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# How Places Influence Crime: The Impact of Surrounding Areas on Neighbourhood Burglary Rates in a British City

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## Abstract

Burglary prevalence within neighbourhoods is well understood but the risk from bordering areas is under-theorised and under-researched. If it were possible to fix a neighbourhood's location but substitute its surrounding areas, one might expect to see some influence on its crime rate. However, by treating surrounding areas as independent observations, ecological studies assume that identical neighbourhoods with markedly different surroundings are equivalent. If not, knowing the impact of different peripheries would have significance for crime prevention, land use planning and other policy domains. This paper tests whether knowledge of the demographic make-up of surrounding areas can improve on the prediction of a neighbourhood's burglary rate based solely on its internal socio-demographics. Results identify significant between-area effects with certain types of periphery exerting stronger influences than others. The advantages and drawbacks of the spatial error and predictor lag model used in the analysis are discussed and areas for further research defined.

## 1. Introduction

The ecological tradition within criminology explains neighbourhood crime in terms of social, demographic and criminogenic risks found within neighbourhoods. The extent to which neighbourhood crime might be affected by the characteristics of nearby surrounding areas is rarely considered (Dietz, 2002; Elffers, 2003). Focusing solely on within-neighbourhood effects assumes no interaction takes place between

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neighbourhoods; those with identical characteristics but dissimilar neighbouring characteristics are considered equivalent (Deitz, 2022, p. 541). This treats the high crime neighbourhood as a 'crime scene' where the conditions that make it vulnerable to crime are to be found.

If it were possible to hold constant the location of a neighbourhood within a city but change some or all of its surrounding areas, it hardly seems tenable that this would not have some effect on that neighbourhood's crime rate. Surprisingly, the question as to whether the spatial arrangement of neighbourhoods, with all their attendant risks, elevates or lowers neighbourhood crime rates is seldom asked. Paradoxically, this mindset co-exists with an awareness that the underlying causes of crime are traceable to broader processes (such as economic recession, demographic and social trends) that do not emanate from neighbourhoods, *per se*, but nonetheless, have an influence there.

Crime patterns and offender movements across neighbourhoods are explored, however, in environmental criminology (Wortley and Mazerolle, 2008) where the emphasis is less on the social correlates of crime and more on the distribution of crime opportunities (Felson, 2002). Thus, urban design and land use may be responsible for the presence of facilities that attract opportunistic offenders (crime generators) or provide sites that are deliberately sought out by them to engage in premeditated illegal activity (crime attractors) (Brantingham and Brantingham, 1995). Permeable streets may lead to larger numbers of passers-by in general, or offer abundant entry points and escape routes for offenders specifically (Newman, 1972). Collectively, these may determine the extent to which motivated offenders, suitable targets and the absence of capable guardians against crime coalesce both spatially and temporally (Cohen and Felson, 1979).

Focusing on crime opportunities is driven by micro-level analyses of vulnerability which, at the area level, focus on buildings, streets and specific sites rather than entire neighbourhoods as the unit of analysis (Weisburd *et al.*, 2009). Brantingham and Brantingham have observed how

> the aggregate distribution of crime seems to be substantially related to the socio-economic and demographic mosaic of cities as well as the location of major population attractors (Brantingham, and Brantingham, 1993, p. 3).

This articulates, very well, the importance of both the ecological and environmental approaches to understanding neighbourhood crime but also raises questions about the elevation or reduction in victimisation risks that stem from the spatial arrangement of neighbourhoods that define the urban mosaic.

The aim of this paper is to assess how far the positioning of neighbourhoods within the social mosaic—what is next to what—impacts upon neighbourhood burglary rates. The choice of domestic burglary is particularly appropriate for testing bordering neighbourhood effects because it is anchored to residential properties that have fixed spatial locations.

## 2. Neighbourhoods and Burglary

Research on the analysis of residential burglary is abundant. Distinctive patterns emerge. Burglaries can concentrate in the same neighbourhoods and along the same streets (spatial clustering, Johnson, 2010), afflict the same households (repeat victimisation, Farrell and Pease, 1993), happen at certain times of the day (Ratcliffe, 2002), feature specific *modus operandi* and occur more in some types of dwelling than in others (Townsley *et al.*, 2003).

Studies that identify burglary patterns can adopt a diversity of research approaches. Not all of them will include a specific focus on 'the neighbourhood' *per se* even though their findings are clearly relevant to understanding crime risks within neighbourhoods. Neighbourhoods can serve as the context within which burglary occurs but can also be part of the explanation. The balance between these two roles varies with the theoretical and methodological perspective.

The notion of 'neighbourhood' is far more deeply embedded in ecological analyses of burglary than in environmental criminology. Ecological perspectives are generally more focused, albeit not exclusively, on socio-demographic influences on crime. Risk factors include concentrated poverty (Wilson, 1987), deficits of social cohesion and collective efficacy (Sampson *et al.*, 1997) and spatial concentrations of both victims and offenders (Bottoms, 2006).

