MULTILEVEL MODELLING OF THE NUMBER OF PROPERTY CRIMES: HOUSEHOLD AND AREA EFFECTS

Andromachi Tseloni [1]

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[1] Associate Professor, Department of International & European Economic & Political Studies, Macedonian University, Egnatia 156, PO Box 1591 54006 Thessaloniki, Greece. Tel. +30-310-891 402, Fax +30-310-891 285. E-mail: **atseloni@uom.gr**

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Abstract:

This study examines household and area effects on the incidence of total property crimes and burglaries and thefts. It uses data from the 2000 British Crime Survey and the 1991 Census Small Area Statistics. Results are obtained from estimated random effects multilevel models, with an assumed negative binomial distribution of the dependent variable. Both household and area characteristics, as well as selected interactions, explain a significant portion of the variation in property crimes. There are also a large number of significant between area random variances and covariances of household characteristics. The estimated fixed and random effects may assist in advancing victimisation theory. The methods have potential for developing a better understanding of factors that give rise to crime and so assist in framing crime prevention policy.

1. PREVIOUS RESEARCH EVIDENCE

The British Crime Survey (BCS) has been widely used for testing victimisation theories and their relative validity (for instance, Trickett *et al*., 1995) as well as unravelling the dynamics of repeat victimisation (Osborn *et al*., 1996). A review of the BCS-based literature on modelling crime risks and crime incidence is given by Tseloni *et al*. (2002). Their study illustrates how crime models can be used to inform policy on crime prevention.

Three important lessons have been learnt to date from modelling crime using the BCS (and to a less extent other crime surveys). First, both individual and area characteristics are important predictors of crime (e.g. Kennedy and Forde, 1990). 'Indeed the factors at these different levels can have counteracting influences' (Tseloni *et al*., 2002, page 92). Both seemingly competing strands of victimisation theory, routine activity (Cohen and Felson, 1979; Felson, 1998) and social disorganization (Shaw and McKay, 1942) are thus empirically valid. Most previous research which tested the relative importance of individual household and area effects on victimisation is based on earlier sweeps of the BCS and the England and Wales Census (for an overview see Tseloni *et al*., 2002). Other studies employed local US data (from Seattle) and the US Census (for instance, Miethe and McDowall, 1993) while Kennedy and Forde (1990) employed the Canadian Victimisation Survey and the Canadian Census. With the exception of Osborn and Tseloni (1998), the entire body of this research models prevalence (i.e. risk of becoming a victim) whereas it ignores crime concentration (i.e. the number of crimes per victim). This issue is revisited in the paragraph after next.

The second result established by victimisation research is that victimisation history is among the most important predictors of subsequent events even after having accounted for individual and area factors (e.g. Ellingworth *et al*., 1997). This effect holds within and across crime types and places prior victimisation alongside routine activity and social disorganization theories as important explanations of crime. Recent evidence however suggests that prior victimisation acts as a proxy for high initial victimisation risks (heterogeneity), which are not otherwise captured by the explanatory variables used in the model (Tseloni and Pease, 2003). Should all individual, household and area characteristics related to the victim be known and accounted for in empirical victimisation models victimisation history may have had little or no predictive power.

The third result, which recurs in a number of studies, is that crime appears to be randomly distributed over households within low crime areas, but it is disproportionately concentrated on a relatively small number of households when the area crime rate is high. Thus, high crime areas are distinguished by higher concentration (i.e. levels of repeat victimisation) than would be expected were crime randomly distributed (see Tseloni *et al*., 2002 page 91). Repeat victimisation manifests itself at differing levels of seriousness across all crime types (for an overview see Pease, 1998) cross-nationally (Farrell and Bouloukos, 2001). The modelling of the victim/non-victim dichotomy, which has been the standard practice in empirical research until recently, ignores repeat victimisation. The higher the observed crime rates the more the predicted victimisation risks from modelling the victim/non-victim dichotomy exceed the observed risks (Osborn and Tseloni, 1998). Modelling the entire distribution of crimes rather than simply the risk of being a victim can account for the crime concentration (Osborn and Tseloni, 1998) evidenced in a number of descriptive or ethnographic studies (for an overview see Pease, 1998). The negative binomial regression model which follows a compound Poisson distribution (McCullagh and Nelder, 1989) allows for this non-randomness of victimisation events (Tseloni, 1995).

Two possible explanations of repeat victimisation appear in the literature, event dependency and 'unexplained' or 'unobserved' heterogeneity (Pease, 1998). 'Event dependency implies that initial victimisation itself leads to a higher probability of a subsequent event. Unobserved heterogeneity arises when two households with identical characteristics and living in the same area face different crime risks due to factors about which we have no information' (Tseloni *et al*., 2002 page 94). Such factors could include lifestyle with reference to households or individuals whereas heterogeneity between areas may be affected by local differences in the social cohesiveness of neighbourhoods or differences in the numbers of active local offenders. Prior victimisation effects, pseudo as they may be (see Tseloni and Pease, 2003), are compatible with event dependency across reference periods. In any event, non-randomness based on cross-section data such as the BCS explicitly depicts unexplained heterogeneity (Heckman, 1981). The term 'unexplained', which is taken here as equivalent to 'unobserved' heterogeneity, is preferred henceforth, since, while the negative binomial model cannot assign it to any particular factor(s), it does capture it.

2. THE CURRENT STUDY

This study models the number of property crimes over household and area characteristics, which according to routine activity and social disorganization theories, respectively, affect crime, via multilevel negative binomial regression models with full contextual random effects. Relevant previous research evidenced few significant interactions between individual and contextual effects (for instance, Miethe and McDowall, 1993; Rountree *et al*., 1994). Interacting household and area characteristics in this study are twofold: interactions between fixed effects, which add to the 'explained' heterogeneity between households with regard to the number of the property crimes they experience, and via between-areas covariances of the random part of the model, which shed some light on their 'unexplained' heterogeneity. It thus aims to improve our understanding of the processes which lead to repeat property victimisation, by estimating and interpreting any random effects of known individual and/or contextual crime covariates beyond household, area and their interactions' fixed effects. In addition these interactions have not been evidenced to date. Crime prevention focussed on repeat victimisation has enjoyed some success in decreasing crime rates in general (Forrester *et al*., 1990). It is of obvious policy interest to examine possible interactions of the factors which predict repeat victimisation, whether their effects vary across areas and, if so, how.

This paper therefore extends previous property victimisation research in a threefold way. First, it takes into account the clustering of households within areas via the multilevel statistical specification (Goldstein, 1995) while modelling the entire distribution of events via the negative binomial regression model (Cameron and Trivedi, 1986; Tseloni, 2000), i.e. accounting for crime concentration. The multilevel negative binomial regression model allows for the estimation of any remaining unexplained heterogeneity between units at each level, i.e. between households or between areas, above the variation of property crimes which household and area characteristics and their interactions can explain. Second, this paper sheds some light on this unexplained heterogeneity by estimating between-areas random effects (variances and covariances).

In particular, random covariances of household characteristics depict area interactions of the respective effects on household crimes whereas covariances of variables at different levels differentiate the effect of the covariate household factor across different areas with respect to the covariate area characteristic (Goldstein, 1995). Estimating and interpreting such random covariances is novel and, as mentioned, when applied to the entire crime distribution, it may expand our understanding of repeat victimisation. Both aforementioned contributions of the current study are methodological with important substantive implications, the latter stemming from the former. Third, the current analysis reveals significant interactions not evidenced in the previous literature which may assist crime prevention policies.

Previous research using the multilevel negative binomial regression focuses on individual and household effects on personal victimisation (for instance, Tseloni and Pease 2004) or burglaries across Europe with households clustered within country (Tseloni and Farrell, 2002). Therefore, their substantive results are not comparable to the current study. The pioneer hierarchical studies by Rountree and colleagues modelled the victim/non-victim dichotomy and omitted covariance parameters from the random parts of the models (Rountree *et al*., 1994; Rountree and Land, 1996). Instead, cross-level fixed interaction terms were estimated (Rountree *et al*., 1994 page 403). Fixed interaction effects however are not necessarily statistical alternatives to random covariances, each depicting a different source of the variation of the dependent variable. Indeed both may apply in a model as this study shows below.

The empirical distributions of property crimes and relevant household characteristics for this study have been taken from the 2000 BCS (Hales *et al*., 2000) with a total of 16,086 households (sample size lower than the full BCS sample for reasons given in the next section) across 905 sampling points, the sampling points being quarter postcode sectors. The area characteristics come from the 1991 Census Small Area Statistics after standardization and addition of a 5% error variance by the BCS fieldwork contractor, the National Centre for Social Research (around half the interviews subcontracted to the Office for National Statistics) to ensure confidentiality.

The next section discusses the observed distribution of household crimes and is followed by an overview of victimisation theories and the development of measurable theoretically informed explanatory variables. Thereafter the statistical model employed in this study is shown. Following the presentation of the results of the analysis the final section discusses them in the light of their theory and policy implications.

