Rates of participation in burglary and motor vehicle theft - Estimates and implications for policy

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This bulletin uses techniques developed in population biology to estimate the number of offenders actively involved in burglary and motor vehicle theft in NSW during the period 2006-2007, as well as the percentage of offenders apprehended and convicted. We estimate the participation rates in burglary and motor vehicle theft to have been approximately 32,000 (burglary) and 23,000 (motor vehicle theft). The overall detection and conviction rates amongst these groups of offenders were found to be much higher than is conventionally assumed (16.6 per cent for burglary and 13.5 for motor vehicle theft). The analysis provides evidence that there are two distinct groups of offenders – one offending at a very high rate and the other at a much lower rate. The majority of frequent offenders are caught and convicted but most infrequent offenders escape conviction. The bulletin concludes by arguing that control of burglary and motor vehicle theft requires a combination of law enforcement targeted at high rate offenders and prevention strategies designed to remove the opportunities and incentives for involvement in crime.

Keywords: offender population, prevalence, offending frequency, burglary, motor vehicle theft.

INTRODUCTION

One of the recurring debates among law enforcement and crime prevention practitioners concerns the relative merits of crime prevention and law enforcement when it comes to controlling high volume property crime. Advocates of crime prevention often point to the low clear-up rate associated with volume property crimes such as motor vehicle theft and burglary, and argue that, since most offenders are never caught, more resources should be devoted to removing the incentives and opportunities for involvement in crime. Advocates of law enforcement argue that a small percentage of offenders accounts for a disproportionate amount of property crime and their apprehension and incapacitation can and does exert a significant suppression effect on crime.

At face value, the arguments of crime prevention advocates seem well supported by evidence. Although the incidence of property crime in Australia has fallen

substantially, clear-up rates for volume property crime are very low. In New South Wales (NSW) in 2008, for example, the percentage of home burglaries and motor vehicle thefts cleared[1] by police within 90 days of being reported was less than five per cent (NSW Bureau of Crime Statistics and Research 2009). Clear-up rates, however, measure the proportion of offences resulting in an arrest (or criminal proceedings), not the proportion of offenders who are apprehended in some designated period of time. Even if the risk of apprehension for a burglary is as low as five per cent, the average offender will be caught after 20 burglaries.[2] Some burglars commit this many burglaries in less than two months (Stevenson & Forsythe 1998).

To make sensible judgements about how to balance resources between crime prevention and law enforcement, it would help to have some idea as to how many offenders are actively involved in particular types of crime and whether they all offend at the same rate. It would also help to

have information on the percentage of offenders that are caught and convicted in a reasonable period of time (e.g. two years). If, for example, the population of offenders is very large and the risk of apprehension very low it would make sense to focus resources on crime prevention rather than law enforcement. If, on the other hand, the population of offenders is comparatively small and the risk of arrest and conviction over time fairly high, then it would make sense to focus resources on law enforcement rather than prevention.

This bulletin provides estimates of the size of the burglar and motor vehicle thief populations in NSW and the likelihood of a burglar or car thief being caught and convicted. The methods used to obtain these estimates have been used to estimate offender populations in the United States. They have, however, only once before been applied to estimate an offender population in Australia. That work is now more than 25 years old was

limited to the Australian Capital Territory. It must be emphasised at the outset that the estimates presented here are based on a number of key assumptions. We present evidence supporting these assumptions but they cannot be regarded as beyond doubt. We consider the consequences for our estimates if the assumptions we make are wrong.

To orient the non-technical reader, the next section of the bulletin provides a brief overview of the methods used to estimate the size of the population of offenders. The following section reviews past work on estimating offender populations. The penultimate section provides estimates of the number of active burglars and vehicle thieves in NSW and their likelihood of apprehension. The final section discusses the findings and their implications for policy.

ESTIMATING HIDDEN OFFENDER POPULATIONS

The problem of estimating the size of hidden populations is well known to wildlife experts, who are regularly called upon to estimate the size of a species population that they cannot directly count. One commonly used approach to this problem is known as capture-recapture. To illustrate the method, suppose we wish to estimate the number of motor vehicle thieves operating in a given area, say, NSW.

Let:

N = The number of motor vehicle thieves in NSW

M = The number caught in 2007

C = The number caught in 2008

R = The number of caught in 2008 who were also caught in 2007

If we are willing to assume that:

(a) the population of offenders is closed (no new offenders arrive and none leave)

(b) the likelihood of catching any particular offender is constant and independent of the number of prior arrests

(c) the likelihood of capture is the same for all offenders

then the ratio M/N should equal the ratio R/C. Since three of these quantities

(C, R and M) are known, we can estimate N. This approach can be generalised to situations in which there are multiple 'captures'.