Shaw and McKay (1942) argued that low socioeconomic status, ethnic heterogeneity and population instability undermined community cohesion and informal social control, particularly of young people, thereby leading to higher crime. Bursik spoke of the deleterious effects of 'social disorganisation' that he defined as "the inability of local communities to realise the common goals of their residents or solve commonly experienced problems" (Bursik, 1988). Socially heterogeneous neighbourhoods, characterised by rapid population turnover and family disruption were at greater risk of social disorganisation. Temporary residents were less likely to facilitate social control, while heterogeneity acted as a barrier to communication, reducing the ability of residents to act collectively (Bursik, 1988). Collective efficacy, the capacity for collective action between trusting neighbours, has been identified as a strong mediating factor on crime rates even in the face of adverse structural conditions such as high unemployment and concentrated poverty (Sampson *et al.*, 1997).

In a recent analysis that linked data from the British Crime Survey (subsequently renamed the Crime Survey for England and Wales) to information on neighbourhood socio-demographics and disorder, neighbourhoods were found to exert independent influences on individuals' fear of crime, not only through visible signs of disorder and recorded crime, but also through their social structure (Brunton-Smith and Sturgis, 2011).

Hipp (2011) studied 352 cities over a 30-year period. He found that the impact of income inequalities on crime at neighbourhood level was stronger in cities with greater economic inequality, economic segregation and ethnic heterogeneity. The high level of inequality in such cities made economic differences particularly salient to residents, generating perceptions of "walled off neighbourhoods with strikingly different economic resources" (Hipp, 2011, p. 655).

Ecological studies of crime are related to a rich tradition of social area analysis in geography and urban sociology (Shevky and Bell, 1955). Their predominant concern has been with how internal neighbourhood characteristics and socio-demographics influence neighbourhood crime outcomes using both the neighbourhood and the households therein as units of analysis. Multilevel models have been developed to measure the relative contribution of household and area effects on property crime victimisation (Tseloni *et al.*, 2002; Tseloni, 2006) but these have been limited to within-area effects. Very few ecological studies have examined between-area effects. What little has been done has focused predominantly on fear of crime rather than burglary risk.

Covington and Taylor (1991) found that in Baltimore, fear of crime within neighbourhoods was elevated, not only by cultural

differences between neighbours within neighbourhoods, but also by differences in the socioeconomic status and ethnicity of residents in the surrounding neighbourhoods.

A study in Merseyside provided early evidence that neighbourhood crime levels might be influenced by the characteristics of surrounding areas (Hirschfield and Bowers, 1997; Bowers and Hirschfield, 1999). An analysis of 45 locations, where affluent areas directly bordered deprived neighbourhoods, found that the former tended to have higher levels of burglary and assault than affluent areas on Merseyside generally (Bowers and Hirschfield, 1999). Affluent areas bordering equally affluent areas had significantly lower crime rates than similar affluent areas surrounded by poorer neighbourhoods. Affluent peripheries were protective 'buffer zones' offering immunity from victimisation to neighbourhoods that already had relatively low crime risks.

With few exceptions, notably highly segregated residential areas and gated communities, the permeability of boundaries between neighbourhoods, for residents as well as offenders, means there is inevitably going to be some degree of interaction between them. People may move between neighbourhoods to visit family and friends, to access services, or as part of the journey to work or in pursuit of selecting a burglary target. Neighbourhoods are not treated in isolation from their surroundings and nor should they be (Lupton, 2003).

## 3. Research Questions

The assessment of between-neighbourhood effects on burglary raises a number of questions. The first is to ask: how can the juxtaposition of different types of neighbourhood be represented? Exploring this necessitates thinking about how to represent the neighbourhood in terms of size and location and, importantly, the socio-demographic characteristics that distinguish it as a place. As the focus is on between-area effects, identifying where the neighbourhood fits within the social mosaic is essential. This requires identifying which other neighbourhoods share a border with it and what they are like as places. Fulfilling these tasks provides a foundation for the main research question—namely

> Does knowledge of the socio-demographic make-up of an area's surroundings improve on the prediction of its burglary rate based solely on its internal socio-demographic composition?

Nested within this are two further questions—namely

> To what extent do different types of surrounding area contribute to an area's burglary rate?
>
> Which combination of surroundings has the greatest impact on an area's burglary rate?

Answering these questions extends the analysis by exploring the differential impacts, on burglary rates, of different types of periphery surrounding individual neighbourhoods. This potentially would enable not only an identification of the implications for a neighbourhood's burglary rate that stem from where it is positioned within the social mosaic, but also the consequences, for neighbourhoods, if their peripheries were to change for any reason (for example, as a result of gentrification or decline).

Finally, we assess the following questions—namely

> What are the likely mechanisms underpinning potential bordering effects?

and

What are their theoretical and policy implications?

The identification of potential bordering influences of different types of residential neighbourhood begs the question as to how such effects arise and why certain types of periphery might have greater impacts than others. We discuss potential mechanisms, the implications for crime prevention and set out an agenda for further research.

## 4. Data and Methodology

The British city of Leeds, was chosen to model between-neighbourhood effects on burglary. Leeds is a microcosm of urban Britain incorporating each of the different types of residential neighbourhood found in other major British cities. This combined with its relatively large number of burglaries made it suitable for examining relationships between neighbourhood juxtapositions and crime.

