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Area and individual differences in personal crime victimization incidence: The role of individual, lifestyle/routine activities and contextual predictors

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Abstract

This article examines how personal crime differences between areas and between individuals are predicted by area and population heterogeneity and their synergies. It draws on lifestyle/routine activities and social disorganization theories to model the number of personal victimization incidents over individuals including routine activities and area characteristics, respectively, as well as their (cross-cluster) interactions. The methodology employs multilevel or hierarchical negative binomial regression with extra binomial variation using data from the British Crime Survey and the UK Census. Personal crime rates differ substantially across areas, reflecting to a large degree the clustering of individuals with measured vulnerability factors in the same areas. Most factors suggested by theory and previous research are conducive to frequent personal victimization except the following new results. Pensioners living alone in densely populated areas face disproportionally high numbers of personal crimes. Frequent club and pub visits are associated with more personal crimes only for males and adults living with young children, respectively. Ethnic minority individuals experience fewer personal crimes than whites. The findings suggest integrating social disorganization and lifestyle theories and prioritizing resources to the most vulnerable, rather than all, residents of poor and densely populated areas to prevent personal crimes.

Keywords

Area predictors, crime counts, individual predictors, lifestyle/routine activities, multilevel/hierarchical negative binomial model, personal criminal victimization

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Introduction

Police work may be characterized as, in part, an attempt to dispense resources in proportion to the crime risk faced by individuals, households and areas. Crime reduction strategies must obviously be based on both personal and household crime rates. Property crime has been studied more extensively than personal crime. There are many reasons why personal crime dynamics may differ from those of property crime and hence why resource allocation decisions to optimize the reduction of personal crime may differ from those optimized to reduce household crime. Most homes are static. Most people are mobile. Thus personal crime may be suffered outside the home area. Within the home area, personal crime may be characterized by a distinctive profile of interacting variables as suggested by lifestyle and social disorganization theories. The present article examines the number of *personal crime* events related to theoretically informed individual and area characteristics to address the following research questions:

- Is personal crime victimization a context or composition problem?
- What predicts the frequency of personal crime victimization?
- How do area attributes condition the (relative) importance of individual predictors of personal victimization frequency?

Previous analyses of crime survey data have established (among other things) two points about rates of personal victimization which are crucial for strategies for the equitable distribution of crime prevention and enforcement resources. First, *areas differ very widely with respect to personal victimisation rates* (Trickett et al., 1992). Analysis of the 1982 British Crime Survey (BCS) showed that, in England and Wales, personal crime prevalence (the proportion of victims in the population) and incidence (the mean number of crimes per head of population) rates were, respectively, 11 and 34 times higher in the highest crime area decile than in the lowest crime decile (Trickett et al., 1992). Eighteen years later, a replication using the 2000 BCS confirmed that a similar pattern prevailed: 20 per cent of areas contributed nearly half of all personal crimes captured by the survey. Personal crime incidence rates in the worst area decile were nearly six times higher than in the 10 per cent safest areas (Kershaw and Tseloni, 2005). The point estimates of area-level crime rates, which are based on survey data, are subject to sampling error and influenced by (small) sample point sizes.[1] The precise extent of the massive differences described above should therefore be taken to be provisional. Nonetheless, they invite attention and remedy, both as an affront to distributive justice and as risking the creation and perpetuation of acute policing problems, as those who can afford to flee the most crime-challenged areas choose to do so. Some slight evidence suggests that the most under-policed areas are high-crime beats in high-crime police command units in high-crime forces (Ross and Pease, 2007).

Once an area receives its funding for crime prevention and enforcement, on what basis should it be distributed *within* the area?. The second important result from the analysis of the victimization survey data mentioned above is that high-crime areas are marked by greater repetition but a lower victimization risk than would have been predicted on the assumption that crime is random (Trickett et al., 1992). Because relatively few individuals in high-crime areas suffer the majority of crimes (Forrester et al., 1988, 1990), optimal intra-area resourcing will not be uniform across the area.

These two key findings, massive areal differences and chronic victimization of individuals within high-crime areas provide both a potential basis for allocation decisions between and within areas, and a clearer path for future victimization research to follow.

It turns out that, looking at *property* crime, one-off and repeat victims do not have different attributes, repeat victims simply having a larger constellation of the same risk factors (Osborn et al., 1996). Therefore, the prediction of both victimization risk and repeat crimes is feasible by a single examination of the distribution of property crime counts via an appropriate statistical approximation that recognizes the non-randomness of successive events (Osborn and Tseloni, 1998). Frequent property victimization is due to both context and composition, while some degree of area differences remains unexplained. Furthermore, the risk factors for frequent property victimization differ across areas (Tseloni, 2006). Therefore lifestyle factors contribute to high crime exposure and victimization only in areas characterized by social disorganization but not elsewhere, hence conditioning the applicability of the former theory. The present article extends this investigation to personal crime to bring researchers and practitioners to a similar level of understanding as is already available in respect of property crime.

The structure of the article is as follows. The underpinning theory of the work is briefly presented, followed by an account of the relevant empirical findings to date. The subsequent section presents the data on the observed distributions of personal crimes and their covariates, together with an overview of the methodology, with Appendices A and B presenting the models' statistical specification and further data tests, respectively. The results of the analyses are then given, followed by insights for theory and policy recommendations and suggestions as to how research might be taken forward.

Victimization theory

Victimization studies typically seek to identify attributes which distinguish victims of crime from other people. In their seminal lifestyle theory of victimization, Hindelang et al. (1978) concluded that individuals have a high likelihood of becoming victims of crime insofar as they work and socialize alongside offenders with whom they share socio-demographic characteristics, such as youth. These characteristics are either indicators of lifestyle not captured by such victimization survey measures or of targets' vulnerability perceived by potential offenders. The contemporaneous 'routine activities theory' posited that the coincidence of a motivated offender, a suitable target and ineffective guardianship satisfies the necessary conditions for criminal victimization (Cohen and Felson, 1979; Felson, 2002).[2] The two theories were originally very similar in their predictions (Gottfredson, 1981), to the extent that empirical research (for instance, Maxfield, 1987; Miethe et al., 1987) tested an amalgamated 'opportunity' theory for crime. Such research examined victimization at the micro/individual level. By neglecting context, the approach is vulnerable to criticisms of victim-blaming (Gottfredson, 1981; Sparks, 1981).

Over 70 years ago at the time of writing, Shaw and McKay (1942) introduced 'social disorganization theory'. This held that *contextual* predictors of crime such as area population density, residential mobility, ethnic diversity, material deprivation and family disruption spawned unsupervised teen groups, weak informal social control mechanisms and lack of local friendship networks in neighbourhoods,[3] all of which contribute to high victimization risk (Sampson and Groves, 1989). Social disorganization theory suffers from the ecological fallacy problem (Schwartz, 1994). It fails to clarify whether area differences in crime are attributable to area profile, i.e. context, or to the attributes and lifestyles of the people who live there – composition – the issue raised in the first bullet point of the Introduction.

The two strands of victimization theory, which respectively delineate population and area heterogeneity, must be taken to be complementary (Kennedy and Forde, 1990) and tested simultaneously. Multilevel or hierarchical statistical analyses over both individual (micro-level) and area (macro-level)[4] crime covariates provide the appropriate tool (see, for example, Snijders and Bosker, 1999). This analytical approach ties together lifestyle and social disorganization theories in a single paradigm by testing whether and how the importance of individual crime predictors varies across areas (Rountree et al., 1994).