PAST RESEARCH

Greene and Stollmack (1981) were among the first to use techniques developed in the biological sciences to estimate the size of offender populations and their article serves as a useful starting point for our discussion. They explored several models of the behaviour of offenders and obtained estimates of population size from each one. The simplest model they examined (known as a homogeneous Poisson model) assumed that the capture process is random and identical for all offenders. On this assumption, the probability that a given individual is apprehended exactly X times over a given period (P(X = x)) is given by the Poisson distribution, the equation for which is:

$$[1] \quad P(X=x) = \frac{\mu^x e^{-\mu}}{x!} \qquad (x = 0,1,2.....)$$

The parameter μ in this equation reflects the average rate of arrest of the population over the specified period. We can obtain an estimate of μ by fitting [1] to an actual distribution of apprehensions. Once we have a value for μ we can insert it into equation [1] and estimate the number of offenders in the population who would have had no apprehensions. This figure can then be added to the population of known offenders to obtain an estimate of the total population of offenders.

The second model they considered assumed that there are two subpopulations of offenders, one with a capture rate μ_1 and the other with a capture rate μ_2, with an unknown proportion p belonging to the first population and 1-p belonging to the second population. The capture rates for the two groups, though, different, are assumed to be fixed and independent of the number of previous apprehensions. This model (known as a heterogeneous Poisson model) leads to a slightly more complex equation for the probability of capturing an offender X times:

$$[2] \quad P(X=x) = \frac{p\mu_1^x e^{-\mu_1}}{x!} + \frac{(1-p)\mu_2^x e^{-\mu_2}}{x!}$$

The first term on the right hand side of equation (4) captures the contribution to the offender population of those with capture rate μ_1, while the second term captures the contribution of those with capture rate μ_2.

Greene and Stollmack (1981) also considered a third model, which assumed that μ is continuously distributed through the offender population according to a gamma distribution, with parameters β and α. The gamma distribution is obtained when n exponentially distributed variables are summed. It is an appropriate distribution to use when each individual in an offender population offends at random intervals but different offenders are believed to offend at varying rates. In this model (referred to here as the gamma model), the probability of an individual in the population being captured X times is given by the negative binomial distribution:

$$[3] \quad P(X=x) = \binom{\alpha+x-1}{\alpha-1}\left(\frac{\beta}{\beta+1}\right)^x\left(\frac{1}{\beta+1}\right)^\alpha$$

Equations [1] to [3] describe the predicted distributions of capture frequencies under different assumptions about the offender population. To estimate the parameters for each equation it is necessary to fit the observed distributions of capture frequency to a prescribed distribution of capture frequency. Because there are no data on the number of offenders caught zero times in a given observation period, however, equations [1] to [3] have to be modified to describe the distribution of capture frequency amongst offenders with at least one capture in the observation period. These modified distributions are known as truncated distributions of capture frequency (because they are truncated at zero).

Greene and Stollmack (1981) fitted the truncated distributions for the homogeneous Poisson model (equation [1]) and the heterogeneous Poisson model (equation [2]) to data on the frequency of arrests among 6,119 adult males who experienced 7,721 index arrests (arrests for serious offences) in 1974 and 6,309 adult males who experienced 7,846 arrests in 1975. The

two models generated markedly different estimates of the size of the offender population. The homogeneous Poisson model led to an estimate of 16,282 offenders in 1974 and 17,675 offenders in 1975. The heterogeneous Poisson model led to an estimate of 29,493 offenders in 1974 and 30,298 in 1975. Which set of estimates is right?

Greene and Stollmack (1981) addressed this issue by measuring the level of agreement between the predicted and the observed number of arrests. The homogeneous Poisson model fitted the data very poorly, predicting too few with one arrest and too many with two. The heterogeneous Poisson model, on the other hand, fitted the data extremely well – so well in fact that Greene and Stollmack (1981) deemed it unnecessary to fit the gamma to the data. They concluded that the aggregate crime rate is shaped by the criminal activity of two groups of offenders – one of which, though small (accounting for less than five per cent of all offenders), was arrested at a very high rate and the other (accounting for the majority of offenders) was arrested at a very low rate.

Collins and Wilson (1990) used similar methods to estimate the size of the population of juvenile offenders involved in vehicle theft in the Australian Capital Territory (ACT). They obtained data on the distribution of court appearances for motor vehicle theft among a sample of 59 adults and 72 juveniles dealt with in the ACT courts in 1987 and compared the fit of three distributions, the homogenous Poisson, the heterogeneous Poisson and the homogenous Poisson with Zelterman's estimator (Zelterman 1988).[3] Like Greene and Stollmack (1981), they found the homogeneous Poisson model fitted the data very poorly as did the homogenous Poisson distribution with Zelterman's estimator. The heterogeneous Poisson model, however, fitted the data very well. Their study suggested that the capture rate of motor vehicle thieves was much higher than the clear up rate would suggest. They estimated that between 38 and 40 per cent of all motor vehicle thieves in the ACT were charged at some point during 1987.