The police recorded crime data comprised all domestic burglaries (successful as well as attempted) in Leeds recorded by West Yorkshire Police in the period 1 April 2000 to 31 March 2002 ($N = 29,170$). Although this period pre-dates the introduction of the National Crime Recording Standard (NCRS) the nature of residential burglary makes it highly unlikely that a *reported* burglary would not be *recorded*. Since approximately 80 per cent of burglaries with loss are reported (Dodd *et al.*, 2004) and unreported crime has been found to cluster in the same places as reported crime (Chainey and Ratcliffe, 2005), recorded burglary presents a reasonable representation of the true level of burglary. The spatial distribution of the observed burglary rates in Leeds is shown on the upper left map in Figure 1.

In the current work, the focus is on the relationship between burglary and the demographic composition of surrounding neighbourhoods (peripheries). This necessitated demarcating neighbourhood boundaries and identifying their socio-demographic composition. Census Output Areas (OAs) provide a consistent, *a priori* means of aggregation and come ready equipped with digital boundaries and social data. Leeds contained 2439 OAs with an average population of around 300 and these provided the spatial framework for producing aggregate burglary counts from disaggregated data and were the source for denominators for the derivation of burglary rates. Their use also facilitates replication of the Leeds analysis for other cities in Britain. This would not be the case for zones defined using *ad hoc* criteria (such as land use, people's perceptions).

OAs were also the zones used in the creation of a nationally available geodemographic classification of small areas in Britain, the Output Area Classification (OAC, Vickers *et al.*, 2005). The different neighbourhoods in Leeds featured in this paper are from the OAC. Geo-demographic classifications, such as OAC, compare small areas across a range of socio-demographic indicators and group them into a discrete number of 'neighbourhood types' that are broadly similar in terms of their household composition, housing tenure, socioeconomic status and employment, age structure, ethnicity and population turnover. They have been used extensively in marketing, resource allocation and in social research including the analysis of health inequalities (Petersen *et al.*, 2011) higher education participation rates (Singleton, 2010) and crime (Ashby and Longley, 2005). A significant benefit of the OAC is that it is a public domain classification, with a clear temporal match to the Leeds burglary data.

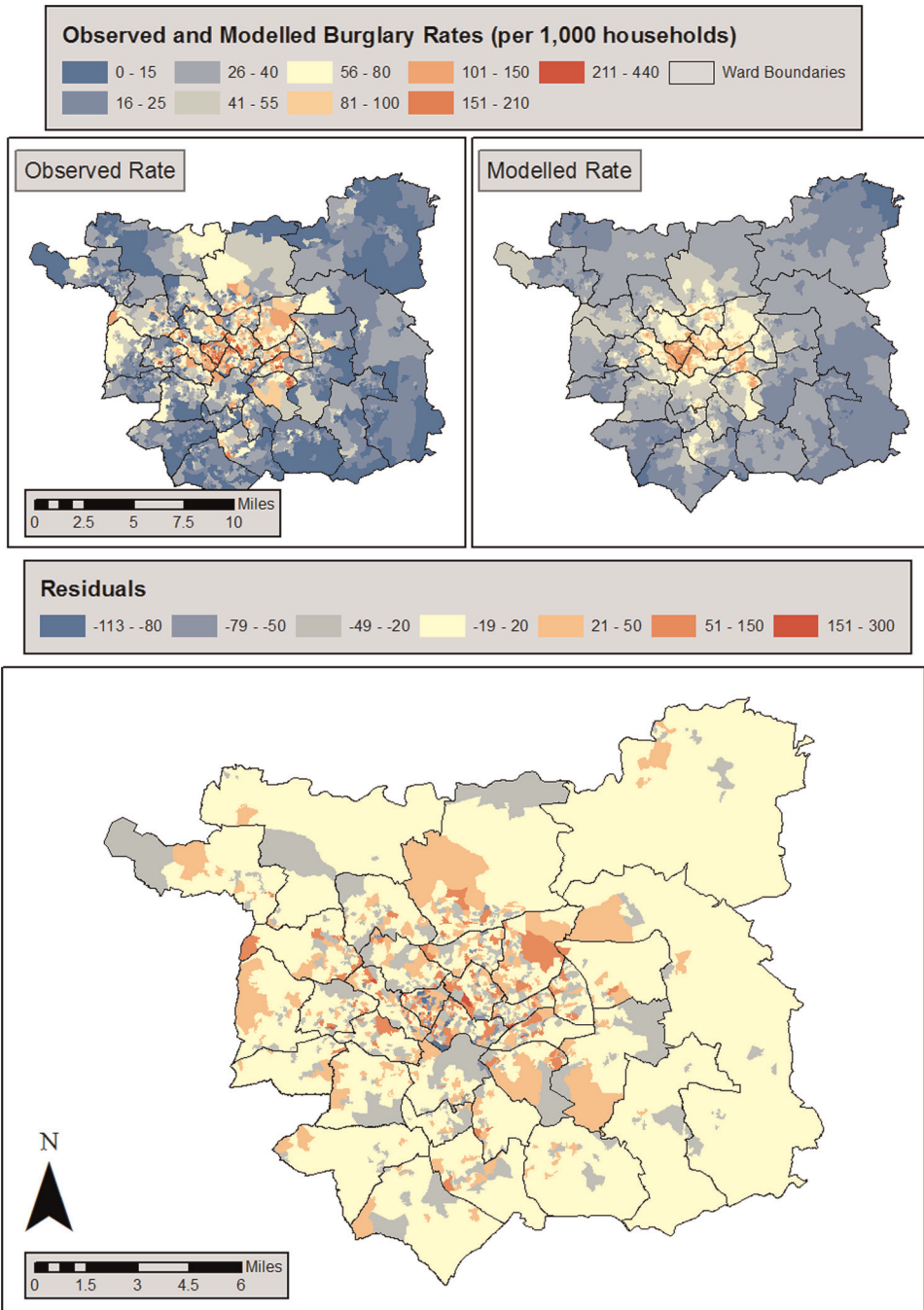The OAC presents a hierarchical classification of area types that, at its most detailed

