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Analysing the effect of betting shops on crime in England

Oluwole Adeniyi[a] 🄳, Ferhat Tura[b] 🄳 and Andy Newton[a] 🄳

ABSTRACT
This study explores the relationship between the clustering of betting shops and crime in England using both spatial and multilevel modelling approaches. Spatial analysis revealed significant clustering of betting shops and crime across all crime types. Results from the multilevel models revealed statistically significant relationships between the number of betting shops and all the crime categories, with the strongest relationships observed with theft and disorder offences. These relationships were observed after controlling for socio-demographic and land-use predictors of crime. To reduce the effect of betting shops on crime, efforts should focus on place management strategies.

KEYWORDS
crime; gambling; betting shop; social disorganization theory; risky facilities; crime attractors and generators

1. INTRODUCTION

The proliferation of gambling opportunities and their potential impact on increased levels of crime have afforded considerable attention in the research literature (Adolphe et al., 2019; Albanese, 2019; Kumar & Yoshimoto, 2017; Lan et al., 2020). Previous studies have approached this from either the perspective of examining individual behaviour or by analysing the spatial relationship between crime, gambling facilities and their surrounding environs, for example, nearby streets or neighbourhoods. Studies of the former investigate the relationship between problematic or addictive gamblers and crime and suggest high-risk individuals may commit crime to support their problematic gambling behaviour (Binde, 2016; Laursen et al., 2016). In contrast, studies at the area level consider gambling establishments as a potential risky facility for crime (Bottan et al., 2017; Kim et al., 2016; Lan et al., 2020). The contention is that the presence of a gambling establishments increases the risk of crime either within or in their immediate vicinity.

A literature review of 32 empirical studies (Albanese, 2019) into the relationship between gambling facilities and crime, predominantly in North America and Australia, revealed mixed findings. Several studies have identified a statistically significant positive relationship between the presence of casinos and crime rates (Arthur et al., 2014;

Bottan et al., 2017; Kim et al., 2016). Other studies have found no relationship between casino or gaming machines and crime (Barthe & Stitt, 2009; Humphreys & Soebbing, 2014; Johnson & Ratcliffe, 2017; Nichols & Tosun, 2017).

In the UK a paucity of studies examine the relationship between gambling facilities and crime, although some studies have explored the spatial relationship between gambling opportunities and deprivation (Adeniyi et al., 2020; Wardle et al., 2014). Portas (2011) described gambling establishments as a blight on the community and classified them as one of the predatory establishments that prey on vulnerable communities. Critics further ascribe that they serve as attractors of antisocial and criminal behaviours (Martin, 2019; Newham Council, 2016), but they frequently rely on the findings from studies conducted in North America, especially in the United States. In addition to being North America focused, most of the studies examine the relationship between crime and casinos.

A further type of gambling establishment that has received less attention is betting shops. The few studies that have explored the relationship between betting shops and crime in the UK also have found mixed evidence. Griffiths (2011) found no linkage between betting shops and crime and strongly disputed the notion of causality between betting shops and crime, whereas Kumar and

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🄳 Supplemental data for this article can be accessed online at https://doi.org/10.1080/00343404.2022.2159355

Yoshimoto (2017) estimated that there is 0.3–1.3% increase in the count of betting shops observed for a 1% increase in crime, and they strongly inferred causality. Cassidy (2014) identified that both patrons and workers of betting shops, especially women, are prone to be victims of crime, especially sexual harassment, burglary and violence. At this point it is pertinent to draw a strong distinction between the gambling landscape in the United States and the UK. Historically, the US gambling landscape is dominated by large-scale casinos, whereas the UK has a greater proportion of betting shops. In the UK, casinos are classified as city-centre attractions in the National Planning Policy Framework (NNPF) by the Ministry of Housing, Communities and Local Government (MHCLG) (2012). In addition, the catchment area of a casino is large, and they cater for both local visitors and tourist population, whereas betting shops serve mostly local communities on a smaller scale.

This paper argues that the US context of gambling/casinos and the evidence identified from this (which is also mixed) is not an appropriate mechanism or evidence base for developing UK policy, especially for betting shops. More importantly, no study in the UK has extensively looked at the relationship between betting shops and crime at a national level. This provides strong justification for this study which seeks to investigate the relationship between presence of betting shops and crime at the lower super output area (LSOA) level nationally across all of England. LSOAs are small neighbourhoods designed to report small area statistics and have an average population of 1500, or 650 households.

This study addresses the following research questions:

- What is the spatial relationship between betting shops and crime?
- Does the relationship subsist after controlling for the impact of neighbourhood characteristics (socio-demographic, deprivation and land-use types)?
- Does the relationship vary by crime type (e.g., theft, burglary, criminal damage, violence)?

This study uses geospatial and multilevel modelling approaches to address these research questions. Based on the literature review, 10 distinct types of police recorded crime (antisocial behaviour (ASB), bicycle theft, other theft, public disorder, shoplifting, theft from person, burglary, criminal damage and arson, robbery, and vehicle crime) have been identified for analysis – as the literature suggests betting shops will have a greater impact on some crime types than others. In addition, the study controls for a range of theory informed predictors of crime. We draw on social disorganization theory (Sampson & Groves, 1989; Shaw & McKay, 1942), risky facilities (Eck et al., 2007), and crime generators and attractors (Brantingham & Brantingham, 1995) perspectives discussed in more detail in the next section.

2. THEORY AND LITERATURE

The spatial patterns of crime are not random and instead are concentrated in time and place (Sherman et al., 1989; Weisburd, 2015). Explanations for these concentrations of crime mainly draw from the literature on opportunity theories of crime, linked to routine activities (Cohen & Felson, 1979), lifestyles (Hägerstrand, 1985), urban mobility flow (Newton et al., 2021; Newton & Felson, 2015), the underlying processes of offender movement, risky facilities (Eck et al., 2007), and the inherent structures of crime locations (Hipp, 2016; Sampson & Groves, 1989; Song et al., 2013).

Eck et al. (2007) suggest explanations for crime concentration can be linked to risky facilities, and they identify how some facilities may be riskier than others. This complements the notion of crime attractors and crime generators (Brantingham & Brantingham, 1995). Some places may be target rich and considered both people generators (Newton, 2018) and crime generators. Whilst offenders do not specifically target these places, the presence of large numbers of people create target rich opportunities for offenders. Alternatively, places may act as attractors for crime, with a reputation for known opportunities for offending often associated with cash economies (Bernasco & Block, 2011). Insufficient place management, for example, a lack of capable guardianship or supervision, may further explain why some facilities are riskier than others (Eck et al., 2017). Whilst explanations tend to focus on place management within facilities, Linning et al. (2021) revisit the work of Jane Jacobs to consider how the 'eyes on the street' may extend place management to the vicinity of risky facilities.