Previous findings

Past research on personal victimization risk[5] suggests that males, the young, the unmarried, those of low income, local authority tenants, adults living alone or with children in the household, students, the unemployed or part-time employed and newcomers to an area are the *individuals* generally more vulnerable to personal victimization (see Kennedy and Forde, 1990). Area heterogeneity is commonly gauged via official statistics and other data sources, such as the Census (Osborn et al., 1992), which are independent of crime survey data (see also the Discussion section). Residents of areas of economic disadvantage (Hope et al., 2001), with proximity to busy places, subject to incivilities (Rountree et al., 1994), suffering poor socio-economic conditions (Miethe and McDowall, 1993), with a high percentage of lone-parent families, single-person households and unemployed people (Kennedy and Forde, 1990) are at high risk of personal crime victimization. Conversely, an area's ethnic heterogeneity is not significantly related to area mean crime risk but (perhaps counter-intuitively) significantly reduces the risk of personal victimization of 'non-white' residents (Rountree et al., 1994). Similarly, neighbourhoods with high immigrant population experience *reduced* risks of violent victimization (Maimon and Browning, 2012).

Tests of social disorganization theory, i.e. those examining *only area predictors*, yield parallel results. Personal crimes were found to be positively associated with the percentage of single-adult households (Osborn et al., 1992; Kershaw and Tseloni, 2005), family disruption (Sampson and Groves, 1989; Tseloni et al., 2010), unsupervised peer groups, poor organizational participation (Sampson and Groves, 1989), residential mobility, population density and material deprivation (Bellair and Browning, 2011; Kershaw and Tseloni, 2005; Tseloni et al., 2010).

Perhaps because of the historical tendency of research to focus on individual *or* area characteristics, neither strand of theory has commanded universal empirical support even when, as advocated here, research has focused on individual and area characteristics together. For instance, some studies have not evidenced any significant difference in personal victimization between men and women (Hope et al., 2001; Rountree et al., 1994), especially within highly vulnerable households (Tseloni, 2000). According to lifestyle theory, being of an ethnic minority is a factor contributing to *high* victimization risk (Hindelang et al., 1978). However, the opposite is shown empirically: ethnic minority individuals are significantly less victimized by personal crimes than are 'white' people overall (Hope et al., 2001; Pauwels and Hardyns, 2010; Tseloni, 2000), in particular within ethnically diverse communities (Rountree et al., 1994), and after accounting for neighbourhood disadvantage (Estrada and Nilsson, 2004). 'Risky' lifestyle and routine activities are also linked to personal victimization in theory. Whether these effects are exclusively individual or area characteristics remains unresolved. Evenings out, carrying valuables, shopping daily or using public transport increase personal victimization, especially for males, single people (Miethe et al., 1987; Tseloni and Pease, 2004), students or the unemployed and lone parents (Maxfield, 1987). Social disorganization theory has not been fully supported by empirical evidence either. For instance, area unemployment and ethnic heterogeneity are not linked to higher personal criminal victimization rates in England and Wales (Osborn et al., 1992) and, when controlling for other variables, neighbourhood characteristics are unrelated to violent victimization in Sweden (Wikström and Dolmén, 2001).

Data and variables

Personal crimes

The empirical distributions of personal crimes are taken from the 2000 BCS for a total of 15,774 respondents, clustered across 905 sampling points (Hales et al., 2000).[6] The sampling points are in effect quarter-postcode sectors (henceforth referred to as 'areas'). The BCS was administered by the Home Office since its inception in 1981, but in 2011 it moved to the Office of National Statistics and was renamed the Crime Survey for England and Wales (CSEW). The acronym BCS will be used throughout this article. The survey employs a multistage stratified sample, representative of the adult (16 years or older) population living in private accommodation in England and Wales. For a brief history and details of the methodology, questionnaire modules and items, and topics covered in the BCS, see Hough and Maxfield (2007) and the various BCS Technical Reports. The sampling frame of the 2000 BCS was the Postcode Address File for England and Wales.

Personal crimes for this study are taken from the 2000 BCS Victim Forms and comprise the offences of common assault, wounding, robbery, theft from the person and 'other theft from person'. They exclude sexual offences as this crime category is seriously under-reported, subject to great year-on-year variability from national survey data, and requires individual analysis. According to standard BCS practice an incident is classified as the most serious crime type that was an element of the event (Hales et al., 2000, Appendix G). The reference period was the calendar year 1999: respondents to the 2000 BCS were invited to report victimization experienced since January 1999. Victims could report up to five *single* or *series* incidents during this period (Kershaw et al., 2000). Series incidents refer to repeated events of the same crime type, which occur under similar circumstances and possibly were committed by the same offenders. They are truncated at five events per Victim Form (Hales et al., 2000). This convention has been subject to valid criticism as understating the importance of chronic victimization (Farrell and Pease, 2007).

The fact that personal crimes can happen anywhere impedes investigating area predictors using place-sampled crime survey data – hence the small number of studies on contextual risk factors on victimization, unlike fear of crime or juvenile delinquency. To overcome this, the current analysis examines only the incidents occurring within a 15-minute walk of home and suffered by respondents who had not moved home in the previous year (see the section on Methodological contribution). Table 1 presents the observed frequency distributions of total personal crimes and three commonly used indicators of repeat victimization: *crime concentration*, i.e. the average number of crimes per victim, *percentage of repeat crimes* and *percentage of repeat victims*. A thankfully small minority (3.1%) of 2000 BCS respondents ($n = 489$) reported personal crime experiences within a 15-minute walk of home. Of the 489 who did suffer such crime, 132 (27%) were repeat victims (also within a 15-minute walk of home). The total number of crimes suffered by the sample

Table 1. Observed frequency distribution for personal crimes[a, b, c] from the 2000 British Crime Survey.

Total personal crimes		
Number	Frequency	%
0	15,285	96.9
1	357	2.3
2	79	0.5
3	29	0.2
4	9	0.1
5	9	0.1
6	4	0.0
7	0	0.0
8	0	0.0
9	1	0.0
10	0	0.0
11	1	0.0
Total	15,774	100.0
Prevalence (number of victims over population)		0.031
Incidence, mean (average number of crimes per person)		0.046
Variance		0.10
Skewness		11.9
Measures of repeat victimization		
Concentration (average number of crimes per victim)		1.5
% Repeat crimes		51
% Repeat victims		27

[a]Incidents occurred within a 15-minute walk from home to respondents who had not moved house in the previous year.
[b]Series incidents are truncated at 5.
[c]Sexual offences are excluded.

was 727, which gives a crime incidence of 4.6 per cent or 0.046 crimes per respondent but 1.48 crimes per victim.

The decisions which this article aspires to inform are those concerning the deployment of police resources. Thus the rationale for stressing crime concentration is the scope which it affords for focusing attention on those recently victimized in order to prevent repetition. Thus an appropriate way of expressing concentration is to say that one-third of all personal crimes are suffered by people who have experienced one or more such victimizations earlier in the same calendar year. Bear in mind that this represents an underestimation of the extent of repetition of victimization. In a victimization survey covering a calendar year, the risk period for a first victimization is a year, but the risk period for a second victimization is the time between the first victimization and the end of the year. The risk period for a third victimization is the even shorter time between the second victimization and the end of the year. In addition, a single victimization in the year covered by the survey recall period may be a repeat of something that happened during the previous year (Farrell et al., 2002).

To return to the present study, the results outlined above indicate that the risk of personal victimization is low, but the extent of repeats is high, especially in light of the above-mentioned BCS crime count truncation rules (Farrell and Pease, 2007). The modelling of the entire distribution of personal crimes is thus vindicated, and indeed clearly necessary to support any defensible deployment of resources.

Covariates

The individual personal crime risk factors identified here include: demographic characteristics (male gender, young age, 'non-white' ethnicity); social attributes (marital status, education, social class); household information (living with children, number of adults, lone parent, tenure, accommodation type, annual income, number of cars and length of residence in the area); and four routine activities: time spent away from home, and frequency of going to pubs and clubs and alcohol drinking. These variables, together with area type (inner city, urban or rural) and region (Wales and the nine Government Office Regions of England), have been taken from the Main and Demographic Questionnaires of the 2000 BCS. Region effects are not captured by area characteristics (Osborn et al., 1992), which are described next.