**Figure 1.** Observed and modelled burglary rates with residuals.

**Table 1.**  Characteristics of OAC super-groups

| Super-group | Super-group label | Super-group characteristics |
| --- | --- | --- |
| 1 | Blue-collar Communities | Housing in these areas is more likely to be terraced rather than flats and residents mainly rent from the public sector. There is a high proportion of 5–14-year-olds. Residents tend to have fewer higher educational qualifications than the national average. A high proportion work in manufacturing, retail or construction |
| 2 | City living | Residents in these urban areas (which include transient and disadvantaged communities) are more likely to live alone. Housing is often made up of flats and residents typically rent their homes from the private sector. Detached homes are rare. Residents are more likely to hold higher educational qualifications and are often first-generation immigrants to the UK |
| 3 | Countryside | Residents in these rural areas are likely to work from home and to be employed in agriculture or fishing. They often live in detached houses; in households with more than one car. Areas are less densely populated. These include villages in the 'rural urban fringe' |
| 4 | Prospering suburbs | Residents in these prosperous areas often live in detached houses and less frequently in flats or terraced housing. Fewer residents rent their homes and homes are more likely to have central heating. Households often have access to more than one car |
| 5 | Constrained by circumstances | Residents in these less affluent communities typically live in flats and rent from the public sector. They are less likely to have higher qualifications. They rarely live in detached houses or in households with more than one car |
| 6 | Typical traits | These are areas of terraced housing, where residents are unlikely to rent from the public sector. There are a range of ethnic backgrounds and types of households. Residents work in a range of industries |
| 7 | Multicultural | Residents in these areas are often non-White, mainly from Asian or Black British backgrounds. Many are first-generation immigrants. Housing is mostly rented from the public or private sectors and is often split into flats |

*Source*: www.localfutures.com/ktpweb/images/OAC_BROCHURE.pdf.

level, identifies 52 sub-groups which nest into 21 groups which, in turn, can be aggregated into seven super-groups (Vickers *et al.*, 2005). Each level of the classification has a label denoting the type of neighbourhood represented. Table 1 describes each of the seven super-groups.

Super-groups were chosen for this analysis because they discriminate well between different types of neighbourhood and, unlike the more detailed tiers of OAC, provide a manageable number of area types

with which to identify spatial neighbourhood juxtapositions.

To the extent that crime patterns vary between neighbourhood types and that the OAC represents local variations in social and demographic patterns, then a natural starting-point for the spatial analysis of the incidence of burglaries by small area is the analysis of variance (ANOVA) model. One of the most appealing features of ANOVA is that it can be computed easily within a statistical package such as SPSS. The ANOVA

structure will be used as a basic reference model in the analysis which follows and can be expressed mathematically as

$$Y = \beta X + \varepsilon \qquad (1)$$

where, $Y$ is a column vector of burglary rates (whose individual elements $y_i$ represent the burglary rate for area $i$; $X$ is a matrix of $N_i = 2439$ zones; and $N_j = 7$ area types in which each element $x_{ij}$ is one if area $i$ is classified into super-group $j$, and zero otherwise; $\beta$ is a column vector of parameters with $\beta_j$ being the crime rate associated with super-group $j$; and $\varepsilon$ is a vector of independent, normally distributed errors for each area ($\varepsilon_i$) with zero mean and variance.

We will see later that the ANOVA model is able to capture variations in burglary to some extent, but has at least three notable characteristics. The first (which applies to all models) is that the use of OAC is an imperfect representation of neighbourhoods and their demographic composition. Secondly, that the crime rate for an OA depends only on the social profile of that OA and not of any neighbouring areas. Thirdly, that the random error terms ($\varepsilon$) for each OA are independent.

