The Under-Reporting of Property Crime: A Microeconometric Analysis*

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Abstract

In this paper we use data from the 1994 and 1996 British Crime Surveys (BCS) to examine the in uence of socio-economic factors on the reporting of crime. Through probit estimation, we nd that the probability of a burglary being reported is signi cantly reduced if the individual is currently unemployed or has been engaged in illicit activity over the past year. We also nd that, as anticipated, the reporting likelihood is much increased if the incident involves a positively valued loss. Using decomposition techniques, we also show that this result is not driven by differences in mean sample characteristics. Our results suggest that the difference between the recorded crime rate and the true crime rate is not constant through the economic cycle. This may have implications for models of crime and economic activity that make use of recorded crime gures..

JEL classi cation: C21; K42; K49
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1 Introduction

There is a vast theoretical and empirical literature on the possible relationship between the economic cycle and the reported crime rate. This literature is comprehensively reviewed in Ehrlich (1996) and Allen (1996). Significant contributions to the debate on the general crime-economy nexus include Stevans (1988), Field (1990), Pyle and Deadman (1994), Hale (1997), and Osborn (1995). It comes as no surprise that the debate on crime, which has been influenced by this work, is fuelled by much controversy. Some of the conflict in the empirical literature is driven by the variety of theoretical foundations underpinning the models estimated. For example, there is considerable debate (typically between economists and criminologists) concerning the relationship between unemployment and property crime, and the results given in the literature are far from unequivocal (Young, 1993). This debate concerns two conflicting theories about the relationship: opportunity theories and motivational theories (Cantor and Land, 1985). Those advocating motivational theories (perhaps the majority view) tend to argue that unemployment or economic hardship, by generating relative poverty, stimulates criminal activity (see for example Phillips *et al.*, 1972; Sjoquist, 1973; Myers, 1993), The opposing view, driven by opportunity theories, suggests that the crime rate falls with increasing unemployment . This might be because of the guardianship effect : as unemployment increases there are more people at home to deter criminals (Cohen *et al.*, 1981; Cohen and Felson, 1979), or it could be because unemployment reduces the wealth of victims (Cohen *et al.*, 1980).

There are several other areas of controversy in this debate. Not withstanding the current controversy on econometric technique, one area that has received attention is the use of official recorded crime figures in empirical models. The frequently cited concern is that official figures may be seriously flawed due to under-reporting. Given the importance of this issue there is surprising little attempt to address the problem in the applied literature. Notable exceptions include Carr-Hill and Stern (1979), and more recently Pudney *et al.* (1997, 1998). Pudney *et al.* attempt to overcome the problem by developing a simulated maximum likelihood procedure to simultaneously estimate the crime rate and the reporting rate. However, even this small literature on the effect of under-reporting dwarfs the applied work that has considered the factors that influence this behaviour. Although Goldberg and Nold (1980) include a model of reporting probability in order to determine whether reporting deters burglars, it is difficult to find any literature on influences of crime reporting. This is surprising given the importance of under-reporting from a public policy perspective. To illustrate this, consider the following example. Let us assume that the true crime rate is an increasing function of unemployment as this hypothesis receives the greatest support in the literature (see Pyle, 1998). We are not able to observe the true crime rate as official figures are based on reported crimes. Rather, we observe measured crime, which is likely to suffer from reporting bias. Now, let us suppose that the micro-foundations of under-reporting suggest a negative relationship between the reporting rate and unemployment, perhaps a result of social exclusion or marginalisation. If this is the case, then this would imply that the difference between the actual crime rate and the measured rate is not constant over the economic cycle. As the unemployment rate increases, the crime rate increases but the measured rates increases at a slower pace (i.e. the measured rate of crime will diverge increasingly from the actual rate). Here we illustrate just one possible consequence of under-reporting, but one can easily conceive of other micro-foundations that influence this behaviour, for example, attitudes to the police; the distribution of household insurance and loss, and cultural differences.

