Modelling property crime using the British Crime Survey

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What Have We Learnt?

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The British Crime Survey (BCS) has been used to develop a number of statistical models that describe property crime victimization at the level of the individual household. This paper gives an overview of what has been learnt from these studies. In terms of the predictors of crime, it is now well established that both household and area characteristics play important roles: in particular, household affluence has a positive effect on crime victimization, in contrast to the negative effect exerted by area affluence. However, findings of the latter part of the 1990s have emphasized that crime victimization cannot be regarded as random even when the statistical model is conditioned on these known characteristics. Based on a more general model which allows for this nonrandomness, the present study uses simulations to illustrate the roles of household and area characteristics in respect of the following: how household types differ in predicted property crime victimizations, both in aggregate and differentially by crime type; how area characteristics are associated with rates of victimization; how household victimization histories affect predictions of subsequent crime events.

Recent years have seen the development of statistical models that set out to explain property crime victimization at the level of the individual household. Such models shed new light on victimization and, potentially, on crime prevention, by indicating the types of households and areas at highest victimization risk. Much of this work has been conducted using data from various sweeps of the British Crime Survey (BCS), which has provided a rich source of detailed micro-level information. It has also been possible to link this micro data with Census variables to provide a picture of the characteristics of the area. Through these statistical models, it is now possible to attach a victimization risk to a specific type of household living in a certain area. Indeed, it is possible to go further and estimate the number of times that such a household will be victimized within a certain period, such as a year. The purpose of this paper is to review what has been learnt to date from these studies.

The pivotal studies of Hindelang *et al.* (1978) and Cohen and Felson (1979) explain victimization risks and annual crime rates through lifestyles and the routine activities of modern society, respectively. According to either theory and given motivated offender(s), the probability of being victimized is a function of the amount and the type

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of interaction amongst individuals and objects in the time-space-target (person or object) risk coordinates. In particular, routine activity theory (Cohen and Felson 1979; Felson and Cohen 1980) asserts that motivated offenders, suitable targets and the absence of effective guardianship are the three necessary elements for a victimization to occur. The very similar lifestyle theory (Hindelang *et al.* 1978; Garofalo 1987; Gottfredson 1981) argues that the way people allocate their time to vocational and leisure activities defines their exposure to situations in which victimization may occur.

With respect to either theory, demographic characteristics of individuals and households may be used to measure role expectations and social constraints on behaviour. Such individual or micro-level characteristics offer clues about people's lifestyle and, therefore, are indicative of the frequency with which conditions necessary to victimization are met.

In contrast to these micro-level theories, social disorganization theories (Shaw and McKay 1942; Sampson and Groves 1989) propose 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 organizations 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 urbanization. Thus, the community context offers the macro level dimensions of victimization models.

A number of studies have emerged in the last decade or so which have sought to test the empirical validity of the above theories using multivariate statistical modelling of self-reported crime victimization data. As noted above, the BCS has been used extensively in this respect. The first BCS sweep of 1982 included a number of direct lifestyle indicators for all respondents, which provided information not available in comparable US data. This attracted international interest in using the BCS for testing victimization theories (for example, Sampson and Wooldredge 1987). A feature of the BCS important for subsequent analysis has been that Census characteristics of the area could be linked to BCS data. For the sweeps 1982 to 1992 under discussion here, this linking took place through the identification of the small area sampling unit (ward or polling district for 1982 to 1988 and postcode sector for 1992).[1] Thus, the BCS has allowed analysis of the roles of individual (micro) and community (macro) explanations of crime.

This paper aims to present the cumulative results of the BCS-based analyses of property crime in England and Wales undertaken over the last decade (see the following section). Relying on the most comprehensive empirical model to have emerged from these studies, the paper also investigates the complex relationship between household characteristics, prior victimization and area profile for the prediction of the number of property crime victimizations for different hypothetical household types in three contrasting areas (in the section 'Simulated Property Crime Distributions'). A concluding discussion of the results is given in the final section.

[1] The old National Crime Survey and the revised National Crime Victimisation Survey (NCVS) of the US contain limited lifestyle information. Further, since 1984 it has concealed the identification of the sampled segments. Being a rotating panel the NCVS has a more complicated data structure than the cross-sectional BCS and serious attrition problems (Lynch and Tseloni 1997). It has therefore been greatly under-utilized for modelling purposes.

Modelling Property Crime using the BCS

Crime can be measured by three indicators: *prevalence*, which indicates the chance of being a victim, *incidence*, which is the number of victimizations per person or household, and *concentration*, which is the number of crimes per victim. It is arguable that which of these three crime measures is used can affect the conclusions drawn. The concepts of prevalence, incidence and concentration apply most naturally at an aggregate level. For an individual household, *crime risk* is analogous to prevalence and we treat these terms as equivalent in what follows. Similarly, the *crime rate* is analogous to incidence, and these two terms are also used interchangeably.

The BCS collects information about the experience of crime victimization over a reference period of about a year. In the case of property crime, this information relates to whether the household of the respondent suffered victimization of various types and the numbers of such victimizations. The principal analyses on which we draw attempt to 'explain' property crime victimization events 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. For households which have moved, any property crimes at the previous address during the reference period are therefore excluded from the analysis. In order to similarly attach the crime event to the area of residence, property crime as used in these earlier studies relates only to the dwelling and its contents. Consequently victimizations during the reference period associated with motor vehicles are excluded, as are thefts from the person. The property crime events included can be categorized into (actual or attempted) burglary, theft from the property or criminal damage.

The analyst not only chooses which category or categories of crime to study, but s/he must also decide which level of aggregation to use and type of crime measure to adopt. The use of the dichotomous 'victim/not a victim' information leads to an analysis of household crime risk, while the use of the number of victimizations provides an analysis of household crime rates. Finally, if attention is confined to victims only, then crime concentration is the issue under investigation. BCS analyses have considered all three measures for household property crime victimization in England and Wales.