The first of these could be challenged on a number of grounds—for example, that the areas are too small or too large, or that the super-group classification is a rather simplistic representation of multidimensional socio-demographic characteristics. Although we comment further on some of the possibilities in the discussion, alternatives and extensions to OAC are outside the scope of the current paper. Objections to features two and three which suggest independence of the crime rates between neighbouring areas have been spelled out in some detail in sections 1 and 2 of this paper. In the analysis which follows, we will explore a variety of models which incorporate the effects of spatial contiguity in both the

crime rates and the errors. Since all of these models extend the basic ANOVA model by incorporating spatial effects in some ways, these will be termed SPANOVA (SPatial ANOVA) models.

To explore the extent to which the surroundings of an area have an impact on its burglary rate, it is necessary to distinguish the location of the focal area and that of the surroundings. The former can be thought of as the 'core' whilst the latter would represent that area's 'periphery' or 'hinterland'. To incorporate these effects in the models we will define a contiguity matrix $\mathbf{W}$. The number of zones bordering area $i$ is given as $d_i$ and the individual cells $w_{ik}$ take the value $1/d_i$ if zone $k$ borders area $i$, and zero otherwise. GIS software (the 'spdep' package in R) was used to produce a contiguity matrix of the 2439 OAs in Leeds.

Now we define a suite of spatial models for the estimation of small-area burglary rates according to the independence or autocorrelation of both the crime rates and the error terms as shown in Table 2. The models include two approaches to incorporating crime rates in the hinterland of each core area, based on scanning actual crime rates (which is introduced in model 2), and the use of average values for each of seven hinterland area types (models 3 and 5). Autocorrelation between the error terms, so that the error in a core area depends on the errors in each of seven hinterland area types, is introduced in models 4 and 5. In the next section, we report on the results of a calibration process for all of the models in Table 2, with a particular emphasis on the way in which the proximity of neighbourhood types in the periphery affects burglary rates in the core areas.

## 5. Results

Having outlined a set of five possible models, the next stage is to assess the relative

**Table 2.**  Spatial models for the estimation of small-area burglary rates

| Model | Name | Description | Mathematical expression |
|---|---|---|---|
| 0 | Null | No variation in crime rates between areas | $Y = \mu + \varepsilon$ |
| 1 | ANOVA | Crime rates vary by area type (OAC) | $Y = \beta X + \varepsilon$ |
| 2 | Spatial autoregressive lag | Crime rate in the core is related to actual crime rates in each area in the periphery | $Y = \rho WY + \beta X + \varepsilon$ |
| 3 | Spatial predictor lag | Crime rate in the core is related to the mix of neighbourhood types in the periphery | $Y = \beta^* WX + \beta X + \varepsilon$ |
| 4 | Spatial error lag | The variation (error) in crime rates in the core is related to the variations between area types in the periphery | $Y = \beta X + \lambda W \eta + \varepsilon$ |
| 5 | Spatial error and predictor lag | The crime rate in the core is related to the mix of area types in the periphery and the variation in crime rates is related to the variation in crime rates in the periphery | $Y = \beta X + \beta^* WX + \lambda W \eta + \varepsilon$ |

merits of the different models. A difficulty with this model suite, however, is that the models are not conveniently 'nested'—that is, where one model can be considered as a special case of another—and this problematises the use of standard statistical hypothesis tests such as likelihood ratio or t-tests. For this reason, at least for the task of model choice, use of the Akaike Information Criterion (AIC) (Akaike, 1973) is adopted, as advocated by Burnham and Anderson (2002). The AIC test assumes that none of the models is true but that some approximate reality more closely than others, so that when faced with a number of alternative models to select from, it is proposed that the one with the minimum AIC should be used.

The AIC is shown for the full model suite in Table 3, along with two related measures. The *relative* AIC (denoted ∆AIC) shows for each model the difference between its AIC and the lowest AIC for all listed models.

The relative likelihoods can be interpreted as the relative probability that each

model minimises the information loss in approximating reality. From this table, the spatial error and predictor lag model (Model 5) was the best performing model and has a relative likelihood of one. This model incorporates the effects of the peripheral OA super-groups and also allowed for auto-correlated error terms (i.e. possible bordering effects that are not accounted for by super-groups alone—the unexplained variance). The analysis suggests that model 5 is the best performer by quite a large margin, as the relative odds of the next candidate (model 2) are only 0.04. Note that the relative odds are related exponentially to the difference in AICs—regardless of the scale of absolute AIC. This surprises some people as in many situations, including that in Table 3 here, the difference seems small in relation to the absolute values. In some respects, AICs are similar to log-likelihood ratios (in fact, under some circumstances they are equivalent) and, like those quantities, it is only the difference between ratios that counts,

**Table 3.** AIC Scores of candidate models

|  | AIC | ΔAIC | RL |
|---|---|---|---|
| Model 5: Spatial error and predictor lag | 23,756.12 | 0.00 | 1.00 |
| Model 2: Spatial autoregressive lag | 23,762.79 | 6.67 | 0.04 |
| Model 3: Spatial predictor lag | 23,821.19 | 65.07 | 0.00 |
| Model 4: Spatial error lag | 24,475.23 | 719.11 | 0.00 |
| Model 1: Basic ANOVA model | 24,814.86 | 1058.74 | 0.00 |

$AIC = 2k - 2\log(L)$ Relative likelihood (RL) $= \exp(-\Delta AIC/2)$

*Notes*: k = number of parameters and L = maximised likelihood of the model.

not the absolute magnitude of the quantities being subtracted.

