Fear of Crime, Perceived Disorders and Property Crime: A Multivariate Analysis at the Area-Level

by

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Abstract: *This work estimates associated models of areas' fear of crime, perceived disorders and property crime rates over area characteristics and region of England and Wales via multivariate (multilevel) modelling. This statistical model, which draws upon data from the 2000 British Crime Survey and the 1991 (U.K.) Census at the postcode sector-level, allows for the estimation of any interdependence among the three dependent variables. The study shows that the effects of area characteristics and region on fear of crime, disorders and property crime rates are not uniform. Roughly half of the between-areas covariance of property crime rates, fear of crime and perceived disorders is explained by the areas' characteristics and regional dummy variables. The estimated multivariate models of this work, apart from expanding theoretical knowledge, may assist crime prevention efforts via identifying the most efficient measure for a set of targets as well as any diffusion or displacement effects between crime reduction and public reassurance initiatives.*

1. INTRODUCTION

The relationship between crime rates and crime perceptions is not straightforward, while previous empirical research, fruitful as it may be, is far from conclusive (Jackson, 2004; for an overview see Hale, 1996). The consensus so far is that fear of crime relates to perceived economic, social and physical vulnerability, both local and individual, as well as public attitudes towards crime (Taylor and Hale, 1986; Jackson, 2004). Perceived disorders have been found to affect fear of crime via informal community cues on crime rates (i.e. Taylor and Hale, 1986; Spelman, 2004). Past victimisation more than doubles the odds ratio of perceiving high anti-social behaviour in one's neighbourhood (Wood, 2004) while it nearly doubles[1] the odds ratio of fear of crime (Hale et al., 1994; Tseloni, 2002).

In previous literature on fear of crime or disorders, crime rates or victimisation are an extra explanatory variable in single-equation models, while in its turn, fear has been used to explain perceived disorders (see, for instance, Spelman, 2004) and vice versa (Taylor and Hale, 1986). Thus each variable has in turn assumed the role of predictor in models of fear of crime or disorders. Since all three measures are endogenous, whereby they occur simultaneously and are affected by more or less the same area and individual characteristics, analysis of their relationship via single-equation modelling produces biased and inconsistent estimates (Judge et al., 1988).

This study attempts to estimate the interdependence of crime rates, fear of crime, and perceived incivilities or disorders at the area-level controlling for areas' demographic and socio-economic characteristics or regional idiosyncracy. It thus estimates the proportion of this interdependence which can be explained by the area's profile and region. To this end, multivariate (multilevel) models which draw upon social disorganisation theory (Shaw and McKay, 1942) are estimated. Multivariate or joint multilevel regression models which have just appeared in non-criminological social policy research, for instance, health (Griffiths et al., 2004), education (Yang et al., 2002) etc., are methodologically the next step to Professor's Pease long history of joint empirical work on victimisation (i.e., Tricket et al., 1992), with Ken's name legendarily coming last or not appearing at all on his insistence! Ken recently employed multilevel methodology to investigate "boosts" and "flags" of repeat personal crimes (Tseloni and Pease, 2004), and had he contributed to the present chapter, the social policy implications of the model below and its results (among other missed improvements) would have been more fully investigated. The following analysis is based on aggregate data at the postcode sector geographical unit, which represents "area" or "community" throughout this discussion (see Lynn and Elliot, [2000] for its appropriateness).

Social disorganisation theory asserts that crime is associated with community (in)efficacy (Shaw and McKay, 1942; Sampson and Groves, 1989). Its proponents contend that the ability of a community to supervise teenage peer groups, develop local friendship networks and stimulate residents' participation in local organisations depends on community characteristics. Social disorganisation and resulting crime and delinquency rates depend on the neighbourhood's *socio-economic status, residential mobility, ethnic heterogeneity, family disruption* and *urbanisation*. Social disorganisation theory could encompass fear of crime and perceived disorders, although it was primarily developed to explain crime rates. Theory on fear of crime has been empirically driven (Hale, 1996), while published research on perceived disorders or incivilities (an equivalent term used in the 80's) is sparse (see end note #22). From what little is known, socially disadvantaged communities tend to register high levels of perceived disorder (Budd and Sims, 2001). Their residents also register high levels of fear of crime, not only due to the areas' actual crime rates but also due to their economic and social vulnerability (Hale, 1996; Forum Européen pour la Sécurité Urbaine, 1996). Community demographic and socio-economic attributes make up the set of covariates of the later crime rates and perceptions models. Crime refers here to property or household crimes.

The effects of area characteristics and region on fear of crime, perceived disorders and property crime rates are *jointly* estimated here via multivariate (multilevel)[2] modelling (Goldstein, 1995; Snijders and Bosker, 1999). Multivariate multilevel (henceforth MvMl) models account for the (residual) covariance between the response or dependent variables (here, for instance, property crime rates and each crime perception, namely fear and disorders), which are taken from the same unit of analysis (in this case, postcode sector: see, Goldstein, 1995; Snijders and Bosker, 1999). Apart from estimating the between-response variables covariances, MvMl modelling produces more efficient estimates than single equation models of each response or dependent variable and more powerful statistical tests of the estimated fixed and random effects (Snijders and Bosker, 1999:200-201). It also allows for comparisons and joint significance tests of the fixed effects of the same explanatory variable on more than one response variable (Snijders and Bosker, 1999:200-201).