To consider these issues further we explore the foundations of under-reporting using microeconometric analysis. There are many aspects to consider in this analysis. Intuitively, one might expect that individuals will fail to report a crime if they perceive the outcome of reporting as negligible. This might be because of previous experience of the criminal justice system, or through personal prejudice, but it may be linked to the insurance status of any items stolen. If the household has no contents insurance then why bother to report the incident? Similarly, if the individual perceives the response of the police as likely to be ineffectual (as may be the case in high property crime rate areas), then that individual is less likely to report the incident. Similarly, are cultural and racial differences likely to affect reporting rates given the varying perceptions of the police and officialdom across communities? In order to explore these issues the balance of this paper is as follows. In the next section we discuss the data set and sample properties. Following this we present the empirical methodology, outlining the method of probit estimation and decomposition techniques. In section 4 we present our results and discussion. The paper is summarised in section 5.

2 Data and sample

In order to investigate the discrepancy between the measured rate of crime and the true rate, we can make use of survey data that provides information about the reporting of crimes. In the UK there are two sources that have been used to explore the extent of measurement error in reported crime statistics:

the British Crime Survey (BCS) and the General Household Survey (GHS). The GHS only considers the reporting of burglary offences and provides little additional detail about the nature and circumstances of the incidents. The BCS, however, is a more extensive victim survey that provides victimisation rates for a large number of categories of offence (the notable exclusions being fraud, drug offences and theft from businesses). The BCS was first administered in 1982 and has been repeated in 1984, 1988, 1992, 1994, and 1996. The initial surveys were administered to around 10,000 households, but the sample size was increased to 15,000 for the 1994 and 1996 surveys. In addition, surveys prior to 1994 were conducted using the electoral register as a sampling frame. From 1994 the method was changed to using the Postcode Address File, bringing the BCS into line with the main household surveys and increasing the representativeness of the possible sample. Other changes in the survey method include the move to Computer-Assisted Personal Interviewing in 1994. Given these changes in sampling methodology, interview technique and sample size, we restrict our analysis to just the pooled 1994 and 1996 sweeps of the BCS. With respect to the sample size, the 1994 survey yields a core sample of 14,500 adults, and the 1996 survey 16,350 adults. Both samples are increased by an ethnic minority booster sample of approximately 2000 black and Asian adults. For more details of the sampling procedure for the 1994 survey see White and Malbon (1995), and for the 1996 survey see Hales and Stratford (1997).

2.1 Current sample

For our analysis we are only interested in those individuals who have experienced some form of property crime over the year preceding the survey. Following Pudney *et al.* (1997), and in order to be consistent with the literature on under-reporting and predictive crime models, we focus on incidents of residential burglary. This major offence is suitable for analysis as we are less likely to suffer from recall bias in our estimates (compared to other offences, respondents are very likely to have a good recall of when a burglary occurred and the circumstances of the crime). Furthermore, with these data we are unlikely to suffer problems with evasion bias. Whereas there are well-documented problems of misreporting in surveys of a sensitive nature (for example see Jones and Forrest, 1992; Fendrich and Vaughn, 1994), there is little reason to believe that survey respondents will misreport their experience of burglary. Although the reduced likelihood of recall or evasion bias give us some confidence in the measure of true crime and the reporting rates the BCS provides, the focus on just burglary offences does reduce our sample size dramatically. However, we are able to include observations on repeat burglary incidents as the BCS allows respondents to complete Victim Forms for up to 3 main incidents (a further 2 incidents are recorded but in much less detail). For our sample we use a modi ed version of the BCS de nition of burglary: entering the respondent s dwelling as a trespasser with the intention of committing theft, rape, grievous bodily harm or unlawful damage [whether the intention is carried through or not] (White and Malbon, 1995, p. 260). In our sample, a burglary occurs if the respondent answers yes to one of the following questions:

1. Has anyone got into this house/ at without permission and stolen or tried to steal anything?
2. Did anyone get into your house/ at without permission and cause damage?
3. Have you had any evidence that someone has tried to get in without permission to steal or to cause damage?

We could limit our sample to just those reporting yes to the rst question, but question 3 allows us to include attempted burglary in our de nition, but given the way the question is posed we must therefore include question 2[1]. Thus our remaining pooled data set, after losses for non-response and restriction to just burglary incidents, consists of 4168 observations, of which 2149 relate to 1994 and 2019 to 1996.