The standard ANOVA can be viewed as a test of the counterfactual—namely, what one would expect to see if there were no periphery effects. The significant improvement of the spatial error and predictor lag model over a standard ANOVA suggests that there is sufficient evidence that the surrounding areas do have an impact on burglary in the core neighbourhoods. The out-performance of model 5—which includes spatial autocorrelation between the geodemographics of the core area and its neighbours—over the standard ANOVA is a clear indication that the inclusion of periphery effects is a closer approximation to reality than the counterfactual. However, sight should not be lost of the fact that the error terms in model 5 are also autocorrelated, indicating that there is further variance that is unexplained by the juxtaposition of the super-groups. Sociodemographic juxtapositions matter, but there are also other processes and interactions that are not yet represented explicitly in the model.

Figure 1 compares the observed burglary rates to the model estimates and the differences between the two. It illustrates that the model appears to capture the general patterns of variation in burglary rates, particularly between the inner city and suburban areas. However, there is no obvious spatial ordering in the distribution of the residuals.

This suggests that there was no systematic pattern in the location of OAs whose burglary rates were substantially higher or lower than those predicted by the juxtaposition of neighbourhoods. Areas where the model was a less effective predictor were scattered throughout the city. If the residuals had displayed a clear spatial pattern, this would point to the presence of spatially ordered processes other than neighbourhood juxtapositions (for example, street networks, land uses) exerting an influence on burglary. The absence of such patterns suggests that, once the spatial effects as specified in the model are accounted for, all that remains in terms of error are spatially uncorrelated random fluctuations—and therefore the model has adequately accounted for spatial patterns in the data.

Table 4 gives parameter estimates for the preferred model. For each OA, the predicted rate of burglary depends on the composition of both the core area and its periphery. For example, if a 'Blue-collar Community' is entirely surrounded by 'Countryside' then the expected burglary rate would be simply $29.95 + 5.35 = 36.30$. If a core area of 'Typical Traits' is bounded by 'City Living' and 'Multicultural' in equal measure, then the expected rate would be $24.42 + (0.5 * 56.14) + (0.5 * 41.78) = 73.38$. The coefficients are presented in Table 4 as an ordered list, with the periphery value for 'Typical Traits' set at zero to anchor the

**Table 4.**   Model coefficient estimates

|  | Estimate | S.E. |
|---|---|---|
| *4a. Core neighbourhood type* |  |  |
| Multicultural | 43.51 | 4.30 |
| City living | 35.72 | 4.26 |
| Blue-collar communities | 29.95 | 3.79 |
| Constrained by circumstances | 29.56 | 3.86 |
| Countryside | 29.20 | 5.49 |
| Prospering suburbs | 25.97 | 3.66 |
| Typical traits | 24.42 | 4.06 |
| *4b. Periphery neighbourhood type* |  |  |
| Periphery: City living | 56.14 | 6.79 |
| Periphery: Multicultural | 41.78 | 6.12 |
| Periphery: Blue-collar communities | 20.81 | 6.02 |
| Periphery: Constrained by circumstances | 15.32 | 5.35 |
| Periphery: Countryside | 5.35 | 9.68 |
| Periphery: Prospering suburbs | 4.52 | 5.07 |
| $\lambda$ (spatial error autoregression) | 0.67 | 0.02 |

estimates. Thus the least desirable area to inhabit is shown as 'Multicultural', while the least attractive border would be 'City Living'.

Nevertheless, care must be exercised in this interpretation as the standard errors reported in Table 4 are fairly large. The 95 per cent confidence interval around each estimate is approximately twice the standard error (S.E.) and, as a rough significance test, any absolute value greater than twice the S.E. can be thought of as significantly different from zero. It may be reasonably safe to infer that 'Multicultural' neighbourhoods provide the least desirable core areas, followed by 'City Living', but there is relatively little to choose between the remaining area types.

The parameterisation of area types in the periphery (Table 4, part b) affords strong and clear support for the idea that the characteristics of the hinterland have a profound influence on burglary rates in the core. In this case, not only is it undesirable to live in close proximity to 'City Living' or 'Multicultural', but much more desirable to have any of 'Countryside', 'Prospering Suburbs' or 'Typical Traits' as adjacent types. In short, 'who lives next to you' looks just as important as 'where you live'. This point can be reinforced if we return to an examination of actual burglary rates as shown in Table 5. These data show average rates for core area types (in the rows of the table) for instances in which there is a dominant