Bouchard (2007) used the homogenous Poisson distribution with Zelterman's estimator to obtain estimates of the number of participants in the marijuana industry in Quebec. Whereas Collins and Wilson (1990) found a poor fit to the observed data, Bouchard reports the fit of this distribution to data on the number of arrests for marijuana cultivation was very good. As he points out, however, this is probably because he grouped those with three or more arrests into one category. This is precisely where the predicted distribution of arrests obtained from a Poisson model gives a poor fit.

The heterogenous Poisson model, like the homogeneous Poisson model, assumes that the likelihood of arrest is independent of the number of previous apprehensions. Not everyone has been persuaded by this assumption. Rossmo and Routledge (1990) developed a model of the arrest process according to which all offenders start with the same arrest probability but some become more skilled at evading capture after their first arrest (i.e. the risk of arrest falls after the first arrest). They tested their model by fitting it to data on arrests of 'migrating fugitives' and street prostitutes and found that it fitted the data very well. The estimate of the size of the offender population in their study was about half that obtained when a heterogenous Poisson offender population model was fitted to the same data.

The Rossmo and Routledge model fitted the data very well because the predicted distribution of arrests for the model they developed is exactly the same as that for the heterogeneous Poisson model. This raises an important question. If different models of the offending process have very similar implications about the distribution of the number of arrests, how do we decide which model is correct? The only way to resolve this issue is to find independent evidence to support the assumptions of a particular model. To support their assumption that the risk of arrest changes after the first arrest, Rossmo and Routledge (1990) drew on data from an unpublished police survey of 65 prostitutes in Vancouver, Canada, indicating that 11 of the 65 had learned from past experience and could not be 'tricked'.[4] This may be sufficient evidence to justify the conclusion that prostitutes

learn how to reduce the risk of arrest but it provides no grounds for believing that the risk of arrest for burglary and/or motor vehicle theft changes significantly after the first arrest.

THE PRESENT STUDY

AIM

The aim of this study, as noted earlier, is to estimate the populations of offenders involved in home burglary and motor vehicle theft in NSW and thereby determine what proportion of these offenders are apprehended and convicted. We focus on burglary and motor vehicle theft for two reasons. Firstly, the true prevalence of both offences is well known, which makes it easier to check the plausibility of our estimates of the size of the burglar and motor vehicle thief populations. Secondly, both offences, though prevalent, have very low clear up rates (NSW Bureau of Crime Statistics and Research 2009).

As with previous studies, we assume that the rate at which a burglar or motor vehicle thief appears in court convicted of a burglary or motor vehicle theft is determined by the frequency with which they commit these offences. To be more precise, we assume that the more frequently people commit burglary and motor vehicle theft, the more frequently they are arrested and convicted of these offences. This assumption is supported by empirical evidence of a close relationship between self-reported offending and the frequency of arrest and conviction (Hindeland, Hirschi & Weiss 1979; Maxfield, Weiler & Widom 200, Farrall 2005). We also assume that there are no entrants or departures from the population of offenders during the period of the study and that the risk of arrest and conviction is constant and independent of the number of previous arrests and convictions. As noted earlier, we will discuss the implications of these assumptions following the results.

METHOD

The first step in estimating the number of burglars and motor vehicle thieves is to select an appropriate model of the process by which convictions are

generated. The initial plan was to evaluate the adequacy of three models: the homogeneous Poisson model, the heterogenous Poisson model and the gamma model. The heterogenous Poisson model fitted the data so well, however, it seemed pointless comparing its fit with that of the gamma model. The results presented below, therefore, concern the relative adequacy of the homogenous and heterogenous Poisson models. Details of the method used to fit the theoretical to the observed distribution can be found in the Appendix.

DATA SOURCE

The data source for the study is ROD: the NSW Bureau of Crime Statistics and Research re-offending database. Details of ROD can be found in Hua and Fitzgerald (2006). In brief, ROD contains details of every person who has appeared in any NSW court since 1994 charged with a criminal offence. The data for this study were drawn from all persons (juvenile and adult) who appeared in court in either 2006 or 2007 or both) and who were convicted of either break and enter (dwelling) or motor vehicle theft. In what follows we refer to a court appearance that results in a conviction of one or other of these offences as a conviction episode.

RESULTS

MODEL FITTING

Table 1 shows the frequency distribution of the number of conviction episodes for break and enter dwelling (BESD) or motor vehicle theft (MVT) during this period.