Alternative explanations of crime concentration consider the structure of neighbourhoods and communities, such as social cohesion (Sampson & Groves, 1989) and the collective efficacy (Sampson et al., 1997) of places. These explanations are concerned with how community structures might influence levels of informal social control and therefore the presence or absence of crime; and how trust and cohesion might increase social enforcement or guardianship that might decrease crime. In addition, several crime and place studies use other neighbourhood characteristics such as deprivation, ethnic heterogeneity, levels of education, housing tenure and price, and employment as explanatory variables for crime (Goudriaan et al., 2006; Snowden, 2019).

Indeed, a challenge here is to unpack the microlevel influence of risky facilities and the potential interaction of this with local neighbourhood and community structures/characteristics. Several studies have examined what might constitute a crime attractor or 'negative environmental attributes' including adult bookstores, pawn shops and cash checking facilities, liquor stores and single-room-occupancy hotels (Loukaitou-Sideris, 1999), and transport exchanges, drug markets, pharmacy stores, insecure parking lots, gas stores and bar districts (Brantingham & Brantingham, 1995).

Drawing upon the social disorganization theory and risky facilities (crime attractors and generators) perspective, this paper argues that betting shops are risky facilities, and therefore the proliferation of betting shops further increases the level of disorganization within communities, which is linked to crime rates (Sampson & Groves, 1989). For instance, introduction of a betting shop in a neighbourhood would lead not only to an increase in the daytime and night-time footfall but also to the flow of commuters in the neighbourhood and act as nodes which will eventually reduce the ability of the neighbourhood to regulate or affect social control (Bursik & Grasmick, 1999; Sampson et al., 1997). They may also serve as a crime attractor or generator – especially if coupled with the presence of other risky facilities such as commercial land-use, retail outlets, pubs, alcohol outlets, bars, shopping centres in these neighbourhoods, as betting shops may further exacerbate potentials for criminal activities.

3. THE DATA

3.1. Police-recorded crime data (PRCD)
PRCD at the LSOA ($N = 32,844$) level was used to examine whether there was a relationship between number of betting shops and crime across England. The data were derived from a publicly available register[1] across two time points (2015 and 2019).

3.2. Betting shops data
Data on betting shops were obtained from the UK Gambling Commission which provides a register of all licenced gambling locations in the UK. The data were collected in two points in time, 2015 and 2019. The addresses and postcodes of all betting shops in England were extracted from the overall UK dataset. The betting shops' addresses were thereafter geocoded using the geocode function of the *ggmap* package in *R* (Kahle, 2019) and further aggregated to LSOA geography ($N = 32,844$).

3.3. Point-of-interest (POI) data
POI data were obtained from Digimap – EDINA, which provides maps and geospatial data for the Ordnance Survey (OS). The POI data available were for 2019 and the same data were used for both 2015 and 2019. The data included geocoded locations of bus stops, food and drink places, which comprise banquets, cafés and tea shops, fast food and take away shops, fish and chips shops, internet cafés, pubs, bars, inns and restaurants in England. These were all aggregated to LSOA geography ($N = 32,844$).

3.4. The UK census, population size and area type data
This study also used the 2011 UK Census to construct several control variables at the LSOA level, such as concentrated disadvantage, residential instability and ethnic heterogeneity ($N = 32,844$). The census data were obtained from NOMIS (the official labour market statistics website of the Office for National Statistics – ONS[2]) and was the same for both 2015 and 2019. We used mid-year population estimates based on the UK Census 2011 for both 2014 and 2018 (ONS, 2015, 2019). We used mid-year population estimates based on the UK Census 2011 for both 2014 and 2018 to be included in the models (ONS, 2015, 2019). The area type variable was on the rural urban classification (2011) of LSOAs in England and Wales (ONS, 2017) ($N = 32,800$).

3.5. Education deprivation data
Data on education deprivation were obtained from the MHCLG for both 2015 and 2019 ($N = 32,844$). They grouped all LSOAs in 10 different deciles (categories). Only deciles 1 and 10 (10% most and least deprived LSOAs, respectively) were adopted for this research.

3.6. Measures of crime
We investigated 10 different types of police recorded crime (i.e., ASB, bicycle theft, other theft, public disorder, shoplifting, theft from person, burglary, criminal damage and arson, robbery, and vehicle crime) and all crime as dependent variables to thoroughly examine the relationship between betting shops and crime in England. These dependent variables are count variables, meaning they take values of 0, 1, 2, etc. We excluded some other crime types such as drugs, other crimes, possession of weapons, and violence and sexual offences. Violence and sexual offences were excluded because of the nature of the data as it was not possible to analyse the effect of betting shops on violence and sexual offences separately. Other crime types mentioned were excluded based on evidence from literature that gambling related crime are mostly non-violent in nature (Banks & Waugh, 2019; Reece, 2010). Table 1 presents descriptive statistics on the dependent variables.

3.7. Theory informed variable selection
Informed by the theories discussed above, several variables were control for (see the data section) whilst examining the association between the number of betting shops and selected dependent variables. They include the following:

- Area type (four urban and four rural areas).
- Population size.
- Ethnic heterogeneity index.
- Percentage of private renter households.
- Percentage of social renter households.
- Education domain of deprivation (deciles).
- Number of bus stops.
- Number of eat and drink shops, which include banquets, cafés and tea shops, fast-food shops, fish and chips shops, internet cafés, pubs, bars, inns and restaurants.
- Percentage of lone-parent households.
- Percentage of households with a head who has a higher managerial occupation.
- Percentage of households with a head who is unemployed.

Area type is an indicator of urbanization. There were four rural area types and four urban area types, which

Table 1. Descriptive statistics of the dependent variables.

Year	Dependent variable	Minimum	Maximum	Mean	SD	Variance
2015	All crime	0	6637	158.42	215.03	46,238.00
	ASB	0	2457	52.07	69.85	4879.20
	Bike theft	0	564	2.50	7.89	62.32
	Other theft	0	1786	13.90	31.85	1014.65
	Public disorder	0	336	5.38	10.55	111.30
	Shoplifting	0	1598	8.53	35.53	1262.47
	Theft from person	0	1278	2.36	17.46	304.71
	Burglary	0	173	11.49	9.53	90.88
	Robbery	0	176	1.48	3.76	14.13
	Criminal damage	0	236	14.83	14.02	196.55
	Vehicle crime	0	192	9.54	9.32	86.81
2019	All crime	0	10,765	178.98	258.68	66,917.81
	ASB	0	1407	36.64	52.25	2729.86
	Bike theft	0	673	2.46	9.26	85.71
	Other theft	0	3214	14.26	44.84	2010.77
	Public disorder	0	770	11.95	21.07	443.77
	Shoplifting	0	1798	9.75	38.62	1491.47
	Theft from person	0	3104	3.15	37.81	1429.66
	Burglary	0	359	10.84	10.34	106.90
	Robbery	0	537	2.53	8.55	73.15
	Criminal damage	0	276	14.91	14.77	218.25
	Vehicle crime	0	365	12.72	13.71	187.95