3. PROPERTY CRIMES

Two types of property crime are investigated in this study, *total household crimes* and residential *burglaries and thefts* (including theft of pedal cycles). Total household crimes comprise *burglary* (including attempts) in a dwelling or non-connected garage/outhouse, *household theft* in a dwelling or from a meter or from outside dwelling (excluding milk bottles), *vehicle theft* (including attempts) of or from car/van, motorbike, motor-scooter or moped, theft of pedal cycle, *arson*, and *criminal damage* (motor vehicle, home or other). Burglaries and thefts include all household crimes, except any motor-vehicle crime and criminal damage. A separate analysis for burglaries & thefts was thought necessary since they entail a high rate of repeats (Tseloni and Pease, 2005) and they have been the subject of many crime prevention interventions in recent years in England and Wales (Kodz and Pease, 2003). Crime rates calculated from the BCS Victim Forms are truncated at 5 events where a series of related victimisation events are reported, this being standard practice in collating results from the BCS (see page 111, Kershaw *et al*., 2000) to avoid very atypical households, with very large numbers of series victimisations, distorting overall averages. An incident is classified as the most serious crime type that occurred during its course (Hales *et al*., 2000, Appendix G).

This study investigates property crimes relating to the current dwelling; this is to ensure that the area characteristics used as predictors relate to the place where the crime(s) took place. Households which have moved during the 2000 BCS reference period (the 1999 calendar year) are therefore excluded from the analysis. For similar reasons only crimes, which took place within a 15 minutes walk distance from victim's home, are included. Research in the US has shown that the decision to move may be related to property crime (including personal theft) victimisation (Dugan, 1999). Preliminary analysis of the 2000 BCS, which compared the full and the 'non-moving, within 15 minutes walk' distributions of total household crimes and burglaries & thefts that are examined here support this US-based evidence only for motor vehicle crimes and/or criminal damages. Therefore the distribution of burglaries & thefts would appear not to be biased due to the exclusion of movers, whereas that of total household crimes is. The Appendix presents significance tests for probability differences between the full and the 'non-moving, within 15 minutes walk' distributions of burglaries & thefts and total household crimes. The 2000 BCS sampled on average 18 'non-moving' households per sampling point with a minimum of 4 and a maximum of 29 households.

Table 1 presents the observed frequency distributions of total household crimes and burglaries & thefts as well as three commonly used indicators of repeat victimisation for each crime aggregate (Tseloni and Pease, 2005). An estimated 20.2% of households were victimised at least once during 1999 with there being close to three crimes per ten households. Indeed 34% of victimised households were repeat victims and 62% of total household crimes were repeats. Each victimised household suffered on average 1.75 crimes during the year. The estimated risk of being a victim at least once of burglary or theft was 10.2%, with 23% risk of repeat victimisation and 1.47 burglaries & thefts per victimised household. 46% of all burglaries & thefts were repeats during 1999. Given the extent of repeat property victimisation modelling the entire distribution rather than the victim/non-victim dichotomy is more appropriate.

The incidence of property crimes is more variable than would be expected if these crimes occurred randomly, with variance exceeding the mean for both distributions. While such overdispersion could potentially be explained by covariates, the negative binomial regression model for counts appears appropriate for their modelling, given this higher than random variability and the high crime concentration and rate of repeat victimisation.

Table 1 about here

4. VICTIMISATION THEORY AND VARIABLE SELECTION

Two main theories of why people become victims of crime exist, lifestyle or routine activity theory (Hindelang *et al*., 1978; Cohen and Felson, 1979; Felson, 1998) and social disorganization theory (Shaw and McKay, 1942). Lifestyle theory operates at the individual level and, while routine activity theory has both micro and macro strains, this analysis stems from its micro version (Cohen *et al*., 1981). Proponents of this theory argue that *at the micro level* the demographic and socio-economic characteristics of individuals and their households, as well as their lifestyle patterns and everyday routine activities, together determine their exposure to crime.

With respect to household crime, they do so by influencing households' chances of attracting motivated offenders in the absence of effective guardians. While lifestyle affects households' exposure to criminal victimisation opportunities via *guardianship* (or lack thereof), the effects of demographic and socio-economic characteristics are mediated through *proximity*. Insofar as households share vicinity with potential offenders, they face increased risk of household crime. From an offender's perspective, personal and household characteristics and lifestyles contribute to determining target *suitability, accessibility* and *desirability* (Miethe and Meier, 1990). Suitability or inertia with respect to property crime refers to the size and weight of valuable goods (Felson and Clarke, 1998). Small goods are more easily removed from a property than bulky ones (Cohen and Felson, 1979; Felson, 1998), but this last factor has been left out from the empirical models below due to lack of data.

Guardianship, i.e. the ability of persons to prevent crime from occurring, can be social (interpersonal) or physical (Meier and Miethe, 1993; Garofalo and Clark, 1992; Rountree and Land, 1996). Social guardianship includes household composition, house occupancy and length of residence in the same area. The longer properties are occupied and the longer people have lived in an area, establishing friendship networks, the more likely it would be that they experience lower victimisation risks. Physical guardianship involves the use of self-protection measures, such as burglar alarm, special door locks etc., and participation in collective activities of crime prevention such as neighbourhood watch (Meier and Miethe, 1993).

Proximity to potential offenders refers to the physical distance between potential targets and populations of potential offenders (Meier and Miethe, 1993). Here type of area and perceived poverty proxy this concept. Type of accommodation indicates accessibility. For instance, flats in a building with guarded entrance are less accessible than a cottage without any special locks or bars in the windows etc. Accessibility is positively related to household crime (Bennett and Wright, 1984). Desirability refers to the (objective or subjective) value of the crime target (Meier and Miethe, 1993). The greater its economic or symbolic value, i.e. its perceived attractiveness, the higher the risk of victimisation (Miethe and Meier, 1990). Tenure, annual household income, social class and number of cars in the models below indicate desirability. Finally age of the 'head of household' is included. Victimisation risks decrease with age and this finding is consistent across crime types, times and countries (Tseloni *et al*., 2002).

In contrast to these micro-level theories, social disorganization theory (Shaw and McKay, 1942; Sampson and Groves, 1989) asserts that crime is determined primarily by community attributes. They 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 disorganization and resulting crime and delinquency rates depend on the neighbourhood's *socio-economic status, residential mobility, ethnic heterogeneity, family disruption* and *urbanisation*. Such community attributes offer the macro-level dimensions of victimisation models.

A large number of variables may be used to describe community context, and not surprisingly, they often exhibit high levels of correlation. Indeed previous work with the 1991 Census (Kershaw and Tseloni, 2005) evidenced high correlations between variables, which could be thought of as measures of community low socio-economic status. To avoid the problem of multicollinearity which might have appeared due to the inclusion of correlated variables an overall poverty factor was constructed by aggregating the percent of lone parent households, households without car, the mean number of persons per room, the percent of households renting from Local Authority, households with non-manual ‘head of household’, and owner occupied households. Percent of households in housing association accommodation also indicates low economic status, but exhibits a low correlation with the Poverty factor.

Other area characteristics may affect residents’ victimisation according to the social disorganization theory and previous empirical evidence (Trickett *et al*., 1995). The percent of households renting privately and persons moved last year can be seen as measures of neighbourhood stability. Racial diversity is indicated by the percent of Black and Asian, namely Indian, Pakistani or Bangladeshi, in an area. Population density is the obvious measure of urbanisation while the percent of single adult non-pensioner households indicates lack of informal social control in a community. The population profile of a neighbourhood, more specifically the supply of potential offenders, has a proxy in the percent of the population aged between 16-24.

Apart from the Census variables we include two BCS-defined nominal variables, one for area type, classified as inner city, urban or rural, and another for region to capture omitted effects operating at a higher level of aggregation. In the models below area type is defined at the household level and region at the area level. Regionally, England and Wales is divided into Wales and the nine Government Office Regions of England. South East is used as the base category in modelling. Sampling points are nested within regions, which identify a third level of aggregation, beyond households and areas. The number of regions, however, is not large enough to provide any significant ‘between-regions’ random variation. Indeed a preliminary three level model (not reported here) provided essentially zero between regions (i.e. level 3) variance of the constant term. Four sampling points straddle pairs of adjacent regions. All households of these sampling points have been recoded to the region where the majority of respondents in the sample point resided. These sampling points could have been modeled using multiple membership models, but this is unlikely to make a difference given how few areas are involved and how little variation between regions exists.

Table 2 summarises the explanatory variables of property crimes. The household variables are all nominal, except for age of the 'head of household' which is an integer. Where more than two categories are used the reference category is indicated as the 'base' in Table 2 or given in parentheses after the variable name in the later tables of the empirical results. Age of the 'head of household' and area characteristics are described in Table 2 by their sample mean value and standard deviation ('SD' in parentheses). The sample mean of the (standardized) area characteristics differs slightly from zero due to the addition of a 5% error variance to ensure confidentiality.

Table 2 about here

5. STATISTICAL MODEL

Goldstein (1995) describes multilevel models for proportions, presenting models for counts only as an extension. We first define the multilevel Poisson model, and then derive the negative binomial model by compounding the Poisson with Gamma random effects.

Let μ_{ij} be the expected number of household victimisations, where i represents households and j areas. The log link function for the Poisson model with random effects is

$$ln\mu_{ij}=n_{ij}=X_{ij}\beta+\sum_{q=0}^{p}u_{qj}\,z_{qij}+\sum_{q=p+1}^{Q-1}u_{qj}\,z_{qj} \qquad i=1,...,I,\ j=1,...,J \qquad (1)$$

where $q=0, 1, \ldots, Q-1$, with Q being the total number of random coefficients in the model including the intercept. X_{ij} is a row vector of K ($K\geq Q$) household and area covariates for the ijth household, including the intercept and possible interactions. $z_{0ij}=1$. $z_{qij}=x_{qij}$, for $q=1, \ldots, p$, are the household characteristics with random effects for the ijth household. $Z_{qj}=x_{qj}$, for $q=p+1,p+2, \ldots, Q-1$, refer to the $Q-p-1$ area covariates with random effects for the jth area. $[u_{qj}]\sim N(0,\Omega_u)$ is the random departure from the jth area (Goldstein, 1995).