2.2 Core characteristics

The BCS asks respondents numerous questions about the nature and circumstances of each crime they have experienced over the year prior to the survey. They are then asked if the police came to know about the matter. This provides the basis of our reporting rates. There are, of course, many follow-ups to this primary question, depending on the interviewee s initial response. For example, if the incident was not reported, the respondent is asked to explain why not, and if the police were informed of the incident, the survey asks how it was reported and who contacted the police. One difficulty we have

[1] Our use of these questions also excludes the part of the BCS de nition of burglary that mentions rape or grievous bodily harm. We do this so as to be consistent with the literature, but partially because of inconsistencies in the way these offences are recorded in the BCS. For example, if a rape takes place during an incident of burglary, it is classi ed as a sexual offence, not a burglary. Furthermore, on inspection of the BCS data, where we are able to observe incidents that fall outside of the property crime element of the de nition, the numbers are negligible.

is in knowing whether the incident was actually recorded by the police (i.e. whether or not the incident actually appears in the recorded crime figures). We do know if the initial report of the incident was the only contact with the police concerning the matter, and whether the police caught the offender, but as we do not know whether a crime number is issued by the police, we have to confine our analysis to reported crime as opposed to recorded crime. However, for the purpose of our investigation, this definition is acceptable as we are only interested in the micro-foundations of crime reporting.

In our sample of 4168 observations, 2099 (50.36%) incidents were reported to the police. Defining an incident that involves loss as one where the respondent places a positive value on any items stolen or damaged, 2668 (64.1%) of our observations involve a loss. Of those incidents that involve loss, 1590 (59.6%) were reported to the police, compared to a rate of 33.93% for those incidents that did not involve a loss. In terms of economic prosperity, loss-involving incidents are fairly evenly distributed between victims who are in work and those who are currently unemployed. For those incidents involving a loss, 78.37% of the incidents were experienced by respondents in work, whereas the figure is 75.27% for those incidents involving no loss.

3 Methodology

In Goldberg and Nold (1980) the household's probability of reporting a crime is modelled as a function of the loss involved, property damage, and the cost of reporting[2]. Whether or not a crime is reported, however, will also depend on a variety of individual attributes, experiences and personal circumstances specific to that incident. For example, an individual's propensity to report a crime may vary between age and ethnic groups, may be affected by the individual's past experience of burglary, their attitudes to the police, and, of course, may be affected if some financial loss is involved, particularly if an insurance claim is to made. These likely influences are easily summarised as:

$$\begin{aligned} \Pr(reporting) &= f(incident\,involves\,loss,\ socioeconomic factors,\\ &\quad incident\,specific\ factors,\ attitudes\,to\,the\,police) \qquad (1) \end{aligned}$$

This function can then be estimated empirically to determine the factors that are significantly associated with the reporting of an incident.

[2] Like the BCS, their data set does not provide adequate information to include a cost of reporting variable in the empirical model but the authors do include some very simple socioeconomic variables.

3.1 Estimation technique

We do not directly observe an individual s tendency to report a crime. Rather, we observe the reporting outcome for each speci c incident, which is a binary outcome: either reported or not. This suggests that we can estimate our model through either a logistic or probit mechanism. As such, we begin our model by de ning a latent variable r_i^* that represents an individual s propensity to report a crime. This drives the observed binary indicator of whether a crime was reported, r_i, through the usual probit mechanism:

$$r_i^* = l_i\alpha + x_i\beta + \varepsilon_i \tag{2}$$

$$r_i = \xi(r_i^* > 0) \tag{3}$$

where $\xi(.)$ is the indicator function, equal to 1 if the individual reports a given crime and 0 otherwise, x_i is a row vector of personal and demographic attributes, β is the corresponding vector of parameters, and ε_i is a disturbance term, normally distributed with mean zero and variance one, conditional on x. The term l_i is a binary variable capturing whether the incident involves a loss. We include this as a separate term to highlight that nancial loss is likely to be a particularly signi cant explanatory variable for reporting through its relationship with insurance. Estimation of (2) through a probit regression is straightforward, and provides us with direct measures of the impact of the various micro-factors on the likelihood of reporting an incident.