Table 1: Number of conviction episodes for BESD and MVT (2006-2007)

Number of conviction episodes	(BESD)	(MVT)
1	4,561	2,677
2	641	329
3	135	69
4	22	18
5	10	2
6	5	1
Total	**5,374**	**3,096**

Table 2: Homogenous Poisson Model: observed v predicted conviction episodes (BESD)

Number of conviction episodes	Observed	Predicted
1	4561	4332
2	641	903
3	135	125
4	22	13
5	10	1
6	5	0
Total	**5,374**	**5,374**

$\mu = 0.417$
Est. no. of persons involved in BESD = 15,762
Kolmogorov-Smirnov Z = 0.0434, p < 0.000

Table 4: Heterogenous Poisson Model: observed v predicted conviction episodes (BESD)

Number of conviction episodes	Observed	Predicted
1	4,561	4,565
2	641	643
3	135	131
4	22	29
5+	15	6
Total	**5,374**	**5374**

Split parameter (p) = 0.0643
$\mu_1 = 0.9602 \quad \mu_2 = 0.1449$
$n_1 = 2,083.55 \quad n_2 = 30,311.65$
Est. no. of persons involved in BESD = 32,395
Kolmogorov-Smirnov Z = 0.087, p = 1.00 (approx)

Table 3: Homogenous Poisson Model: observed v predicted conviction episodes (MVT)

Number of conviction episodes	Observed	Predicted
1	2,677	2,617
2	329	428
3	69	47
4	18	4
5+	3	0
Total	**3,096**	**3,096**

$\mu = 0.327$
Est. no. of persons involved in MVT = 11,096
Kolmogorov-Smirnov Z = 0.019, p = 0.593

Table 5: Heterogenous Poisson Model: observed v predicted conviction episodes (MVT)

Number of conviction episodes	Observed	Predicted
1	2,677	2,677
2	329	329
3	69	70
4	18	16
5+	3	4
Total	**3,096**	**3,096**

Split parameter (p) = 0.0459
$\mu_1 = 1.0024 \quad \mu_2 = 0.1181 \quad n_1 = 1,049 \quad n_2 = 21,829$
Est. no. of persons involved in MVT = 22,878
Kolmogorov-Smirnov Z = 0.013, p = 1.0 (approx)

Most of those convicted of these offences only had one court appearance. Around 11-12 per cent in both categories of crime had two appearances. A small percentage had more than two appearances, with the maximum number of appearances (resulting in a conviction) being six for both BESD and MVT.

Table 2 (BESD) and Table 3 (MVT) show the results of fitting the homogeneous Poisson model. The Kolmogorov-Smirnov results indicate that there are significant differences between predicted and observed values for burglary but not for motor vehicle theft. Models for both offences generally predict too few

offenders with large numbers of court appearances.

Table 4 (BESD) and Table 5 (MVT) show the results of fitting the heterogeneous Poisson distribution to the observed distributions in Table 1. The notes at the bottom of each table show the estimated fraction of the offender population offending at a high rate (p), the rate at which criminal conviction episodes are occurring in the high rate group (μ_1) and the rate at which they are occurring in the low rate group (μ_2).

The heterogenous Poisson model gives a much better fit to the data. There are no significant differences between predicted

Table 6: Estimated number of conviction episodes by offender group (BESD and MVT)

Conviction episodes offenders	BESD			MVT		
	High rate offenders	Low rate offenders	All BESD	High rate offenders	Low rate offenders	All MVT
0	797	26,224	27,021	385	19,397	19,781
1	768	3,799	4,565	386	2,291	2,677
2	367	275	643	193	135	329
3	118	13	131	65	5	70
4	28	0	29	16	0	16
5	5	0	5	3	0	3
6	1	0	1	1	0	1
Total	**2,084**	**30,311**	**32,395**	**1,049**	**21,828**	**22,877**

and observed values. In fact the fit is remarkably good for both burglary and motor vehicle theft. We therefore proceed to use the heterogeneous model to estimate the size of the burglar and motor vehicle thief populations.

ESTIMATION OF OFFENDER POPULATIONS

Comparing Tables 4 and 6 we can see that, in the case of BESD, 5,374 offenders were caught and convicted out of a total estimated population of 32,395. This suggests that over the two-year period, 16.6 per cent of the active BESD population was caught and convicted. Note that this is 3.45 times higher than the 90-day police clear up rate for burglary would suggest (NSW Bureau of Crime Statistics and Research 2009, p. 52). In the case of MVT (see Tables 5 and 6), 3,096 offenders were captured and convicted out of a total estimated population of 22,878, which suggests that over the two-year period, 13.5 per cent were caught and convicted. This is 3.3 times higher than the MVT clear-up rate would suggest (NSW Bureau of Crime Statistics and Research 2009, p. 52).