Two crime prevention uses of MvMl models of crime rates and perceptions are immediately apparent. First, crime policy initiatives informed by such models may focus on one or multiple targets by affecting the most influential predictor, respectively. This is because the models can inform on the relative importance of each area characteristic for each dependent variable – i.e. crime, fear of crime or disorder – as well as all three jointly. Resource allocation would be more efficient if it focuses on different area characteristics depending on whether there are single or multiple policy outcomes (see also concluding section). For instance, if poverty was greatly associated with crime rates but had little to do with fear of crime, whereas population density was significant for both targets, then policies which aim at reducing both fear of crime and crime rates would be most effective when resources are allocated according to population density. Given this fictitious empirical result and policy targeting, resource allocation based on poverty could only affect fear of crime via its (residual) covariance with crime rates but not in a direct manner. As long as each area characteristic displays similar direction of associations with all three dependent variables, the choice of policy "measure" affects its efficiency without unpredicted harm. Second, crime prevention or public reassurance initiatives informed by estimated MvMl models allow for the prediction of externalities or in criminological terminology displacement or diffusion effects (Pease, 1998). If the measure affects the set of response variables or target(s) with (same) opposite signs, the (latter) former effect would occur.[3] In the above example, use of poverty instead of population density, while affecting fear of crime at a minimum, did not increase it.

Imagine now that poverty was negatively associated with fear of crime. Then, even if fear of crime was not on the agenda, crime reduction policies based on areas' poverty would adversely affect fear of crime. In other words (uninformed) policies may reduce one social problem at the expense of intensifying another.

The models for crime rates and perceptions of this study are estimated over area characteristics and region with postcode sector being essentially the only unit of analysis. Regionally, England and Wales is divided into Wales and the nine Government Office Regions of England. Sampling points are nested within regions which identify a higher-level of aggregation beyond postcode sector. The number of regions, however, is not large enough to provide any significant "between-regions" random variation (Browne and Draper, 2000). Individual attributes which apart from area characteristics significantly affect victimisation, fear of crime and perceived disorders (see, for instance, Kennedy and Forde, 1990; Hale, 1996; Wood, 2004, respectively) could have offered a lower-level of analysis. They are however by design ignored in this study in order to facilitate area-level predictions and, consequently, crime prevention and/or public reassurance initiatives.

The next section presents the variables, responses and covariates, which are employed in this study. The statistical methodology and the results of the estimated MvMl models are given thereafter. A concluding section summarises the results in the light of their implications for theory and puts forward how they may assist crime prevention and public reassurance initiatives.

2. THE DATA

2.1. Fear of crime, perceived disorders and property crime

Property crime rates, fear and disorder measures are taken from the 2000 British Crime Survey (henceforth BCS, Hales et al., 2000) across 889 sample points,[4] the sample points being quarter postcode sectors.

Property crime rate is an aggregate count of burglaries (including attempts), thefts from property and thefts of or from vehicle. This crime type was selected for a number of reasons. Apart from vehicle crime, the area of its occurrence is known, and subsequently property crimes can be linked to area's profile (see below). They are also better explained by area characteristics (Kershaw and Tseloni, 2005), while they are just as distressing to the victims as personal crimes are (Norris et al., 1997). The incidence rate of an area's property crime is examined. "Incidence rates" are defined as the average number of crime incidents per household per calendar year. As the focus was on predicted average local area rates, respondents who moved during 1999 have been excluded from the analysis. Their experience of crime may well not reflect typical risk for the area they have moved to. Vehicle crime rates were calculated over vehicle owning households only. Again as the intention was to predict average *local* area risks, any incidents which happened outside 15-minute walks from respondent's home have been excluded.

Measures of fear of crime and disorder problems have been constructed from scoring BCS respondents' answers on questions on "worry about crime" and "problems in your area," respectively. In particular, the fear measure was based on six questions that ask respondents how worried they are about "having your home broken into and something stolen," "being mugged or robbed," "being raped," "being physically attacked by strangers," "being insulted or pestered by anyone, while in the street or any other public place," and "being subject to a physical attack because of your skin colour, ethnic origin or religion." A score is built up from responses to each question, with any "very worried" response adding 2 to the score, any "fairly worried" adding 1 to the score and other responses adding zero (these being "not very worried," "not at all worried" or "not applicable").