The variables reflecting constructs of social disorganization theory have been taken from the 1991 UK Census, which was linked to the BCS by the National Centre for Social Research, the 2000 BCS fieldwork contractor, to safeguard respondent confidentiality.[6] These variables include measures of residential mobility (the percentage of households renting privately, of single-adult non-pensioner households and the percentage of households moving into an area in the previous year); ethnic heterogeneity (the percentage of households with Afro-Caribbean or Asian[7] 'head', for which larger numbers measure increased heterogeneity with respect to the national average of the uniformly 'white' population); population density; the percentage of population 16–24 years as a proxy for unsupervised groups of young people; and the percentage of households in housing association accommodation and a poverty index[8] as proxies of material deprivation. All Census variables have been standardized and include a 5 per cent error variance to preserve respondent confidentiality. So an area with a zero measure is nationally average, and an area with a measure of +1 or –1 is one standard deviation above or below the national average, and so on. A caveat should be entered that there is an 8-year gap between the area profiles and the BCS reference period. This will serve to reduce the size of relationships between victimization and area (not individual) covariates.

Table 2 sets out descriptive statistics of the individual and area covariates of personal crimes. Apart from respondent age, all the personal crime covariates, which were taken from the BCS, are categorical and their base category is indicated in this table.

With one exception, the base or reference categories of all the categorical explanatory variables in the models below were selected to coincide with the respective sample modes. The exception was accommodation type, where 'detached' was taken as the base category. Semi-detached rather than detached houses are the most prevalent in England and Wales. The mean values for respondent age and area characteristics and the modal categories for the remaining individual attributes are given in the estimated mean personal crimes and the model summary statistics of the Results section.

Methodological contribution

The 2000 BCS sample is restricted as seen earlier by (at least a year) length of residence of the respondent in their current home, clustered across 905 sampling points or 'areas'. Sampling point sizes varied between 4 and 29 respondents (average 18 individuals with a 5.9 standard deviation) per sampling. Individuals (level 1 units) are thus nested within areas (level 2 units), forming a natural hierarchical data structure and requiring multilevel analysis. With the exception of pioneers Pamela Wilcox Rountree and her colleagues (Rountree, 1994),[9] who introduced the multilevel

Table 2. Description of covariates of personal crimes.

Individual-level covariates ($N = 15{,}774$)	%	Mean (min, max)	Standard deviation
Individual and household characteristics			
Male	45.5		
Age		51 (16, 99)	17.6
'Non-white'	3.3		
Marital status			
Single	15.9		
Married (base)	60.5		
Divorced	11.1		
Widowed	12.5		
Educational attainment			
Without qualifications	36.9		
Trade apprenticeships, O-levels, etc.	28.9		
A-levels	11.1		
Higher education (base)	23.1		
Number of adults			
One	29.9		
Two (base)	55.8		
Three or more	14.3		
Children in the household	28.6		
Lone parent	4.6		
Tenure			
Owners (base)	75.4		
Social renting households	17.5		
Private renting households	7.1		
Accommodation type			
Detached (base)	25.5		
Semi-detached house	35.6		
Terraced house	27.6		
Flat or maisonette or other	11.3		
Annual household income			
Under £5,000	10.3		
Between £5,000 and £9,999	16.3		
Between £10,000 and £29,999 (base)	44.7		
Over £30,000	22.2		
No response	6.5		
Social class of 'head of household'			
Manual	53.3		
Professional (base)	30.8		
Non-classified	15.9		
Number of cars			
No car	21.4		
One car	46.2		
Two cars (base)	26.7		
Three or more cars	5.7		
Length of residence in the area			
Less than 2 years	6.9		
Two to 5 years	20.2		
Five to 10 years	18.1		
More than 10 years (base)	54.8		

(continued)

Table 2. (continued)

Individual-level covariates (N = 15,774)	%	Mean (min, max)	Standard deviation
Routine activities and lifestyle indicators			
Away from home on an average weekday			
Less than 3 hours	28.6		
Three to 7 hours	27.8		
More than 7 hours (base)	43.6		
Frequency of visits to pubs			
Never (base)	47.2		
Less often than once a week	29.8		
Once a week	15.6		
Three or more times a week	7.4		
Frequency of visits to clubs			
Never (base)	89.7		
Less often than once a week	8.2		
Once a week	2.1		
Frequency of drinking alcohol			
Never or less often than once a month (base)	24.7		
Once a month or more but less often than once a week	16.8		
Once or twice a week	28.0		
Three to four times a week	14.3		
Daily	16.2		
Area characteristic			
Type of area			
Inner city	11.8		
Urban	62.3		
Rural (base)	25.9		
Area-level covariates (N = 905)			
Percentage of households renting privately		–0.19 (–1.03, 4.95)	0.65
Percentage of single-adult non-pensioner households		–0.16 (–1.00, 2.46)	0.42
Poverty index[a]		–0.44 (–7.24, 14.39)	3.34
Percentage of Afro-Caribbean		–0.08 (–0.43, 5.05)	0.70
Percentage of Asian[b]		–0.04 (–0.46, 5.08)	0.78
Percentage of population 16–24 years old		–0.06 (–0.93, 4.03)	0.26
Percentage of households in housing association accommodation		–0.10 (–0.65, 5.00)	0.66
Percentage of persons moved in last year		–0.08 (–0.50, 1.97)	0.23
Population density (persons per 10 hectares)		0.02 (–0.86, 5.05)	0.82
Government Office Regions			
North East	6.2		
Yorkshire/Humberside	9.6		
North West	13.1		
East Midlands	8.2		
West Midlands	9.9		
Eastern	11.4		
Greater London	9.6		
South East (base)	14.2		

(continued)

Table 2. (continued)

Individual-level covariates ($N = 15{,}774$)	%	Mean (min, max)	Standard deviation
South West	10.3		
Wales	7.5		

[a]Aggregate factor calculated as (0.859 × percentage of lone-parent households) + (0.887 × percentage of households without car) – (0.758 × percentage of non-manual) – (0.877 × percentage of owner-occupied households) + (0.720 × mean number of persons per room) + (0.889 × percentage of households renting from local authorities).
[b]Indian, Pakistani or Bangladeshi.

methodology to victimization research, area and individual predictors of personal victimization have been examined without looking at the clustering of individuals within areas. The research on predictors of personal crime in previous research, including the above-cited work, tends to treat victimization status as binary. One is either a victim or not a victim. This is a major limitation. Crime concentration, i.e. the number of crimes per victim, as noted earlier, is higher than expected in high-crime places (Osborn and Tseloni, 1998; Trickett et al., 1992). High crime rates are the product of *fewer victims* than victimization risk models predict and *more crimes per victim.* Interestingly and probably importantly, this pattern, which is true for place, is equally true for time. The crime drop of the past 15 years is associated with significant reductions in repeat relative to single victimization rates (see Thorpe, 2007). The pattern has implications for within-area resource allocation, as will be discussed later. Put crudely, the police do not respond to the first call for service from a victim of personal crime and thereafter ignore calls from the same person. Risk modellers, insofar as they wish to produce applicable work, should not proceed as though that were the case by treating victimization as binary.

In short, the two necessary components in yielding applicable research on crime distribution entail the combination of macro and micro approaches to modelling and the inclusion of the whole range of counts of victimization incidents suffered.

The study reported here seeks to address the gap in the literature identified above by predicting the risk and frequency of personal victimization across individual *and* contextual predictors. Examining the entire distribution of personal victimization from never victimized to chronically victimized and applying the multilevel methodology on a national dataset provides a more realistic basis for the allocation of crime management resources.

The number of personal crimes has been modelled via multilevel negative binomial regression with extra negative binomial variation (Cameron and Trivedi, 1986; Goldstein, 1995; Tseloni, 2000). Appendix A gives details of the statistical specification of the model, the modelling strategy for this work and how the estimated coefficients are interpreted to inform assessment of crime risk and prevention.