included: (1) Rural town and fringe, (2) Rural town and fringe in a sparse setting, (3) Rural village and dispersed, (4) Rural village and dispersed in a sparse setting, (5) Urban city and town, (6) Urban city and town in a sparse setting, (7) Urban major conurbation, and (8) Urban minor conurbation. We created seven dummy variables where rural town and fringe was selected as the reference category. Ethnic heterogeneity index is based on the Her-findahl–Hirschman index (HHI), which is calculated as:

$$1 - (B^2 + A^2 + M^2 + W^2)/(B + A + M + W + O)^2 \qquad (1)$$

where B, A, M, W and O are the number of residents black, Asian, mixed, white and other ethnicities, respectively, who are living in an LSOA. A score of 1 implies a total heterogeneity, whereas a score of 0 refers to the perfect homogeneity (Bernasco & Block, 2011; Lan et al., 2020). The percentage of private renter households serves as an indicator of residential mobility/instability. The percentage of social renter households, lone-parent households, households with a head who is unemployed and education domain of deprivation are indicators of the concentrated disadvantage and inequality (Lan et al., 2020; Sampson et al., 1997). Education domain of deprivation measures the lack of attainment and skills in the local population and take values ranging from 1 to 10, where 1 is the most deprived and 10 is the least deprived LSOA (MHCLG, 2019). We created dummy variables

for education deciles 1 and 10 to test the effect of living in most and least deprived areas on crime, separately.

For households with a head in higher managerial occupation (proxy for income), the counts of POIs were added to the models because they are crime generators and attractors which often indicate land uses and influence crime patterns (Lan et al., 2020; Wheeler, 2019). Table 2 presents descriptive statistics for the independent and control variables.

3.8. Data cleaning and processing

There was no missing data except for the categorical area type variable ($N = 32,800$). Therefore, although there are 32,844 LSOAs in England, the final sample size of the study was 32,800. In terms of data processing, the census variables were already available at the LSOA level. Therefore, no aggregation was performed for them. To ensure spatial consistency the betting shops and POI data were also aggregated to the LSOA level. In addition, PRCD was monthly, which required aggregation at the year level. For each police force we used the -street.csv Excel spreadsheets (e.g., 2015-01-avon-and-somerset-street.csv, where 2015 indicates the year and 01 the month).

4. METHODOLOGY

4.1. Spatial analysis

This study first employed clustering analysis to detect incidence of the different crime categories and betting shops

Table 2. Descriptive statistics of the independent and control variables.

Year	Predictor variables	Minimum	Maximum	Mean	SD
2015	Population size	817	8567	1653.68	343.52
	# Betting shops	0	31	0.33	1.17
	Percentage				
	Education decile 1	10			
	Education decile 10	10			
2019	Population size	715	14,696	1703.74	425.86
	# Betting shops	0	27	0.28	1.02
	Percentage				
	Education decile 1	10			
	Education decile 10	10			
2015 and 2019 same	# Bus stop	0	118	9.20	8.14
	# Eat and drink	0	818	4.68	12.14
	Ethnic heterogeneity index	0	0.83	0.19	0.20
	% Private renter	1.3	90.3	16.20	11.69
	% Social renter	0	92.5	17.40	17.21
	% Lone parent	0.10	47.10	10.67	5.17
	% Higher SEC	2.66	78.54	31.27	12.22
	% Unemployed SEC	0.23	36.77	5.57	4.59
	Percentage				
2015 and 2019 same	Area type 1	9			
	Area type 2	0.4			
	Area type 3	7.2			
	Area type 4	0.6			
	Area type 5	44.1			
	Area type 6	0.2			
	Area type 7	35			
	Area type 8	3.7			

Note: #, Number of; SEC, socio-economic classification; education decile 1 = most deprived 10% lower super output areas (LSOAs); education decile 10 = least deprived 10% LSOAs.
Area type: (1) Rural town and fringe, (2) Rural town and fringe in a sparse setting, (3) Rural village and dispersed, (4) Rural village and dispersed in a sparse setting, (5) Urban city and town, (6) Urban city and town in a sparse setting, (7) Urban major conurbation, and (8) Urban minor conurbation.

across the two years to show areas of co-location and high clustering using local indicator of spatial association (LISA) (Anselin, 1995) and Getis–Ord Gi statistic (Getis & Ord, 1992). These methods have been widely used to show significant spatial clustering and concentration of hotspots (Carpio-Pinedo et al., 2022; Cravo et al., 2015; Rae, 2012).

For the LISA, HH cluster means the occurrence of high–high associations, that is, similar neighbourhoods clusters with similar high observation values. LL represents low occurrence with neighbours also having low occurrence. HL or LH are outliers. They represent spatial association of dissimilar values: high values surrounded by low values for the former, and low values surrounded by high neighbouring values. Getis–Ord Gi statistics identify hotspots (positive and statistically significant z-score values) of betting shops and crime occurrences across at 90%, 95% and 99% confidence intervals.

In addition, spatial weights were defined to implement the LISA and Getis–Ord, check for spatial dependency using Moran's I (Anselin, 1995) and develop spatially lagged variables used in the model. Spatial weights are widely used to estimate the relationship/connectedness between observational spatial units. The weight was created by estimating the neighbours of each spatial unit based on contiguous boundaries (Anselin & Sergio, 2014).

4.2. Multilevel modelling

Table 1 suggests that all dependent variables are over-dispersed, meaning their variances exceed their means. Therefore, the negative binomial specification (Cameron & Trivedi, 1998; Osgood, 2000) is the appropriate method for the current study. The number of crimes in 2015 and 2019 per LSOA can be considered as repeated observations within each LSOA. The nature of the dataset provided thereby a two-level hierarchy: number of crimes in years ($n = 2$) nested within LSOAs ($n = 32,800$).[3]

After the spatial analysis, this study used a series of multilevel negative binomial regression models (Cameron & Trivedi, 1998; Snijders & Bosker, 1999) to examine whether there was an association between the number of betting shops and crime types, controlling for

neighbourhood factors that might influence crime in England. Multicollinearity among the independent and control variables in the models were assessed and all variance inflation factor (VIF) values were less than 5, suggesting very low multicollinearity issues (Hair et al., 2018) (see Table A1 in Appendix A in the supplemental data online).

The first model included only random intercepts (base model), followed by the addition of the population size variable and the betting shops variable, which is the key independent variable in the study (model 1). We then added all other predictor variables to model 1, which we called model 2.