The disorder measure is based on answers to four questions that ask respondents how much of a problem are "teenagers hanging around in the street," "vandalism, graffiti or other deliberate damage to property," "people being attacked or harassed because of their race or colour" and "people using or dealing drugs." A score is built up with any "very big problem" response adding 3 to the score, a "fairly big problem" adds 2, a "not very big problem" adds 1 and "not a problem at all" adds zero following the standard Home Office (UK) coding (Budd and Sims, 2001). Apart from the first one, these disorders point to identifiable crime types. In theory they consist of "indirect victimisation," namely fear-inspiring impact of local crime which is spread via communication of victimless crimes or those suffered by others (Taylor and Hale, 1986).[5] In practice they relate to the crime-bordering types of anti-social behaviour as they are defined by the Home Office (2004). The last three lines of Table 2 in the results section below give some descriptive statistics of the empirical distributions of the dependent variables of this study.

While the following discussion appears to take property crime rates and measures of fear of crime at face value, the measurement issues of these constructs from survey data should not be overlooked (see for instance Farrall et al., 1997). Non-Response and response bias (including telescoping) may distort the level estimates of crime rates

(Schneider, 1981). It is also well known that surveys do not measure the true value of fear of crime (for instance, Jackson, 2004) while perceived disorders are just that, i.e., subjective. Intuitively one might argue that area-level aggregates such as the ones employed here would tend to cancel out over- and under-reporting across individuals within an area.

2.2. Area characteristics and region

The area characteristics are derived from the 1991 census.[6] The census variables have been rescaled by the BCS fieldwork contractor[7] with normalisation[8] and addition of a random term with 5% of the variance of the census variable, this being done to ensure respondent confidentiality.[9]

A large number of variables may be used to describe community context, and, not surprisingly, they often exhibit high levels of inter-correlation (Osborn et al., 1992). In particular, preliminary work (Tseloni, 2001) with the 1991 census indicated high correlations between variables, which could be thought of as measures of low socio-economic status. Bearing this in mind, an overall area "poverty factor"[10] has been constructed by aggregating the following variables: the percentage of lone parent households, the percentage of households without car, the mean number of persons per room, the percentage of households renting from local authority, the percentages of households with non-manual "head of household," and owner-occupied households. The individual components have been aggregated with the loadings which factor analysis via varimax rotation had indicated. The last two variables carry negative loadings.

The percentage of households in housing association accommodation, which is an additional indicator of low economic status, exhibits low correlation with the poverty factor, probably reflecting a wider spread of housing association properties, as compared to those owned by local authority, across both poor and affluent areas. Preliminary analysis also showed low correlation between the poverty factor and other area characteristics considered, these being: percentage Black households,[11] percentage Asian households,[12] percentage of the population aged 16-24 years, percentage single adult non-pensioner households, percentage of persons moved last year and population density. The simple bivariate correlations between these area characteristics are given in Table 1. The highest correlation is observed between the percentage of single-adult non-pensioner households and the percentage of persons who had moved last year (0.64) but, as will be seen in the next sub-section, this correlation is inconsequential to the final estimated models.

Table 1 about here

Apart from low socio-economic status, the area characteristics of this analysis act as proxies for the (social disorganisation) theoretical concepts of ethnic heterogeneity, residential mobility and urbanisation, while family disruption effects are entangled within those of low socio-economic status due to, as mentioned, the high correlation of the respective census variables. In particular, the percentage of Black and Asian households are constructs of ethnic heterogeneity. Residential mobility is indicated by the percentage of single adult non-pensioner households and persons who had moved in last year, while population density evidently measures urbanisation. The percentage of population aged

16-24 years old gives the teenage peer groups who may be unsupervised and subsequently may offend and/ or induce fear and clues of disorder to other citizens.

The seven individual area attributes discussed here, the poverty factor and nine regional dummy variables, i.e. taking value one for the respective region and zero otherwise, were included in the original regression models for each dependent variable. The regional dummy variables relate to Wales and the eight standard (English) Government Office Regions outside of Greater London. Greater London was chosen as the reference or base region whereupon each dummy's effect is contrasted with it.

3. ESTIMATED MODELS

3.1. Methodology

The statistical specification of the MvMl model is described by Goldstein (1995) and Snijders and Bosker (1999) and is repeated here after making it consistent with the study's empirical model.

Let z_{ij}, with $i=1\ ,2,\ 3$ and $j=1,\ 2,\ \ldots A$, where A is the total number of postcode sectors in the sample, denote (three) dummy variables, each indicating a response or dependent variable Y_{ij}, i.e., Y_{1j} indicates property crime rate, Y_{2j} fear of crime score, and Y_{3j} perceived disorder score; x_{kj}, with $k=1,\ 2,\ \ldots K$, represents K area-level covariates (in this case both area characteristics and regional dummy variables); u_{ij} is the between areas random part of the intercept; and β_{ki}, with $k=0,\ 1,\ \ldots K$ a set of coefficients including the intercept for the *i-th* response variable. The MvMl model, here with 2 levels, i.e., one for the response variable (i) and a second for the postcode sector (j), is formally written as follows:

$$Y_{ij} = \sum_{s=1}^{s=3} \beta_{0s} z_{sij} + \sum_{k=1}^{k=K} \sum_{s=1}^{s=3} \beta_{ks} z_{sij} x_{kj} + \sum_{s=1}^{s=3} u_{sj} z_{sij} \qquad (1)$$

$$z_{sij} \begin{cases} 1, s=i \\ 0, s\neq i \end{cases}, \ \mathrm{var}(u_{ij}) = \sigma_{ui}^2, \text{ and } \mathrm{cov}(u_{sj}\, u_{ij}) = \sigma_{usi} \text{ for } s\neq i$$