To delineate the context within which personal crimes occurred based on the geography available in the crime survey data, the current analysis examines only the incidents occurring within a 15-minute walk of home and suffered by respondents who had not moved home in the previous year. The sample size is hence lower than the original BCS sample. The percentage frequencies and tests for probability differences between the complete and the 'non-moving, within 15-minutes' walk incidents' distributions of personal crimes are given in Appendix B to check for potential sample selection bias (Xie and McDowall, 2008). The two distributions are effectively identical and, therefore, the restrictions do not compromise the analysis in the sense that the probability of a given number of victimizations is similar for those always victimized near home to that of the sample as a whole. Nonetheless, it is acknowledged that the details of victimizations are likely to be different for home-near and home-distant victimizations (Nilsson and Estrada, 2007).

Results

Reference and representative individuals

The reader is reminded that the central purpose of this article is to establish the effects of area and individual characteristics, alone and in interaction, on the rate at which people fall victim to personal crime. The pattern of results is represented in Table 3. Four models in total are presented in Table 3: Model 1 includes fixed individual and household effects and a random intercept; Model 2 is augmented with routine activities/lifestyle effects; in Model 3 area effects are added; and Model 4 includes significant (cross-cluster) interactions of the above.

The intercept, which is given in the first row of figures of Table 3, is the expected mean number of personal crimes by the 'base' person, as described below.[10] To appreciate the association of the chosen variables with victimization, benchmarks are required, with the attributes just described representing the chosen (arbitrary) benchmark. This allows not only comparison of an area–individual combination with the benchmark person, but also the comparison of any individual–area combination with any other, as set out below. Thus the *reference individual* is a 51-year-old married female without children in her household, living in an occupier-owned detached house for over 2 years on a household annual income of less than £30,000. She is expected to experience on average 0.012 personal crimes (calculated as

$$\hat{\mu}_0 = 0.012 = \exp(-3.012 - 0.028 \times 51)$$

from Model 1). This remains the same if this woman goes to pubs fewer than three times a week and to clubs less than once a week (Model 2). When area profiling is added to the model, we find that if she resides in a non-inner-city area of England and Wales with national average population density and poverty (–0.44 from Table 2), her personal victimization incidence rises to 0.014 (Model 3) and 0.019 if she lives in either a semi-detached or a detached house (Model 4). For increased rates associated with other housing types, please read on.

The detached house, as seen in Table 2, is not the most prevalent in England and Wales. For this reason, alternative calculations of the mean personal crimes for the sample's *representative individual* (i.e. with modal and mean characteristics) are provided in the first row of the additional estimates section of Table 3. The *reference* individual lives in a detached house. The *representative* individual lives in a semi-detached house. The expected mean personal crime victimization of the representative individual (0.019 for most models) is employed in calculating the ICC and the between-individual unexplained variance of personal crimes (last two rows of Table 3), discussed next.

To what extent is the number of personal crimes explained between areas and between individuals?

An arguably important contribution of this work lies in addressing this subsection's title via overcoming the ecological fallacy problem. To this end, the unexplained (by the models' covariates) between-area and between-individual variances of crimes and the ICC (see Eq. 4, Appendix A) are

Table 3. Multilevel negative binomial models with extra binomial variation of the number of personal crimes over individual, household and area characteristics.

	Model 1	Model 2	Model 3	Model 4
Fixed parameters $\exp(\hat{\beta}_q)$				
Intercept	0.05***	0.04***	0.05***	0.07***
Individual and household characteristics				
Male	1.07	1.02	1.02	–
Age	0.97***	0.98***	0.98***	0.98***
'Non-white'	0.46**	0.48**	0.36***	0.40***
Marital status (married)				
Single	1.87***	1.75***	1.72***	1.91***
Divorced	3.02***	2.86***	2.84***	2.45***
Widowed	1.98***	1.87**	1.89***	–
Children (under 16 years old) in the household	1.46**	1.52***	1.52***	1.37**
Three or more adults (16 years old or older) in the household	1.72***	1.64***	1.64***	1.51***
Lone parent	1.49*	1.52**	1.51**	–
Tenure (owners)				
Social renting	1.40**	1.45***	1.33**	1.42**
Private renting	1.39*	1.37**	1.34*	1.36*
Accommodation type (detached house)				
Semi-detached house	1.61***	1.59**	1.36*	–
Terraced house	1.98***	2.00***	1.62***	1.30**
Flat or maisonette or other	2.24***	2.25***	1.65**	1.37*
Over £30,000 annual household income	0.74*	0.74*	0.76*	0.72**
Non-classified by social class	0.16***	0.16***	0.17***	0.17***
Less than 2 years in the area	1.47**	1.49***	1.50**	1.51**
Deviance (degrees of freedom)	361.78*** (17)	337.16*** (17)	301.86*** (17)	237.80*** (13)
Lifestyle/routine activities indicators				
Going to pubs three or more times a week	–	1.59***	1.58***	–
Going to clubs once a week	–	1.45	1.48*	–
Deviance (degrees of freedom)	–	13.21*** (2)	13.27*** (2)	–
Area characteristics				
Inner city	–	–	0.62**	–
Poverty[a]	–	–	1.07***	1.06***
Population density	–	–	1.24***	1.33***
Deviance (degrees of freedom)	–	–	29.97*** (3)	28.62*** (2)
Interactions				
Divorced with children	–	–	–	1.68**
Going to pubs three or more times a week and having children	–	–	–	2.21***
Males going to clubs once a week	–	–	–	2.19***
Widowed and area population density	–	–	–	1.84**
Inner city and population density	–	–	–	0.73***
Deviance (degrees of freedom)	–	–	–	41.85*** (5)

(continued)

Table 3. (continued)

	Model 1	Model 2	Model 3	Model 4
		Random parameters, $\hat{\alpha}$, $\hat{\nu}$ and $\hat{\sigma}^2_{u0}$		
Between-individuals overdispersion parameters				
$\hat{\alpha}$ (standard deviation)	1.63*** (0.03)	1.58*** (0.03)	1.54*** (0.02)	1.44*** (0.02)
$\hat{\nu}$ (standard deviation)	3.96*** (0.46)	4.12*** (0.45)	4.17*** (0.42)	5.31*** (0.44)
Between-areas variance, $\hat{\sigma}^2_{u0}$ (standard deviation)	0.05 (0.12)	0.04 (0.12)	0.00 (0.00)	0.00 (0.00)
		Additional estimates for sample representative individual		
Mean personal crimes[b]	0.019	0.019	0.014	0.019
Between-individuals variance[b]	0.031	0.030	0.029	0.027
Intra-class correlation, ICC[b]	0.59	0.56	0.00	0.00

Models based on 15,774 cases.
Baseline model (standard deviations):

$$\ln \hat{\mu}_{ij} = \underset{(0.16)}{-1.29^{***}} + u_{0j} - \underset{(0.00)}{0.04^{***}}\, age_{ij}, \hat{\sigma}^2_{u0} = \underset{(0.14)}{0.26^{**}},$$

$$Var(\hat{Y}_{ij}) = \underset{(0.04)}{1.25^{***}}\hat{\mu}_{ij} + \frac{\hat{\mu}^2_{ij}}{\underset{(0.84)}{15.02^{***}}},$$

Baseline model's $\hat{\mu}_{ij}$, between-individuals variance and ICC for a 51-year-old individual: 0.036, 0.045 and 0.85, respectively.
***p-value < 0.01, **0.01 < p-value < 0.05, *0.05 < p-value < 0.10.
One-tail tests for variance parameters (Snijders and Bosker, 1999: 90–91).
[a]Aggregate factor calculated as (0.859 × percentage of lone-parent households) + (0.887 × percentage of households without car) – (0.758 × percentage of non-manual) – (0.877 × percentage of owner-occupied households) + (0.720 × mean number of persons per room) + (0.889 × percentage of households renting from local authorities).
[b]The sample representative individual is a 51-year-old married female without children in her household, living in an occupier-owned semi-detached house (or detached in Model 4) on household annual income of less than £30,000. She lives in the same non-inner-city area of England and Wales with national average population density and poverty for over 2 years. This woman goes to pubs and clubs less often than three times and once a week, respectively.

given in the last rows of Table 3 and refer to models with an increasing number of covariates (from Model 1 to Model 4).