**Table 5.**   Variation in burglary rates by area type

| Area type (core) | Area type (periphery) | | | | | | |
|---|---|---|---|---|---|---|---|
|  | Blue-collar | City living | Countryside | Prospering suburbs | Constrained | Typical traits | Multicultural |
| Blue-collar communities | 22 (41) | – | 8 (1) | 16 (14) | 26 (57) | 16 (36) | 61 (8) |
| City living | 24 (2) | 73 (96) | – | 20 (16) | 16 (3) | 20 (17) | 43 (17) |
| Countryside | 63 (1) | – | 8 (7) | 13 (17) | – | 11 (9) | – |
| Prospering suburbs | 28 (7) | 54 (5) | 24 (9) | 20 (224) | 46 (4) | 27 (55) | 44 (2) |
| Constrained circumstances | 24 (35) | 41 (2) | – | 16 (7) | 26 (158) | 14 (34) | 48 (11) |
| Typical traits | 19 (12) | 57 (11) | 8 (6) | 22 (41) | 31 (23) | 21 (182) | 32 (8) |
| Multicultural | 52 (2) | 50 (19) | – | 23 (4) | 38 (12) | 33 (7) | 37 (159) |

area type in the periphery (shown in the columns of the table). Data are only shown in Table 5 for OAs in which more than 50 per cent of the total number of areas that border them are of a single type. For example, if a core OA of type $x$ is surrounded by six areas and at least four of these are of type $y$, then the burglary rate in this area is included in row $x$ and column $y$ of the table. Otherwise, the OA would not be included in this analysis.

Table 5 shows the average burglary rate and in parenthesis the number of OAs across this average is observed. For example, in 'Blue-collar' areas in which the dominant periphery is prospering suburbs then the average burglary rate is 16 crimes per 1000 households, and there are 14 OAs of this type. Cells in which there are less than 10 observations are shown in grey as potentially unreliable. Some of the trends which have been detected in model 5 and discussed earlier can also be seen quite clearly in these data. For example, if we look at OAs with 'Typical Traits', if these are adjacent to 'Prosperous Suburbs' then the rate is just 22, but this jumps all the way to 57 when the neighbours are 'City Living'. In areas which are 'Constrained by Circumstances', we can see more than a threefold variation between hinterlands which are 'Typical' and those which are 'Multicultural'.

## 6. Discussion

The spatial model demonstrates that the demographic make-up of surrounding areas can improve on the prediction of a neighbourhood's burglary rate based solely on its internal socio-demographics. It does not, however, shed any light on the mechanisms by which these effects arise—for example, whether a certain type of bordering OA actually stops burglaries by deterring individuals in some way, or just increases crime risk by a lower amount than an alternative periphery. This ultimately requires undertaking qualitative research on whether the juxtaposition of different types of neighbourhood impacts upon offenders' choice of burglary targets and, if so, how.

The model does provide a new perspective on burglary risk by treating the autocorrelation of spatially aggregated crime data, not as a statistical error to be corrected, but as part of the explanation as to why socio-demographically similar neighbourhoods may have elevated or lower burglary rates because of what surrounds them. The proposition that a neighbourhood's crime risk is never influenced by its surroundings is clearly untenable.

Peripheral effects need to be conceptualised in terms of 'contributing' to burglary rates observed in the core rather than 'raising' them. If this is done, one can think in terms of how much lower crime would be if a neighbourhood's surroundings had 'favourable' rather than 'unfavourable' geo-demographics in terms of crime risk. For example, the model indicates that, for Leeds, a 'Multicultural' core entirely surrounded by 'City Living' would have an estimated burglary rate of 99.6 burglaries per 1000 households. The core effect alone would contribute 43.5 per 1000 households (44 per cent of the total rate) and the presence of the hinterland would contribute the remaining 56.1 per 1000 households (56 per cent of the total rate). Given that, in nearly all cases, an element of the core's crime rate will be attributable to what surrounds it, that same 'Multicultural' core surrounded entirely by 'Prospering Suburbs' would have the crime rate of 48.0 (43.5 per 1000 + 4.5 per 1000) rather than 99.6 per 1000.

Despite considerable same-type clustering, there were examples of 'fractured ecologies' where the social and spatial processes that shape the urban fabric (Byrne and

Sampson, 1986) resulted in some neighbourhoods being located cheek-by-jowl with markedly different communities—for example, where large social housing schemes have been built near to prosperous suburbs on the periphery of cities. These are geodemographically dispersed neighbourhoods, out of place in their surroundings, some with elevated crime risks and others benefiting from lower crime depending on the composition of the periphery.

One can anticipate what mechanisms might be at play. The most likely are the effects that bordering areas have on offender decision-making and choice of target. Burglary offenders often offend within their own neighbourhoods, former neighbourhood and other 'anchor points' such as friends' homes, leisure sites as well as drug market locations (Wiles and Costello, 2000). They may venture into proximate neighbourhoods to commit burglaries because of a greater concentration of crime opportunities, lower levels of guardianship, poor natural surveillance or a combination of all of these. When they offend outside their immediate neighbourhood, there may be a greater propensity to do so in areas that are socially similar to their own (Reynald *et al.*, 2008) and provide a more comfortable and attractive environment, offering camouflage and protection against exposure. The current model assumes that periphery effects contribute a fixed increment to burglary rates when combined with core areas. This precludes being able to assess interactions between specific cores and peripheries. Moving to core-dependent periphery estimates might give a better indication of the relationship between different supergroups.