The dummy variable z_{ij} takes the value 1 when the data (on both response and covariates) refer to the dependent variable Y_{ij} and 0 when they do not. Effectively, z_{ij} values are such that only relevant terms are retained in any of the models. σ_{ui}^2 is the unexplained variance of the *i-th* response variable while σ_{usi} is the unexplained covariance between the *s-th* and *i-th* responses after accounting for the covariates' effects (here postcode-level characteristics and regional dummy variables).[13]

Table 2 presents the estimated area and regional effects on property crime rates, fear of crime and perceived disorders as well as the between-areas (unexplained) (co-) variation of the variables in question. The results have been obtained after application of the 2000 BCS weights.[14,15] In particular, Table 2 is divided in three parts: the first presents the estimated coefficients and (multi-parameter) Wald tests for respective groups of predictors as well as the estimated between-areas (unexplained) (co-) variation of the final MvMl models of property crime, fear of crime and perceived disorders; the second part gives a baseline multivariate model (see next sub-section) or the multivariate *empty* model (Snijders and Bosker, 1999, page 203); and the third, as mentioned in the section on the dependent variables, describes the observed distributions of the three variables of interest without the application of the BCS weights.

Each estimated fixed effect, namely coefficient, or between-areas variance or covariance, in Table 2 has an indication of its statistical significance. This is based on Wald tests, which are χ^2 distributed with one degree of freedom. Any predictor with a

Wald test p-value higher than 0.10 in each estimated model was excluded from them. Thus the percentage of single adult non-pensioner households has been dropped from the final models of (the first part of) Table 2.

Multi-parameter Wald tests, which are χ^2 distributed (Greene, 1997; Snijders and Bosker, 1999) with the appropriate degrees of freedom, test for the joint statistical significance of respective groups of predictors. Each set of covariates, i.e., area characteristics and regional dummy variables, is highly statistically significant in comparison with χ^2 distributions with 7 and 9 degrees of freedom, respectively, implying that both meso- (area) and macro- (region) characteristics are important for the prediction of areas' property crime, fear and perceived disorders. The relative importance of these sets of covariates for predicting each dependent variable as well as the relative importance of each covariate for the simultaneous prediction of areas' property crime, fear and disorders will be discussed in the sub-section on area and region effects below.

Table 2 about here

3.2. Property crime, fear and disorders: Communicated effects

How much property crime, fear of crime and perceived disorders relate to one another when other effects are ignored is given in a *baseline model*, whereby each dependent variable is regressed to a constant term with all predictors suppressed to zero. In the case of the MvMl specification this is also called *multivariate empty model* (Snijders and Bosker, 1999:203) and is presented in the middle part of Table 2. The constant term of the baseline model gives the mean predicted values of property crime incidence, fear and disorders (0.36, 3.16 and 3.84, respectively) for an area with nationally average characteristics. These are essentially equal to the 2000 BCS national average values (0.34, 3.00 and 3.61, respectively) for crime, fear and disorders with the small difference of 0.2 being possibly due to the application of the 2000 BCS weights (see also note d below Table 2). The multivariate empty model includes also estimates of the between areas variance matrix of each dependent variable. Property crime shows the highest between-areas variation, while fear of crime and disorders vary considerably less. The employment of area predictors and region reduces the between-areas unexplained variation of property crime and crime perceptions (see the estimated variances in the first part of Table 2).[16] Thus, areas of England and Wales experience very different property crime rates, while their perceptions of fear of crime and disorder are rather similar.

Does accounting for area characteristics and region reduce the (unexplained) covariance of crime rates and perceptions? This is answered in the affirmative. Comparing the final model with the empty (baseline) model there is considerable difference between the associated variance-covariance matrices, with the final model apparently accounting for roughly half the between-areas (unexplained) covariation of property crime, fear and disorders. The covariances of property crime with fear or disorders drop from 0.20 to 0.09 and 0.30 to 0.16, respectively, while that between fear and disorders declines from 1.96 to 0.93 (see Table 2). The remaining unexplained (co-) variation may be partly due to individual characteristics which by design are omitted from this analysis (see also introduction and concluding discussion).