Trickett *et al.* (1992) examined all three crime measures for aggregate property crime at the area level. In effect, that study provided a descriptive analysis of property and personal crimes, based on area measures of incidence, prevalence and concentration obtained by aggregating 1982 BCS victimization information. No attempt was made to explain the incidence of crime using other variables. Rather, the paper established that the distribution of crime is different in high compared with low crime areas. More specifically, 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, given the overall area crime rate, high crime areas are distinguished by smaller prevalence and higher concentration than would be expected were crime randomly distributed. This nonrandomness was found to be highly statistically significant. Much of the subsequent analysis undertaken by the authors of that paper has been seeking to explain those findings.

One attempt at such an explanation is provided by Osborn *et al.* (1992). Area crime rates are again under study in that paper, which uses Census area information, together with dichotomous indicators for the regions of England and Wales, as explanatory variables in separate models for property crime prevalence and incidence observed in

the 1984 BCS. Nevertheless, these authors ultimately have only limited success in explaining the distinctive features of crime victimization over areas. Their models for prevalence have a better fit than those for incidence, leading them to conclude that 'incidence, and hence multiple victimization, is a more complex phenomenon than is the victim/nonvictim dichotomy' (Osborn *et al.* 1992: 279). Hence, the authors speculate that the factors which separate multiple from single victims may be better explained at the micro rather than the macro level.

In fact, statistical modelling studies of BCS data at the level of the individual household have primarily focused on the 'victim/not a victim' dichotomy using the technique of logistic regression. In other words, they have studied the micro-level analogue of prevalence, and the resulting models can be used to predict the victimization risk of a particular household. The predictors typically include both household characteristics and the characteristics of the area of residence, reflecting the micro and macro influences proposed in victimization theories. This body of research includes Sampson and Wooldredge (1987), Trickett *et al.* (1995), Ellingworth *et al.* (1997) and, in relation to fear of crime, Hale *et al.* (1994).[2]

These studies agree that both types of explanatory variables (individual and community) significantly affect household victimization risk. Indeed, the factors at these two different levels can have counteracting influences. 'To caricature, richer people in poorer areas suffer property crime particularly heavily' (Trickett *et al.* 1995: 291). This finding about the different roles of household and area affluence recurs in a number of other papers and relates to studies of household crime rates (Osborn and Tseloni 1998) as well as to crime risks (Osborn *et al.* 1996; Ellingworth *et al.* 1997). Another consistent finding is that the age of the 'head of household' is a statistically important factor, with predicted victimization declining as age increases (Sampson and Wooldredge 1987; Trickett *et al.* 1995; Osborn *et al.* 1996; Ellingworth *et al.* 1997; Osborn and Tseloni 1998). Clearly, age may be indicative of lifestyle. A direct lifestyle measure is available to Sampson and Wooldredge (1987) from the 1982 BCS, but comparable measures are not used in the other studies since the relevant BCS sweeps did not collect the same lifestyle information from all respondents. Although they vary about the form of the variable, the above studies typically also indicate that having one adult in a household positively increases predicted crime. Where investigated, the presence of children and household ethnicity are typically found to be relatively unimportant.

It has already been noted above that recent work has used Census information to capture area characteristics in models of household property crime. This is the case in Trickett *et al.* (1995), Osborn *et al.* (1996), Ellingworth *et al.* (1997), Osborn and Tseloni (1998). These studies agree that, in addition to area affluence playing a negative role for crime prediction, the presence of teenagers (the proportion of the population aged 5 to 15 or 16 to 24) is positively associated with household crime. Despite some differences, these studies using the 1984 or 1992 BCS paint a consistent picture overall about the characteristics of households and areas which are important for predicting household property crime victimization.

[2] Maxfield (1987), Tseloni *et al.* (1994) and Tseloni and Pease (1998) have also presented victimisation risk models based on the BCS data. However these studies ignore the macro dimension of the phenomenon.

The specific contribution of Trickett *et al.* (1995) is to examine not only the aggregate of all property crimes, but also its separate components of burglary, theft and criminal damage. Their results indicate that different factors affect these components, suggesting that results based on composite property crime variables ought to be interpreted with caution.

Although examining the dichotomous victimization variable, Ellingworth *et al.* (1997) focus on the role of prior victimization for subsequent property crime risks. Their analysis again deals with all property crime, together with the components of burglary, theft and criminal damage. Here the authors exploit information in the 1992 BCS about victimization experiences in the four years prior to the reference period of the survey.[3] Although the dependent variables relate only to household property crime, the predictors of prior assault and car theft, in addition to burglary, are generally found to be important. These results point to the importance of multiple victimization, not only over time but also over crime types. Multiple victimization over property and personal crime is also studied by Hope *et al.* (1999), who find a positive correlation between unexplained property and personal crime risks in a two-equation model.

As documented in Chenery *et al.* (1996) and Ellingworth *et al.* (1995), multiple and/or repeat events account for most of the incidents reported in the BCS. This is true regardless of whether crime counts are taken from the screening questions or the victim forms of the BCS (Chenery *et al.* 1996). Thus, crime prevention which addresses repeat victimization would decrease crime rates in general (Farrell 1995; Pease 1998).

Given the disproportionate importance of households which experience multiple victimization in terms of their contribution to the overall crime rate, it is of obvious policy interest to examine whether factors can be identified which act as predictors of multiple victimization. Osborn *et al.* (1996) consider this question in the context of data from the 1984 BCS. They take the distribution of crime to represent 'a series of "hurdles" or transitions between states—i.e. from nonvictim to victim and from lower to higher frequency levels—which are not necessarily independent of each other' (Osborn *et al.* 1996: 227). The principal statistical technique used is the bivariate probit model with censoring, where the censoring reflects the simple fact that the transition to repeat victim is irrelevant unless the initial victimization hurdle is crossed.

In some ways, the results of that paper are disappointing. Although Osborn *et al.* (1992) had hypothesized that the key characteristics which distinguished repeat from single victims may lie at the micro level, this later study could uncover little evidence of the existence of such distinguishing factors. In other words, the same factors which lead to a first victimization may remain responsible for the subsequent ones. It follows that single and repeat victimization should rather be modelled by a single set of explanatory variables. Nevertheless, the role of the factors apparently changes once the initial victimization 'hurdle' is crossed such that 'probabilities of repeat victimization will tend to be more similar across households than are initial victimization risks' (Osborn *et al.* 1992: 241).