3.2 Decomposition

Given that we suspect that incidents involving some form of loss are more likely to be reported, a worthwhile line of inquiry is to explore whether those incidents involving a loss would be reported in the absence of that loss. In other words, we need to determine whether it is the loss itself that drives the reporting differential, or whether the differential is due to differences in underlying characteristics between those people who experience loss and those who do not (i.e. are those people who report losses are signi cantly different in terms of their characteristics than those who report incidents without loss?). To do this we can use an Oaxaca-type decomposition (Oaxaca, 1973), a technique widely used in the labour economics literature to explore wage differentials. This is achieved by splitting our sample into those incidents involving a loss and those which do not. We then re-estimate equation (2) separately for each group, but exclude the loss term in the regression, rewriting it as:

$$r_i^* = x_i\beta + \varepsilon_i \quad (4)$$

where r_i, β, x_i, and ε_i are speci ed as above. Following Gomulka and Stern (1990), the separate estimates of (4) are used to determine the predicted differential in reporting rates via two alternative decompositions[3]:

$$\hat{r}^L - \hat{r}^N = [\bar{P}(\hat{\beta}^L, X^L) - \bar{P}(\hat{\beta}^N, X^L)] + [\bar{P}(\hat{\beta}^N, X^L) - \bar{P}(\hat{\beta}^N, X^N)] \quad (5)$$

$$\hat{r}^L - \hat{r}^N = [\bar{P}(\hat{\beta}^L, X^N) - \bar{P}(\hat{\beta}^N, X^N)] + [\bar{P}(\hat{\beta}^L, X^L) - \bar{P}(\hat{\beta}^L, X^N)] \quad (6)$$

where β is the estimate of the coefficients from the probit equation (4), varying according to which group is used (superscript L for incidents involving loss, superscript N for those with no loss). The terms $\hat{r}^L$ and $\hat{r}^N$ are the respective average of the predicted reporting probabilities for incidents with loss and incidents without. The expression $\bar{P}(\hat{\beta}^L, X^L)$ is the average across the sample of the predicted probabilities using the estimated coefficients for the sample of incidents with loss and the corresponding mean characteristics, and the other expressions vary according to whether coefficients and characteristics are used for incidents with or without loss. Thus in equation (5), the left hand square-bracketed expression provides an estimate of the difference in predicted reporting probability due to differences in regression coefficients, and the second term gives the difference attributable to differences in the underlying characteristics of the sample. The expressions in equation (6) yield the same estimates but with the non-loss involving incidents as the base group.

4 Results and discussion

4.1 Probit estimates

Our probit estimates of the probability of reporting a burglary incident are given in Table 1. We provide estimates for the whole sample alongside separate estimates for incidents involving a loss and those which do not. The

[3] We specify two decomposition equations due to uncertainty in indexing our base group. Ordinarily we might be certain that one group is the base (i.e. if we were considering the impact of a new treatment then our base case would be those who had not had the treatment), but we are not 100% certain as to whether incidents involving a loss are our base. Whether or not this presents a problem becomes evident if the two equations provide radically different estimates of the predicted reporting differential.

model is specified simply with the set of covariates discussed above. We do not include an insurance variable due to the way questions are asked in the BCS (respondents are only asked about insurance coverage if they experience loss or damage that is valued positively - we deal with this later). For a description of all the covariates reported here, and their descriptive statistics, see Table A1 in the Appendix. The base characteristics for the regressions are: white, married male, unskilled occupation with no formal qualifications, currently resident in the West Midlands, with no reported drug use. Rather than presenting the estimated coefficients we give the marginal effects (dF/dx in Table 2), although the coefficients are used later for the decompositions. We do this because probit (or logit) estimated coefficients cannot be interpreted directly as the impact on the dependent variable of a one unit change in the independent variable, particularly when the explanatory variables are predominately 0-1 dummies[4].

[4] Effectively the marginal effects show by how much the predicted probability of reporting an incident changes (at the means of all other variables) when the dummy variable in question becomes true (i.e. equals 1). In order to do this for a probit, one has to determine $Pr(r_i \neq 0|x_i) = \Phi(x_i\beta)$ when the dummy variable = 0 and for when it equals 1, and calculate the difference in this predicted probability (where Φ is the standard cumulative normal distribution, and $x_i\beta$ is the probit index).