The estimated bivariate correlations of the areas' property crime, fear and perceived disorders when no area characteristics or region are accounted for are 0.35 and 0.44 between crime and fear or disorders, respectively, and 0.62 between levels of fear and disorders[17] while the respective correlations from the final MvMl model are 0.23, 0.32 and 0.46. Thus roughly one-fourth of the between-areas correlation of levels of fear of crime and perceived disorders as well as property crime and disorders is due to the demographic and socio-economic characteristics of the areas and regional idiosyncracy. Areas' profile and region is also responsible for about one third of the between-areas correlation of property crime and fear of crime.[18]

3.3 Area effects

The constant term of the final MvMl models gives an estimate of what the property crime rate, fear of crime and level of disorders would be in an area located in Greater London (i.e., the region for which no dummy variable was created) that had also the national average area characteristics. The estimated mean value of property crime incidence (0.27) for such a hypothetical location is marginally lower than the 2000 BCS observed national property crime rates (0.34). By contrast, the estimates for fear and disorders (3.28 and 4.33, respectively) are higher than the respective observed national average levels from the 2000 BCS. These deviations are due to a Greater London effect.

Regional dummies are by far most relevant for predicting fear of crime, rather than property crime and disorders, with the respective Wald test values being 76.18, 33.45 and 26.17 with 9 degrees of freedom. Apart from the North West all regions have significantly lower levels of disorders, while most regions (i.e., North, Yorkshire/Humberside, East Anglia, South West and Wales) also show lower fear of crime than Greater London. By contrast, areas in the North West register significantly higher fear of crime while most regions have significantly higher property crime incidence rates than London.

Area characteristics are more important for the prediction of areas' levels of fear of crime and disorders than property crime (respective Wald values of 345.05, 283.42 and 181.51 with 7 d.f.). The most important predictor of property crime, fear and disorders *jointly* is Poverty (Wald test equal to 97.05 with 3 degrees of freedom). The estimated effect of a unit increase of Poverty on the dependent variables is 0.03, 0.13 and 0.17, respectively. The second most (jointly) significant area predictor is the percentage of Asian households (Wald test equal to 60.38 with 3 degrees of freedom) of which an additional standard deviation[19] increases fear of crime and disorders by 0.44 and 0.20, respectively, while it is inconsequential for property crime. The remaining area characteristics effects are given immediately below in descending order of their (joint) statistical significance.

A standard deviation increase of population density is estimated to boost property crime, fear and disorders by 0.10, 0.13 and 0.27, respectively. Similar increase of the percentage of persons moved last year is related to actually lower fear and disorders by 1.24 and 0.89, respectively, while it does not affect property crime. A standard deviation rise of the percentage of Black households reduces property crime by 0.05 but increases fear by 0.24, while it is essentially irrelevant for perceived disorders. An additional standard deviation of the percentage of population aged 16-24 years old raises property crime, fear and disorders by 0.12, 0.56 and 1.24,[20] respectively. The percentage of young population, despite being highly statistically significant, is the least important for the prediction of all the dependent variables (Wald statistic equal to 16.74 with three degrees of freedom).

4. DISCUSSION

In the preamble to this chapter the author intended to identify the interdependence of local (property) crime rates, fear of crime and perceived disorders, which is due to common area characteristics and region, via the multivariate multilevel statistical specification. In doing so more efficient estimates of area and region effects on crime rates and perceptions have been produced than via single-equation modelling of each dependent variable (Snijders and Bosker, 1999).

To summarise, this study evidences that area characteristics predict fear of crime and disorders better than property crime rates, which is in agreement with previous work (Kershaw and Tseloni, 2005). “The better prediction for fear and disorder may reflect less variable attitudes between individual respondents within similar areas’ compared to ‘their’ own ‘experience’ of crime (e.g., residents in an area may well tend to agree on the problems that afflict their area, but will not tend to have the same experience of crime)” (Kershaw and Tseloni, 2005:17). Previous research on property crime incidence alone shows that its between-households variability is 9.5 times greater than its between-areas variability (Tseloni, 2005). This being said, few area characteristics are important predictors of property crime.

Low socio-economic status and urbanisation (indicated in the models here via poverty and population density) significantly increase local property crime rates. Both effects are in broad agreement with theory (Shaw and McKay, 1942) and previous empirical research (Kennedy and Forde, 1990; Osborn et al., 1992; Osborn and Tseloni, 1998; Tseloni, 2006). This study's negative effect of an area's ethnic minority (via the percentage of Black households) on property crime contradicts the social disorganisation theory (Shaw and McKay, 1942) and also seems counter-intuitive. Nevertheless cumulative previous empirical research indicates this negative relationship between area's ethnic minority population and local or household property crime *rates* without, to the best of my knowledge, counter-evidence (with one exception).[21] In particular, Osborn et al. (1992) evidence that a standard deviation increase of ethnic minority households reduces area's property crime incidence by 0.18 when other area characteristics remain the same. A similar rise of the percentage of Asian households in an area reduces the mean number of resident households' property crimes by 0.12% (Osborn and Tseloni, 1998), while the mean number of burglaries and thefts drops by 0.10% due to an additional standard deviation of the percentage of Black households (Tseloni, 2006) under the assumption of identical household and other area characteristics.