This last finding is of fundamental importance for the modelling of the incidence of property crime victimization. It implies that even when household and area characteristics are used to model the risk of victimization, the distribution of observed property

[3] A dummy variable is also included for the experience of a fire over a two-year period, including the survey reference period.

crime events cannot be represented as the chance outcome of a sequence of independent events which result from this constant underlying risk. Either victimization events within the reference period are not independent of each other or the observed characteristics used to model crime risk are not sufficient to explain the differing true risks faced by households. The former possibility is known as event dependency, while the latter is called unobserved heterogeneity.

Event dependency implies that an initial victimization 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. In the context of the micro variables used in recent BCS studies, such factors could include lifestyle. The importance of prior victimization in models of victimization risk (see particularly Ellingworth *et al.* 1997) is compatible with event dependency. Nevertheless, this is far from conclusive evidence. Prior victimization may simply be acting as a proxy for high victimization risk that is not otherwise captured by the explanatory variables used in the model. Thus, a statistically important role for prior victimization is also compatible with unobserved heterogeneity. Lauritsen and Davis-Quinet (1995) examine the roles of event dependency and unobserved heterogeneity in the context of US panel data for the crime victimization and they are able to conclude that both are important. However, with cross-section data, such as that available from the BCS, event dependency and unobserved heterogeneity cannot be satisfactorily distinguished (Osborn *et al.* 1996).

In the light of the findings summarized above, Osborn and Tseloni (1998) model the entire distribution of property crimes at the level of the individual household. Household property crimes reported in the 1992 BCS are measured as the numbers of burglaries, thefts, criminal damages and their composite of aggregate property crime. Micro and macro (area) level information, together with prior victimization effects, are used as explanatory variables. The statistical model employed is a form of the negative binomial model, which explicitly allows for unobserved heterogeneity. While that model is not designed to account for event dependency during the reference period, the authors argue that the heterogeneity captured may also reflect such event dependency. This is the most general model used to date for capturing the characteristics of property crime as revealed by the BCS.[4]

Thus, the models of Osborn and Tseloni (1998) effectively summarize what has been learnt from the statistical models estimated from BCS data. They emphasize the apparent nonrandomness of crime victimization, even once we control for micro and macro level characteristics. In addition, they again show the roles played by the micro and macro characteristics in predicting crime victimization. In relation to this, the next section uses these models to address the following four issues:

- How do household types differ in the incidence and risk of property crimes?
- Do different household types suffer different types of property crimes?
- How does area of residence affect property crime for a household?
- How does prior victimization history affect property crimes?

[4] Tseloni (1995) employs the same statistical model to predict the distribution of threats. Relying only on individual characteristics, this study is not presented here.

More specifically, we employ the Osborn and Tseloni's (1998) empirical models for burglaries, thefts, criminal damages and aggregate property crimes to calculate predicted property crime rates for hypothetical households in selected areas of England and Wales.

As already mentioned, one of the advantages of the negative binomial regression model is that it allows the estimation of the probability distribution of crimes. From such probability distributions, incidence can be obtained as the estimated crime rate (or mean of the distribution) while prevalence or risk can be found as the estimated probability of at least one victimization. Although concentration rates (the estimated number of crimes per victim) can also be examined (Tseloni and Pease 1996), the discussion below is concerned primarily with incidence and prevalence.

Simulated Property Crime Distributions

As a basis for the comparisons promised in the 'bullet points' of the previous section, we consider a number of hypothetical households. Each is described by a unique set of values for the household level covariates included in the empirical models. A number of contrasts is sought in relation to victimization proneness and frequency, such as poor versus affluent households, couples versus single adults, young versus old, and child-minding versus childless families. As mentioned, these contrasts proxy differences in routine activities or lifestyles. For instance, elderly people or parents of young children might be anticipated to have a quiet and family-oriented lifestyle whereas young adults without children might mix more with non-family members and spend time outside home.

With these issues in mind, we identify eight hypothetical households in terms of the household characteristics[5] which appear in the models of Osborn and Tseloni (1998).

Affluent couple with children: Two adults live in a detached or semi-detached owner occupied house with child(ren) under 16; they have resided in the area for more than two years, have two cars, the 'head of the household' is 35 and has a non-manual occupation.
Non-Affluent couple with children: Two adults live in an owner-occupied terraced house with child(ren) under 16; they have resided in the area for more than two years, have one car, the age of the 'head of household' is 35 with a manual occupation.
Single young adult: Lives alone in a private rented first floor flat, has resided in the area between one and two years, has one car, is 25 years old and in a non-manual profession.
Lone parent: One adult lives in a rented council ground floor flat with one or more children under 16, has resided in the area for more than two years, has no car, is 20 years old with socio-economic status classified as manual.

[5] All the hypothetical households belong to the base ethnic category, namely white, and they have no prior victimisation history unless this is explicitly considered (see section 'How does prior victimisation history affect property crimes?' below). We also assume that the households were contacted at the first call by the interviewer.

Couple with adult children: Three or more adults live in an owner occupied detached or semi-detached house; they have lived in the area for more than two years, have two cars, the 'head of the household' is 50 and non-manual.
Affluent elderly couple: Two adults live in an owner-occupied detached or semi-detached house with no children; they have lived in the same area for over two years, have one car, the 'head of the household' is 65 and non-manual.
Non-affluent elderly couple: Two adults live without any children in an owner-occupied terraced house; they have resided in the area for more than two years, have no car, the age of the 'head of household' is 65 and is classified as manual.
Elderly widow: Lives alone in owner-occupied ground floor flat; s/he has resided in the area for more than two years, has no car, is 75 and of manual category.

Not all the factors used for these household types contribute equally to the prediction of household property crime rates. Indeed, some of the factors produce statistically insignificant estimates for some models and this affects the precision of the property crime predictions (Johnston 1984: 194–5). See Osborn and Tseloni (1998) for the statistical significance of these household covariates.

For demonstrating the effects of the area of residence, three areas of England and Wales are selected for the analysis. These are an affluent area, an inner city deprived area and an 'average' one. Unlike the fictitious households, the areas presented in Table 1 actually exist, however, their names are concealed in order to ensure statistical confidentiality. All three areas are in England and were sampled in the 1992 BCS. The affluent area is in the south east, with the remaining two in the north west. In fact, however, the south east/north west distinction is relatively unimportant compared to the role of the area characteristics as measured in the 1991 Census. These characteristics, as used in the empirical models, are presented in Table 1 after standardization. For instance, the average number of cars per household is above the national average in the affluent area, well below it in the inner city and slightly lower than the national mean in the average area. Variations in council housing, proportions of lone parent households and deprivation similarly underline the differences among these areas.