Table 6 shows the relative contribution that high and low rate BESD offenders make to the total number of conviction episodes accrued by the population of persons committing BESD. Table 6 also shows the corresponding results for MVT.

Two things stand out about Table 6. The first is that, the vast majority of high rate offenders (62 per cent for BESD; 63 per cent for MVT) were convicted at least once during the two-year observation

period. In fact, 25 per cent of the high rate burglars and nearly 27 per cent of high rate motor vehicle thieves were convicted two or more times. The second point to note is that the vast majority of low rate offenders (87 per cent of low rate BESD offenders, 89 per cent of low rate MVT offenders) were *not* convicted at all over the two-year observation period.

DISCUSSION

The aim of this paper was to estimate the proportions of burglary and motor vehicle theft offenders who are apprehended over a two-year period. We estimate that, during the period 2006/07 in NSW, approximately 32,000 people committed a home burglary and 23,000 committed a motor vehicle theft. Approximately 17 percent of the former group and 14 per cent of the latter group were convicted at least once over the two-year observation period.

If the heterogenous Poisson model provides an accurate description of the process generating convictions, there are two groups of offenders involved in these offences; one of which offends and is convicted at a high rate, the other of which offends and is convicted at a much lower rate. High rate burglars are convicted at a rate that is more than 6.6 times higher than low rate offenders, while high rate motor vehicle thieves are convicted at a rate that is more than 8.5 times higher than low rate motor vehicle thieves. Thus, although high rate burglars make up just 6.4 per cent of the burglar population, they account for about 39

per cent of all convictions for burglary. Similarly, although high rate motor vehicle thieves make up just 4.6 per cent of the motor vehicle thief population, they account for 34 per cent of all convictions for motor vehicle theft.[5] In short, the vast majority of high rate offenders were convicted at least once and many were convicted several times. The vast majority of low rate offenders, on the other hand, were not convicted at all during the observation period.

Before discussing the implications of these findings we need to consider how plausible they are. One way of assessing them is to compare the fit of the predicted distribution to the observed distribution of the number of conviction episodes. If the model is correct, the departures of observed from predicted should be within the limits of chance. The Kolmogorov-Smirnoff values in Tables 2 and 3 indicate that for both offences, the fit is remarkably good. In fact, as the associated p-values indicate, there is for all practical purposes no difference between the numbers of offenders predicted and the number observed for either category of crime. Our estimates of the size of the offender population and the risk of conviction certainly fit the observed data very well.

Another way to assess the plausibility of our estimates is to compare them with other independent estimates of offender populations. Baker (1998) conducted a self-reported offending study among a represented sample of 5,178 NSW secondary school students. She found that 5.4 per cent of those surveyed reported involvement in break and enter

in the preceding 12 months, while 4.7 per cent reported involvement in motor vehicle theft over the same period. Given the size of the secondary school student population at the time, this would imply that, over a 12-month period, approximately 23,800 students committed a burglary and approximately 20,700 students committed a motor vehicle theft. Given that her estimates of involvement in burglary and motor vehicle theft were confined to offending by secondary school students, whereas our estimates include all offenders (juvenile and adult), one might have expected her estimates to be somewhat lower than ours. It should be noted, however, that at the time Baker conducted her study, burglary and motor vehicle theft in NSW were much more prevalent than they are now (Australian Bureau of Statistics 1999; 2008b).

A third way of assessing the plausibility of our results is to see whether there is any independent evidence for the assumptions on which they are based. There are three key assumptions in the model we have used to estimate the population of offenders. The first is that there are two groups of offenders, one of which offends at a very high rate and one of which offends at a much lower rate. The second is that the population of offenders is closed over the period of the study, that is, no new offenders arrive and none leave. The third key assumption is that the probability of conviction is independent of the number of previous convictions. Let us examine each of these assumptions in turn.

Early evidence provided strong support for the assumption that there are two distinct populations of offenders with different offending rates. Farrington, Blumstein and Moitra (1986) analysed the correlates of recidivism amongst offenders in the Cambridge Study of Delinquent Development and found evidence that there are two distinct groups, which they labelled, respectively, 'desisters' and 'persisters'. Patterson, Debaryshe and Ramsey (1990) found evidence for what they call 'early' and 'late' starters and hypothesised that the genesis of offending in the former group lies in coercive parenting whilst for the latter group it lies in delinquent peer

influence. Moffitt (1993) research also suggests a distinction between what she calls 'adolescent-limited' and 'life course persistent' offenders. She contends that the delinquency observed in 'life course persistent' offenders is due to a combination of genetic and environmental factors, whereas the delinquency observed in 'adolescent-limited' offenders is due to the onset of puberty and exposure to antisocial peers.