A note below Table 3 gives the estimates of a model with just an intercept and the covariate of age (baseline model). This is used as a benchmark. If only the age of the potential victim is taken into account, then the mean number of personal crimes against any 51-year-old individual (sample's mean age) is 0.036. This estimate is not far off the observed mean of Table 1 and is remarkable. It means that, ignoring all other individual, lifestyle and area characteristics, personal crimes are highly correlated *within* areas, as the intra-class correlation (ICC, at sample's mean age) of 0.85 indicates. This supplements past evidence that personal crimes are considerably concentrated across areas of England and Wales (Kershaw and Tseloni, 2005; Trickett et al., 1992). But can area crime concentration be explained by population heterogeneity and area heterogeneity, at least insofar as they are adequately measured here? To anticipate, area crime concentration defined in these terms is *fully* attributable to (measured) population and area heterogeneity.

The between-area unexplained variance of personal crimes falls by 81 per cent from 0.26 to 0.05 as a result of incorporating individual and household attributes in the model, and by a further 2 per cent when lifestyle is added. This considerable reduction also renders between-area variance statistically non-significant (see fourth row from last of Table 3). The ICC falls by 31 per cent when estimating the effects of individual and household characteristics (down to 0.59 from 0.85), and by a further 5 per cent after including lifestyle features (0.56: see last row of Table 3). Finally, adding area characteristics *totally eliminates* both the unexplained between-area variance and the intraclass correlation of personal crimes. This suggests that the fraction of personal crimes variability that is due to area is actually one-third accounted for by dint of individuals' characteristics, the remaining two-thirds being attributable to the kind of area they live in. Therefore crime differences between areas originate primarily from the fact that vulnerable individuals are clustered in the same areas and to a lesser degree from area attributes.

This discussion addresses the first research question of this study and the ecological fallacy problem of the social disorganization theory mentioned in the Victimization theory section. The results suggest that social disorganization with regard to personal crimes refers mostly to the socio-demographic composition of the area population and less the areas' context. Resident individuals' socio-demographic and lifestyle characteristics, area poverty (a factor which encapsulates high proportions of lone-parent households, households without a car, social renters and crowded homes, alongside low proportions of non-manual and owner-occupied households) and high population density (away from inner cities, which are now desirable places to live) fully explain the area differences in personal crimes.

That said, the differences in rate of personal crimes *between individuals* are *not* fully explained by measured population and area heterogeneity and their interactions. Unmeasured personal characteristics remain important (see penultimate row of Table 3). Incorporating individual and household attributes other than age reduces the personal crime differences between individuals by 31 per cent. Two further reductions, by 3 per cent each, are due to lifestyle and area characteristics, respectively, while the interactions explain a final 7 per cent fall. The last model of Table 3 accounts for an overall 40 per cent drop in the unexplained variance between individuals compared to the baseline. Significant unexplained individual differences in personal crimes remain, perhaps due to omission of important factors from the current analysis (see Discussion section).

Individual predictors of personal crimes

The effects of individual characteristics and their statistical significance do not change materially across the four models of Table 3 except for accommodation type and some interaction parameters. The following paragraphs discuss the parameters of Model 4, but refer to the other models where this is informative. This study shows that males are not different from females with respect to suffering personal crime except when they adopt a certain lifestyle (see later discussion on interaction effects). Indeed, the individual coefficient for males is effectively zero, implying that men and women experience similar numbers of personal victimizations, although these may be of different crime types. Age has a negative linear[11] effect on the (natural) logarithm of mean personal crimes. Growing older reduces the mean number of personal crimes by 2 per cent per year. Black or Asian people experience 60 per cent fewer personal crimes per head than do 'whites'. Both gender and ethnicity results seem inconsistent with theory and are revisited in the Discussion section.

Single (by 91%) and divorced (by 245%) people experience more personal crimes than those who are married, while the individual effect of widowhood in Models 1 to 3 (roughly 90% more crimes) is conditioned by population density (see the subsection on Interacting predictors). Having children in the household also raises the mean number of personal crimes by 37 per cent. Lone parents experience about 50 per cent (Models 1 to 3) more personal victimizations than other parents. This is almost equivalent to the 'divorced with children'[12] interaction of Model 4. A similar effect (51%) is due to living in a 'three or more'-adult household compared to two-adult households. Therefore household composition is a significant predictor of personal crimes, as evidenced in previous research (Hope et al., 2001; Maxfield, 1987). Living in social rented housing or in privately rented accommodation increases personal crimes suffered by 42 per cent and 36 per cent, respectively, relative to owner-occupation. Living in terraced houses or flats is associated with 30 per cent or 37 per cent more personal crimes, respectively, than living in a detached or semi-detached house. Household income of £30,000 or more is associated with 28 per cent fewer personal crimes, which implies that affluence is a protective factor. New residents in an area suffer 51 per cent more personal victimization than do residents of longer standing, as seen in past analyses.

These results support opportunity-based theoretical explanations. Affluence, flagged by high income, home ownership and living in a detached or semi-detached house, clearly is a protective factor against personal crimes. This is perhaps so because people can afford to live in 'nicer' neighbourhoods and stable communities away from potential offenders. Being married but not living with children may also proxy (relative) affluence and distance from potential offenders, as well as informal guardianship between partners. The considerable risk factor of being divorced may be due to victimization by a former partner, but this is not tested explicitly here. Therefore, foregoing associations are *theoretically* justified by differential crime exposure either via socializing away from safe environments or living in proximity to offenders. Why people who cannot be classified by social class experience 83 per cent fewer crimes remains a mystery. Frequent (three or more) pub visits per week and going weekly to clubs increases the number of personal crimes suffered by about 58 per cent and 48 per cent, respectively (Models 2 and 3) but, as Model 4 reveals, these are risky activities for only some population sub-groups. The issue is discussed below in the subsection on Interacting predictors.

Area predictors of personal crimes

Area characteristics individually associated with personal crimes are poverty and population density. A unit increase in the poverty index raises the number of personal crimes suffered by 6 per cent. People living in the worst area according to the poverty index face nearly four times more personal crimes than those residing in the best such area (2.34 against 0.65 or for the representative individual 0.044 against 0.012). These estimates are calculated for identical personal, household and other area characteristics and lifestyle. In practice, these two population groups are arguably of different socio-economic mix and, therefore, their personal victimization gap would be further accentuated.

The number of personal crimes increases by 33 per cent with a one standard deviation rise in an area's population density. Thus residents of the sample's most densely populated area face five times more personal crimes than those in the sample's least crowded area (4.15 vs 0.78 or 0.079 vs 0.015 for the representative individual). This is so for identical individual attributes and lifestyle of resident populations except for the widowed or inner-city dwellers (see next subsection). It should be noted that there may well be areas in England and Wales outside the 2000 BCS sample with more extreme population density or poverty index values at both ends than those entailed in the above calculations. If so, the area disparities of personal crimes would be even greater.

Interacting predictors of personal crimes

The results described to this point detail the individual effects of personal, household, area and lifestyle risk factors on the number of personal crimes. In addition to these (and for lone-parent, inner-city living and lifestyle/routine activities instead of these) a number of significant interaction effects exist which, to the writers' knowledge, have not been reported in the previous literature. They include individual-factor–cross-cluster (individuals within areas) interactions – see the last set of fixed parameters in Model 4, Table 3. To ease interpretation, Table 4 presents the number of personal crimes against individuals with all plausible combinations of interacting characteristics and otherwise representative attributes. The figures in bold incorporate the interaction effects, whereas the rest (in regular font) give the simple product of the respective individual effects, as discussed in the last section.