Our general approach is to assume that each hypothetical household may live in each of these areas. In practice, however, some areas are more plausible than others for a particular household type. The Average area is the point of reference since all our household types could be located there. The non-affluent and the single adult households (possibly with the exception of elderly widow) could also reside in the Inner City. The two

TABLE 1 *Standardized characteristics of selected areas*

Variable	Average area	Affluent area	Inner City area
Cars per household	–0.363	0.642	–1.543
Council housing (proportion)	–0.556	–0.803	0.985
Private rented housing (proportion)	–0.489	0.181	1.173
Single parent household (proportion)	0.334	–0.822	2.394
Population 5 to 15 (proportion)	–0.496	–1.774	0.147
Indian sub-continent population (proportion)	–0.435	–0.304	0.162
Deprivation	–0.920	–1.970	3.760

See Osborn and Tseloni (1998) for definition of the Deprivation variable.

affluent couples and the single adult without children might also live in the Affluent area. All area characteristics employed are statistically significant for predicting aggregate property crimes (using a 10 per cent significance level), except for the proportion of council houses. Osborn and Tseloni (1998) present the statistical significance of the area covariates in their property crime models.

We now turn to a discussion of the questions posed at the end of the second section.

Does crime differ by household type?

Table 2 displays the estimated incidence and prevalence (or mean crime rate and crime risk respectively), together with the probability distribution, for aggregate property crimes experienced in the course of one year by our hypothetical households should they reside in the selected areas. It includes details for only a subset of cases judged to be plausible. In other words, it presents only some combinations of the eight households and the three areas. All 24 combinations are included in the corresponding Figure 1, where the estimated incidence rates are shown.[6]

The hypothetical lone parent household is estimated to be substantially more vulnerable to property crimes than our other household types. Should s/he live in the Inner City area s/he is estimated to face an average 1.83 property victimizations and a victimization risk of 43 per cent (Table 2) over a year. This is compatible with a lack of guardianship playing a role, with the single young adult also yielding relatively high values.

At the other extreme, the hypothetical non-affluent elderly couple and elderly widow are the least victimized of all eight households. In the Average area the non-affluent elderly couple has an estimated average of 0.12 property victimizations and a victimization risk of 9.4 per cent. A single elderly person has fractionally higher incidence and risk of property crime than a couple if all other factors (age included) are identical. These estimates illustrate the key role found for age of 'head of household' in the statistical models and they contradict the tabloid image of increased victimization risks of elderly people living alone.

A prevailing pattern through much statistical analysis (discussed in the second section) is that affluent couples, either young or elderly, show higher estimated crime rates and risks than the corresponding non-affluent. In this respect, property victimization seems to be driven by the availability of targets for criminal activity.

Do different household types suffer different property crimes?

Recent empirical research (Trickett *et al.* 1995; Ellingworth *et al.* 1997; Osborn and Tseloni 1998) has evidenced that specific household and area characteristics play different roles across types of property crime. This issue has not been addressed by theory to date despite its obvious practical value. Clearly, victimization to different types of crime might imply different approaches to crime prevention.

[6] It would have been tedious to report here all the simulations undertaken in the study. We would be happy to share the details of any calculations of interest upon request.

TABLE 2 *Estimated mean rates, risks and probability distributions of aggregate property crimes for hypothetical households*

Hypothetical household types and areas	Estimated mean rate	Estimated risk	Estimated victimization probabilities for r crimes						
			r = 0	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6+
Affluent young couple with children									
in Average Area	0.2919	0.1866	0.8134	0.1232	0.0390	0.0145	0.0058	0.0024	0.0018
in Affluent Area	0.1407	0.1098	0.8902	0.0866	0.0176	0.0042	0.0011	0.0003	0.0001
Non affluent young couple with children									
in Average Area	0.2289	0.1581	0.8419	0.1116	0.0309	0.0100	0.0035	0.0013	0.0008
in Deprived Inner City Area	0.8814	0.3432	0.6568	0.1524	0.0738	0.0420	0.0256	0.0163	0.0331
Couple with adult children									
in Average Area	0.1908	0.1386	0.8614	0.1024	0.0254	0.0074	0.0023	0.0008	0.0004
in Affluent Area	0.0920	0.0775	0.9225	0.0657	0.0098	0.0017	0.0003	0.0001	0.0000
in Deprived Inner City Area	0.7346	0.3156	0.6844	0.1509	0.0694	0.0375	0.0218	0.0131	0.0228
Single young adult									
in Average Area	0.2898	0.1857	0.8143	0.1229	0.0387	0.0143	0.0057	0.0024	0.0018
in Affluent Area	0.1397	0.1092	0.8908	0.0862	0.0174	0.0041	0.0011	0.0003	0.0001
in Deprived Inner City Area	1.1157	0.3792	0.6208	0.1525	0.0782	0.0471	0.0304	0.0205	0.0505
Lone parent									
in Average Area	0.4748	0.2514	0.7486	0.1418	0.0560	0.0260	0.0130	0.0067	0.0079
in Deprived Inner City Area	1.8282	0.4313	0.5687	0.1493	0.0818	0.0526	0.0363	0.0261	0.0852
Affluent elderly couple									
in Average Area	0.1455	0.1127	0.8873	0.0883	0.0183	0.0045	0.0012	0.0003	0.0001
in Affluent Area	0.0701	0.0614	0.9386	0.0538	0.0064	0.0009	0.0001	0.0000	0.0000
Non affluent elderly couple									
in Average Area	0.1158	0.0939	0.9061	0.0767	0.0136	0.0028	0.0006	0.0001	0.0000
in Deprived Inner City Area	0.4457	0.2425	0.7575	0.1398	0.0539	0.0243	0.0118	0.0060	0.0067
Elderly widowed									
in Average Area	0.1181	0.0954	0.9046	0.0777	0.0139	0.0029	0.0007	0.0002	0.0000