The probability distribution for Y_{ij} follows the Poisson. Thus the probability that Y_{ij} takes the specific value y_{ij} is

$$Pr(Y_{ij}=y_{ij})=\{exp(-\mu_{ij})\ \mu_{ij}^{y_{ij}}\}/\{y_{ij}!\}, \qquad y_{ij}=0,1,\ldots \qquad (2)$$

This model, where $E(Y_{ij})=var(Y_{ij})=\mu_{ij}$, is clearly not applicable here (see Table 1).

The negative binomial regression model allows for between households random variation in the expected number of (Poisson-distributed) events μ_{ij} in (2).

$$ln\lambda_{ij}=n_{ij}+e_{0ij} \qquad (3)$$

where $exp(e_{0ij})$ follows a gamma probability distribution $\Gamma(\nu)$, with $E\{exp(e_{0ij})\}=1$ and $var\{exp(e_{0ij})\}=\alpha=\nu^{-1}$ (Cameron and Trivedi, 1986). Integrating with respect to e_{0ij} the probability distribution which results from combining (3) and (2) we obtain one version of the multilevel negative binomial model (MNBM II), the multilevel extension of the negative binomial model Negbin II which was defined by Cameron and Trivedi (1986).

$$Pr(Y_{ij}=y_{ij})=\{\Gamma(y_{ij}+\nu)\,\nu^{\nu}\,\lambda_{ij}^{y_{ij}}\}/\{y_{ij}!\,\Gamma(\nu)(\nu+\lambda_{ij})^{\nu+y_{ij}}\}$$

$$y_{ij}=0,1,\ldots \qquad (4)$$

The MNBM II gives the same expected mean of households crimes as the multilevel Poisson above, $E(Y_{ij})= \lambda_{ij}=exp(n_{ij})$. Its variance, however, is given by

$$var(Y_{ij})= \lambda_{ij}+\alpha\,\lambda^2_{ij} \qquad (5)$$

allowing for overdispersion. Indeed the extra-Poisson variation at level-1 is defined by α (with $\alpha>0$) and λ^2_{ij}. α gives the coefficient of overdispersion and ν is the precision parameter (Cameron and Trivedi, 1986). Overdispersion in the models of this study explicitly measures population unexplained heterogeneity rather than event dependence due to the cross-section nature of the data (Heckman, 1981).

The estimated models below have been obtained using iterative generalized least squares (IGLS) estimation with first order marginal quasi-likelihood (MQL) approximation via the software package MLwiN (Goldstein *et al.*, 1998). The validity of MQL estimates is discussed in the last section of this paper.

6. RESULTS

6.1. General Remarks

A model with all household and area level attributes (listed in Table 2), was initially estimated for each crime type. Children in the household, length of residence at the address, house occupancy during weekday and any fire in the house during the previous year at the household level, as well as percent of adult non-pensioner households, percent Asian, percent population aged 16-24, percent households in housing association accommodation and percent persons moved last year at the area level had essentially zero effects with estimated coefficients lower than their corresponding standard errors. Therefore these variables have been dropped from the estimated models given in the later tables.

Six models are discussed in this paper, three for each dependent variable, i.e. total household crimes and burglaries & thefts. Model 1 consists of estimated fixed effects of household and area covariates. Fixed interaction effects, especially for regions, are added in Model 2. In particular, interactions of each region with each variable in Model 1 were tested. Similarly any plausible interaction of two variables, private renting and lone parent, which had shown very large between-areas random variances in earlier estimated models (not reported here), were progressively fitted. Those with Wald test p-values greater than 0.10 (χ^2 distributed with one degree of freedom) at the time of inclusion were dropped from Model 2. Model 3, the most comprehensive, includes estimated fixed and full (i.e. variances and covariances) random effects of household and area characteristics as well as significant fixed interaction effects. The estimated between-areas variance-covariance matrix of Model 3 was gradually built up by allowing contextual random effects for each explanatory variable in Model 2. Random effects with either zero variances and covariances, which imply that the estimated respective coefficients hold across areas, or standard errors greater than their respective random parameters were omitted from the random part of final Model 3.

Tables 3 and 4 give the results of Models 1 and 2 and the fixed part of Model 3 for total household crimes and burglaries & thefts, respectively. Wald tests for each set of covariates, i.e. household, area and their interactions, with their appropriate degrees of freedom are presented under the corresponding set of covariates. Each set of covariates, i.e. household, area, and their interactions, is highly statistically significant in comparison with χ^2 distributions with the respective degrees of freedom implying that these explanatory variables are important for the prediction of total household crimes and burglaries & thefts. Entries in Tables 3 and 4 are the exponent of the estimated coefficient [*exp*(*b*)] and each estimate has an indication of statistical significance. This is based on Wald tests, which are χ^2 distributed with one degree of freedom (Greene, 1997). Unlike the standard practice of employing age categories or a single age count a second order polynomial of age enters the models of the current study implying an inverse U-shaped effect of age on property victimisation incidence. Wald tests (χ^2, 2 d.f.) for both parameters of the age polynomial are presented in the row following their display in Tables 3 and 4. Finally, the estimated intercept (or constant), as well as the between-households, $\hat{a}$, and between-areas, $\hat{\sigma}^2_{u0}$, unexplained heterogeneity for each Model 1 and 2 with their respective standard errors in parentheses are also presented.

The random parameters and their standard errors for Model 3 for each dependent variable are presented later in Table 8. A baseline model with just the constant and its two random variances, $\hat{a}$ and $\hat{\sigma}^2_{u0}$, for each dependent variable is given as a benchmark at the end of this table. Wald tests for the between-areas variance and covariances relating to each variable with random effects as well as an overall Wald test for all random parameters in each model are given in Table 8. With the exception of one adult household for burglaries & thefts and social renting for total household crimes each presented set of random parameters is highly statistically significant. The p-values for random parameters have been corrected to account for one-tail tests (Snijders and Bosker, 1999, page 90).

Tables 3 and 4 about here

6.2. Reference Household

The constant term summarises the effects of all the reference categories of the included nominal variables on the expected mean number of household crimes assuming zero age of the ‘head of household’ and zero values for all the area Census characteristics. For a meaningful interpretation let the ‘head of’ the reference household be 53 years old, the sample mean age. Thus the ‘base’ two adult household of annual income between £10,000 and £29,999, that owns two cars, manages well on its income, is of professional social class and lives in a self-owned detached house in a rural South East area with sample mean characteristics but without neighbourhood watch, is expected to experience 0.34 total household crimes per calendar year [calculated as $exp(-1.2356+0.0188*53-0.0003*53^2)$, where –1.2356 is the Model 3 intercept of Table 3 and -0.0003 and 0.0188 the coefficients of the second order polynomial of age in the same model, i.e. the respective *ln(0.29), ln(0.9997)* and *ln(1.02)* from Table 3]. A similar household but without protection against intruders and regardless of car ownership is expected to experience 0.12 burglaries & thefts per calendar year [calculated as $exp(-1.9841+0.0076*53-0.0002*53^2)$ from Model 3 in Table 4, taking into account that the displayed numbers are the exponents of the respective values presented in the previous formula].

The mean number of property crimes for the reference household is lower than the respective population mean for each crime aggregate. The next section discusses the estimated fixed effects of household and area characteristics as deviations (in percentages) from the above predicted number of property crimes for the reference household.

6.3. Fixed Effects

The majority of the estimates of household and area influences on property victimisation (Tables 3 and 4) support the routine activity/lifestyle hypotheses and to a less extent the ones of social disorganization theory outlined earlier in this paper. The empirical evidence not in support of these theories includes three or more adults in the household, protection measures, and Greater London effects as well as the lack of an effect for house occupancy and a number of area characteristics, such as racial diversity, population mobility and the percentage of young adults. Tentative explanations of these discrepancies from theory are given in the following paragraphs of this section.

For each property crime aggregate, total household crimes and burglaries & thefts, most coefficient estimates are essentially identical across Models 1, 2 and 3. The following discussion focuses on Model 3, which is the most comprehensive, while notable discrepancies across the three models for each dependent variable are mentioned.

Age of the 'head of household' affects property crimes via a second order polynomial with the effect being more significant for total household crimes than burglaries & thefts. For instance the mean number of total household crimes and burglaries & thefts becomes (0.37, 0.29) and (0.13, 0.10) for 'head of' household aged 10 years either side of the mean age (43, 63, respectively). Households of three or more adults experience about 16% more crimes that otherwise identical two adult households. This contradicts the routine activity theory, according to which more adults should present higher guardianship in a household. It is possible however that this variable captures households of many cohabiting, usually young, adults rather than extended families. Such households may possess more goods attractive to burglars, be less security conscious and, subsequently, be a more attractive and profitable target.

Lone parent households suffer 62% more total household crimes and 290% more burglaries & thefts than households of otherwise identical characteristics. This striking (by far the highest) effect presumably represents lack of guardianship as well as social vulnerability not otherwise captured in the models. The very large lone parent effect on burglaries & thefts varies by socio-economic status (see section 6.4). Social renting increases household crimes by at least 40% compared to owner occupancy, possibly due to entangled effects of social vulnerability and/or proximity to potential offenders. An initial individual private renting effect (Model 1, Tables 3 and 4) was eliminated after allowing for interactions.

