Australian Government

Australian Institute of Criminology

A discrete-time survival study of drug use and property offending: implications for early intervention and treatment

Jason Payne

Technical and Background Paper

No. 24

A discrete-time survival study of drug use and property offending: implications for early intervention and treatment

Jason Payne

Technical and Background Paper

No. 24

Australian Government

Australian Institute of Criminology

ISSN 1445-7261
ISBN 1 921185 26 0

Please note: minor revisions are occasionally made to publications after release.
The online versions available on this website will always include any revisions.

Published by the Australian Institute of Criminology
GPO Box 2944
Canberra ACT 2601
Tel: (02) 6260 9272
Fax: (02) 6260 9293
Email: front.desk@aic.gov.au
Web site: http://www.aic.gov.au

Disclaimer
This research paper does not necessarily reflect the policy position of the Australian Government.

Edited by the Australian Institute of Criminology
Typeset by Looking Glass Press

Table of contents

Tables

Figures

Executive summary

The nexus between drug use and criminal offending is of great interest to policy makers and researchers alike. The possibility that both illegal activities are interrelated provides promise that targeted interventions, such as drug diversion programs and drug courts, may have a tangible influence in reducing the social and economic costs of crime to the community. Although most in the academic and policy arenas agree that drugs and crime are interconnected, the nature of the relationship remains highly contested. This report contributes to this debate through an examination of drug use initiation and criminal escalation where it seeks to identify whether:

- drug use initiation increases the likelihood of offence escalation, and whether particular drugs play a more or less important role in increasing offending
- delayed onset of drug use increases or decreases the risk of offence escalation
- self-reported motives for the engagement in offending help to predict onset and escalation risk.

This study uses data from the Australian Institute of Criminology's Drug Use Careers of Offenders Study (DUCO) to examine the temporal pattern of drug use and offending. DUCO was an interviewer-administered self-reported survey of offending and drug use, conducted in 2001 among adult male prisoners in Queensland, Western Australia, Tasmania and the Northern Territory. Using a survival analysis technique, this study examines the risk profile of 1,500 property offenders and their likelihood of escalating to regular offending. Drug use, including cannabis and other illicit drugs, are modelled as temporal predictors as a means of estimating their effect on increasing or decreasing escalation risk across the criminal career. The multivariate analysis finds that:

- Specific demographic characteristics were linked to an increased risk of escalation. In particular young and/or Indigenous offenders were more likely to escalate to regular offending within the first ten years of their criminal career. This effect holds regardless of whether the offender was a drug user or not.
- Drug use initiation increases the risk of escalation to regular offending. Cannabis has a direct, independent effect on increasing the risk of escalation, while the use of other illicit drugs increases this risk over and above that which is attributable to cannabis alone. The risk is greatest for offenders who initiate both cannabis and other illicit drugs in the same year.
- The risk associated with drug use decreases with each year of use. If an offender starts using drugs, but does not escalate to regular offending in that same year, the risk of escalating then decreases with each subsequent year that escalation does not occur.
- The risk of immediate escalation to regular offending is lower for offenders who begin to use drugs later in their criminal career.
- Offenders who had used drugs prior to committing their first offence were more at risk of escalating to regular offending than non-drug users, but less at risk than offenders who commenced drugs after their first offence.
- Economic compulsive motives for offending ('I commit crime to fund my drug habit') were more likely to be reported by offenders who escalated through drug use and into regular offending within the first five years of their criminal career.
- Psychopharmacological motives ('I commit crime because I am high on drugs') were more likely to be reported by offenders who escalated through drug use and progressed to regular offending later in their criminal career.

The results of this study provide some important findings for the development of policies aimed at preventing crime:

- preventing drug use will reduce the probability that an offender will transit to regular offending
- in the absence of prevention, delaying drug use will also result in tangible improvements in lifetime offending outcomes
- offenders are most at risk of becoming regular offenders in the year of their first use of drugs
- the treatment needs of offenders will differ depending on when in their criminal career they begin to use drugs
- prevention policies should target younger offenders
- policies should target offenders who commence drug use subsequent to or concurrent with their first offence, as it is in this time period that drug use exerts the most risk.

Introduction

From the late 1980s to early 2000, Australia witnessed significant, unabated increases in the incidence of criminal offending. Since this time the prevalence of both property and some violent crimes has declined, although Australia's experience of these modest downward trends has lagged behind most other western countries. The Australian Bureau of Statistics (ABS) showed that in 2003 alone, there were more than 353,000 victims of burglary, 638,000 victims of theft and 98,000 victims of motor vehicle theft (ABS 2004). At this rate, Australia recorded an average of two victims of theft every minute of every day.