Local crime perceptions are positively related to poverty, ethnic heterogeneity, urbanisation and the percentage of 16-24 years old, while areas with higher residential mobility actually register lower levels of fear of crime and perceived disorders in broad agreement with previous empirical work (see for instance Hale et al., 1994). This study's results on fear of crime confirm previous evidence that individuals' worries about victimisation are greatly influenced by perceived (here, economic and social) vulnerability and perceived (lack of) social cohesion or trust, and consequently they are partly expressions of concern for the community (see, for instance, Jackson, 2004; Spelman, 2004; Taylor and Hale, 1986). *The lack of an effect* of the percentage of single adult non-pensioner households on local levels of fear here or its negative effect on individuals' fear (Hale et al., 1994) further supports this conclusion. In light of the absence of previous research,[22] the above theoretical discussion also refers to perceived disorders. All the area characteristics of this study affect both crime perceptions in the same direction except for the percentage of Black households, which is essentially not related to disorders. The result that, apart from the North West, most regions register significantly higher property crime rates but lower crime perceptions than Greater London is arguably an additional indication that community concern is channelled through crime perceptions.

The main contributions of this work are:

- estimating the proportion of respective covariances and bivariate correlations of property crime, fear of crime and perceived disorders which is due to area characteristics and region; and,
- estimating the relative importance of each area characteristic for jointly predicting property crime, fear and disorders.

How can crime prevention initiatives benefit from this or methodologically similar work? Crime initiatives informed by estimated MvMl models may select the most influential area characteristic depending on whether they focus on one or multiple targets. For instance crime initiatives, which address only property crime, would employ their (usually limited) resources most efficiently if they allocate them across areas with high population density. If property crime is targeted *together with* fear of crime, concentrating on poverty would be most effective, according to the results of this study (ironically population density and poverty do not in reality operate as in the fictitious case given in the introductory section). Such a policy would further appease perceptions of disorders owing to diffusion of benefits. Were initiatives designed to tackle high levels of both crime perceptions apart from poverty, they should take into account the percentage of Asian households, the percentage of persons moved last year and the percentage of young population, in that order.

Most area characteristics, which have been used here, are associated with property crime and perceptions in the same direction, thus leading to diffusion of benefits of crime prevention or public reassurance initiatives, which readily address only one issue. According to the estimates of Table 2 above, displacement can only occur between property crime and fear if initiatives employ the percentage of Black households, which affects the two responses with opposite sign. Diffusion/displacement effects of crime prevention or public reassurance policies between more than one target, such as those discussed above, are due to the estimated associations of area characteristics with crime rates and perceptions. The estimated residual covariance between crime rates, fear of crime and perceived disorders invariably consists of an additional source of diffusion of benefits, especially between fear of crime and perceived disorders. Thus, considering both estimated direct effects of area characteristics on each response variable and indirect ones via the between-responses residual covariance, policies which by design are implemented to reduce one problem, i.e. crime rates or fear or disorders, would most likely reduce all three.

The results also show that there are regional differences in crime, fear of crime and disorder. For example, we see that compared to London, Yorkshire has an increased crime incidence rate, but on average the residents have less fear of crime and problems with perceived disorder. This demonstrates the importance of place and context in policy development; there is no “one size fits all” solution. For example, it could be advisable to change the relative balance of policy in Yorkshire to have a greater emphasis on actual crime prevention and less emphasis on fear reduction than in London.

Finally, the results raise an interesting debate about the initial motivations and pre-conceptions of practitioners. In the past, they may have had a hunch that their property crime scheme may also have an impact on fear of crime, or they may have incorrectly assumed a synergy between schemes where there was in fact a conflict, or they may have been in ignorance of any displacement or diffusion effects between crime reduction and problem perception reduction. Results of the type reported above, if disseminated, would give practitioners a chance to consider the possible knock-on effects of a scheme in a particular type of area before implementation. Hence implementation could be planned with these effects in mind. [23]

The estimated unexplained random variances and covariances of the models of this study entail the effects of individual characteristics, which by design have been left out of this analysis (see the introductory section). Employing MvMl modelling on individual victimisation, levels of fear and perceived disorders while accounting for, apart from area, individual characteristics and prior victimization experiences is the obvious extension of this research in order to estimate the proportion of the (so-far unexplained) covariance between crime rates and perceptions, which is due to individual characteristics and experiences. Finally, estimating any spatial autocorrelation via MvMl models of crime rates and perceptions could have completed the picture of displacement/diffusion effects in terms of crime prevention geography. Such an analysis however is not possible with the present data set, which conceals identification of postcode sectors to preserve statistical confidentiality.