In interaction, divorced people with children experience 68 per cent more personal crimes than others over and above their increased crime incidence due to (a) being divorced and (b) living with children. In total, therefore, they are faced with over five times more personal crimes than are married people without children, and twice more than divorced people without children (Table 4). Thus, a 51-year-old divorced woman living with children but otherwise having reference characteristics has a mean rate of 0.11. In reality divorced women with children are likely to be much younger and have additional individual and contextual risk factors, such as residence in social rented housing. This (or any other plausible combination) can be calculated from the figures in Table 3. Our 51-year-old divorced woman living with children but otherwise having reference characteristics has a mean rate of 0.11, which should be multiplied by 1.42 (see Table 3) to yield 0.15. Further, if she visits pubs more than three times a week then her expected mean victimization is $0.15 \times 2.21 = 0.33$. In addition to marital status, lifestyle accentuates personal victimization for parents living with children: going to pubs three or more times per week increases personal crimes suffered by 121 per cent, resulting in three times more incidents than for non-parents who are frequent pub-goers (Table 4).

The second interaction with respect to lifestyle is that males who go to clubs at least once a week thereby roughly double (119%, Tables 3 and 4) their personal victimization rate. Because clubs serve alcohol later than pubs' closing times, this interaction arguably reflects exposure to heavy alcohol consumption in public places. Otherwise men do not experience more personal crimes than women.

The models evidence two cross-cluster interactions between individual- and area-level predictors. Widowed people are more vulnerable than married people when they live in areas of higher population density: for instance, they experience 145 per cent more personal crimes in areas with one standard deviation population density above the national average. Table 4 gives the mean personal crimes for individuals of differing marital status, who live in the lowest and highest population density areas of the 2000 BCS sample (last two columns of Table 4). The widowed, who are the marital status group least victimized by personal crime in low-density areas (0.009), are faced with almost two personal crimes per year (1.7 from Table 4) in the most densely populated areas (assuming otherwise sample representative characteristics). Their extreme vulnerability in such areas remains, even if the plausible age difference between them and other marital status groups is factored in. For instance, a 71-year-old widowed person living in the highest population density

Table 4. Estimated mean number of personal crimes accounting for interaction effects (in bold) of marital status, lifestyle and area type with children in the household, male and area population density for an individual with otherwise sample representative characteristics[a].

	Living with children	Not living with children	Male	Area population density	
				Minimum	Maximum
Marital status					
Single	0.050	0.036	–	0.029	0.151
Married	0.026	0.019	–	0.015	0.079
Divorced	**0.108**	0.047	–	0.037	0.194
Widowed	0.026	0.019	–	**0.009**	**1.738**
Lifestyle					
Going to pubs three or more times a week	**0.058**	0.019	–	–	–
Going to pubs less often than three times a week	0.026	0.019	–	–	–
Going to clubs once a week	–	–	**0.042**	–	–
Going to clubs less often than once a week	–	–	0.019	–	–
Area type					
Inner city	–	–	–	**0.020**	**0.016**
Non-inner city	–	–	–	0.015	0.079

[a]A 51-year-old individual, living in an occupier-owned semi-detached house (or detached in Model 4) on household annual income of less than £30,000. She lives in the same area of England and Wales with national average poverty for over 2 years.

area is expected to experience, on average, one personal crime per year (1.08). By contrast, a 21-year-old single person living in the same area is faced with about a third of the older person's expected number of personal crimes (0.31). Both calculations assume otherwise representative characteristics. Figure 1 gives the predicted mean personal crimes over areas' population density for married (the reference group) and widowed people (based on Model 4 of Table 3)[13] and illustrates the exponential increase of personal crimes against the latter in crowded residential areas.

The second cross-cluster interaction refers to inner city by population density[14] and offsets the latter individual coefficient: residents of inner cities with population density one standard deviation above the national mean experience effectively similar numbers of personal crimes as non-inner-city residents of less densely populated areas with otherwise identical characteristics. For population densities higher than one standard deviation from the national mean, inner-city residents face falling numbers of personal crimes compared to their clones in non-inner-city areas. In the most densely populated areas inner-city residents face less than a quarter of personal crime per head than do others (see Table 4). This is also illustrated in Figure 2, which displays the density effect for inner cities and other area types on the predicted mean personal crimes. The differences are not particularly large, but they are worth mentioning, as this result at first glance may seem at odds with victimization theory, but an attempt to explain it is given below.

Discussion

The aim of this work was to model the entire distribution of personal crimes, accounting for individual clustering within areas. The justification lies in the practical implications for the resourcing of crime reduction in ways proportional to presenting risk. This is not possible when consideration

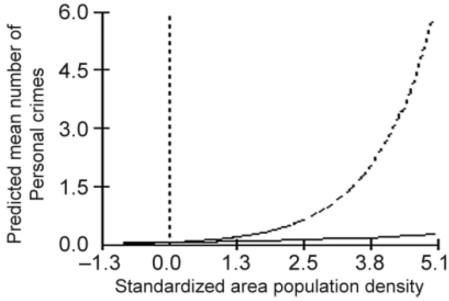

Figure 1. Predicted personal crimes for widows and others across area population density.

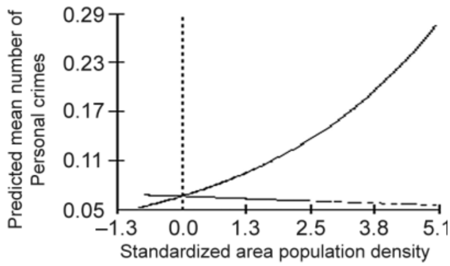

Figure 2. Predicted personal crimes for inner-city residents and others across area population density.

is restricted to crime prevalence. The article revisits the population and area heterogeneity of personal crimes in the light of systematic crime concentration and non-randomness of successive events,[15] which has been evidenced in previous studies, and the clustering of individuals within areas. To this end, it examined the number of such crimes over lifestyle/routine activities and social disorganization constructs via multilevel negative binomial specification. Previous research seems to have overstated the role of area in personal crime disparities across England and Wales. This study provided information on such non-spurious area gaps and distinguished them from individual differences in experiencing personal crimes. The conditional (i.e. population subgroup-specific) area crime concentration, *not* due to measured heterogeneity, was implicated in the intra-class correlation (ICC) estimates. Incidentally, the ICC calculation for the negative binomial specification with extra binomial variation, i.e. Eq. (4) in Appendix A of this article, has not been formally articulated to date. It is arguably an incidental contribution of the study reported here.

The main findings are as follows: the frequency of personal crimes is predicted by individual and area attributes, as well as conditioned routine activities, i.e. those routine activities which are contingent on the possession of a personal characteristic, e.g. parenthood. Although some unexplained heterogeneity between individuals remains, the measured factors *fully* account for the area clustering of personal crimes in England and Wales. The area differences in personal crime rates predominantly reflect variations in aggregate *measured* differences between individuals and to a lesser extent *measured* area characteristics, such as poverty and population density. Individuals with similar personal crime vulnerability are geographically concentrated in the same neighbourhoods. The current study offers new evidence that the area variability of personal crimes is thereby fully explained in England and Wales. Previous research in Sweden is consistent with the position taken here. It showed that large area violent victimization differences are the result of selection processes, namely segregation of vulnerable individuals in the same areas (Nilsson and Estrada, 2007). By contrast, significant *unexplained* variation of violent victimization risks has been evidenced in Seattle, although the area clustering of such risks, i.e. the ICC statistic, is not readily available (Rountree et al., 1994: 404). Further tests are required to settle this issue, including perhaps re-analysing the Seattle data with respect to violent victimization counts instead of risk, examining exactly the same crime types, and/or employing comparable sets of predictors across studies.