The fixed part of model 2, for example, accommodates time-varying (measured for each LSOA on each occasion at level 1, represented by the subscript ij) and time-independent predictors (measured for each LSOA at level 2 represented by the subscript j). The random part includes occasion- and LSOA-specific random effects/residuals. A full two-level negative binomial model (model 2) is specified as follows:

$$yij \sim -veBinomial(\pi_{ij})$$
$$\log(\pi_{ij}) = \beta_0j + \beta_1 \log Population\_size_{ij}$$
$$+ \beta_2 Betting\_shop_{ij} + \beta_3 Bus\_stop_j + \beta_4 Eat\_drink_j$$
$$+ \beta_5 Ethnic\_heterogeity\_index_j + \beta_6 Private\_renter_j$$
$$+ \beta_7 Area\_type\_2_j + \beta_8 Area\_type\_3_j + \beta_9 Area\_type\_4_j$$
$$+ \beta_{10} Area\_type\_5_j + \beta_{11} Area\_type\_6_j + \beta_{12} Area\_type\_7_j$$
$$+ \beta_{13} Area\_type\_8_j + \beta_{14} Education\_decile\_1_{ij}$$
$$+ \beta_{15} Education\_decile\_10_{ij} + \beta_{16} Higher\_Managerial_j$$
$$+ \beta_{17} Unemployed_j + \beta_{18} Social\_renter_j$$
$$+ \beta_{19} Lone\_parent_j + e_{ij} + u0_j$$

$$\beta_{0j} = \beta_0 + u_{0j}$$
$$[u_{0j}] \sim N(0, \sigma_{u0}^2) \tag{2}$$
$$[e_{ij}] \sim N(0, \sigma_e^2)$$

The fixed part gives the general trends across all LSOAs; the random part allows for between- and within-LSOA variations around this general line. For example, we added a random LSOA intercept (u_{0j}) and assumed that the random intercepts come from a Normal distribution.

Having implemented the multilevel negative binomial models, we wanted to account for spatial dependency by adding the spatial lag of the outcome variables to model 2s to develop model 3s. However, it is not possible to account for spatial effects using the negative binomial model. Including the spatial lag in the exponential function has limitations (Glaser, 2017). Therefore, the dependent variables in model 3s were treated as continuous variables (log transformed).

The spatial autoregression model (SAR) takes into consideration the spatial spillover effect of the dependent variable and has been used by numerous studies to account for spatial dependency (Guliyev, 2020; Nilsson, 2022). Therefore, the spatial lag is taken as the average of all

neighbourhood LSOAs using the spatial weight explained in the spatial analysis section.

A full two-level linear model (model 3) is specified as follows:

$$y_{ij} = \beta_{0j} + \beta_1 \log Population\_size_{ij} + \beta_2 Betting\_shop_{ij}$$
$$+ \beta_3 Bus\_stop_j + \beta_4 Eat\_drink_j$$
$$+ \beta_5 Ethnic\_heterogeity\_index_j + \beta_6 Private\_renter_j$$
$$+ \beta_7 Area\_type\_2_j + \beta_8 Area\_type\_3_j + \beta_9 Area\_type\_4_j$$
$$+ \beta_{10} Area\_type\_5_j + \beta_{11} Area\_type\_6_j$$
$$+ \beta_{12} Area\_type\_7_j + \beta_{13} Area\_type\_8_j$$
$$+ \beta_{14} Education\_decile\_1_{ij} + \beta_{15} Education\_decile\_10_{ij}$$
$$+ \beta_{16} Higher\_Managerial_j + \beta_{17} Unemployed_j$$
$$+ \beta_{18} Social\_renter_j + \beta_{19} Lone\_parent_j$$
$$+ pW_{20} Lagged\_outcomei_{ij} + e_{ij} + u_{0j}$$

$$\beta_{0j} = \beta_0 + u_{0j}$$
$$[u_{0j}] \sim N(0, \sigma_{u0}^2) \tag{3}$$
$$[e_{ij}] \sim N(0, \sigma_e^2)$$

5. RESULTS

5.1. Spatial patterns of betting shops and crime in England

The LISA analysis shows some interesting patterns across the two years with similarities in the location of HH clusters for both betting shops and all crime (aggregate of all crimes). These areas include Middlesbrough, London and other major historical centres in England. Most similar and obvious patterns are evident with the HL clusters (outliers) across both phenomena, that is, areas with high betting shops and crime occurrences surrounded by low incidences of both betting shops and crime. Figures 1 and 2 show the LISA maps for Middlesbrough and London for 2015 and 2019 for both betting shops and crime patterns. The maps show important similarities in the spatial patterns of betting shops and crime with evidence of co-location of HH clusters across both cities.

As expected, crime patterns show more evidence of HH clusters compared with betting shops across both areas in Figures 1 and 2; most of the neighbourhoods with high crime clusters (HH) coincide with neighbourhoods with a high clustering of betting shops (HH) or outliers (HL and LH).

Table 3 shows the result of the Getis–Ord with the number of LSOAs with significant clustering for both crime and betting shops and further reinforces the results of the LISA maps. As shown, similar LSOAs in 2015 and 2019 (8.42% and 7.91%, respectively) are classified as having a hotspot of both betting shops and crime occurrence at 90% and 95% confidence levels.
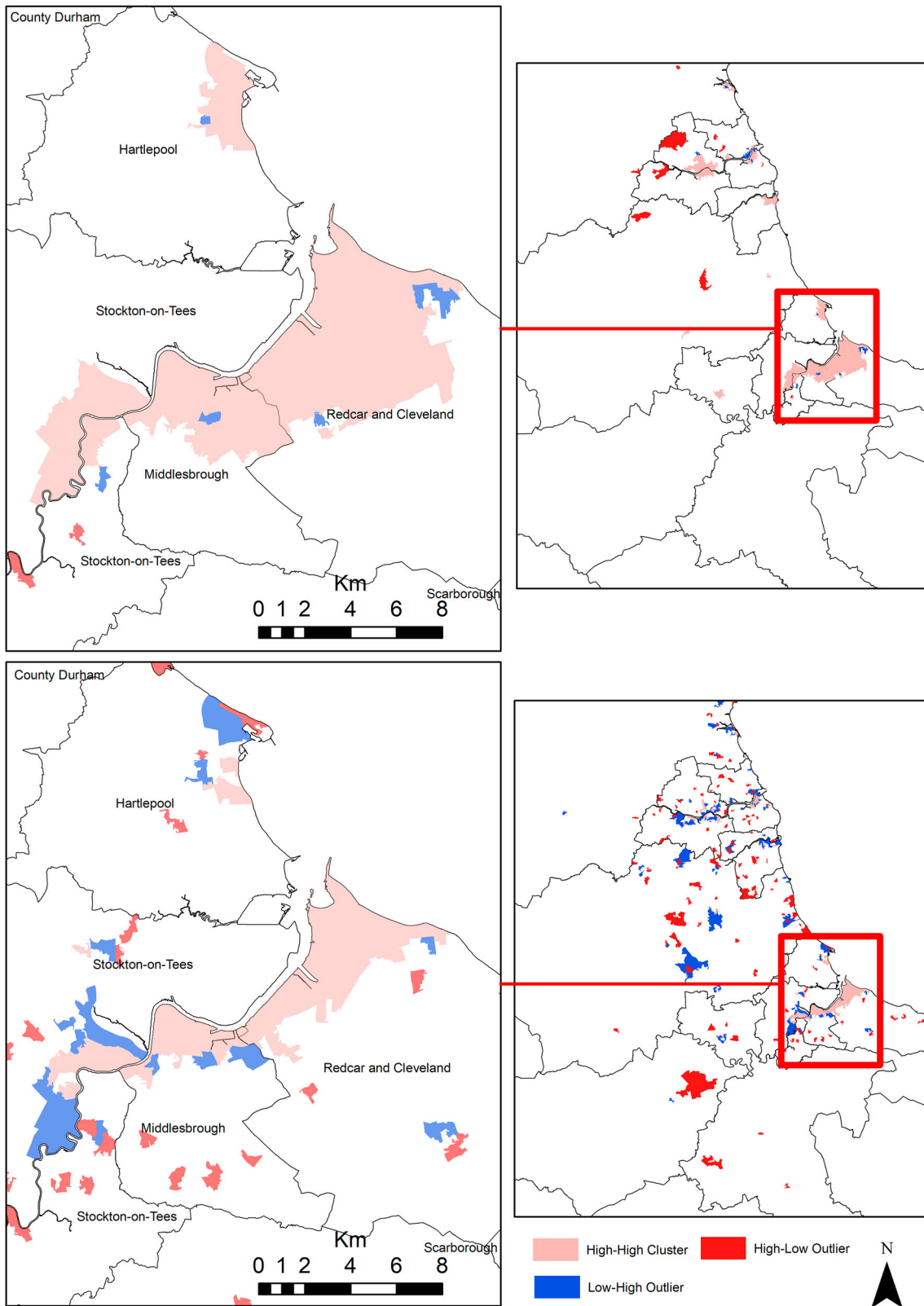
Figure 1. Local indicator of spatial association (LISA) maps of betting shops and all crime categories (combined) in Middlesbrough in 2015: (top) all crimes and (bottom) betting shops.
Sources: Contains Ordnance Survey (OS) data © Crown copyright and database right (2017) and National Statistics data © Crown copyright and database right (2015).