Hidden behind these seemingly high rates of criminal victimisation is the financial cost of crime imposed upon the Australian community. A report released by the Australian Institute of Criminology (AIC) in 2003 estimated the total annual cost of crime at $32 billion (Mayhew 2003). The largest component of this was attributable to fraud and other white collar crimes (31% or $5.8 billion) with crimes involving theft, such as burglary, shoplifting and motor vehicle theft accounting for a further 28 percent ($5.3 billion). These figures, while significant, are unlikely to represent the true monetary cost of crime, and while every effort is made to achieve an accurate estimate, the fact is that the majority of criminal offenders remain undetected and the majority of victimisation goes unreported (ABS 2003b). Moreover, the impact of crime is never exclusively financial. Crime victims endure a wide range of psychological and emotional distress, all of which are difficult to quantify and all of which add further complexities to understanding the cost of crime (Taylor & Mayhew 2002).

The only national program that estimates the extent of drug use among the Australian population is the National Drug Strategy Household Survey (NDSHS). Established under the Australian Government's National Drug Strategy, the household survey is conducted every three years and asks respondents to self report their use of licit and illicit drugs. The results indicate that for respondents 14 years and older, the most recent national lifetime prevalence rates were 33.6 percent for cannabis, 1.4 percent for heroin and 9.1 percent for amphetamines (Australian Institute of Health and Welfare 2005). In terms of recent use, 11.3 percent of respondents reported using cannabis in the 12 months prior to the survey, 0.2 percent reported recent use of heroin and 3.2 percent reported the recent use of amphetamines.

Although the prevalence rates of illicit drug use have remained relatively stable over the years, other trends have been observed:

- the average age at which users first began drug use has continued to decline
- 3.3 percent of Australians report driving while under the influence of illicit drugs and 13.4 percent under the influence of alcohol
- one in 10 Australians have been verbally abused by someone under the influence of illicit drugs and one in four by someone under the influence of alcohol
- one in 50 Australians have been physically assaulted by someone under the influence of drugs or alcohol (Australian Institute of Health and Welfare 2005).

While the NDSHS is the only indicator available of national drug use prevalence, it is likely to under-represent groups in the community who are most likely to use illicit drugs. These include the homeless, incarcerated offenders and chronic injecting drug users. To fill this gap, a number of research projects have emerged. The Australian Institute of Criminology's Drug Use Monitoring in Australia project for example, surveys police detainees on their recent drug use and the National Drug and Alcohol Research Centre's Illicit Drug Reporting System surveys convenience samples of intravenous drug users. Both these projects provide valuable information about the extent of drug use among traditionally under-represented drug using populations.

Although both drug use and crime can be discussed as discrete, independent social phenomena, the likelihood that the two are interrelated provides an interesting, but complex, dimension to the drug treatment and crime prevention debates. For many years now, researchers in Australia and overseas have demonstrated a clear link between drugs and crime, with offenders using more drugs more often than their non-offending counterparts. But while the literature concedes that drugs and crime are related, quantifying the severity and direction of causality continues to evade researchers. In his review of 20 years of drugs and crime literature, Menard (2001) summarised five possible theoretical models, each having some, but not definitive empirical support. These are that:

- drug use leads to and causes crime
- crime leads to and causes drug use
- drug use and crime directly influence one another in a pattern of mutual causation
- drug use and crime are unrelated, but are caused by a range of other common factors
- substance use and crime are influenced by the same or a similar set of causal factors, but may also exert some direct influence on one another.

To further explore the link between drugs and crime, a number of theoretical propositions have been developed relating to the nature and direction of causality. The main works include Goldstein's tripartite model (1985) and Parker's selective disinhibition theory (1993). In the tripartite model, Goldstein (1985) suggests that drug use may cause crime because crime may be committed:

- as a means to obtain money for drugs or to support a drug habit (economic compulsive)
- as the direct result of the physiological and biological effects of drug ingestion and intoxication (psychopharmacological)
- as a result of participation in, and protection of an illegal drug market (systemic).

The tripartite model has been widely used as a basic explanatory model for three different types of drug related crime, all of which have at some point been supported by quantitative or qualitative data obtained from offenders themselves (Makkai & Payne 2003a). While Goldstein's early model has received wide support, perhaps the strongest criticism is that while many offenders report being intoxicated at the time of their offending, there is little scientific evidence that illicit drugs other than alcohol result in a biological reaction and propensity for aggression and violence (Parker & Auerhahn 2004). In fact, for many drug types, such as heroin and cannabis, the evidence more strongly suggests a protective, rather than a causal or exacerbation effect.

Almost 10 years after Goldstein, in 1993 Robert Nash Parker developed the theory of selective disinhibition. His theory was an attempt to account for the large number of intoxicated persons who do not otherwise engage in criminal activity, and to explain how drugs, despite having no proven biological or physiological effect may result in increases in aggression and violence. He argued that drug ingestion need not result in a chemical reaction that increases violence, but rather drug use and subsequent intoxication may act as a means to disinhibit the normative values that might otherwise prevent violence. Parker believed that violence and aggression in the community are usually inhibited by social and moral norms regarding appropriate behaviours. These norms are disinhibited during periods of drug use, although the precise nature and process of disinhibition is complex and difficult to quantify. While Parker suggests that disinhibition results from a range of factors both at the individual level and within the community he points to expectancy factors (the extent to which individuals expect intoxication to result in aggression) as playing an important and key role.