Table 1.
The probability of reporting a burglary: probit estimates[5]

	Full Sample		No loss		Loss	
Covariate	dF/dx	|t|	dF/dx	|t|	dF/dx	|t|
AGE/10	-.004	1.060	-.005	.430	-.005	1.150
MAR0MALE	-.017	.760	-.003	.090	-.024	.860
MAR0FMAL	.006	.260	.001	.040	.009	.350
MAR1FMAL	.061***	2.750	.054	1.480	.059**	2.230
BLACK	.054*	1.780	.069	1.410	.049	1.320
ASIAN	.019	.660	.057	1.130	.002	.060
OTHER	-.055	1.180	.002	.030	-.077	1.380
UNEMPL	-.094**	2.380	-.059	1.020	-.112**	2.250
SOC1	-.056	1.400	-.050	.840	-.059	1.190
SOC2	-.030	.770	.017	.290	-.056	1.170
SOC3	-.067	1.580	-.066	1.040	-.060	1.140
EDU1	-.005	.170	-.029	.650	.013	.390
EDU26	-.038**	1.910	-.042	1.290	-.033	1.390
ANYYEAR	-.096***	4.040	-.085**	2.400	-.102***	3.380
MEMBNWS	.054**	1.940	.082*	1.810	.041	1.250
BADPOLIC	-.014	.670	-.001	.020	-.022	.850
PREVINCD	-.018**	2.090	.026**	2.370	-.075***	6.040
PCNAME	-.005	.240	.007	.240	-.013	.520
LOSS	.249***	15.050	-	-	-	-
WEEKEND	.033**	1.930	.027	1.030	.051***	2.480
NIGHTTIME	.041***	2.540	.063**	2.450	.047**	2.380
NORTH	.094***	2.450	.097	1.520	.093**	2.060
YORKS	.061*	1.780	.041	.710	.068*	1.730
NWEST	-.016	.480	-.018	.340	-.010	.240
EASTM	.062	1.540	.027	.410	.083*	1.760
EASTA	-.032	.540	-.045	.520	-.017	.240
SEAST	.044	1.270	.071	1.200	.031	.740
SWEST	.058	1.300	.163**	2.100	.006	.120
WALES	.023	.450	.056	.700	.010	.160
LOND	.048	1.510	.047	.870	.046	1.250
observations	4168		1500		2668	
χ^2 (d.f.)	356.58 (31)		48.84 (30)		107.53 (30)	
Log Likelihood	-2710.64		-936.47		-1746.12	

Note: *** = signi cant at 1% level, ** = signi cant at 5% level,
* = signi cant at 10% level

[5] The estimates include a survey year dummy that is not reported here.

The results given in Table 1 suggest that there is some variation in the probability of reporting across various socioeconomic groups. Compared to the base, married females are significantly more likely to report an incident, unless it involves no loss. Individuals who are currently unemployed are less likely to report incidents compared to the base (making the probability of reporting lower by 10%), as are those with non-degree qualifications (but neither are significant if the incident involves no loss). An interesting result is the effect of self-reported drug use. We included a variable to capture whether the individual had reported any drug use in the past year (ANYYEAR) as it is quite conceivable that such individuals are less likely to want to have contact with the police. Our results support this hypothesis, with the drug use variable being negative and highly significant across all samples.

The impact of the variables capturing the individual's previous contact with police and experience of burglary are quite predictable, although there appears to be no link between reporting and dissatisfaction with the police. This result holds however we define this relationship with the police, even if the relationship is positive (i.e. if the respondent knows or is related to someone in the police). Other influential factors include being part of a neighbourhood watch scheme, which has a positive influence on the probability of reporting (although it is not significant for the sample of incidents involving loss). Interestingly, if the incident is not the first in the past year (variable PREVINCD) then this has a significant negative influence on the likelihood of the incident being reported, (unless the current incident involves no loss, in which case it is more likely to be reported). This result is difficult to explain. The PREVINCD variable may be capturing some of the effects of previous exposure to the police, or could simply reflect an individual's change in attitude to burglary if the incident occurs more than once in the year.