Other things being equal, annual household income of over £30,000 is associated with a 20% increase in household crime compared to £10,000-£29,999, which is consistent with the attractiveness hypothesis of the routine activity theory at the individual household level. Since other explanatory variables are part of the picture the most affluent will tend to live in types of area that reduce their crime risks (i.e. 'other things' tend not to be equal). This result is broadly in line with other research (Trickett *et al*., 1995) that indicated that the *most* affluent households in the poorest areas are at greatest risk of property victimisation and is revisited in the discussion section. Not managing well on the household’s income is associated with about 21% more property crimes. This arguably captures the higher victimisation of relatively poor households and agrees with previous European research evidenced on burglary (Tseloni and Farrell, 2002; Tseloni *et al*., 2004). Indeed, the majority of poor households, namely those under £5,000 or within the range of £5,000-£9,999, reported that they did not manage well on their income (77 and 65%, respectively) whereas only 15% of respondents in affluent households felt the same way.

Owning no car or just one car decreases total household crimes by 54% and 21%, respectively, compared to two cars, whereas households with three or more cars suffer 31% more such crimes. Exposure to risk and target attractiveness is the obvious explanation of these estimated effects. Apart from being profitable targets with various uses (Pease, 1998), cars are visible signs of affluence (Osborn and Tseloni, 1998; Tseloni, 2000). The absence of car ownership effects on burglary/theft victimisation implies that it is specifically linked to motor-vehicle crime and/or vandalism. Again, care needs to be taken in interpreting these results as they relate to comparisons where 'all other factors are equal', but in reality the average household and area characteristics of households with different numbers of cars will not be equal.

Households living in semi-detached houses or flats or maisonettes or other (henceforth flats etc.) experience 14% more total household crimes than otherwise identical households in detached houses, whereas those in terraced houses a 37% increase. Accommodation type is surprisingly unrelated to burglaries & thefts except via a lone parent living in flats etc. interaction. Previous research based on the 1992 BCS found that car ownership and terraced house were strongly related to all property crimes, i.e. burglary, theft and criminal damage, (Osborn and Tseloni, 1998). A possible explanation of this discrepancy is that these two variables in the Osborn and Tseloni models, which lacked a direct indication for household income, captured affluence at the individual level.

Neighbourhood watch in the area is associated with fewer household crimes by about 10% while protection measures are related to a 18% increase in burglaries &

thefts but do not significantly predict total household crimes. Both of these crime covariates have shown contradictory research evidence. For instance, Tseloni and colleagues (Tseloni *et al*., 2004; Tseloni and Farrel, 2002) found a positive relationship between security measures and burglary whereas Miethe and colleagues (Miethe and Meier, 1990; Miethe and McDowall, 1993) and Budd (1999) evidenced a negative one. One possible explanation lies in the construct itself. Research, which evidenced negative effects of protection measures on burglary, used either an ordered scale of measures (none, some, serious) or a binary for the most serious ones. By contrast, a positive relationship has been found between having any protection measures at all (as a binary variable) and burglary. Another possibility is that burglary and repeat burglary victims may have introduced prevention measures in the wake of burglary. Thus this positive relationship by no means reflects causation but mirrors the lack of an appropriate indicator, namely one that estimates the risk/rates of property crimes before and after the installation of protection measures, in cross-sectional data. Apart from burglary other property crime types are in theory unaffected by protection measures. Neighbourhood watch had no significant effect on property crimes drawn from the 1992 BCS (Osborn and Tseloni, 1998).

Households whose ‘heads’ cannot be classified to any social class experience roughly 90% fewer property crimes whereas manual classes experience just over 10% fewer crimes than professional households. The effect of ‘non-classified’ social class is hard to interpret without additional evidence.

Living in an urban area increases total household crimes by nearly 32% and burglaries & thefts by 16% while households living in the inner city experience about one and a half times these respective increases. This is due to proximity to potential offenders according to the micro version of the routine activity theory. From the social disorganization perspective, which explains crime at the (macro) community level, urbanization is an important mediating factor for high crime rates. The statistical significance of these estimates for burglaries & thefts is weakened due to the inclusion of contextual random effects. We now turn to discussion of the area level covariates in the estimated models of Tables 3 and 4.

Area effects on household crimes are considerably weaker and fewer than effects of household characteristics albeit overall highly statistically significant. This discrepancy is revisited in the final discussion section. When poverty increases by one standard deviation in an area total household crimes suffered by each household in the area would increase by 4% and burglaries & thefts by 7%. The mean number of property crimes increases by roughly 13% due to one standard deviation rise of the percent of households renting privately. Similar increase of the areas' population density affects total household crimes and burglaries & thefts by 34% and 12%, respectively. Indeed, according to the social disorganization theory poor areas with high density and turnover of population experience high crime rates. The effect of the percentage of Afro-Caribbean in an area on burglaries & thefts disappeared when fixed interactions entered Model 2.

Some regions of England and Wales do not differ statistically with reference to household crime victimisation when household and area characteristics are taken into account. Indeed only three regions have notably fewer property crimes than the base, South East. The predicted reductions in household crimes and burglaries & thefts, respectively, are 40% and 34% (North East), 17% and 23% (West Midlands) and 27% and 39% (Eastern). Again this result assumes national mean area characteristics and base household ones whereas in reality the area and household profiles of South East may generate low crime rates. Fixed interaction effects, which are discussed next, shed some light on property crime regional differences not otherwise accounted for in the estimated models as well as some conditioning of the private renting and lone parent effects.

6.4. Interaction Effects

Tables 5 to 7 give estimated (multiplicative) effects of interacting characteristics on property crimes. To ease comparisons each statistically significant category of each interacting nominal variable is presented while the base (multiplicative) effect which refers to a household 'with otherwise reference characteristics' is given as one. The expected number of property crimes experienced by a household with the respective characteristics in each cell of Tables 5 to 7 and 'otherwise reference characteristics' can be calculated by multiplying the figures in Tables 5 (Part A) and 6 by 0.34 and those in Tables 5 (Part B) and 7 by 0.12 (see section 6.2). Apart from the respective individual effects, bold figures of Tables 5 to 7 entail the respective interaction coefficient from Tables 3 and 4. Fixed interactions of regional variables (including cross-level ones) showed significant effects on property crimes. Apart from Greater London's population density, all interaction effects are particular to each crime aggregate, i.e. total household crime and burglaries & thefts. Their interpretation is summarised below.

Tables 5 to 7 about here

Crime-protective factors (such as 'no car' and manual social class) are even more so in the Greater London and North East regions while commonly crime-conducive characteristics (such as population density, percent households renting privately, social renting and terraced housing) operate in the opposite direction in these regions (Tables 3 to 5). Similarly, the poverty effect on burglaries and thefts is roughly outbalanced in South West. By contrast, manual social classes of this region or households in South West areas with above the national average population density experience the highest expected number of burglaries & thefts in England and Wales (Tables 4 and 5, Part B). Private renters who live in urban areas experience more total household crimes than in inner cities or rural areas (see Table 6). Lone parents who do not live in a house experience 7.5 more burglaries & thefts than other flats etc. residents and nearly twice as many as lone parents in houses. By contrast, lone parents of manual social class or medium-low (£5,000 - £9,999) or high (over £30,000) annual household income experience fewer burglaries & thefts than lone parents of professional class or other income groups (Tables 4 and 7). The next two sub-sections describe the random part of the estimated models of this study.

6.5. Unexplained Heterogeneity

As mentioned, the last three rows of Table 8 show the baseline model for each property crime aggregate. The exponent of the estimated intercept, which represents the mean number of property crimes when no additional information is known about the household, equals the respective mean of the observed crime distributions given in Table 1. $\hat{a}$ is the unexplained heterogeneity between households or coefficient of overdispersion and $\hat{\sigma}^2_{u0}$ the between-areas unexplained heterogeneity of property crimes without any crime covariates.

Table 8 about here

The between households or areas unexplained heterogeneity gradually decreases as the models account for household and area characteristics (baseline vis-a-vis Model 1), plus their interactions (Model 1 vis-a-vis Model 2), plus random variances and covariances (Model 2 vis-a-vis Model 3). Indeed the initial estimated between households unexplained heterogeneity, $\hat{a}$, eventually drops by roughly one quarter (from 3.80 to 2.65) for total household crimes whereas it more than halves (6.90 to 3.15) for burglaries & thefts (Table 8). There remains, however, significant between households unexplained heterogeneity after having accounted for household and area characteristics, their interactions as well as random contextual effects. This implies that household victimisation is influenced by a greater range of characteristics than those measured in the 2000 BCS and, subsequently, included in the empirical models. These unknown or unmeasured characteristics may include, for instance, lifestyle information other than 'hours house is empty during weekday', such as holiday routines and/or whether the house is left unoccupied before or after dark. The nature and upkeep of the dwellings' exterior condition and whether they are obscured from public view influence burglary victimisation (Winchester and Jackson, 1982; Cromwell *et al*., 1991). Prior victimisation, which is omitted from the models due to lack of such information in the 2000 BCS, arguably proxies some unexplained heterogeneity (Tseloni and Pease, 2003).