Figure 2. Local indicator of spatial association (LISA) maps of betting shops and all crime categories (combined) in London in 2019: (top) all crimes and (bottom) betting shops.
Source : Contains Ordnance Survey (OS) data © Crown copyright and database right (2017) and National Statistics data © Crown copyright and database right (2015).
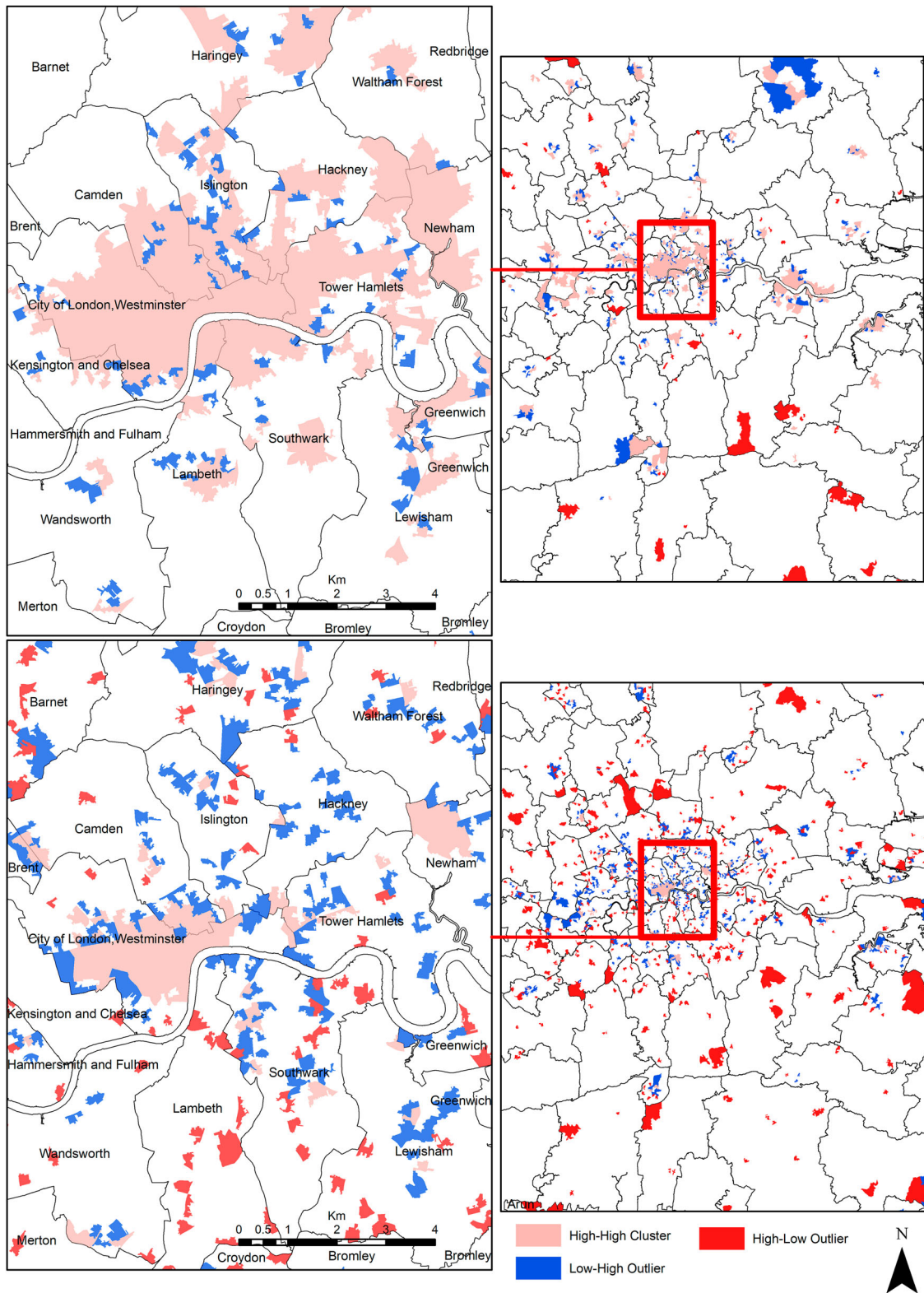
5.2. The effect of betting shops on crime in England

Tables 4 and 5 present results from two-level negative binomial models (i.e., model 2s) and two-level linear models (model 3s), respectively, that tested the relationship between the number of betting shops and all crime, bicycle theft, ASB, other theft, public disorder, shoplifting, and theft from person in an LSOA (see Tables A2–A8 in

Table 3. Number of lower super output areas (LSOAs) with significant clustering of betting shops and all crimes.

	2015			2019		
	Betting shop	Crime	Intersection[a]	Betting shop	Crime	Intersection[a]
Hotspot: 90% confidence	2303	2991	1532	2230	2709	1425
Hotspot: 95% confidence	1873	2422	1232	1816	2202	1172
Hotspot: 99% confidence	0	1737	0	0	1558	0

Note: [a]Intersection means the number of LSOAs that have both significant clustering of betting shops and crime across the different confidence.

Appendix A in the supplemental data online for the base models and model 1s; and Tables A9–A12 online for the results on the relationship between betting shops and burglary, criminal damage, robbery, and vehicle crime). The base models included only random intercepts, while model 1s and 2s controlled for various other variables that might affect the relationship between the number of betting shops and crime types analysed here, drawing upon the existing literature. Using Akaike information criterion (AIC) criteria to compare the models (e.g., base model versus model 1, model 1 versus model 2; see the rows that are before the last rows in Tables A2–A8 in Appendix A online), subsequent models better fitted the data compared with the previous models (e.g., model 1 against the base model).