More recent research, using statistical techniques (e.g. latent class analysis) to identify groups of offenders, suggests that there may be a larger number of groups. The number of groups posited to exist by those using these techniques, however, varies markedly from study to study, with some finding just two groups and others finding up to seven distinct groups. Dulmen et al. (2009) found the number of groups of offenders found to exist varied with the kind of criminal behaviour being examined, the way in which it was measured, the frequency with which it was measured, the period over which it was measured and whether or not females were included in the sample. In light of the contradictory findings in the literature on the number of distinct groups of offenders, all that can be said is that all studies converge in finding at least two distinct groups. Some find evidence that there are more.

The second key assumption is that the population of offenders is closed over the period of the study, that is, no new offenders arrive and none leave. It is reasonable to assume that few active offenders leave the criminal population as the average criminal career is thought to last about five years (Blumstein, Cohen, Roth and Visher 1986). It is impossible to determine, however, whether or not there are new entrants to the populations of offenders involved in motor vehicle theft and burglary and, if so, how there are. We therefore need to consider the consequences if this assumption is incorrect.

If new offenders are entering the population after the the starting point for the study, then μ_1 or μ_2 or both will be underestimated. Since our estimate (see Appendix) of the number of offenders N is given by:

$$\overline{N} = \frac{N}{p(1 - e^{-\mu_1}) + (1 - p)(1 - e^{-\mu_2})}$$

the effect of underestimating μ_1 or μ_2 will be to overestimate N. This, in turn, will lead to an understimate of the percentage of offenders apprehended.

The third key assumption is that the probability of detection and conviction is independent of the number of previous convictions. This would be untrue if (for example) being detected or convicted exerted a deterrent effect. It would also be untrue if a substantial proportion of burglars were imprisoned and unable to offend for long periods. There is little evidence that sanctions imposed by courts exert much deterrent effect (Doob & Webster 2003). Surveys of secondary school students, on the other hand, suggest that the number of burglars or motor vehicle thieves appearing in court is probably a very small fraction of the total offender population (Weatherburn 2004, p. 147). Thus the assumption that the likelihood of detection is independent of the number of previous detections does not seem unreasonable as a first approximation. If all offenders do start with the same conviction probability but the risk of conviction falls after the first conviction then the true number of offenders is smaller and the true risk of conviction higher than our estimates suggest (Rossmo & Routledge 1990, p. 306).

Turning now to the policy implications of our findings, the first point to note is that police efforts to apprehend and convict burglars and motor vehicle thieves are more effective than a casual perusal of clear-up rates might suggest. More than sixty per cent of high rate burglars and motor vehicle thieves are apprehended and convicted within two years. This provides justification for the considerable police resources devoted to apprehending and prosecuting recidivist property offenders. It also provides justification for efforts to reduce recidivism amongst convicted property offenders even though they only represent a small percentage of the total offender population. Their disproportionately large contribution to the total volume of offending means that small reductions in rates of re-offending can be expected to have a significant effect on crime.

The utility of the criminal justice system as a crime control tool is, however, limited by the fact that the vast majority of low rate burglary and motor vehicle theft offenders are unlikely ever to get caught. This means their behaviour is impossible to influence through incapacitation or rehabilitation and is unlikely to be influenced by the threat of more severe punishment. The best way to reduce offending by those who are unlikely to get caught is to block the opportunities and incentives for involvement in crime. A number of strategies are known to be effective in reducing burglary and motor vehicle theft, including better household and vehicle security, property marking and 'cocoon' watch. A comprehensive review of what works in the prevention of household and vehicle theft can be found in Eck (2002). The National Motor Vehicle Theft Reduction Council also maintains a website[6] with detailed information on prevention strategies for motor vehicle theft in Australia.

Finally, our results also highlight both the strength and limitations of incapacitation as a crime control tool. The very high rates of offending and arrest found among a small proportion of offenders indicate that the imprisonment of these offenders would have a significant effect on crime. Most studies examining the hypothetical benefits of higher imprisonment rates (e.g. Weatherburn, Hua & Moffatt 2006), however, assume that there is no difference in the frequency of offending amongst those who go to prison, those who are convicted but not sent to prison and those who are arrested by police but not convicted. Canela-Cacho, Blumstein and Cohen (1997) have argued that this is unlikely to be true because high rate offenders are more likely to be arrested, more likely to be convicted multiple times and more likely to end up in prison.

The present results provide confirmation of this. They suggest, moreover, that increasing the imprisonment rate is more cost-effective in controlling burglary and motor vehicle theft when prison is used sparingly than when it is used a lot. When there are significant numbers of high rate offenders in the community, increasing their imprisonment rate can be expected to have a significant effect on crime. As the proportion of convicted offenders given a prison sentence increases, however, more and more low frequency offenders get caught up in the custodial net. This raises the cost of imprisonment but reduces its marginal effectiveness in controlling crime.