Ignoring for a moment the coefficient of overdispersion and the variance-covariance matrix of the full contextual random effects models in Table 8, the size of the between-areas estimated variance of the intercept**,** $\hat{\sigma}^2_{u0}$, of Model 2 (see Tables 3 and 4) indicates that the between-areas unexplained variation of property crimes is considerably lower than between households for each crime aggregate. This estimate may be used to calculate the difference in the crime rate between areas in the 2.5th and 97.5th centiles. After adjusting for household and area characteristics and their fixed interactions total household crime rates are about 6 times (*exp[(√0.20)x2x1.96]*) higher in a ‘high’ crime area compared to a ‘low’ crime area. Similarly the rate of burglaries & thefts is about 4 times (calculated as $exp[(\surd 0.15)x2x1.96]$) higher. Having ignored the coefficient of oversdispersion the above are under-estimates, therefore the between-areas unexplained heterogeneity is far from negligible.

The between-areas unexplained heterogeneity follows the structure given by the variance-covariance matrix of the estimated random components of Model 3 (see Table 8). Despite being far from conclusive (see the discussion section for caveats), these random effects offer helpful insights on such, otherwise unexplained, between-areas differences in household victimisation.

6.6. Estimated Between-Areas Random Coefficients

Between-areas random variances of household covariates may be used to estimate the lower and upper limits of the respective estimated mean effect given in Tables 3 or 4 (Snijders and Bosker, 1999). Their between-areas random covariances refer to the between-areas relationship of the respective estimated mean effects and ‘are analogous to’ interaction effects (Goldstein, 1995, page 52). The estimated variances of the models in Table 8 are moderate with there being considerable (in absolute value rather than relatively to its mean, see also the next discussion section) variance of the lone parent effect on burglaries & thefts.

Total household crimes for lone parent households, who otherwise have the reference characteristics, vary from 0.37 [calculated as $exp\{ln(1.62)-2*\surd(0.54)\}$] to 7.03 [$exp\{ln(1.62)+2*\surd(0.54)\}$] between areas at the 2.5^{th} and 97.5^{th} percentile of English and Welsh areas after having accounted for household and area characteristics. The mean number of crimes suffered by lone parents is 0.47 (i.e. $0.29*1.62$, ignoring age). The mean number of burglaries & thefts experienced by lone parent households is 0.51 ranging from 0.31 to 49.40 [calculated as $exp\{ln(3.90)-2*\sqrt{(1.61)}\}$ and $exp\{ln(3.90)+2*\sqrt{(1.61)}\}$, respectively] between the 2.5th and 97.5th percentile of English and Welsh areas. The negative intercept covariance of lone parent implies that in areas where the reference household experiences above average property crimes being a lone parent household tends to increase them below average and vice versa. The neighbourhood watch intercept covariance below is similarly interpreted. As with fixed effects, the estimates of this discussion refer to a household with base characteristics (see section 6.2) except for the variables under question.

Social renters experience from 0.64 to 3.32 total household crimes and from 0.23 to 8.50 burglaries & thefts in 95% of English and Welsh areas. Private renters experience between 0.21 and 6.42 burglaries & thefts. Private renting correlates significantly with lone parent. The negative covariance implies that in areas with above average private renting effect on burglaries & thefts lone parent households experience less than averagely higher crime rates and *vice versa*.

Households living in semi-detached houses experience between 0.61 and 2.16 crimes in 95% of the areas. The positive intercept covariance implies that in areas with above average total household crimes for the reference household those in semi-detached dwellings face also more than averagely higher crime rates compared to households in detached accommodation and *vice versa*. By contrast, in areas where semi-detached house dwellers face more than averagely higher crime rates compared to households in detached accommodation lone parent households experience less than average crime increases and *vice versa*. Total household crimes are between 0.21 and 6.17 for flat etc. dwellers in 95% of the areas of England and Wales. In areas where flat etc. dwellers face above 14% crime rise compared to detached house occupants lone parent households also experience above average (i.e. more than 62%)

crime increases and *vice versa* as implied in their positive covariance. By contrast, in areas where flat etc. dwellers face above average crime rise social renters experience below average (i.e. less than 46%) increase of total household crimes compared to owner occupiers and *vice versa*.

The neighbourhood watch variance parameter is negligible for total household crimes whereas it indicates that burglaries & thefts vary from 0.31 to 2.56 between 95% of the areas. Neighbourhood watch has positive covariance with lone parent for both crime aggregates, which may be interpreted as follows. In areas where lone parents experience above average crime increases compared to others, households with neighbourhood watch schemes are more than averagely protected against property crimes. Similarly in areas with more than average increases of total household crimes for flats etc. dwellers or of burglaries & thefts for social renters neighbourhood watch is more of a protective factor, exerting an above average effect. By contrast, where semi-detached dwellers experience above average total household crime rises compared to detached house dwellers neighbourhood watch decreases them less than averagely and *vice versa*.

The mean number of burglaries & thefts experienced by households with annual income under £5,000 varies between 0.21 and 6.11 in 95% of the English and Welsh areas. Its negative covariance with one adult household implies that in areas where the latter experience above average reductions of burglaries & thefts compared to two adult households very poor households experience below average such crime rises compared to those with £10,000-£29,999 annual income and *vice versa*. In areas with more than average rises of burglaries & thefts for private renters or reductions owing to neighbourhood watch schemes very poor households experience more than average increases of the same crimes compared to those with £10,000-£29,999 annual income and *vice versa*.

The negatively correlated effects of manual 'head of household' and private or social renting for burglaries & thefts imply that in areas with above average rise of such crimes for non-home owners households whose 'head' is of manual social class experience below average crime reduction, i.e. manual becomes less of a protective factor against burglaries & thefts and vice versa. In areas with above average one adult (negative) effect burglaries & thefts decrease more than average due to manual social class and vice versa. The manual social class effect shows negligible and statistically insignificant variance. The last section puts forward some theory and crime prevention implications of these empirical results.

7. DISCUSSION

This study has modelled the number of domestic property crimes over socio-economic characteristics of households and their areas of residence via a 2-level negative binomial regression model with random coefficients. The majority of the estimated individual effects support the micro level version of routine activity theory (Cohen and Felson, 1979; Cohen *et al*., 1981) and social disorganization theory at the macro level (Shaw and McKay, 1942). By far the highest association with property crimes is that of lone parents due to social vulnerability, as implicated by the negative interaction with annual income over £30,000, and lack of guardianship implicated by its flats etc. interaction on burglaries & thefts. These are in broad agreement with recent evidence from Sweden that single mothers experiencing high violent and threatening behaviour are also subject to welfare deficiencies such as health, education, financial situation, employment and social relations (Estrada and Nilsson, 2004). The second highest influence on property crimes comes from social renting possibly via social vulnerability and proximity to potential offenders. Offender ethnographic studies (for instance, Wiles and Costello, 2000) evidenced that they tend to pick up their targets in the course of their every day activities rather than outside their own environment (Cromwell *et al*., 1991). This also relates to the positive area poverty effect on property crimes. The contrasting effects of affluence at the household and area levels evidenced in the models for both crime aggregates, i.e. total household crimes and burglaries & thefts, are in line with other research (Trickett *et al*., 1995; Tseloni *et al*., 2002). ‘Richer people in poorer areas suffer property crime particularly heavily’ (Trickett *et al*., 1995, page 291). The most affluent will tend to live in types of area that reduce their crime risks. Burglaries in more affluent areas are likely to be the result of planned journeys rather than opportunities (Bowers and Johnson, 2002). The lowest effect is for households whose ‘head’ could not be classified in any social class.

Age of ‘head of household’ in the models affects property crimes, and particularly total household crimes, via a second order polynomial. Thus the number of total household crimes and burglaries & thefts rises with the age of the ‘head of household’ up to the ages of 31 and 45 years old, respectively, after which it starts declining. This pattern does not seem to have been evidenced before in victimisation research. Age to date has been fitted linearly demonstrating thus a (low) negative linear effect on victimisation (for instance, Trickett *et al*., 1995; Tseloni *et al*., 2004) or via age groups entering either as a limited number of integer values (for instance Miethe and McDowall, 1993) or a binary variable of ‘older’ groups versus ‘younger’ ones (Miethe *et al*., 1987). The lack of an effect for ‘hours the house is empty during weekdays’ may suggest either that this straightforward home un-occupancy measure is a weak construct of ‘physical guardianship’ or that ‘physical guardianship’ may be unrelated to victimisation when ‘social guardianship’ is accounted for.

At the area level type of area (inner city or urban) and population density are the strongest predictors of property crimes. The inner city effect has been recurring in a large number of empirical studies (for an overview see Tseloni *et al*., 2002). Surprisingly racial diversity, population mobility and the proportion of young adults in an area did not affect property crimes notwithstanding social disorganization assertions. Since the percentage of private rented housing proxies neighbourhood stability in the models population mobility may have been redundant. The lack of an effect of the proportion of young adults (16-24 years) on property crimes has also been evidenced in previous UK-based research, which analysed property crimes from the 1992 BCS with area characteristics from the 1991 Census (Ellingworth *et al*., 1997; Osborn and Tseloni, 1998; Hope *et al*., 2001). These studies revealed further that the population proportion of 5 to 15 years old significantly predicts property crimes and more so vandalism. Older studies based on the 1984 BCS and 1981 Census however had found that the area proportion of 16-24 year olds significantly increases property crime (Osborn *et al*., 1992; Trickett *et al*., 1995). Therefore it might be that the age of potential delinquents in England and Wales has dropped between 1981 and 1991.