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Table 1: Bivariate Correlations Between Area Characteristics

	Age 16-24	Blacks	Indian-Bangladesh-Pakistani	Movers	Population density	Housing association	Single adult non-pensioners	Poverty[a]
Age 16-24	1							
Blacks	0.285	1						
Indian-Bangladesh-Pakistani	0.351	0.468	1					
Movers	0.528	0.236	0.157	1				
Population density	0.311	0.576	0.402	0.316	1			
Housing association	0.299	0.291	0.278	0.314	0.378	1		
Single adult non-pensioners	0.474	0.437	0.295	0.642	0.566	0.460	1	
Poverty[a]	0.379	0.374	0.282	0.109	0.469	0.382	0.323	1

Note: All correlations are significant at p-value<=0.01 (two-tailed).

[a] Aggregate factor calculated as (0.859 percent lone parent households+0.887 percent households without car-0.758 nonmanual-0.877 percent owner occupied households+ 0.720 mean number of persons per room+0.889 percent households renting from LA).

Table 2: Area Effects on Property Crime Rate, Fear and Disorder from the 2000 British Crime Survey (Multivariate Multilevel Modelling)

Area Characteristics	Property Crime Incidence	Fear of Crime[a]	Perceived Disorders[b]	*Wald test (3 d.f.)*
	Estimated Fixed Effects			
Age 16-24	0.12*	0.56**	1.24***	16.74***
Blacks	-0.05**	0.24***	0.01	24.02***
Indian-Bangladesh-Pakistani	0.02	0.44***	0.20**	60.38***
Movers	0.03	-1.24***	-0.89**	29.62***
Population density	0.10***	0.13*	0.27***	36.20***
Housing association	-0.004	0.002	0.14$^{\#}$	3.88
Poverty[c]	0.03***	0.13***	0.17***	97.05***
Wald test of area effects (7 d.f.)	181.51***	345.05***	283.42***	-
<u>Regions</u>				
North	-0.03	-0.82***	-1.00***	16.23***
Yorkshire/Humberside	0.16***	-0.45**	-0.70**	23.90***
North West	0.18***	0.50**	-0.08	20.07***
East Midlands	0.11**	0.05	-0.72**	16.87***
West Midlands	0.07	0.14	-0.61**	13.04***
East Anglia	0.09	-0.60**	-0.90**	15.25***
South East	0.13***	-0.15	-0.37$^{\#\#}$	15.13***
South West	0.10**	-0.38*	-0.61**	13.49***
Wales	0.02	-0.88***	-0.84**	17.14***
Wald test of regional effects (9 d.f.)	33.45***	76.18***	26.17***	-
Total Wald test (16 d.f.)	222.83***	589.06***	415.22***	-
Constant	0.27***	3.28***	4.33***	-
	Between areas variance-covariance			
Property Crime Incidence	0.098***			
Fear of Crime	0.090***	1.618***		
Perceived Disorders	0.159***	0.932***	2.563***	
	BASELINE MODEL			
Constant	0.36***	3.16***	3.84***	
	Between areas variance-covariance			
Property Crime Incidence	0.123***			
Fear of Crime	0.201***	2.691***		
Perceived Disorders	0.301***	1.958***	3.760***	
	DESCRIPTION[d]			
Mean	0.34	3.00	3.61	
Min/ Max	0/ 18	0/ 12	0/ 12	
Standard Deviation	0.92	3.24	2.64	

Note: The 2000 British Crime Survey adult (for fear of crime and disorders) and household (for property crime incidence) weights have been applied to the data before multivariate multilevel regression analysis.

[a] Respondents who reported very and fairly worried enter the calculation of fear with loadings 2 and 1, respectively.

[b] Respondents who reported very, fairly and not a very big problem enter the calculation of disorder with loadings 3, 2 and 1, respectively.

[c] Aggregate factor calculated as (0.859 percent lone parent households+0.887 percent households without car-0.758 nonmanual-0.877 percent owner occupied households+ 0.720 mean number of persons per room+0.889 percent households renting from LA).

[d] The descriptive statistics refer to data without weights.

[*] 0.05 < p-value <= 0.10.
[**] 0.005 < p-value <= 0.05.
[***] p-value <= 0.005.

[#] It just misses the 0.10 critical value with X^2 =2.67 rather than 2.71.
[##] It just misses the 0.10 critical value with X^2 =2.38 rather than 2.71.

ENDNOTES

[1] To be precise, the respective effects are 86% and 89%. The term odds ratio refers to the ratio of two probabilities: the probability or likelihood of occurrence, in this instance of reporting fear of crime, over the probability of non-occurrence.

[2] The term "multilevel," which is equivalent to "hierarchical," modelling is employed here. The models of this study are pseudo- multilevel or pseudo- hierarchical (see also later endnote no. 12) because the units of analysis are not clustered into higher-level ones.

[3] Note that here we are discussing displacement or diffusion caused by policies affecting issues other than those directly targeted (for example, a crime prevention policy positively affecting fear of crime in the area) and not displacement as it is more traditionally defined in the criminological literature (e.g., Repetto, 1976).

[4] 16 sample points have been dropped from this analysis as they consisted of combined small postcode sectors for which census-based area characteristics could not be reliably ascribed.