NOTES

1. For our purposes the clear up rate is the proportion of incidents of a particular offence type for which a Person of Interest (POI) is found and against whom legal proceedings are initiated

2. If p = the probability of detection for burglary and offending is random, then the average number of burglaries before the first detection is $1/p$ or 20 if p is taken as .05.

3. Zelterman's estimator is an alternative to maximum likelihood methods in fitting an homogenous Poisson distribution to a set of data. It only uses data from the first two categories, rather than the entire empirical distribution.

4. A 'trick' refers to a situation where a police officer poses as a customer and asks a suspected prostitute to engage in paid sex. If the prostitute agrees, she is then arrested.

5. High rate burglars are apprehended and convicted at an average rate of .9602/two years. Our estimates suggest that there are 2,084 high rate burglars (see Table 1). Multiplying these two figures indicates that high rate burglars account for approximately 2000 conviction episodes. This is 37 per cent of the total number of conviction episodes for the entire group over the relevant period. The calculation for high rate motor vehicle thieves proceeds in an identical fashion.

6. www.carsafe.com.au

REFERENCES

Australian Bureau of Statistics 1999, *Crime and Safety Australia*, Cat. No. 4509.0, Australian Bureau of Statistics, Canberra.

Australian Bureau of Statistics 2008a, *Recorded Crime-Victims*, Australian Bureau of Statistics, Cat. No. 4510.0, Canberra.

Australian Bureau of Statistics 2008b, *Crime and Safety: New South Wales*, Cat. No. 4509.1, Australian Bureau of Statistics, Canberra.

Baker, J. 1998, *Juveniles in Crime-Part 1: Participation Rates and Risk Factors*, NSW Bureau of Crime Statistics and Research, Sydney.

Blumstein, A., Cohen, J., Roth, J. A. & Visher, C. A. (eds.) 1986, *Criminal Careers and Career Criminals*, vol. 1, National Academy Press, Washington DC.

Bouchard, M., 2007, A Capture-Recapture Model to Estimate the Size of Criminal Populations and the Risks of Detection in a Marijuana Cultivation Industry, *Journal of Quantitative Criminology*, vol. 23, pp. 221-241.

Canela-Cacho, J.A., Blumstein, A. and Cohen, J. 1997, 'Relationship between offending frequency (λ) of imprisoned and free offenders', *Criminology* vol. 35: pp. 133-175.

Collins, M.F & Wilson, R.M. 1990, Automobile Theft: Estimating the Size of the Criminal Population, *Journal of Quantitative Criminology*, vol. 6(4), pp. 395-409.

Doob, A. & Webster, C. 2003, Sentence Severity and Crime: Accepting the Null Hypothesis. *In Crime and Justice: An Annual Review of Research*, vol. 30, M. Tonry (ed.), The University of Chicago Press, Chicago.

Eck, J. 2002, Preventing Crime at Places, In Sherman, D.P. Farrington, B.C. Walsh, D.L. MacKenzie (eds.), 2002, Evidence-Based Crime Prevention, Routledge, London, pp. 241-294

Blumstein, A., Farrington, D.P. & Moitra, S. 1985, Delinquency careers: Innocents, desisters and persisters, in *Crime and Justice: An Annual Review of Research*, vol. 6, M. Tonry & N. Morris, (eds.). The University of Chicago Press, Chicago, pp. 187-219.

Farrall, S. 2005, Officially recorded convictions for probationers: The relationship with self-report and supervisory

observations, *Legal and Criminological Psychology*, vol. 10(1), pp. 121-131.

Greene, M.A., & Stollmack, S. 1981, Estimating the number of criminals. In Fox, J.A. (ed.), *Models in Quantitative Criminology*, Academic, New York, pp.1-24.

Hindelang, M.J., Hirschi, T. & Weis 1979, The Illusion of Discrepancy between Self-Report and Official Measures, *American Sociological Review*, vol. 44(6), pp. 995-1014.

Hua, J. & Fitzgerald, J. 2006, Matching court records to measure re-offending, *Crime and Justice Bulletin* 95, NSW Bureau of Crime Statistics and Research, Sydney.

Maxfield, M.G., Weiler, B.L. & Widom, C.S. 2000, Comparing self-reports and official records of arrests, *Journal of Quantitative Criminology*, vol. 16, no. 1, pp. 87-110.

Moffitt, T.E. 1993, Adolescent-Limited and Life-Course-Persistent Antisocial Behaviour: A Developmental Taxonomy, *Psychological Review*, vol. 100(4), pp. 674-701.

NSW Bureau of Crime Statistics and Research 2009, *Recorded Crime Statistics 2008*, NSW Bureau of Crime Statistics and Research, Sydney.