Area racial diversity, to my knowledge, has not been found to be positively related with property crimes. In fact a number of studies (Osborn *et al*., 1992; Ellingworth *et al*., 1997; Osborn and Tseloni, 1998; Hope *et al*., 2001) evidenced a significant negative relationship between the proportion of households whose ‘head’ is of ‘Asian’ origin and property crimes, especially the number of criminal damages. Therefore the empirical evidence at least from the US and the UK concedes that ethnic heterogeneity does not contribute to high crime rates in a neighbourhood. Other research has evidenced negative (Rountree *et al*., 1994; Osborn and Tseloni, 1998) or lack of (Miethe *et al*., 1987; Tseloni *et al*., 2004) race effects at the individual level on property crimes, especially when accounting for neighbourhood characteristics (Smith and Jarjoura, 1989).

The current empirical evidence that area characteristics effects, albeit statistically significant, are lower than individual household effects implies that household victimisation first and foremost relates to households' profile and lifestyle. This is supported by previous modelling of crime prevalence and incidence rates at the postcode sector level (Kershaw and Tseloni, 2005). Consequently any area-targeting policies of property crime reduction are likely to be less efficient than household-profile based policies. Having said that the possibility of relatively low area effects due to the nearly ten years gap between area measures and property crimes should not be dismissed. The estimated cross-level interactions in this study revealed that regional effects on property crimes vary according to accommodation type, car ownership, tenure and social class.

The estimated effect of each variable *without* random effects (such as area type, age of the 'head of household', annual household income over £5,000, area characteristics etc.) is consistent across areas of England and Wales similarly to a standard negative binomial regression model. In other words it may be safely, depending on its statistical power, applied to predict the number of household crimes experienced by a household delineated by such non-random characteristics regardless of the area it resides as long as the respective effects (including any interactions) enter the calculation of the prediction multiplicatively. Any discrepancy between the observed and predicted number of household crimes for identical households is due to between-households unexplained heterogeneity, $\hat{a}$.

The between-areas random components of the final estimated models in Table 8 differ by about 50% between total household crimes and burglaries & thefts. These random effects imply that the estimated effects of household characteristics on its victimisation vary between areas with identical area characteristics not just between households (due to their unexplained heterogeneity, $\hat{a}$). The mean effect (in Tables 3 or 4) of the household characteristics *with* random effects gives its mean across areas, i.e. nationally (beware that Scotland and North Ireland are excluded from the BCS sample) but according to area they affect property crimes above or below this national average. The larger the between-areas variance of the random effect compared to the respective mean the lower the predictive power of this mean. The highest variation of effect is shown by household annual income under £5,000 on burglaries & thefts and by flats etc. on total household crimes with respective coefficients of variation over 6. The coefficient of variation for private renting effect on burglaries & thefts is also large, over 5. Indeed the mean effect of these variables was not statistically significant in Tables 3 and 4.

Random covariances between household characteristics' effects shed some light on conflicting or collaborating effects, which operate in certain areas of England and Wales rather than nationally, in addition to the ones evidenced in the fixed part of the estimated models. In the light of the above remark that household-level risk factors are more important than area ones, random covariances add important insights. They offer substantive evidence of displaced or communicable crime risks between households within areas. Indeed negative covariances between two positive effects imply that crime is displaced across the respective household types. For instance, burglaries & thefts seem to transfer from lone parents to private renters within areas. Similarly total household crimes are displaced between semi-detached house dwellers and lone parents as well as flats etc. dwellers and social renters within areas. Positive covariances between two effects of opposite direction also indicate within area crime displacement. Burglaries & thefts are displaced between households in neigbourhood watch schemes and lone parents or those with annual household income under £5,000 or social renters whereas total household crimes are displaced between flats etc. dwellers and households in neigbourhood watch schemes. Crime contagion is implied by positive covariances between two negative or positive coefficients or negative covariances of effects which operate in opposite directions. Thus total household crimes are communicable between flats etc. dwellers and lone parents as well as semi-detached house dwellers and households with neighbourhood watch. Burglaries & thefts are communicable between one adult households or private renters and annual household income under £5,000, households whose 'head' is of manual social class and social or private renters or single adult households. Crime prevention policies based on household profiles would be efficient if they target few characteristics with communicable effects. They may bear poor overall crime reduction results if they ignore the within area risk displacement between household types.

This work expands previous efforts (for an overview see Tseloni *et al.,* 2002) to explain property crime victimisation by allowing for crime concentration, as well as individual, area and interaction fixed and random effects. The clustering of households within areas had not been accounted for in models of the entire crime distribution, which include repeats, neither had random covariances between crime covariates been estimated or interpreted to date. The second order age polynomial and the lone parent, private renting and regional interactions, which have been evidenced in this study, advance empirical knowledge of the phenomena of victimisation. Having said that the current study has limitations. The most serious is that information on victimisation history, which is the strongest predictor of current property victimisation (Ellingworth *et al*., 1997; Osborn and Tseloni, 1998), was omitted due to data unavailability. Recent evidence suggests that prior victimisation proxies initial unexplained heterogeneity which evades crime surveys (Tseloni and Pease, 2003). Second, the random parameters estimates taken via IGLS estimation methods may lack precision since only MCMC methods give 95% confidence intervals for random parameters (Goldstein *et al*., 1998). First order MQL approximation may seriously underestimate the random-effects variances of limited dependent variable models, especially with inadequate sample size of above level-1 units (Browne and Draper 2000). If crime prevention was to be based on these modelling results precision would have been essential and worth the additional computational cost which MCMC methods require for such a large data set and number of covariates. The current results offer an indication of the relationships underlying random covariances of property victimisation covariates which, underestimated as they may be, have substantive implications and policy relevance. Third, the exclusion of movers and crimes that happened outside a '15-minute walk' from home, which was necessitated from modelling crimes by area characteristics, may have produced biased estimates for total household crimes. The restricted distribution of number of crimes ('non-moving, 15-minute walk') differs significantly from the complete distribution. This is not the case for burglaries & thefts (see the Appendix) for which the model results can be thought of as a benchmark for total household crimes. While the estimated model of burglaries & thefts explains their variability considerably better than the one for the total number of household crimes, the final models for the two crime aggregates are in broad agreement except for the interaction effects and to a less extent the contextual random parameters.

This work could be extended into the multilevel modelling of other significant crime types as well as fear of crime and perceived disorder. The last two indicators are directly related to quality of life, arguably even more so than actual crime, and have recently gained much policy attention (Hale, 1996). The 2001 Census describes the areas sampled in the 2000 BCS more accurately than the 1991 Census. Such information could also be linked, ideally with the 2001 and 2002 BCS sweeps, to provide a starting point for more sensitive modelling of area effects upon crime. There is also potential, with the enlarged annual BCS (the BCS has a 40,000 annual sample from 2001, see Simmons *et al*., 2002) to apply these models to segments of the England and Wales population with greater homogeneity with respect to area variables. This would help to untangle the real risk factors present in areas with higher levels of crime and assist policymakers in targeting preventative effort. From the researchers' point of view, development of such models would offer the potential to significantly advance victimisation theory.

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APPENDIX

Research evidenced from the US has shown that the decision to move may be related to property crime (Dugan, 1999). The results of significance tests for probability differences between the full and the ‘non-moving, within 15 minutes walk’ distributions of burglaries & thefts and total household crimes are presented in the Appendix Table.

Appendix Table about here

These show no significant differences in the probabilities of suffering four or more total household crimes and any number of burglaries & thefts. Thus the full and the ‘non-moving, within 15 minutes walk’ distributions of burglaries & thefts are statistically equivalent except for the category of no victim. This implies that the majority of the omitted households in our analysis had not suffered any burglary or theft in 1999. The respective, i.e. full and ‘non-moving, within 15 minutes walk’, distributions of total household crimes differ statistically for 3 or less crimes. Since total household crimes includes burglaries & thefts one can safely conclude that this difference is only due to motor vehicle crimes or criminal damage.

Table 1: Observed frequency distribution for household crimes from the 2000 British Crime Survey

Number of	Total household crimes			Burglaries and thefts		
	Frequency	%		Frequency	%	
0	12,839	79.8		14,450	89.8	
1	2,129	13.2		1,252	7.8	
2	596	3.7		232	1.4	
3	229	1.4		73	0.5	
4	118	0.7		34	0.2	
5	85	0.5		32	0.2	
6	42	0.3		7	0.0	
7	23	0.1		3	0.0	
8	9	0.1		-	-	
9	4	0.0		-	-	
10	4	0.0		-	-	
11	4	0.0		1	0.0	
12	1	0.0		-	-	
13	2	0.0		1	0.0	
18	1	0.0		1	0.0	
Total	16,086	100.0		16,086	100.0	
Mean			0.35			0.15
Variance			0.93			0.30
Measures of Repeat Victimisation						
Concentration			1.75			1.47
% Repeat Crimes			34			46
% Repeat Victims			62			23

Table 2: Description of household crime covariates

Household characteristics	%	Mean (SD)
Age of 'head of household'		53 (16.2)
Number of adults		
One	30.0	
Two (base)	55.6	
Three or more	14.4	
Children	28.9	
Lone parent	4.7	
Tenure		
Owners (base)	75.1	
Social rented sector	17.6	
Private rented sector	7.2	
Annual household income		
Under £5,000	10.3	
Between £5,000 and £9,999	16.3	
Between £10,000 and £29,999 (base)	44.6	
Over £30,000	22.2	
No response	6.6	
Not managing well on household income	41.8	
Social Class of 'head of household'		
Manual	53.1	
Professional (base)	30.9	
Non-classified	16.0	
Number of cars		
No car	21.5	
One car	46.2	
Two cars (base)	26.6	
Three cars	5.7	
Accommodation type		
Detached (base)	25.3	
Semi-Detached house	35.4	
Terraced house	27.7	
Flat or maisonette or other	11.6	
Neighbourhood watch	29.0	
Any protection measures	35.1	
House empty during weekday		
Less than 3 hours	43.6	
Between 3 to 7 hours	31.1	
More than 7 hours (base)	56.4	