The final group of influences are incident specific. Not surprisingly, if the incident involves a loss then this has a highly significant (absolute t value = 15.05) impact on the probability of the incident being reported[6]. The results suggest that if the incident involves a loss the this adds 0.249 (i.e.25%) to the probability of the incident being reported. In addition, where incidents occur at the weekend or at night, this significantly influences the likelihood of reporting (although weekend is not significant for incidents involving no loss). We also observe some regional affects, with the likelihood

[6] Following Goldberg and Nold (1980), a second model was estimated that included a number of dummy variables representing incremental bands of loss (i.e. 0-£49, £50-£99, £100-£199, etc.). These results, available on request, are very similar to those presented in Table 2. The main difference is that all the loss dummies are positive and significant, but their coefficients increase with the size of the loss.

of the incident being reported increasing if it occurs in the North of England or in Yorks/Humberside, compared to the base region (West Midlands).

4.1.1 Decompositions

Concentrating on our reporting differentials, the results of our decompositions are presented in Table 2. The rst gure in Table 2 shows the difference in reporting probability between incidents involving a loss and those which do not. The gures following this are the proportions of this difference explained by differences in coefficients and characteristics respectively.

Table 2.
Claimers/non-claimers reporting probit decompositions

Difference in means	
$\hat{r}^L - \hat{r}^N$	0.264
Difference in coefficients	
$\{\bar{P}(\hat{\beta}^L, X^L) - P(\hat{\beta}^N, X^L)\}$	0.250 (94.9%)
$\{\bar{P}(\hat{\beta}^L, X^N) - P(\hat{\beta}^N, X^N)\}$	0.247 (93.6%)
Difference in characteristics	
$\{\bar{P}(\hat{\beta}^N, X^L) - P(\hat{\beta}^N, X^N)\}$	0.014 (5.1%)
$\{\bar{P}(\hat{\beta}^L, X^L) - P(\hat{\beta}^L, X^N)\}$	0.017 (6.4%)

The rst observation about the gures in Table 3 is that there is a 26.4% difference in reporting probability when an incident involves a loss, all other things being equal (and regardless of which group we use as the base). Thus, calculating the probability of an incident being reported at the means of all variables, there is a 33.5% chance of an incident being reported if it involves no loss, but a 59.9% chance if it does involve loss. In terms of what drives this reporting differential, Table 3 provides us with two alternative measures according to which we consider the base group. If we consider incidents involving no loss as the base, 94.9% of the reporting differential is caused by differences in estimated coefficients, with the remaining 5.1% difference being due to differences in mean characteristics. The components of the reporting differential are similar when incidents involving loss are considered the base (93.6% and 6.4% respectively). These results tell us that around 95% of the reporting differential can be primarily attributable to the impact of loss. The (much smaller) remainder of the differential is therefore due to the differences in mean characteristics between the two sub-samples.

The decomposition results are important, particularly if the link between loss and reporting is related to insurance purchase and economic prosperity.

To illustrate this we split our full sample into two groups. Group 1 consisted of those in either managerial/professional or skilled professions (59.9%) and group 2 consisted of those in partly or unskilled occupations and those who were currently unemployed (40.1%). The distribution of incidents involving loss was evenly spread between group 1 and group 2. For group 1, 65.4% experienced incidents involving loss, whereas the rate for group 2 was 62.0%. If we consider just the incidents involving loss, we expect the reporting rate to be very similar for both groups given the results presented above (we have observed that reporting differentials are not much affected by differences in characteristics). Indeed, the reporting rate for group 1 where the incidents involve loss is 61.6%, with the rate for group 2 only slightly lower at 57.5%. What is illuminating, however, is the large difference in insurance coverage between the two groups. For the rst group, who are economically more prosperous, 61.6% of the incidents involving loss are covered by insurance, whereas for group 2, the rate is much reduced at 37.9%. This nding is consistent with other surveys and is particularly worrying. As we are certain that those on lower income are much less likely to insure their contents (e.g. Lewis, 1989), then as crime rates increases as the economy slows down, the redistributive effect of insurance is increased.