According to the results from the negative binomial models (see model 2s in Table 4), the relationship between the number of betting shops and all crime types analysed here are statistically significant at the 0.001 level and positive, even after controlling for different risk factors that might affect crime rates and considering the spatial autocorrelation of neighbouring LSOAs (see model 3s in Table 5). That is, the reported coefficient estimates from model 2s demonstrate that areas with a greater number of betting shops experience more crime (all types of crime analysed here). If we take the exponent of the coefficients of the betting shop variable in model 2s (i.e., incidence rate ratio – IRR), we can also obtain a sense of the substantiveness of the effect of the number of betting shops on the crime types analysed here, individually. The expected number of all crime, bike theft, ASB, other theft, public disorder, shoplifting, and theft from other person is expected to increase by 4% (calculated as $\exp(0.044) = 1.04$) (Table 4), 6%, 7%, 5%, 7%, 16% and 10% for a 1 SD (standard deviation) increase in the number of betting shops, respectively, after controlling for all other variables in the models. These show that the presence of betting shops has a greater impact on shoplifting and theft from other person compared with other crime types. See Tables 4 and 5 and Tables A2–A12 in Appendix A in the supplemental data online for the relationship between the number of betting shops and control variables.

We also investigated LSOA (level 2) variances (see the last rows of Tables 4 and 5) for the crime types analysed here. To confirm if these LSOA-level clustering matters, the variance partitioning coefficients (VPCs) were calculated, as shown in Tables 4 and 5. The VPC shows that approximately 70%, 46%, 42%, 64%, 13%, 69% and 42%

of the variance in all crime, bicycle theft, ASB, other theft, public disorder, shoplifting, and theft from person, respectively, is accounted for by neighbourhood differences. Therefore, LSOA (level 2) differences have the highest impact on all crime, other theft, and shoplifting compared with the year differences (level 1). However, both level attributes have almost similar effects on bicycle theft, ASB and theft from person, and time differences (level 1) have the highest impact on public disorder.

The results from the spatial dependency (SAR) models (model 3) in Table 5 show a positively significant spatial lag. As the coefficients of the spatial lags are significant across all the SAR models, they demonstrate the existence of significant spatial dependency in the dependent variables. The results therefore show that the level of crime in an area is dependent on the level of crime in neighbouring LSOAs. Taken into consideration the spatial dependency of neighbouring LSOAs, the higher the betting shop provision, the higher the likelihood of crime in a neighbourhood.

6. DISCUSSION AND CONCLUSIONS

This study explored the relationship between the number of betting shops and 10 different police recorded crime types. In response to the first research question, LISA and Getis–Ord Gi analysis identified significant clustering and co-location of licensed betting outlets and all crime. This finding is consistent with some previous international studies (Bottan et al., 2017; Kim et al., 2016; Lan et al., 2020) that found the introduction of gambling outlets correlated with increased crime rates in North America.

In response to the second research question, we conducted several negative binomial multilevel models to investigate the association between the number of betting shops and crime, while controlling for various theory informed predictors of crime. The study found that the presence of a betting shop increases the likelihood of all crime categories explored in this research. Even after controlling for neighbourhood characteristics, the association remains positive and significant. This further corroborates the results of the spatial analysis and confirms that betting shops in England and casino-type gambling provisions in the North American landscape have similar effects, although the dynamics of the relationships might be different.

In response to the third research question, this study examined the spatial relationship between a range of crime categories and betting shops. After controlling for

Table 4. Relationship between betting shops and the major crime categories (model 2 – Negative Binomial Model – NBM).

	All crime	Bike theft	Antisocial behaviour	Other theft	Public disorder	Shoplifting	Theft from person
Intercept	−1.692	−8.257	−1.737	−3.556	−5.769	−9.734	−8.859
	(0.089)***	(0.244)***	(0.124)***	(0.148)***	(0.158)***	(0.456)***	(0.292)***
Population size (log)	0.772	0.808	0.600	0.618	0.894	1.174	0.738
	(0.012)***	(0.033)***	(0.017)***	(0.020)***	(0.021)***	(0.061)***	(0.039)***
# Betting shops	0.044	0.059	0.066	0.051	0.066	0.148	0.097
	(0.003)***	(0.006)***	(0.004)***	(0.004)***	(0.005)***	(0.011)***	(0.007)***
# Bus stops	0.011	0.009	0.010	0.022	0.011	0.025	0.014
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***
# Food and drink shops	0.017	0.015	0.016	0.019	0.023	0.054	0.029
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***
Ethnic heterogeneity index	−0.160	0.459	−0.649	0.187	−0.521	−1.138	1.520
	(0.019)***	(0.051)***	(0.025)***	(0.032)***	(0.031)***	(0.107)***	(0.059)***
% Private renters	0.019	0.044	0.022	0.023	0.021	0.042	0.041
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Education decile 1	0.053	0.124	−0.021	0.068	0.093	−0.045	−0.038
	(0.008)***	(0.023)***	(0.012).	(0.014)***	(0.016)***	(0.038)	(0.029)
Education decile 10	−0.045	0.130	−0.093	−0.056	−0.127	−0.149	−0.060
	(0.008)***	(0.023)***	(0.012)***	(0.013)***	(0.016)***	(0.040)***	(0.028)*
Area type 2	−0.185	−0.559	−0.068	−0.181	−0.198	0.201	−0.032
	(0.041)***	(0.140)***	(0.052)	(0.068)**	(0.067)**	(0.220)	(0.155)
Area type 3	−0.205	−0.672	−0.399	0.017	−0.309	−1.678	−0.385
	(0.013)***	(0.045)***	(0.017)***	(0.021)	(0.022)***	(0.078)***	(0.054)***
Area type 4	−0.610	−1.258	−0.728	−0.283	−0.683	−2.263	−0.776
	(0.034)***	(0.148)***	(0.045)***	(0.057)***	(0.061)***	(0.218)***	(0.163)***
Area type 5	0.231	0.969	0.252	0.119	0.323	0.460	0.497
	(0.009)***	(0.028)***	(0.012)***	(0.015)***	(0.015)***	(0.051)***	(0.036)***
Area type 6	0.091	0.244	0.174	0.024	0.211	0.496	0.663
	(0.057)	(0.168)	(0.073)*	(0.095)	(0.092)*	(0.311)	(0.191)***
Area type 7	0.206	0.523	0.144	0.103	0.395	0.267	0.660
	(0.010)***	(0.031)***	(0.013)***	(0.017)***	(0.017)***	(0.058)***	(0.039)***

Table 4. Continued.