The results of this work partly support the assertions of lifestyle/routine activities theory: for instance, divorced people, especially those with children, and single people experience more personal crimes than do other groups because of higher exposure. Social disorganization theory is supported with respect to material deprivation and population density in England and Wales. For instance, personal crime rates vary by a factor of 5 between the least and most densely populated areas. By contrast, ethnic diversity, residential mobility and the proportion of young people in the population – a proxy for potential offenders – are not related to personal crimes. In addition, individual predictors *are* conditioned by context, as Rountree et al. (1994) contended. The study's findings, which deserve some emphasis here, are those that provide new or undigested evidence on population and area heterogeneity. First, routine activities are *not* associated with personal crime suffered independently of individuals' socio-demographic attributes. Men experience more personal crimes reported to the survey than do women, insofar as they are frequent club-goers, but going to pubs three or more times per week is risky only for parents living with children. Lifestyle qualifying interactions, but for different activities, have been evidenced in previous research. Therefore, the link of outgoing lifestyle with personal crime victimization depends on the *type* and *frequency of activity* as well as the specific *socio-demographic group* that adopts it. Second, evidence of a protective 'non-white' ethnic background effect (negative association) on personal crimes is provided in the current work. Empirical findings with respect to similar or lower vulnerability of ethnic minorities compared to 'whites' has consistently challenged the lifestyle theory's contention (and lay views) that being of ethnic minority origin is linked to high levels of personal victimization. In addition to previous published results (see Previous findings section), recent BCS-based analyses evidenced that Muslims and Hindus have a lower victimization risk than Christians, and immigrants experience less violence and similar personal theft risk than people born in the UK when area and other individual characteristics are controlled for (Hargreaves, 2012; Papadopoulos, 2012). Therefore the inconsistency of empirical findings with theory is easily explained by the fact that ethnicity is confounded with other socio-economic characteristics and area of residence. In their absence from analyses their effects are mediated through ethnicity (Clancy et al., 2001).

The third novel finding concerns the extreme vulnerability with which widowhood within densely populated areas is associated. If replicated, this is of particular policy concern, especially given the current demographic trends, pressures on pension funds and issues with elderly care homes.[16] Conversely, the vulnerability of inner-city residents *falls* as population density *rises*. Inner-city residence was not associated at all with personal crimes in analyses of an earlier BCS sweep. The inner-city 'protective' status in respect of personal crimes, especially in crowded residential areas, is explained on the basis of increased guardianship. Perhaps as a response to the crime problems of the 1980s, inner cities underwent substantial regeneration and land-use diversification (mixing private housing, leisure activities and retail shopping), which incorporated target hardening and adoption of new security technologies (Smith et al., 2002). Within inner cities, crime opportunities may have become limited by formal and informal guardianship, such as, respectively, private security and passers-by or overlooking neighbours.

The study's results, if replicated, can inform a *graded* crime prevention approach for allocating resources to the most vulnerable individuals within the highest crime-problem areas. Previous and present work have identified material deprivation and high population density as the area predictors of high crime rates. Within such areas few (rather than the majority of) individuals experience a disproportionate number of crimes. Individuals with a constellation of demographic and socio-economic characteristics associated with frequent victimization deserve to be prioritized. This points to a graded or indeed 'multilevel' or 'hierarchical' crime prevention approach of protecting vulnerable individuals residing in high-crime areas.[17] This work implies that the considerable gaps in area personal crime rates would narrow if crime prevention policies are deployed in poor and densely populated areas. Further, focusing efforts on protecting vulnerable residents (as implicated via population heterogeneity estimates), rather than spread over all, would eliminate these gaps in a cost-effective way. This is arguably a promising approach for tackling crime, but expanding on it is outside the study's scope. The current analysis is a stepping stone for empirical work, which could inform the ranking of areas into deciles or quartiles of *expected* crime seriousness for subsequent deployment of the graded crime policy operational responses suggested above.

The current study, despite having contributed to theory-testing, methodology and policy, could be developed in a number of ways. Composite personal crimes may confound the effects of some predictors, such as gender, but examining individual personal crime types was not possible here owing to an insufficient number of incidents. Similarly, examining the relative victimization of specific 'non-white' ethnic categories was limited by the insufficient number of respondents. Previous work in the UK that examined this question across different ethnic groups relied on merged BCS sweeps across more than one year. A major predictive factor of victimization by personal crime is victimization history, namely crime experiences that occurred prior to the reference period. The effects of victimization history are exacerbated by outgoing lifestyle and vary widely according to area of residence. This study, however, overlooks victimization history because of the unavailability of data. The above are the main substantive limitations of the work. With regard to methodology, the large proportion of non-victims of personal crimes arguably indicates that the zero-inflated negative binomial (Wang, 2003) or the hurdle model (Mullahy, 1986) may provide better approximations than does the current specification. Neither statistical model yet includes covariance structure for the clustering of individuals within areas in software packages. Therefore, their employment cannot address the study's objectives. Finally, the 8-year gap between area measurements and victimization frequency may have contributed to finding only two significant area predictors. One way to address this would have been to aggregate individual responses to create contextual measures. However, relying on the survey data for both contextual and individual predictors of the same variables, for example household and area affluence, does not offer new information and therefore causes multicollinearity. Ideally, the analysis should have drawn on contemporaneous individual and contextual information from different data sources, such as the 2002/03 BCS, which recorded crimes that occurred from April 2001 to March 2002, and the 2001 Census or the 2012/13 Crime Survey for England and Wales (CSEW, the current title of the BCS) and the 2011 Census. At the time of writing this, however, the closest to the 2001 Census crime survey data with area identification is the 2008/09 CSEW, with a roughly similar time gap as in the data used here. The advantage of using the data set pre-merged by the survey contractors is that area is more finely defined by sampling points rather than Lower Super Output Areas (LSOAs), which is the lowest geography of the 2008/09 CSEW.

To conclude: area, individual, household and conditioned lifestyle attributes fully explain the considerable area differences in personal crimes and a substantial part (about 40%) of their variation between individuals. All remaining unexplained heterogeneity is between individuals. Adding victimization history and modelling the excess zeros as an initial binary selection process will arguably expand our understanding of personal crime victimization frequency.

Appendix A: Multilevel negative binomial specification over units of analysis at two levels – individuals clustered within areas

The mean number of personal crimes, μ_{ij} for the ith individual who resides in the jth area, is linked to individual and area covariates via the Poisson log link function with random parameters:

$$\begin{gathered}\ln \mu_{ij} = n_{ij} = X_{ij}\,\beta + u_{0j}\,z_{0ij}, \\ i = 1, \ldots, 15774;\ j = 1, \ldots, 905, [u_{0j}] \sim \mathrm{N}(0, \sigma^2_{u0})\end{gathered} \tag{1}$$

where X_{ij} is a row vector of covariates for the ijth individual including the intercept; β is a vector of coefficients or fixed parameters including the intercept, β_0; z_{0ij} is the random part of the intercept; and u_{0j} is the random departure for the jth area which follows the Gaussian theoretical distribution with variance σ^2_{u0}.

The multilevel negative binomial model is obtained if the expected number of personal crimes varies randomly between individuals (i.e. level 1 units) as in Eq. (2) below:

$$\ln \mu_{ij} = n_{ij} + e_{ij} \tag{2}$$

where $\exp(e_{ij})$ follows a Gamma probability distribution (Cameron and Trivedi, 1986). Assuming extra binomial variation, one version of the negative binomial model is obtained (Cameron and Trivedi, 1986), where the respective mean and variance of the number of personal crimes (Y_{ij}) for the ijth individual are:

$$\mathrm{E}(Y_{ij}) = \mu_{ij} = \exp(n_{ij}) \text{ and } \mathrm{var}(Y_{ij}) = \alpha\mu_{ij} + \mu^2_{ij}/\nu \tag{3}$$

where α and ν are positive scalars, ν/α^2 is the overdispersion of events and the reciprocal, α^2/ν, is the precision parameter. Owing to the cross-sectional nature of the BCS data, overdispersion here is due to unexplained heterogeneity (Heckman, 1981) between individuals with regard to the number of personal victimizations (rather than event dependence or spells) which the covariates of the model may explain.