Table 2: Description of household crime covariates (continued)

Household characteristics	%	Mean (SD)
Length of residence		
Less than 2 years	7.0	
Two to 5 years	20.4	
Five to 10 years	18.2	
More than 10 years (base)	54.5	
Type of area		
Inner city	12.0	
Urban	65.3	
Rural (base)	25.7	
Area characteristics (Standardized values)		
Percent households renting privately		-0.18 (0.66)
Percent single adult non-pensioner households		-0.16 (0.43)
Poverty*		-0.42 (3.36)
Percent Afro-Caribbean		-0.07 (0.72)
Percent Asian#		-0.03 (0.79)
Percent of population 16-24 years		-0.06 (0.27)
Percent households in housing association accommodation		-0.10 (0.67)
Percent persons moved in last year		-0.08 (0.24)
Population density		0.04 (0.84)
Government Office Regions		
North East	6.1	
Yorkshire/Humberside	9.6	
North West	13.0	
East Midlands	8.1	
West Midlands	9.8	
Eastern	11.3	
Greater London	10.2	
South East (base)	14.2	
South West	10.3	
Wales	7.4	

* 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).

Indian, Pakistani or Bangladeshi.

Number of valid cases 16,086.

Table 3: Estimated fixed effects of household and area characteristics for the prediction of the number of total household crimes

	Model 1 (individual fixed effects)	Model 2 (Model 1 & interactions)	Model 3 (Model 2 & random effects)
Household Covariates		*Exp(b)*	
Age of 'head of household'	1.02**	1.02**	1.02**
Age of 'head of household'^{2}	0.9997***	0.9997***	0.9997***
Wald test for quadratic Age (d.f.=2)	64.12	64.18	65.06
Number of adults (Two)			
One	0.93	0.93	0.93
Three or more	1.16**	1.15**	1.15**
Lone parent	1.74***	1.71***	1.62***
Tenure (Owners)			
Social renting	1.37***	1.44***	1.46***
Private renting	1.19**	0.95	0.95
Annual household income (£10,000-£29,999)			
Under £5,000	1.11	1.11	1.10
£5,000-£9,999	1.07	1.07	1.08
Over £30,000	1.17***	1.17***	1.18***
No response	0.89	0.88	0.88
Not managing well on household income	1.20***	1.20***	1.20***
Number of cars (Two)			
No car	0.45***	0.46***	0.46***
One car	0.80***	0.80***	0.79***
Three or more cars	1.31***	1.31***	1.31***
Accommodation type (Detached)			
Semi-Detached house	1.16**	1.13**	1.14**
Terraced house	1.35***	1.37***	1.37***
Flat or maisonette or other	1.22**	1.16	1.13
Neighbourhood watch	0.89**	0.89**	0.90**
Social class of 'head of household' (Professional)			
Manual	0.89**	0.90**	0.89**
Non-classified by social class	0.10***	0.10***	0.10***
Type of area (Rural)			
Inner city	1.42***	1.43***	1.48***
Urban	1.36***	1.32***	1.32***
Wald test for all household characteristics fixed effects (degrees of freedom)	912.56 (23)	883.78 (23)	885.03 (23)

Table 3: Estimated fixed effects of household and area characteristics for the prediction of the number of total household crimes (continued)

	Model 1 (individual fixed effects)	Model 2 (Model 1 & interactions)	Model 3 (Model 2 & random effects)
Area Covariates		*Exp(b)*	
Poverty[#]	1.05***	1.04***	1.04***
Percent households renting privately	1.06	1.10**	1.12***
Population density	1.21***	1.36***	1.34**
Region (South East)			
North East	0.68***	0.60***	0.60***
Yorkshire/Humberside	1.01	1.02	1.04
North West	1.00	0.99	1.00
East Midlands	0.97	1.00	0.98
West Midlands	0.82**	0.82**	0.83*
Eastern	0.71***	0.73***	0.73***
Greater London	0.55***	0.96	0.95
South West	1.02	1.04	1.05
Wales	0.86	0.90	0.87
Wald test for area characteristics fixed effects (degrees of freedom)	99.89 (12)	113.47 (12)	118.15 (12)
Interactions			
Urban x Private renting	-	1.40**	1.41**
Greater London x Terraced house	-	0.59***	0.59***
Greater London x No car	-	0.72**	0.72**
Greater London x Population density	-	0.71***	0.72***
North East x Social renting	-	0.55**	0.53***
North East x Poverty	-	1.07**	1.07**
North East x Percent households renting privately	-	0.76**	0.74**
Wald test for interaction effects (degrees of freedom)	-	52.54 (7)	50.00 (7)
Intercept	0.29***	0.29***	0.29***
Random Parameters			
$\hat{a}$ (std. error)	2.87 (0.07)	2.80 (0.07)	(in Table 8)
$\hat{\sigma}^2_{u0}$ (std. error)	0.22 (0.03)	0.20 (0.03)	(in Table 8)

Entries are exponents of estimated coefficients [*exp(b)*], except where stated; Models based on 16,086 cases.

*** p-value<0.01, **0.01<p-value<0.05, *0.05<p-value<0.10.

[#] 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 4: Estimated fixed effects of household and area characteristics for the prediction of the number of burglaries and thefts

	Model 1 (individual fixed effects)	Model 2 (Model 1 & interactions)	Model 3 (Model 2 & random effects)
Household Covariates		*Exp(b)*	
Age of 'head of household'	1.01	1.01	1.01
Age of 'head of household'^{2}	0.9998	0.9998	0.9998
Wald test for quadratic Age (d.f.=2)	27.64	29.12	28.67
Number of adults (Two)			
One	0.91	0.91	0.93
Three or more	1.17*	1.17*	1.17*
Lone parent	2.37***	3.74***	3.90***
Tenure (Owners)			
Social renting	1.39***	1.39***	1.40***
Private renting	1.15**	1.18	1.17
Annual household income (£10,000-£29,999)			
Under £5,000	1.20*	1.17	1.14
£5,000-£9,999	1.05	1.15	1.15
Over £30,000	1.14	1.20**	1.21**
No response	0.88	0.89	0.87
Not managing well on household income	1.20***	1.20***	1.22***
Neighbourhood watch	0.89	0.89*	0.89*
Any protection measures	1.18***	1.18***	1.18***
Social class of 'head of household' (Professional)			
Manual	0.87**	0.87*	0.87*
Non-classified by social class	0.12***	0.11***	0.11***
Type of area (Rural)			
Inner city	1.26	1.28*	1.25
Urban	1.19**	1.18**	1.16*
Wald test for all household characteristics fixed effects (degrees of freedom)	382.10 (18)	324.31 (18)	342.86 (18)

Table 4: Estimated fixed effects of household and area characteristics for the prediction of the number of burglaries and thefts (continued)

	Model 1 (individual fixed effects)	Model 2 (Model 1 & interactions)	Model 3 (Model 2 & random effects)
Area Covariates		*Exp(b)*	
Poverty#	1.06***	1.06***	1.07***
Percent households renting privately	1.14***	1.14***	1.14***
Percent Afro-Caribbean	0.90*	-	-
Population density	1.13**	1.15**	1.12*
Region (South East)			
North East	0.62***	0.64***	0.66**
Yorkshire/Humberside	1.17	1.18	1.20
North West	1.11	1.12	1.15
East Midlands	1.02	1.02	1.04
West Midlands	0.77*	0.75**	0.77*
Eastern	0.70***	0.57***	0.61***
Greater London	0.60***	0.76	0.78
South West	1.22	0.96	1.00
Wales	0.85	0.87	0.88
Wald test for area characteristics fixed effects (degrees of freedom)	92.77 (13)	84.99 (12)	84.21 (12)
Interactions			
Lone parent x Manual	-	0.57**	0.54***
Lone parent x £5,000-£9,999	-	0.55***	0.53***
Lone parent x Over £30,000	-	0.40*	0.35*
Lone parent x Flat or maisonette or other	-	1.96**	1.91**
Eastern x Manual	-	1.45*	1.40*
Greater London x Manual	-	0.75	0.75
Greater London x Population density	-	0.81**	0.83**
South West x Manual	-	1.38*	1.41*
South West x Population density	-	1.40**	1.54***
South West x Poverty	-	0.92**	0.92**
Wald test for interaction effects (degrees of freedom)	-	45.02 (10)	48.81 (10)
Intercept	0.14***	0.14***	0.13***
$\hat{a}$ (std. error)	4.43 (0.13)	3.80 (0.12)	(in Table 8)
$\hat{\sigma}^2_{u0}$ (std. error)	0.16 (0.04)	0.15 (0.04)	(in Table 8)

Entries are exponents of estimated coefficients [*exp(b)*], except where stated; Models based on 16,086 cases. *** p-value<0.01, **0.01<p-value<0.05, *0.05<p-value<0.10.