There was a high degree of spatial clustering among OAs belonging to the highest burglary super-groups (Multicultural and City Living, Table 5) which suggests that the potential for offenders from these neighbourhood types to commit burglary in the same area type, was high (albeit not necessarily involving flows from immediately adjacent OAs). The model showed that combinations of cores and peripheries from these two super-groups predicted the highest burglary rates. These effects have a number of interpretations. The juxtaposition of a different high crime core and peripheral super-group results in: (a) greater offending just within the core by resident offenders; or (b) interaction between the two involving offender journeys to crime from the periphery to the core; or (c) is attributable to other processes not encapsulated by either the super-groups or the model.

The first proposition implies no physical interaction involving the movement of offenders between the two but rather that being surrounded by a different super-group acts as a barrier to offender movement resulting in the deflection of offences back into the core. The second proposition implies that the core is more of a direct 'victim' of the criminogenics of the periphery in that the presence of offenders in the hinterland raises burglary rates in the core. For this to happen, offenders would need to commit offences in areas that are socially dissimilar from their home neighbourhood. The degree of dissimilarity, however, is likely to be lower between these two high crime neighbourhoods than other super-group combinations as both are relatively disadvantaged communities with mixed populations and similar types of housing. The third proposition includes the possibility, *inter alia*, that heterogeneity within the super-groups masks subtle, but important, differences between OAs belonging to the same category. This warrants analysis at a finer level of OAC but would require a larger number of observations than included in this study to make it reliable (see next section).

There is also the possibility that the selected neighbourhoods could reflect

offenders' alternative choice of targets when displaced from their first choice by a crime prevention intervention or police activity, given that crime tends not to displace into neighbourhoods that are substantially different in their social, economic and demographic characteristics (Brantingham and Brantingham, 2003).

It is likely to be the case that the propensity to offend in proximate neighbourhoods is greater still where access to these areas is easier due to the greater permeability of the street network. What remains to be tested is how much of the elevated burglary rates, in certain neighbourhood configurations, is due to street accessibility and how much is attributable to the socio-demographic composition of the juxtaposed areas.

Routine activity theory (Cohen and Felson, 1979) suggests that other factors may influence burglary rates—for example, if offenders cross an OA into neighbouring OAs (whether socially similar or not) as part of their daily routine, this will add to their familiarity with the crossed output area and possibly increase the chances of them offending there also.

# 7. Conclusions and Further Research

The research presented in this paper is the first attempt at examining the impact of neighbourhood spatial configurations on burglary levels and has demonstrated not only that there are significant between-area effects, but also that specific types of neighbourhood on the periphery have the greatest impacts. However, there are a number of caveats that need to be stated.

An inevitable limitation of using OAs is that they are not necessarily 'true neighbourhoods' in terms of their socio-demographics, size or boundaries. Neighbourhoods are created by the interaction of people and place

and are neither fixed bounded entities nor experienced in the same way by every resident (Lupton, 2003). OAs may also be too small to capture bordering effects. Even if the core, the periphery or both were to be defined using larger spatial units, this would not offer immunity from the modifiable aerial unit problem (Openshaw, 1984). The definition of OA contiguity—namely, that the boundary of one area just has to touch that of another—does not take into account the length of the shared boundary and runs the risk of defining peripherality too loosely and of including areas that have limited connections with each other.

However, OAs were designed to be largely socially homogeneous spatial units of roughly equal population size giving them a socio-geographical identity as opposed to being a purely administrative zone. Moreover, it would have been far more difficult to get a sense of the different types of residential area and how they intermingle spatially from an analysis of individual variables.

OAC super-groups also have their limitations. The seven-tier super-group level of OAC may be too broad to encapsulate fully the factors that elevate or reduce crime risks both within neighbourhoods and between them. The very existence of the OAC's finer-grained nested classifications at the group and sub-group levels indicates that the super-groups have some degree of heterogeneity. Although focusing upon super-groups in Leeds has been sufficient to demonstrate the existence of between-area effects on burglary, there would be clear advantages in up-scaling the analysis to a national level. This would enable any systemic patterns in neighbourhood juxtapositions to be identified across a number of cities and would produce a sufficiently large number of observations to move to the more detailed 'group' level of OAC, thereby reducing any social heterogeneity

between OAs belonging to the same supergroup. The number of observations was too small to make this viable in Leeds.

In some cases, according to the model, peripheries contribute more crime to a core area's burglary rate than the core area itself. An enhancement would be to use disaggregated data on both burglaries and the residential location of the offenders who committed them, to determine if this is reflected in offender journey to crime patterns. This would enable the implicit assumption, that core area burglary is committed overwhelmingly by offenders from the periphery, to be tested.

The mechanisms by which spatial configurations potentially influence offender targeting would also benefit from qualitative exploration. For example, how far cores and peripheries, identified using geodemographics and OAs, are recognisable on the ground physically could be examined through the perceptions of residents, offenders and police officers.

To conclude, whilst traditional ecological analyses undoubtedly play a role in understanding area crime risks, the influence of between-area effects, identified in this paper, takes the ecological approach to a new level; an exciting new world where a neighbourhood's crime risk is influenced not only by its internal characteristics but also by those of its surroundings.

## Funding

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