[5] The remaining BCS questions on neighbourhood problems, which were excluded from this analysis, include perceiving rubbish/litter, rundown homes, noisy neighbours, abandoned cars and people sleeping rough. They allude to the theoretical concept of social vulnerability (Skogan and Maxfield, 1981), while according to anti-social behaviour classification they refer to "nuisances" rather than "criminal acts" (Home Office, 2004).

[6] Results for the 2001 Census were not available at the time the data file was constructed.

[7] The 2000 BCS fieldwork contractor was the National Centre for Social Research, with around half the interviews subcontracted to the Office for National Statistics.

[8] Values of each census variable were normalised by subtracting their mean and dividing by their standard deviation. A 5% error has also been added to ensure confidentiality.

[9] Linking the actual census variables to the data could allow the Home Office and others to infer the exact location of the postcode sectors used in sampling. This would contravene the National Centre for Social Research policy for safeguarding respondent confidentiality.

[10] One might question the use of the “poverty” factor, which is derived via principal component analysis of the correlated census variables, instead of direct application of any deprivation index. According to a BCS stratification analysis, which was carried out contemporarily to this study, census variables perform better than deprivation indices (Smith and Loyd, 2001). The use of deprivation indices in this analysis was also hindered because they relate to administrative geography.

[11] By Blacks we refer to African-Caribbeans.

[12] By Asians we refer to persons of Indian/Bangladesh/Pakistani ethnicity.

[13] The model of this analysis is not truly multilevel since apart from the pseudo level 1, which indicates the multivariate structure (i.e., the fact that more than one dependent variable exists) and has no random part (Snijders and Bosker 1999), there is only one unit of analysis, namely the postcode sector. The estimated MvMl models below have been obtained via the software package MLwiN (Goldstein et al., 1998).

[14] The 2000 BCS adult and household weights have been applied to crime rates, fear and disorder appropriately.

[15] All variables of this study were tested for Gaussian approximation. Indeed, the observed distribution of property crime rate from the 2000 BCS and area characteristics

from the 1991 Census are skewed. Power or logarithmic transformations (Marsh, 1988), which best improved its skewness and kurtosis, were applied to the original data. The so transformed data improved the linearity of the estimated model of property crime, which also produced fewer outliers compared to the model based on the original crime variable. By contrast, the overall explanatory power and predicted distribution was not affected. To simplify the interpretation of the results the models discussed here employ the original data after application of the BCS weights. The estimated model of property crimes, which employs transformed data, can be made available to interested readers upon request.

[16] The respective coefficients of (unexplained) variation for property crime, fear of crime and disorders before and after area-level effects are 0.97, 0.52 and 0.50 (calculated as $[(\sqrt{0.12})/0.36]$) $[(\sqrt{2.69})/3.16]$ and $[(\sqrt{3.76})/3.84]$, respectively) and 1.16, 0.39 and 0.37 (respective calculations: $[(\sqrt{0.10})/0.27]$, $[(\sqrt{1.62})/3.28]$ and $[(\sqrt{2.56})/4.33]$) respectively. The coefficient of (unexplained) variation from the final MvMl model of property crime is surprisingly higher than that from the model without covariates. This can possibly be justified by that most regions have higher estimated property crime rates than Greater London under the assumption of similar area characteristics (see next section).

[17] The bivariate correlations between the response variables, i.e., property crime and fear, property crime and disorders, and fear and disorders are calculated from the baseline model as $[0.20/(\sqrt{0.12}\sqrt{2.69})]$, $[0.30/(\sqrt{0.12}\sqrt{3.76})]$, and $[1.96/(\sqrt{3.76}\sqrt{2.69})]$, respectively. Not surprisingly, the estimated correlations from the multivariate empty model equal the respective simple bivariate correlations from the 2000 BCS.

[18] In particular, area characteristics and region reduce the (unexplained) correlation between areas' property crime and levels of fear or perceived disorders by 34% and 28%, respectively, and that between areas' fear of crime and perceived disorders by 26%.

[19] A unit of any census variable actually represents one standard deviation since their values are standardised (see above end note #7).

[20] The high estimated effect of the percentage of population 16-24 years old on perceived disorders is not surprising since the latter entails "teenagers hanging around in the street."

[21] Kershaw and Tseloni (2005), who evidence a positive effect of the percentage of Asian (as well as a *negative* effect of the percentage of Black) households on local property crime rates, is the only exception. Since they employ the same data set as here in a single-equation framework this (partial) inconsistency may be due to different methodology.

[22] The only published work on perceived disorders to date is at the individual level by Wood (2004), who employs the 2003/04 BCS. Kershaw and Tseloni (2005), who employ the same data set as here, do not offer independent confirmation to this research evidence.

[23] This is at least how we see the policy implications of this work presently. Since Ken Pease who is a perpetual source of crime prevention ideas has – at the time of writing – yet to see this analysis, this discussion is only tentative.