], 1) ### random effects for shared component
for (k in 1:3) {
loggamma[k] ~ dnorm(0, 5.9)
loggamma.c[k] <- loggamma[k] - loggamma.mean
gamma[k] <- exp(loggamma.c[k])
}
loggamma.mean <- mean(loggamma[1:3])
loggamma[4] <- 0
gamma[4] <- 0

### type-specific spatial random effects
for (k in 1:K) {
s[k, 1:N] ~ car.normal(adj[], weights[], num[], tau.s[k])
}

### recover type-specific unstructured random effects
for (i in 1:N) {
for (k in 1:K) {
e[i,k] <- log.mu[i,k] - eta[i,k]
}}

for (k in 1:K) {
alpha[k] ~ dflat()
sd.s[k] ~ dnorm(0,10)|(0, )
sd.e[k] ~ dnorm(0,10)|(0, )
tau.s[k] <- 1 / pow(sd.s[k],2)
tau.e[k] <- 1 / pow(sd.e[k], 2)
b1[k] ~ dnorm(0, 0.001)
b2[k] ~ dnorm(0, 0.001)
b3[k] ~ dnorm(0, 0.001)
b4[k] ~ dnorm(0, 0.001)
}}
}

```