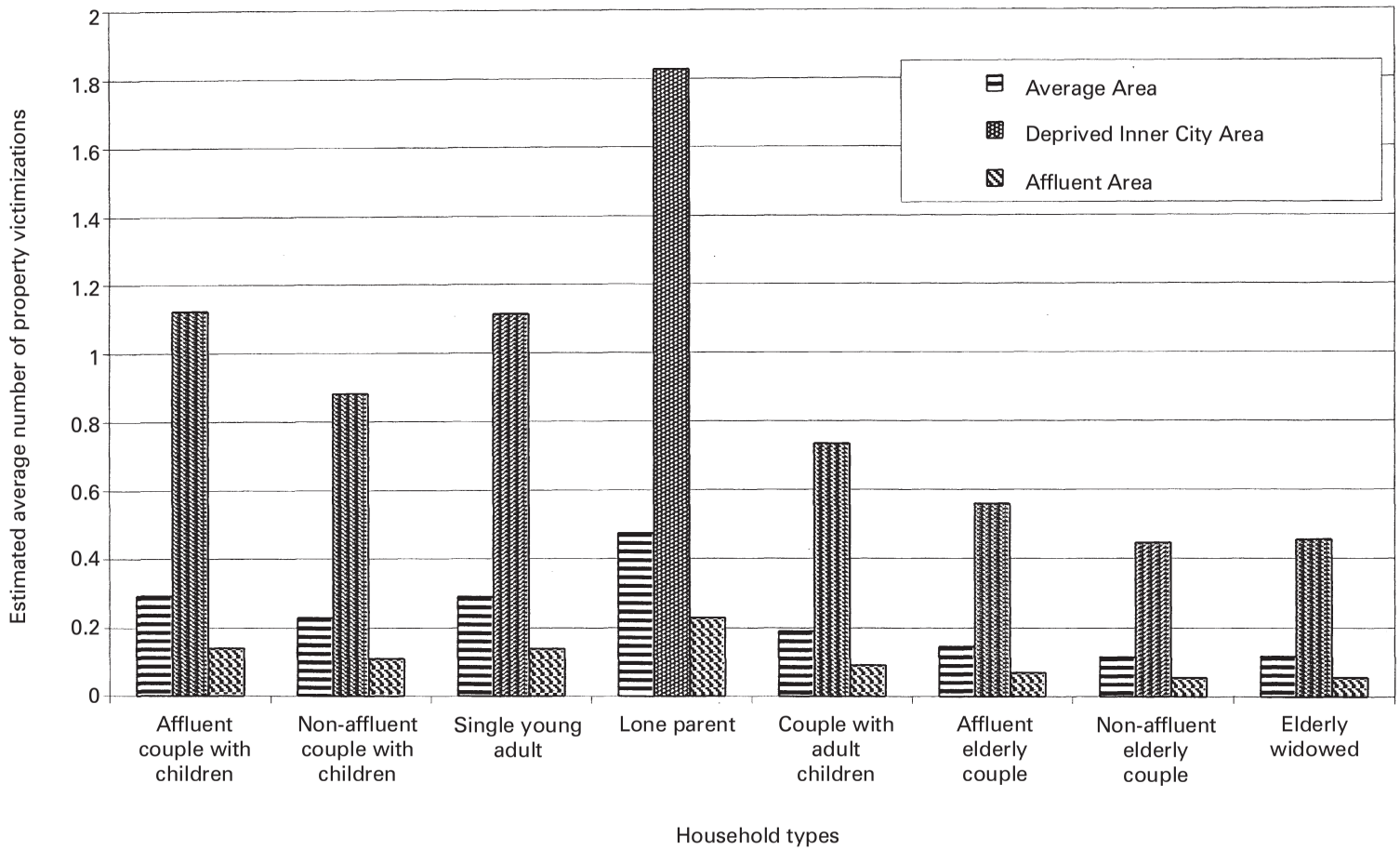

FIG. 1 Estimated mean rates of aggregate property crime victimization for hypothetical households in selected areas of England and Wales

As mentioned, Osborn and Tseloni (1998) estimate separate models for burglary, theft and criminal damage. Figure 2 displays the estimated incidence of property crime types for each hypothetical household under the assumption that it lives in the Average area. Corresponding estimated prevalence values are shown in Figure 3.

Across these crime types, affluent households are estimated to be burgled relatively more frequently while non-affluent are estimated to suffer relatively more thefts. This is true whether incidence (Figure 2) or risk (Figure 3) is examined. The lone parent is estimated to be more vulnerable to burglary and theft, but not criminal damage, than any other household type. Further, comparison of the incidence and prevalence graphs indicates more repeat thefts than burglaries for this household type.[7] Such relationships between crime categories and type of household are not surprising. Burglary is a profit-related crime and, as such, it takes planning (Cornish and Clarke 1986), whereas theft is opportunistic. Further, burglary relies on (non)-occupancy of target dwellings and hence on the lifestyle of the householder.

The role of affluence is particularly accentuated for burglary. Another important predictor of burglary seems to be lack of guardianship as depicted in the elevated incidence rates of all single adult households. Due to the latter, the hypothetical elderly widow is estimated to be more frequently burgled than the elderly couples, notwithstanding the picture drawn considering all property crimes (see section 'Does crime differ by household type?' above).

In contrast to the case of burglary, theft rates seem to be similar for all hypothetical households excluding the elderly and the lone parent household types. Criminal damage is the least frequent property crime, with estimated incidence rates more evenly distributed across households than is the case for the other property crimes. Putting this a different way, the available characteristics are less successful in predicting criminal damage than other crime categories.

How does area affect household property crime?

The crime distribution across the selected areas for any given type of household has already been apparent: whatever the type of household, those in the Inner City experience far more crimes than those in other areas. The Average area is also some way above the Affluent area. These patterns are clear in Table 2 and Figure 1. This is in line with previous research, which establishes the irrefutable importance of area covariates (Ellingworth *et al.* 1997; Osborn *et al.* 1992; Rountree *et al.* 1994; Sampson and Groves 1989; Trickett *et al.* 1995).