	All crime	Bike theft	Antisocial behaviour	Other theft	Public disorder	Shoplifting	Theft from person
Area type 8	0.316	0.487	0.503	0.174	0.224	0.677	0.477
	(0.015)***	(0.044)***	(0.019)***	(0.025)***	(0.025)***	(0.084)***	(0.054)***
% Higher SEC	−0.007	0.011	−0.009	0.002	−0.007	−0.018	0.017
	(0.000)***	(0.001)***	(0.000)***	(0.001)**	(0.001)***	(0.002)***	(0.001)***
% Unemployed SEC	0.014	−0.026	0.016	0.014	0.016	−0.010	0.027
	(0.001)***	(0.003)***	(0.001)***	(0.002)***	(0.002)***	(0.005).	(0.003)***
% Social renters	0.012	0.029	0.015	0.013	0.016	0.015	0.026
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***
% Lone parent	0.009	−0.007	0.012	−0.007	0.006	−0.002	−0.019
	(0.001)***	(0.002)	(0.001)***	(0.001)***	(0.001)***	(0.004)	(0.002)***
Level 2 variance	0.157	0.68	0.185	0.39	0.111	4.34	0.901
AIC	693,370	210,021	568,129	412,676	379,220	274,028	162,544
Level 2 VPC	0.70	0.46	0.42	0.64	0.13	0.69	0.42

Note: #, Number of; SEC, socio-economic classification; education decile 1 = most deprived 10% lower super output areas (LSOAs); education decile 10 = least deprived 10% LSOAs; AIC, Akaike information criterion; Level 2 VPC = LSOA-level variance partition coefficient.
Area type: Ref category is area type 1. Area type: (1) Rural town and fringe, (2) Rural town and fringe in a sparse setting, (3) Rural village and dispersed, (4) Rural village and dispersed in a sparse setting, (5) Urban city and town, (6) Urban city and town in a sparse setting, (7) Urban major conurbation, and (8) Urban minor conurbation.
***, ** and *Significant at 0.001, 0.01 and 0.05, respectively.
Estimates are reported with standard errors shown in parentheses.

Table 5. Relationship between betting shops and the major crime categories (model 3 – spatial autoregression model (SAR)).

	All crime	Bike theft	Antisocial behaviour	Other theft	Public disorder	Shoplifting	Theft from person
Intercept	−1.568	−3.128	−2.420	−3.284	−4.556	−3.245	−2.276
	(0.088)***	(0.116)***	(0.119)***	(0.135)***	(0.129)***	(0.207)***	(0.106)***
Population size (log)	0.735	0.391	0.641	0.602	0.708	0.512	0.252
	(0.012)***	(0.016)***	(0.016)***	(0.018)***	(0.017)***	(0.028)***	(0.014)***
# Betting shops	0.065	0.071	0.084	0.074	0.105	0.165	0.093
	(0.003)***	(0.003)***	(0.003)***	(0.004)***	(0.004)***	(0.006)***	(0.003)***
# Bus stops	0.012	0.004	0.011	0.020	0.008	0.010	0.003
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
# Food and drink shops	0.011	0.010	0.008	0.015	0.011	0.032	0.019
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***
Ethnic heterogeneity index	−0.218	0.172	−0.552	0.128	−0.333	−0.455	0.750
	(0.019)***	(0.024)***	(0.025)***	(0.028)***	(0.026)***	(0.046)***	(0.022)***
% Private renters	0.015	0.019	0.012	0.020	0.010	0.016	0.015
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***
Education decile 1	0.031	0.078	−0.059	0.061	0.042	−0.003	−0.032
	(0.008)***	(0.012)***	(0.012)***	(0.013)***	(0.013)**	(0.018)	(0.010)**
Education decile 10	−0.039	0.040	−0.089	−0.048	−0.097	−0.045	−0.058
	(0.007)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***	(0.017)**	(0.010)***
Area type 2	−0.102	−0.210	0.068	−0.144	−0.018	0.048	−0.103
	(0.041)*	(0.049)***	(0.051)	(0.059)*	(0.054)	(0.097)	(0.046)*
Area type 3	−0.203	−0.168	−0.364	0.015	−0.204	−0.524	−0.092
	(0.013)***	(0.015)***	(0.016)***	(0.019)	(0.017)***	(0.030)***	(0.014)***
Area type 4	−0.544	−0.269	−0.553	−0.227	−0.374	−0.741	−0.152
	(0.034)***	(0.041)***	(0.043)***	(0.049)***	(0.045)***	(0.081)***	(0.038)***
Area type 5	0.179	0.324	0.107	0.100	0.132	0.253	0.103
	(0.009)***	(0.011)***	(0.011)***	(0.013)***	(0.012)***	(0.022)***	(0.010)***
Area type 6	0.116	−0.003	0.185	0.034	0.155	0.268	0.088
	(0.057)*	(0.069)	(0.072)*	(0.083)	(0.076)*	(0.136)*	(0.064)
Area type 7	0.160	0.170	0.043	0.070	0.213	0.142	0.168
	(0.010)***	(0.012)***	(0.013)***	(0.015)***	(0.013)***	(0.024)***	(0.011)***

(*Continued*)

Table 5. Continued.

	All crime	Bike theft	Antisocial behaviour	Other theft	Public disorder	Shoplifting	Theft from person
Area type 8	0.252	0.149	0.201	0.152	0.057	0.348	0.099
	(0.015)***	(0.018)***	(0.019)***	(0.022)***	(0.020)**	(0.036)***	(0.017)***
% Higher SEC	−0.005	0.004	−0.003	0.001	−0.002	−0.007	0.007
	(0.000)***	(0.000)***	(0.000)***	(0.000)**	(0.000)***	(0.001)***	(0.000)***
% Unemployed SEC	0.011	−0.014	0.006	0.012	0.006	−0.006	0.009
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)**	(0.001)***
% Social renters	0.010	0.012	0.011	0.012	0.010	0.006	0.011
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***
% Lone parent	0.015	−0.004	0.022	−0.006	0.018	−0.003	−0.016
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)	(0.001)***
P	0.001	0.033	0.009	0.003	0.033	0.003	0.003
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Level 2 variance	0.16	0.165	0.208	0.291	0.121	0.92	0.154
AIC	61413	117514	114202	127808	143604	170677	102891
Level 2 VPC	0.73	0.43	0.53	0.58	0.23	0.76	0.48

Note: #, Number of; education decile 1 = most deprived 10% lower super output areas (LSOAs); education decile 10 = least deprived 10% LSOAs; SEC, socio-economic classification; P, spatial lag of dependent variable; AIC, Akaike information criterion; Level 2 VPC = LSOA-level variance partition coefficient.
Area type: Ref category is Area type 1. Area type: (1) Rural town and fringe, (2) Rural town and fringe in a sparse setting, (3) Rural village and dispersed, (4) Rural village and dispersed in a sparse setting, (5) Urban city and town, (6) Urban city and town in a sparse setting, (7) Urban major conurbation, (8) Urban minor conurbation.
***, ** and *Significant at 0.001, 0.01 and 0.05, respectively.
Estimates reported with standard errors are shown in parentheses.

neighbourhood characteristics, we found that the spatial correlations between betting shops and crime were highest for shoplifting, theft from other persons, public disorder and ASB. This may be expected given that these establishments are often located in local communities, and their opening hours tend to be daytime rather than evening. Relationships were less strong for burglary, and other more violent crimes such as robbery, often associated with violence and risky facilities in the night-time economy, especially those venues with larger capacities that hold several hundred people.