Patterson, G.R., DeBaryshe, B., & Ramsey, E. 1990, A developmental perspective on antisocial behaviour, *American Psychologist*, vol. 44, pp. 329-335.

Rossmo, D.K & Routledge, R. 1990, Estimating the Size of Criminal Populations, *Journal of Quantitative Criminology*, vol. 6(3), pp. 293-313.

Stevenson, R.J., Forsythe, L.M.V. & Weatherburn, D. 2001, The stolen goods market in New South Wales, Australia, *British Journal of Criminology*, vol. 41, pp. 101-118.

van Dulmen, M.H., Goncy, E., Vest, A. & Flannery, D. 2009, Group-Based Trajectory Modeling of Externalizing Behaviour Problems From Childhood through Adulthood: Exploring

Discrepancies in the Empirical Findings. In J. Savage (ed.), *The Development of Persistent Criminality*, Oxford University Press, Oxford, pp. 288-314.

Weatherburn, D., Hua, J. & Moffatt, S. 2006, How much crime does prison stop? The incapacitation effect of prison on burglary, *Crime and Justice Bulletin* 93, NSW Bureau of Crime Statistics and Research, Sydney.

Weatherburn, D. 2004, Law and order in *Australia: Rhetoric and Reality*, Federation Press, Sydney.

Zelterman, D. 1988, Robust estimation in truncated discrete distributions with application to capture-recapture experiments, *Journal of Statistical Planning and Inference*, vol. 18, pp. 225-237.

APPENDIX

Maximum Likelihood Estimate for Zero Truncated Heterogenous Poisson Distribution

Estimation procedures follow closely the Collins and Wilson (1990) study used to estimate the size of the criminal population involved in automobile theft. Assuming that the sample data come from a mixture of two zero truncated Poisson distributions with means μ_1 and μ_2 and mixing proportion p for the first distribution. Thus the probability that an object has x occurrences is

$$P(X = x) = \frac{pe^{-\mu_1}\mu_1^x + (1-p)e^{-\mu_2}\mu_2^x}{Dx!},$$

$$x = 1,2,3,\cdots$$

where

$$D = p(1-e^{-\mu_1}) + (1-p)(1-e^{-\mu_2}).$$

We use the Maximum Likelihood Estimate (MLE) to estimate the Parameters and. The likelihood function for a sample space with observed values $x_1, x_2, \cdots, x_s$ is

$$L(p,\mu_1,\mu_2) = \prod_{i=1}^{s} P(X = x_i).$$

The log likelihood function is thus

$$\log L(p,\mu_1,\mu_2) =$$

$$\sum_{i=1}^{s} \log\left(pe^{-\mu_1}\mu_1^x + (1-p)e^{-\mu_2}\mu_2^x\right)$$

$$-s \cdot \log\left(p(1-e^{-\mu_1}) + (1-p)(1-e^{-\mu_2})\right) - \sum_{i=1}^{s} x_i!$$

The maximal value of this function is achieved at the point where the partial derivatives with respect to p, μ_1 and μ_2 are all zero. We thus end up solving the following system of equations:

$$\begin{cases} \partial \log L(p,\mu_1,\mu_2)/\partial p = 0 \\ \partial \log L(p,\mu_1,\mu_2)/\partial \mu_1 = 0 \\ \partial \log L(p,\mu_1,\mu_2)/\partial \mu_2 = 0. \end{cases}$$

To solve these equations, we used the Newton-Raphson algorithm for higher dimensions, which is outlined here.

To solve for x, such that

$$F_i(x_1, x_2, \cdots, x_n) = 0, \quad i = 1,2,\cdots,n,$$

first define the Jacobian matrix as

$$\mathbf{J} = (\mathbf{J}_{ij})_{1 \le i,j \le n} \text{ where } \mathbf{J}_{ij} = \partial F_i/\partial x_j,$$

and then form the following iteration

$$\mathbf{X}_{\text{new}} = \mathbf{X}_{\text{old}} - \mathbf{J}^{-1}\mathbf{F}(\mathbf{X}_{\text{old}}),$$

where $X = (x_1, x_2, \cdots, x_n)^T$ are column vectors.

Suppose that the sample size is N, then the expected number of objects with zero occurrence is

$$\overline{F_0} = N \frac{pe^{-\mu_1} + (1-p)e^{-\mu_2}}{p(1-e^{-\mu_1}) + (1-p)(1-e^{-\mu_2})},$$

and the expected total number of objects including objects with zero occurrence is

$$\overline{N} = \frac{N}{p(1-e^{-\mu_1}) + (1-p)(1-e^{-\mu_2})}.$$

Estimates of parameters have been obtained by a SAS implementation of the Newton-Raphson algorithm for the MLE for the heterogenous Poisson model.