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 5: Interaction effects of regions in England & Wales on the expected number of property crimes for a household with otherwise reference characteristics

	North East	West Midlands	Eastern	Greater London	South West	Remainder
Part A	Total household crimes[a,c]					
Household characteristics						
Semi-Detached house	0.68	0.95	0.83	1.14	1.14	1.14
Terraced house	0.82	1.14	1.00	**0.81**	1.37	1.37
Other Accommodation Type	0.60	0.83	0.73	1.00	1.00	1.00
No car	0.28	0.38	0.34	**0.33**	0.46	0.46
One car	0.47	0.66	0.58	0.79	0.79	0.79
Two cars	0.60	0.83	0.73	1.00	1.00	1.00
Three or more cars	0.79	1.09	0.96	1.31	1.31	1.31
Social renting	**0.46**	1.21	1.07	1.46	1.46	1.46
Private renting	0.60	0.83	0.73	1.00	1.00	1.00
Owners	0.60	0.83	0.73	1.00	1.00	1.00
Area characteristics						
Population density	0.80	1.11	0.98	**0.96**	1.34	1.34
Percent households renting privately	**0.50**	0.93	0.82	1.12	1.12	1.12
Poverty	**0.67**	0.86	0.76	1.04	1.04	1.04
Part B	Burglaries and thefts[b,c]					
Household characteristic						
Manual	0.57	0.67	**0.74**	0.87	**1.23**	0.87
Non-classified by social class	0.07	0.08	0.07	0.11	0.11	0.11
Professional	0.66	0.77	0.61	1.00	1.00	1.00
Area characteristics						
Population density	0.74	0.86	0.68	**0.93**	**1.72**	1.12
Poverty	0.71	0.82	0.65	1.07	**0.98**	1.07

Table 6: Interaction effects of accommodation and area types on the expected total household crimes for a household with otherwise reference characteristics[a,c]

	Inner city	Urban	Rural
Social renting	2.16	1.93	1.46
Private renting	1.48	**1.86**	1
Owners	1.48	1.32	1

Table 7: Interaction effects of lone parent on the expected number of burglaries and thefts for a household with otherwise reference characteristics[b,c]

	Lone Parent	Other
Manual	**1.83**	0.87
Non-classified by social class	0.43	0.11
Professional	3.90	1.00
Annual household income £5,000-£9,999	**2.07**	1.00
Annual household income over £30,000	**1.65**	1.21
Other annual household income	3.90	1.00
Flat or maisonette or other accommodation	**7.45**	1.00
(Semi-) Detached or Terraced house	3.90	1.00

[a] Calculations based on figures of Table 3. [b] Calculations based on figures of Table 4.
[c] Non-statistically significant coefficients in Tables 3 and 4 enter as 1.

Table 8: Estimated random parameters of household and area characteristics for the prediction of the number of household crimes

Covariates	Total household crimes	Burglaries and thefts
Estimated between-areas Variances – Covariances [$\hat{\sigma}^2_{kk}$ (std. error) - $\hat{\sigma}_{kl}$ (std. error)]		
Intercept ($\hat{\sigma}^2_{u0}$)	0.14 (0.05)	0.14 (0.11)
One adult household, intercept	-	-0.03 (0.11)
One adult household	-	0.28 (0.20)
Wald test for One adult household random parameters (d.f.=2)		2.07
Lone parent, intercept	-0.15 (0.09)	-0.36 (0.19)
Lone parent, One adult household	-	-0.24 (0.26)
Lone parent	0.54 (0.25)	1.61 (0.51)
Wald test for Lone parent random parameters (d.f.)	5.72 (2) $^{@}$	13.04 (3) ***
Social renting, intercept	-0.01 (0.06)	-0.15 (0.13)
Social renting, One adult household	-	-0.13 (0.16)
Social renting, Lone parent	-0.12 (0.13)	-0.12 (0.25)
Social renting	0.17 (0.12)	0.82 (0.24)
Wald test for Social renting random parameters (d.f.)	2.25 (3)	11.35 (4) *
Private renting, intercept	-	0.12 (0.16)
Private renting, One adult household	-	0.19 (0.21)
Private renting, Lone parent	-	-1.57 (0.34)
Private renting, Social renting	-	0.07 (0.26)
Private renting	-	0.72 (0.37)
Wald test for Private renting random parameters (d.f.=5)		22.63 ***
Semi-Detached house, intercept	0.07 (0.05)	-
Semi-Detached house, Lone parent	-0.29 (0.11)	-
Semi-Detached house, Social renting	0.02 (0.08)	-
Semi-Detached house, Private renting	-	-
Semi-Detached house	0.10 (0.09)	-
Wald test for Semi-Detached house random parameters (d.f.=4)	11.94 **	
Flat or maisonette or other, intercept	0.01 (0.09)	-
Flat or maisonette or other, Lone parent	0.46 (0.21)	-
Flat or maisonette or other, Social renting	-0.15 (0.13)	-
Flat or maisonette or other, Private renting	-0.10 (0.12)	-
Flat or maisonette or other	0.72 (0.23)	-
Wald test for Flat or maisonette or other random parameters (d.f.=5)	18.76 ***	
Neighbourhood watch, intercept	0.03 (0.05)	-0.17 (0.11)
Neighbourhood watch, One adult household	-	-0.11 (0.14)
Neighbourhood watch, Lone parent	0.36 (0.13)	0.73 (0.24)
Neighbourhood watch, Social renting	-0.02 (0.09)	0.36 (0.16)
Neighbourhood watch, Private renting	-	0.16 (0.20)
Neighbourhood watch, Semi-Detached house	-0.13 (0.06)	-
Neighbourhood watch, Flat or maisonette or other	0.19 (0.12)	-
Neighbourhood watch	0.02 (0.09)	0.28 (0.17)
Wald test for Neighbourhood watch random parameters (d.f.=6)	14.65 *	16.91 ***

Table 8: Estimated random parameters of household and area characteristics for the prediction of the number of household crimes (continued)

Covariates	Total household crimes	Burglaries and thefts
Estimated Variances – Covariances [$\hat{\sigma}^2_{kk}$ (std. error) - $\hat{\sigma}_{kl}$ (std. error)]		
Annual household income under £5,000, intercept	-	-0.05 (0.15)
Annual household income under £5,000, One adult household	-	-0.39 (0.20)
Annual household income under £5,000, Lone parent	-	-0.10 (0.29)
Annual household income under £5,000, Social renting	-	0.17 (0.20)
Annual household income under £5,000, Private renting	-	0.53 (0.28)
Annual household income under £5,000, Neighbourhood watch	-	0.46 (0.20)
Annual household income under £5,000	-	0.71 (0.33)
Wald test for Annual household income under £5,000 random parameters (d.f.=7)		13.73[@]
Manual 'head of household', intercept	-	0.11 (0.10)
Manual 'head of household', One adult household	-	0.27 (0.12)
Manual 'head of household', Lone parent	-	0.19 (0.20)
Manual 'head of household', Social renting	-	-0.25 (0.14)
Manual 'head of household', Private renting	-	-0.59 (0.17)
Manual 'head of household', Neighbourhood watch	-	-0.08 (0.11)
Manual 'head of household', Annual household income under 5,000	-	-0.15 (0.16)
Manual 'head of household'	-	0.07 (0.14)
Wald test for Manual 'head of household' random parameters (d.f.=8)		23.63***
Wald test for all between-areas random effects including $\hat{\sigma}^2_{u0}$ (degrees of freedom)	94.06 (21)	117.52 (36)
	Estimated coefficient of overdispersion	
$\hat{a}$ (std. error)	2.65 (0.07)	3.15 (0.13)
	Baseline Models	
Exp(Intercept)	0.35***	0.15***
$\hat{a}$ (std. error)	3.80 (0.08)	6.90 (0.16)
$\hat{\sigma}^2_{u0}$ (std. error)	0.40 (0.04)	0.36 (0.05)

Models based on 16,086 cases.

p-values corrected for one tail test (Snijders and Bosker 1999, p. 90):
[@]0.025<p-value<0.05, * 0.01<p-value<0.025, ** 0.005<p-value<0.01,
*** p-value<0.005.

Appendix Table:

Complete and ‘non-moving/15-minute walk’ distributions of total household crimes and burglaries and thefts and probability difference test results.

Number of crimes	Total household crimes without restrictions	Total household crimes with restrictions	Z values for probability difference	Burglaries and Thefts without restrictions	Burglaries and Thefts with restrictions	Z values for probability difference
0	75.58	79.81	9.43	88.89	89.83	2.82
1	15.73	13.24	-6.56	8.34	7.78	-1.88
2	4.60	3.70	-4.17	1.67	1.44	-1.74
3	1.82	1.42	-2.90	0.50	0.45	-0.69
4	0.92	0.73	-1.94	0.24	0.21	-0.59
5	0.67	0.53	-1.70	0.21	0.20	-0.31
6	0.32	0.26	-0.99	0.08	0.04	-1.27
7	0.13	0.14	0.28	0.03	0.02	-0.83
8	0.08	0.06	-0.93	0.01	0	-1.00
9	0.04	0.02	-0.71	-	-	-
10	0.03	0.02	-0.15	-	-	-
11	0.04	0.02	-0.71	0.01	0.01	-0.48
12	0.02	0.01	-0.90	-	-	-
13	0.02	0.01	-0.31	0.01	0.01	0.09
18	0.01	0.01	0.09	0.01	0.01	0.09
Total number of cases	18,207	16,086		18,207	16,086	