Furthermore, the VPC estimates derived from the cluster variance of the multilevel models show that LSOA characteristics play a vital role in the relationship between betting shops and most of the crime categories. Therefore, the inherent characteristics of neighbourhoods exert the most influence on the relationship between betting shops and crime. These findings support both the social disorganization and crime attractors and generators theories. For instance, spatial structures, such as betting shops, bus stops, and eat and drink places, were found to increase the likelihood of experiencing all categories of theft and other crime categorizations. These findings support the crime generators and attractors of crime pattern theory (Brantingham & Brantingham, 1995). In addition, ethnic heterogeneity, private renters, social renters, high education deprivation and urban area types, which were attributed to impact positively on the crime categories examined, are supported by the social disorganization theory (Sampson & Groves, 1989).

Previous studies indicate that betting shops (Adeniyi et al., 2020) and crime (Kawachi et al., 1999; Weisburd, 2015) are concentrated particularly in deprived areas. Since there are many correlates of crime at the neighbourhood level, this study tried to distinguish the effect of betting shops on crime by controlling for other factors that might affect crime. Accordingly, this study has made original contributions to the literature by addressing the paucity in the literature on the relationship between betting shop provisioning and crime across England at the national level. The study further contributes to the literature by focusing on different categories of police-recorded crime and betting shops (as against casinos) to provide a more nuanced understanding of the impact of betting shop provision on crime over two different time points.

Although statistically significant findings in relation to the role of betting shops on crime are evident, this study in no way suggests causality. For example, it is highly likely that the significant clustering of betting shops and crime might also have been affected by the presence of other crime generators or attractors that we have not considered in this study. Thus, the relationship between betting shops and crime is multifaced, as can be evidenced from this research. The issue could be that crime might be occurring within the premises of betting shops which makes betting shops serve as crime generators. On the other hand, they might serve as crime attractors as they might provide opportunities for offenders and victims to interact.

Therefore, efforts need to be put in place to reduce the potentials of betting shops to serve as crime attractors and generators.

A range of policy implications can be derived from this study. Our findings suggest that all risk factors of crime converge in deprived areas, and thus create opportunities for more crime in those areas as the relevant theories suggest (Brantingham & Brantingham, 1995; Sampson & Groves, 1989). That is, areas with greater number of betting shops, bus stops, eat and drink places, ethnic diversity, deprivation in education, and a higher percentage of private and social renters experience more crime. Therefore, given recent austerity measures and reduced police funding (National Audit Office (NAO), 2018), resources should be channelled towards areas with the combinations of risk factors identified above.

According to Linning et al. (2022), structural and concentrated disadvantages within neighbourhoods include population mobility, retail outlets, food outlets, indicators of poverty, private renters, social renters and betting shops as our research has uncovered. Interventions to reduce the impact of betting shops on crime should move from focusing on individuals and at-risk populations to trying to improve and foster strong informal controls in neighbourhoods. This could be achieved by focusing on how to improve or organize negative spatial structural conditions and concentrated disadvantages. Not only that, but interventions should also try to focus on local place managers who create spatial structures within neighbourhoods. Linning et al. have shown that estate agents, property owners and planning officials, for example, create spatial structures, thereby creating factors that provide opportunities for crime (e.g., crime attractors and generators).

Therefore, there should be a shift in intervention to begin to focus on place management strategies that focus on influencing the action of creators of spatial structures to invoke more responsible and inclusive creation process. For instance, local planning committees can take a public health approach by intervening along the gambling pathway especially with regulations at a local level. A saturation point/level can be introduced that makes it nearly impossible/difficult for a betting operator to open a new outlet in areas with already high provisioning or saturation.

7. LIMITATIONS AND RECOMMENDATION FOR FUTURE STUDIES

This study makes an original contribution to the literature by investigating the relationship between betting shops and crime across England. However, some limitations are worth noting. First, this study does not account for online or mobile gambling which is becoming a major concern for policymakers and public health practitioners. Most betting organizations continually seek to encourage participants to migrate online partly due to the less stringent online regulations. For instance, the £2 cap on fixed odds betting terminals introduced in the UK is not applicable to online gambling retailers. Future studies can

investigate the impact of online or mobile gambling on crime.

Second, aggregating data to a spatial scale always introduces the generalization effect referred to as the modifiable area unit problem (Nelson & Brewer, 2017; Openshaw, 1984). This might influence the reliability of the results obtained from aggregated data such as the census, and crime and gambling datasets. As a result, this research adopted the lowest appropriate geography (LSOA) to reduce the effect of the modifiable area unit problem.

Third, although this study controlled for several theory informed predictors of crime, we acknowledge 'the complexity of the natural and built environment, the political, economic, social and cultural contexts and structures of areas and the actions of individuals and corporate bodies within areas' (Bottoms & Wiles, 1992, cited in Trickett et al., 1995, p. 274). That is, the models were limited to the variables included in them due to the lack of data. To overcome this shortcoming, future studies might consider using the Commercial Victimisation Survey which aims to estimate the level of crime against businesses.

Fourth, this study did not examine individual victimization risk and propensity to offend by 'problematic' gamblers seeking to fund their gambling behaviour. No publicly available UK dataset examines this, and it can be considered outside the scope of the study, which focused on risky facilities and risky places. However, future studies may consider the interaction effect between the risk factors afforded by problematic gamblers and the nature and characteristics of places where they are more likely to offend.

Fifth, PRCD also introduced some limitations. 'Unlike the CSEW [Crime Survey for England and Wales], PRCD figures do not include crimes that have not been reported to the police or incidents that the police decide not to record' (Flatley, 2014, p. 5). Further limitations of the PRCD are as follows: (1) 'non-standardised recording practice across police forces and over time'; and (2) 'changes in offence classification and legal definitions over time' (Tseloni & Tilley, 2016, p. 4). However, the CSEW has limitations when conducting analysis at the LSOA level as the CSEW sample size is too small to be representative at the LSOA level (Tseloni & Tilley, 2016). This limitation of the CSEW provided strong justification to use the PRCD.

Finally, in relation to the data used, the census data, POI and area type used for this study are for a one year period (2011). This is because these datasets are not available. In addition, this study considered only two time points (2015 and 2019) due to the static nature of data collection on betting shops. Future studies might consider extending the timeframe adopted for this research. More importantly, future studies should further explore the findings of this study by conducting a comparative analysis looking at different cities across the UK to further understand the influence of local dynamics on the relationship between betting shops and crime.

NOTES

1. See https://data.police.uk/data/.
2. See https://www.nomisweb.co.uk/.
3. There are 32,844 LSOAs in England; however, due to missing cases for the area type variable, the total number of LSOAs in the present analysis is 32,800.

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