While affluence demonstrates a strong positive relationship with property crime and especially burglary at the micro level, the opposite is true at the macro level. This is evident for all property crimes in Figure 1 and has been previously established (Ellingworth *et al.* 1997; Smith and Jarjoura 1989). This is compatible with the supply of potential offenders outweighing the low availability of targets.[8] Indeed, potential

[7] This estimated pattern of hypothetical lone parents experiencing high prevalence and relatively low incidence rates has also been evidenced for threats reported in earlier sweeps of the BCS (Tseloni 1995). It makes a case worthy of further exploration.

[8] The existence of increased protection devices in rich areas would not deter a motivated offender given that s/he has enough time to break in and the property is not visible from busy public areas (Winchester and Jackson 1982).

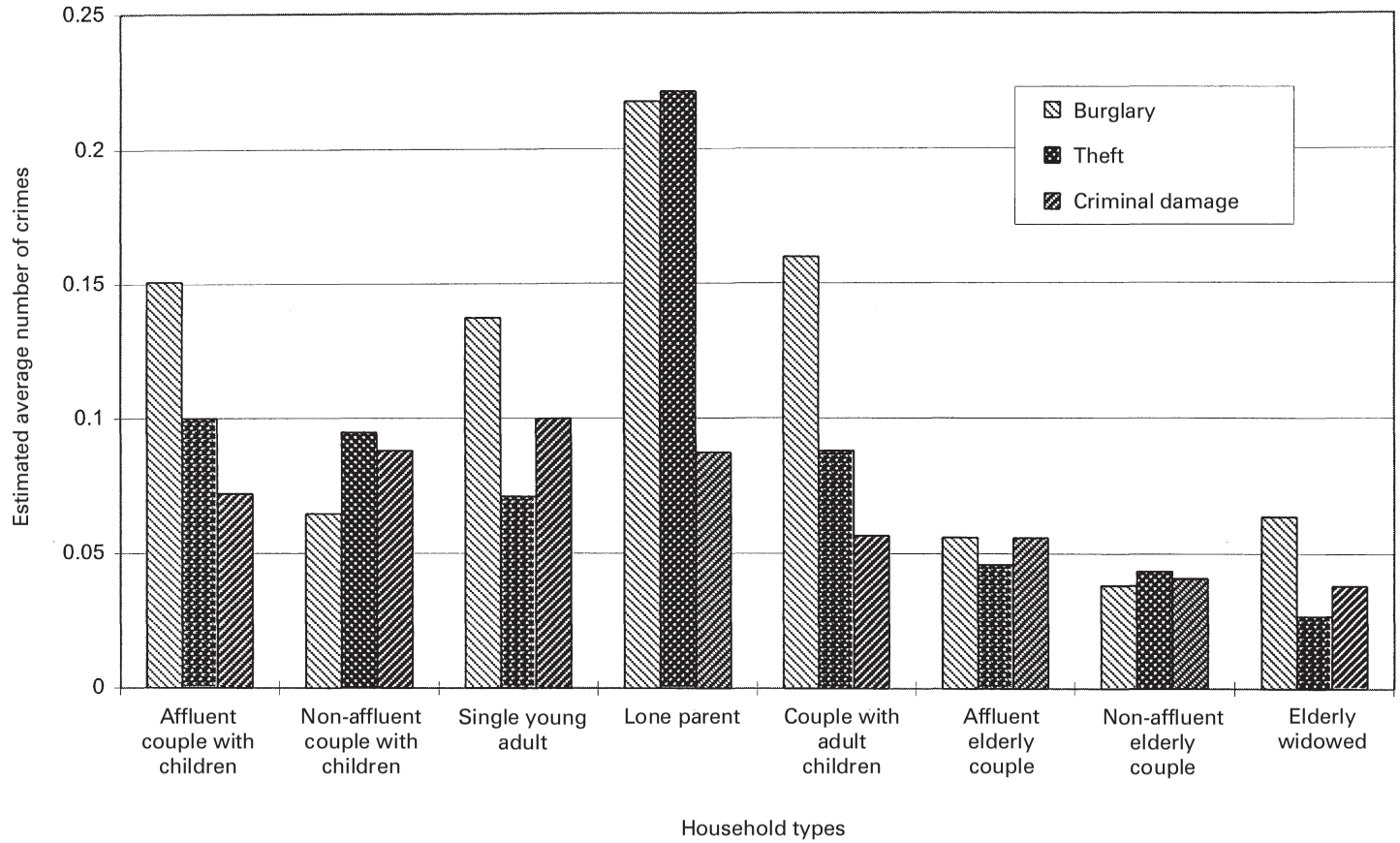

FIG. 2 Estimated mean rates in property crime categories for hypothetical households in Average Area