5 Concluding remarks

One of the purposes of this paper has been to add more fuel to the controversial debate on the whole crime/economy nexus. We present the rst attempt to model the under-reporting of crime using UK data. To do this we use the British Crime Survey, which yields a rich environment in which to test the micro-foundations of the propensity to report crime. We began our analysis by hypothesising that the reporting of crime, particularly burglary, is likely to be related to a number of socioeconomic factors, once we control for individual attributes and incident speci c factors. Using maximum likelihood estimation techniques, we have found that the probability of an incident being reported is signi cantly decreased if the victim is currently unemployed. This supports our suggestion that the difference between the true rate of crime and the measured rate of crime varies as economic activity varies.

Linked to the economic cycle is the relationship between loss, insurance and the probability of reporting a crime. We have found that incidents involving a positively valued loss are fairly evenly distributed between those in work and respondents who are currently unemployed. This implies that as the crime rate increases, the increase in burglaries involving loss will be more or less spread evenly across the two groups. However, the distribution of insurance coverage is not evenly distributed between the groups, with those on higher incomes having a much higher tendency to insure household contents. What is more, we have shown that incidents involving loss have a much higher probability of being reported than incidents that do not involve loss. This generates two causes of concern. We know that the level of insurance coverage increases with income (Lewis, 1989), thus, during a downturn in the economic cycle we anticipate insurance coverage to decrease as relative prosperity worsens. This implies that individuals who are affected by economic downturn suffer considerably, as the incidence of burglary will increase but less of the incidents are covered by insurance. Our second concern is that this relationship will have a further impact on the disparity between measured crime and actual crime that was illustrated above.

Finally, we highlight a particularly interesting result concerning criminal activity and reporting. We found that there is a signi cant negative association between involvement in drug use and reporting of crimes. Clearly individuals who have some illegal behaviour to hide from the authorities are much less likely to report incidents to police. This raises another question mark over the relationship between measured crime and actual crime, particularly during periods of economic downturn when illegal activity is likely to increase.

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Appendix - Table A1: Variable descriptions and descriptive statistics

Variable	Description	Mean	Std. Dev.
	Personal characteristics		
AGE/10	Respondent s age/10	3.751	2.434
MAR0MALE	1 = single male	0.227	0.419
MAR1MALE	1 = married male	0.320	0.466
MAR0FMAL	1 = single female	0.229	0.420
MAR1FMAL	1 = married female	0.225	0.417
WHITE	1 = white	0.784	0.412
BLACK	1 = Black (African, Caribbean, other)	0.090	0.287
ASIAN	1 = Asian (Indian, Pakistani, Bangladeshi)	0.094	0.292
OTHER	1 = Chinese, other ethnic origin, or none	0.031	0.174
UNEMPL	1 = currently unemployed	0.227	0.419
SOC1	1 = managerial/professional occupation	0.292	0.455
SOC2	1 = skilled occupation	0.306	0.461
SOC3	1 = partly skilled occupation	0.124	0.329
SOC4	1 = unskilled occupation	0.037	0.189
EDU1	1 = degree or higher quali cation	0.173	0.378
EDU26	1 = non-degree quali cation	0.570	0.495
EDU7	1 = no formal quali cations	0.257	0.437
ANYYEAR	1 = has taken any drug in past year	0.150	0.358
	Attitudes and exposure to police		
MEMBNWS	1 = part of neighbourhood watch scheme	0.098	0.297
PREVINCD	number of previous incidents in past year	0.801	0.954
BADPOLIC	1 = previously dissatis ed with police	0.191	0.393
PCNAME	1 = know someone in police	0.224	0.417
	Incident speci c attributes		
LOSS	1 = incident involves loss	0.640	0.480
WEEKEND	1 = incident occurred at weekend	0.650	0.477
NIGHTIME	1 = incident occurred at night	0.518	0.500
NORTH	1 = resident in North of England	0.081	0.273
YORKS	1 = resident in Yorks/Humberside	0.132	0.338
NWEST	1 = resident in North West England	0.162	0.369
EASTM	1 = resident in East Midlands	0.069	0.254
WESTM	1 = resident in West Midlands	0.094	0.292
EASTA	1 = resident in East Anglia	0.024	0.153
SEAST	1 = resident in South East England	0.124	0.330
SWEST	1 = resident in South West England	0.050	0.217
WALES	1 = resident in Wales	0.036	0.186
LOND	1 = resident in London	0.228	0.419