The intra-class correlation, ICC (Snijders and Bosker, 1999), which depicts intra-group correlation, is instrumental for disentangling the individual and area influences on the number of personal crimes. It gives the correlation of personal crimes between two randomly selected individuals residing in the same randomly chosen area (Snijders and Bosker, 1999) and implies persistent area *unexplained* heterogeneity. In plain English, it estimates the extent to which personal crimes are clustered within areas. Allowing here for extra-binomial variation, the ICC of the multilevel negative binomial model with random intercept is given by

$$\rho = \frac{\sigma^2_{u0}}{\sigma^2_{u0} + \alpha\,\mu_{ij} + \mu^2_{ij}\,/\nu} \tag{4}$$

Because the model is non-linear (Eq. 1) and most explanatory variables are categorical, the mean, μ_{ij}, and variance of personal crimes, var(Y_{ij}), from Eq. (3) and the ICC from Eq. (4) are functions of the individual and area attributes included in the models. Therefore different predictors would give slightly different values of these measures.[18]

The modelling strategy is as follows: a saturated model was initially estimated with all individual, household, lifestyle and area attributes of Table 2 included. Only parameters with p-values of their respective χ^2_1 lower than 0.10 were retained (except for the coefficient of male).[19] To ease interpretation of the results the exponentials of the estimated coefficients, $\exp(\hat{\beta}_q)$, are given in Table 3 together with an indication of their respective statistical significance. These are based on Wald tests which are χ^2_1 distributed, i.e. with one degree of freedom. Deviance statistics, which are χ^2 distributed with appropriate degrees of freedom, are shown as indications of the joint statistical significance of each set of covariates (i.e. individual and household, lifestyle, area and their interactions). The p-values for random parameters have been corrected to account for one-tail tests (Snijders and Bosker, 1999: 90) as they can only take positive values (see Eqs 1 and 3).

$\text{Exp}(\hat{\beta}_q)$s give the multiplicative effect on the mean number of personal crimes due to the respective (categorical) attribute or a unit increase in the value of a quantitative characteristic, such as age. A unit increase in any area characteristic with the exception of poverty implies a one standard deviation increase. Therefore $\exp(\beta)$s greater than 1 indicate a positive association with personal crimes, and vice versa. Detailed explanation of the coefficient's interpretation is given elsewhere (Hilbe, 2011; Osborn and Tseloni, 1998).

Appendix B: Observed distributions of personal crimes for the complete 2000 BCS sample and this study's sample of 'non-moving and/or within 15-minutes' walk victimized' respondents

Personal crime	Frequency		
Count	With restrictions	Without restrictions	Z-value for p difference
0	96.9	96.7	0.24
1	2.3	2.3	0
2	0.5	0.5	0
3	0.2	0.2	0
4	0.1	0.1	0
5	0.1	0.1	0
6	0.0	0.0	–
7	0.0	0.0	–
8	0.0	0.0	–
9	0.0	0.0	–
10	0.0	0.0	–
11	0.0	0.0	–
Mean	0.05	0.05	
Standard deviation	0.32	0.39	
Number of cases	15,774	19,411	

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Notes

1. Within small sampling points selecting, successfully contacting and interviewing respondents who have been victimized, especially by low-volume crime types, such as personal crime, is not very likely. Therefore crime rate estimates for (small) sampling points are highly unreliable, yet they are used to classify an area into high or low crime. In light of the above, the best use of crime survey data for informing crime prevention is to rank areas into large enough groupings, such as quartiles, with respect to *estimated* (rather than observed) crime rates obtained from multilevel or hierarchical statistical modelling analysis (Lynn and Elliot, 2000).
2. Routine activities theory also explains how societal changes affect crime opportunities and therefore crime rates but it is not examined in the macro-perspective here.
3. The geographical outline of the 'area' or 'neighbourhood' is defined on the basis of electoral wards or postcode sectors in the UK, Census tracks in the US and Canada, as well as local authorities and other administrative jurisdictions.
4. The term 'macro' is employed here to denote area measures as a simple contrast to individual ones. It is acknowledged that the term commonly refers to national indicators, whereas area ones are 'meso', i.e. in between individual and national measures. Because the study focuses on a single-year single-country crime rate and therefore lacks the 'real macro' dimension, 'macro' is used here for simplicity.
5. A large body of research has employed police-recorded crimes to investigate the association between area characteristics and crime. It is, however, overlooked in this study because its focus is the incident rather than the potential victim owing to the nature of police records.
6. The 2000 BCS data are employed here due to being readily linked with area information from the 1991 Census for previous work at the request of the Home Office (Kershaw and Tseloni, 2005; Tseloni, 2006). The merging of the two data sets was carried out by the BCS contractors to safeguard data confidentiality. The 2001 Census was not available at the time. Even if it were it would not constitute an appropriate source of area explanatory factors of crime incidents that occurred 2 years earlier, in 1999.
7. Indian-subcontinent, Pakistani or Bangladeshi.
8. As in previous research, a number of area-level variables were strongly correlated and their individual inclusion would have resulted in multicollinearity (Osborn et al., 1992). The poverty index, which was obtained via principal components analysis (Varimax rotation), overcomes this problem. It is calculated as: ($0.859 \times$ percentage of lone-parent households) + ($0.887 \times$ percentage of households without car) – ($0.758 \times$ percentage of non-manual) – ($0.877 \times$ percentage of owner-occupied households) + ($0.720 \times$ mean number of persons per room) + ($0.889 \times$ percentage of households renting from local authorities). The values of the variables that compose the poverty index were standardized.
9. This has been a short-lived claim as, while writing this, a multilevel study on adolescents' violent victimization appeared (Maimon and Browning, 2012). It should also be noted that violence is included in the count of local victimization, which was modelled over individual and contextual characteristics of individuals clustered within Belgian municipalities (Pauwels and Hardyns, 2010).

10. The intercept summarizes the effects of all the reference or omitted categories of the included nominal variables on the mean number of personal crimes ignoring age of the individual and zero values for the included area Census characteristics. The latter, thanks to standardizing (see the Data and variables section), represent the national average (except for the poverty index) and are, therefore, intuitive. For a meaningful interpretation, however, any age between 16 and 99 years old should be assumed. Here the sample mean age of 51 years old (see Table 2) is used.
11. In preliminary analysis a non-linear age effect was fitted but it was not significant.
12. In preliminary analysis the interaction of single with children was not statistically significant.
13. The predictions differ from the figures of Table 4 because they ignore the effects of age and poverty which, as said, were set to sample representative values for the calculations of Table 4.
14. To clarify, both variables refer to area predictors, but, as they are measured at different levels, they arguably make up a cross-cluster interaction. Inner city is measured at level 1 from the BCS and population density at level 2 from the Census.
15. This work readily accounts for population heterogeneity because of the cross-sectional nature of the data. Having said this, the statistical specification employed allows calculation of the probability of any number of events without adding new information at each succession (Osborn and Tseloni, 1998).
16. Single-adult (mostly pensioner) households have been on the rise (by 73% between 1981 and 2008) and will continue to do so (Dorling, 2011). When coupling this with the current risks in pension schemes and problems with care homes providers (Bowers, 2011) it is likely that more single-pensioner households, who are arguably seen as easy targets, will be wedged in urban areas with high crime exposure.
17. As this and previous work suggest, however, it would be naïve to incorporate lifestyle factors in crime prevention policy before surveys are in a position to distinguish across a detailed set of activities and domains (Lynch, 1987) with large enough samples to warrant statistical reliability across these population subgroups.
18. The estimated models below have been obtained using the iterative generalized least squares (IGLS) estimation with first-order marginal quasi-likelihood (MQL) approximation via the software package MLwiN 2.22 (Rasbash et al., 2004). The 2000 BCS adult weight has not been applied because the work is concerned with model selection rather than crime level or trend estimates.
19. The coefficient of *male* is highly non-significant in the models without interactions but it has been retained because of the importance of gender for theory and previous research (Hindelang et al., 1978).

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