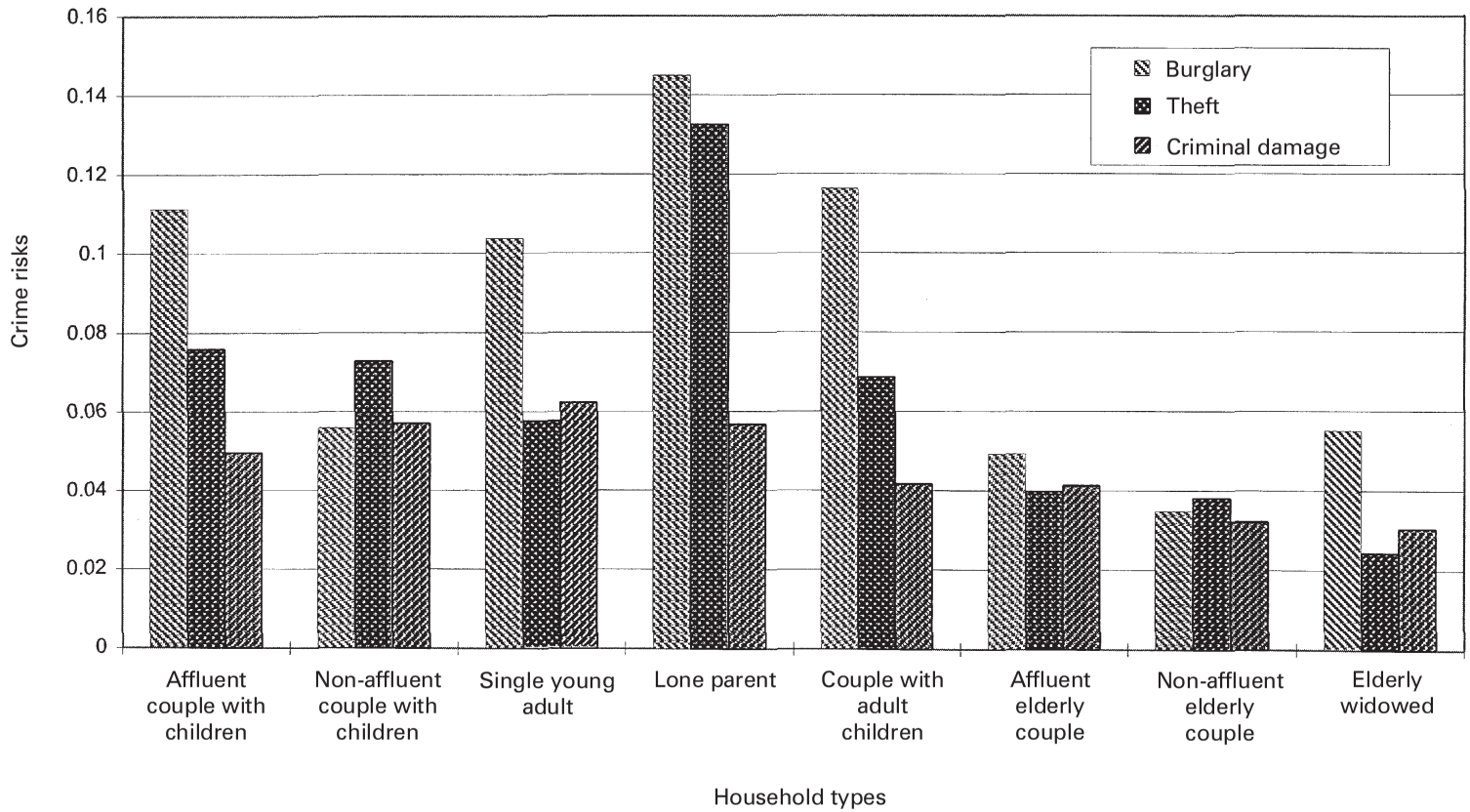

FIG. 3 Estimated risks in property crime categories for hypothetical households in Average Area

burglars seem to pick up their targets in the course of their everyday activities and not outside their own environment (Cromwell *et al.* 1991).

The current discussion extends earlier work in two directions. Being concerned with the results of multivariate modelling, it examines how the burden of area inequality is allocated over the different types of households and how household inequality is demonstrated within each area. It is evident from Figure 1 that household crime inequality is emphasized in the Inner City area, whereas the distribution of property crime incidence across households in the Affluent area is relatively uniform.

Further, the greatest area inequality effect falls on the households which are already most at risk. For our hypothetical household types, these are the lone parent, the affluent young couple with children and the single young adult. For the single young adult, for example, the estimated crime rate ranges from 0.14 crimes in the Affluent area to 1.12 in the Inner City area. On the other hand, estimated crime risk rises relatively less, from 11 per cent to 38 per cent. This is a feature of the negative binomial model used here. For given heterogeneity, the higher incidence faced by residents of deprived areas generates increases in crime concentration relatively more than increases in prevalence (Osborn and Tseloni 1998).

How does prior victimization history affect property crimes?

To date, theories have failed to acknowledge how victimization history alters and/or flags the probabilities of subsequent events. The empirical models by Osborn and Tseloni (1998) suggest that prior victimization has strong predictive power for crime incidence across all property crime categories examined, with the exception of criminal damage. Prior victimizations with highly statistical significant effects were car theft, burglary and assault in the four years preceding the survey reference period. The last, despite being a personal crime, had the greatest effect of all priors for each property crime category except burglary (Osborn and Tseloni 1998). Similar results have previously been evidenced for crime risks in Ellingworth *et al.* (1997), Tseloni and Pease (1998).

Table 3 presents the estimated means and risks of property crimes and their probability distribution for some selected hypothetical households in the Average area, contrasting experience of prior burglary, car theft, or assault as against the situation where no prior victimization has occurred. By design, the households with some prior victimization meet the absolute exposure prerequisites for having suffered at least one of the above crimes (Garofalo 1987).

Through the design of the negative binomial model, the effects of victimization history are constant for incidence but not prevalence. The effects of prior victimizations are demonstrated by the following comparisons. For households with no prior victimizations as against those who have suffered a prior car theft, incidence increases by approximately 28 per cent and prevalence by 17 per cent or more. For a prior burglary, incidence rises by about 45 per cent and prevalence rises by at least 26 per cent. Most interestingly, prior assault raises incidence by around 70 per cent and prevalence by at least 38 per cent. Some light on this issue is shed by Hope *et al.* (1999), who find a statistically significant correlation between risks of property and personal crime which remain unexplained after allowing for the effects of measured predictors. The role of prior assault here could be at least partial due to it proxying the common unmeasured predictors which influence both personal and property crime risks.

TABLE 3 *Victimisation history effects on estimated mean rates, risks and probability distributions of aggregate property crimes for hypothetical households in average area*

Hypothetical household types and victimization history	Estimated mean rate	Estimated risk	Victimization probabilities for r crimes						
			r = 0	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6+
Affluent young couple with children									
with no victimization history	0.2919	0.1866	0.8134	0.1232	0.0390	0.0145	0.0058	0.0024	0.0018
with prior burglary only	0.4234	0.2354	0.7646	0.1381	0.0521	0.0230	0.0109	0.0054	0.0058
with prior car theft only	0.3726	0.2180	0.7820	0.1335	0.0476	0.0199	0.0089	0.0042	0.0040
with prior assault only	0.4973	0.2580	0.7420	0.1431	0.0576	0.0272	0.0138	0.0073	0.0090
Single young adult									
with no victimization history	0.2898	0.1857	0.8143	0.1229	0.0387	0.0143	0.0057	0.0024	0.0018
with prior burglary only	0.4204	0.2344	0.7656	0.1379	0.0518	0.0229	0.0108	0.0053	0.0057
with prior car theft only	0.3699	0.2170	0.7830	0.1332	0.0473	0.0197	0.0088	0.0041	0.0039
with prior assault only	0.4938	0.2570	0.7430	0.1429	0.0574	0.0270	0.0137	0.0072	0.0088
Couple with adult children									
with no victimization history	0.1908	0.1386	0.8614	0.1024	0.0254	0.0074	0.0023	0.0008	0.0004
with prior burglary only	0.2768	0.1802	0.8198	0.1208	0.0371	0.0134	0.0052	0.0021	0.0015
with prior car theft only	0.2436	0.1651	0.8349	0.1147	0.0329	0.0111	0.0040	0.0015	0.0010
with prior assault only	0.3251	0.2002	0.7998	0.1280	0.0427	0.0167	0.0070	0.0031	0.0026
with all prior crimes	0.8937	0.3453	0.6547	0.1525	0.0741	0.0423	0.0259	0.0165	0.0339
Affluent elderly couple									
with no victimization history	0.1455	0.1127	0.8873	0.0883	0.0183	0.0045	0.0012	0.0003	0.0001
with prior burglary only	0.2110	0.1492	0.8508	0.1075	0.0284	0.0088	0.0029	0.0010	0.0006
with prior car theft only	0.1857	0.1358	0.8642	0.1010	0.0246	0.0070	0.0022	0.0007	0.0003
with prior assault only	0.2479	0.1671	0.8329	0.1155	0.0335	0.0114	0.0041	0.0016	0.0010

Of the hypothetical households illustrated in Table 3, the estimated crime risks of the affluent young couple with children are the least affected by a prior crime experience while the most affected is the affluent elderly couple. For the illustrative case of a couple with adult children, prior experience of burglary, theft and assault together leads to estimated incidence being multiplied by around four and a half, with prevalence being scaled by 2.5, as compared to a situation where no prior victimization had occurred. Indeed, this case with all priors yields an estimated number of 0.9 property crimes and a crime risk of just over one third, in contrast with the no priors case where the estimated incidence is 0.2 and crime risk 14 per cent.

Victimization history is a complex correlate as it is not clear whether it links to victims' lifestyle or to the fact that crime is the daily reality of the environments in which they live. Regardless of its origin it creates a subgroup of chronic victims who merit social policy's intervention since their victimization experiences contribute substantially to national high crime rates (Chenery *et al.* 1996; Ellingworth *et al.* 1995).

Discussion and Conclusions

The second section of this paper stressed that measured household and area covariates are not able to explain the distribution over households of BCS property crime victimization data. This only becomes apparent when repeat victimization is examined, pointing to the importance of considering both prevalence and incidence. Our illustrations in the section 'Simulated Property Crime Distributions' indicate the role of prior victimization in predicting subsequent victimization rates and risks, while they also indicate the differential contribution over crime categories of repeated crimes against the same victim to incidence. For example, our calculations imply that the hypothetical lone parent household type is prone to repetition of theft relatively more than burglary. A basic conclusion of the illustrations here and other recent statistical analyses of the BCS (including Ellingworth *et al.* 1997; Osborn *et al.* 1996; Hope *et al.* 1999) is that experience of a victimization should itself be thought of as a property crime predictor alongside community and individual factors.

That section also identified four issues on which models estimated using BCS data could shed some light and it is to these that we now return. The first concerns household differences in the incidence of property crime. Perhaps unsurprisingly, households do differ in this respect, with affluent households being more at risk than otherwise equivalent non-affluent households. Similarly, age of the 'head of household' is important.

The second question is whether different types of property crime are directed against households of particular types. This can be answered in the affirmative. For example, the greater crime proneness of affluent households is particularly evident for burglary, whereas theft shows little difference between the affluent and non-affluent. The hypothetical lone parent household is particularly prone to theft. The hypothetical widowed elderly, insofar as they are victimized at all, suffer burglary rather than theft or criminal damage. These broad patterns may be interpreted in terms of occupancy patterns and general lifestyle.

The third issue whose consideration was promised was the effect of area on property crime rates experienced by households. Area differences are clear in our results, with

affluent areas being least vulnerable, with property crime rates and risks typically around half those of the Average area and a substantially smaller fraction of the Inner City ones.

The final issue to be addressed concerns the effect of victimization history on the rates of property crime suffered. As noted earlier, there is such an effect, and one of considerable size. Those previously victimized, particularly by assaultive crime, had elevated risks and rates of property crime victimization. Theft is the type of property crime most increased by suffering a prior assault. A possibility which should be examined in subsequent work is that some survey respondents may assume a victim role, which leads them both to notify victimization in the period covered by the BCS, and also in the period before it. Cross section data, such as the BCS cannot test this, so use must be made of a panel design survey such as the National Crime Victimisation Survey or of crimes reported to the police.

Given that the findings are not artefacts of a cross-sectional design, the social policy and crime prevention implications are believed to be as follows:

- Community development measures should be deployed in areas whose characteristics are associated with high levels of property crime incidence. In particular, this implies areas associated with low levels of affluence and high proportions of teenagers.
- General crime prevention programmes should be directed at those whose individual characteristics are those associated with different levels of crime incidence, and which are tailored to the particular circumstances. Thus, for example, our results indicate that programmes directed at the elderly affluent should concentrate on first burglaries, and those directed at lone parents should focus upon the possibility of chronic theft.
- The predictive role of prior victimization should be acknowledged in the deployment of crime prevention resources. Those with at least one victimization of any type in the past, and especially assault, are arguably the first who should be protected. Pease (1998) reviews implemented crime prevention programmes so far attempted that operate in this way, together with relevant research.

One qualification which needs to be made to the results reviewed here is that no analysis has yet attempted to examine whether different types of households systematically differ with respect to their crime experiences. The hypothetical households used in this paper have been built up by taking plausible combinations of characteristics, rather than by separately analysing the various types. With the British Crime Survey now being undertaken at regular intervals, there may be scope for pooling different sweeps in order to undertake an analysis by actual (rather then hypothetical) household types. This, however, remains a future project. Another related topic of future research is to explicitly allow interactions between the three types of crime predictors (prior victimization, household characteristics and area characteristics). While we have learnt a great deal from recent BCS analyses, there is scope for further elaboration on issues of concern with crime victimization.

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