Although this brief review of Goldstein's tripartite model and Parker's theory of selective disinhibition provides a basis upon which to conceptualise the drug-crime debate, they are but a few of the possible explanations provided throughout the literature. This technical report is not a comprehensive analysis of the theoretical research but rather seeks to provide empirical evidence that drug use exacerbates crime and increases an offender's likelihood of progressing to regular offending. The paper seeks to quantify the impact of illicit drug use initiation on the probability that an offender will escalate to regular property offending. In doing so, it uses a discrete-time survival analysis technique to estimate the unique period-by-period hazard rates for a sample of 1,500 offenders incarcerated in Australian prisons in 2001.

The model building process described in this report seeks to answer seven important questions:

- Does an offender's initiation and subsequent use of illicit drugs increase the probability of escalation to regular property offending?
- Does the initiation of hard illicit drugs (heroin, speed, cocaine or LSD) increase the probability of escalation above that attributable to cannabis use?
- At what point in an offender's criminal career does drug use initiation exert most pressure for escalation?
- Is the resulting change in probability proportional for every year an offender uses illicit drugs, or does the probability of escalation change over time?
- Are offenders who use drugs prior to their first offence at greater risk of escalation than offenders who use illicit drugs after their first offence?
- Can the lifetime probability of escalation be mitigated through policies aimed at preventing drug use, or in the absence of prevention, can a delay in drug use initiation result in a decrease in the lifetime probability of escalation to regular property offending?
- Are the self-reported motives for engagement in offending different according to the timing of drug use initiation and escalation to regular offending?

These questions and their answers help to unravel the complex web between drug use and crime. They demonstrate the opportunity to capitalise on the development of policy options aimed at dealing with both problems simultaneously.

Methodological context

The drug use careers of offenders study (DUCO)

This research seeks to identify the impact of drug use initiation on the probability of escalation to regular property offending. It examines the self-reported drug use and criminal careers of a sample of 1,500 incarcerated male offenders whose criminal career commenced with a property offence. These data are a subset of the 2,135 incarcerated offenders who were surveyed by the AIC in 2001 in Queensland, Tasmania, Western Australia and the Northern Territory.

Sampling method

A detailed summary of the data collection and sampling methods of the DUCO study are described elsewhere (Makkai & Payne 2003a). In brief, these data were collected in a geographically stratified systematic random sample of prisoners in Western Australia, Queensland and the Northern Territory. In Tasmania, due to the small number of male prisoners, a complete census of the incarcerated population was undertaken. The response rates varied between 68 and 94 percent with an average response rate of 73 percent across all four jurisdictions.

Comparisons were made between the sample and the total inmate population on basic demographic variables obtained through administrative information provided by the corrective services agencies. The comparisons showed no significant difference, although Indigenous offenders were slightly under-represented in the DUCO sample (Makkai & Payne 2003a).

The self-reported data contained in the DUCO project were collected in an interviewer administered questionnaire. The questionnaire asked offenders to report their lifetime offending history across 13 different offence types from within three core offence typologies. Similarly, offenders were also asked to report their use of 13 different drug types.

Reliability of the estimates

Historically, the study of criminal and drug use behaviour has been restricted to either official records, such as police or court based data, or self-reported survey data from selected samples of offenders. Both data sources present significant limitations in accuracy and reliability. Official police records underestimate the true level of an individual's offending profile and are unlikely to include any data on an offender's first offence. The alternative, self-reported survey data, is similarly impacted by a number of limiting factors, not the least of which is an offender's capacity and willingness to recall historical events, particularly events for which they may not have yet been convicted. In measuring crime, the limitations imposed by the data collection and analysis methods need to be accepted and the results interpreted accordingly.

The present study is interested in the longitudinal sequence of events (drug use and crime) that are rarely linked in official administrative datasets. There is no alternative but to rely on the self-reported survey data from an identified convenience sample of incarcerated Australian offenders. International studies have shown that self-reported lifetime offending is generally reliable, and more accurate than other forms of official data, including police records (Peterson, Braiker & Polich 1980). Moreover, although official records contain only a fraction of an offender's self-reported offending history, official records and self-reported records closely correspond with each other (Farrington 1989; Hindelang, Hirschi & Weis 1979).

In terms of self-reported drug use, a recent Australian study has found that offenders with poor socioeconomic status and a history of prior imprisonment were most likely to report their drug use history accurately (McGregor & Makkai 2003). That indicates that self-reported drug use among the DUCO sample of incarcerated offenders is likely to be reasonably accurate and reliable.

Survival analysis

The question examined in this report is whether illicit drug use increases the probability of escalation to regular property offending. In examining this, the interest is not only in the probability that escalation occurs (the question of *if*), but also whether any covariates can help to explain *when* it occurs. Survival analysis is a statistical modelling technique used with longitudinal event occurrence data. Originally developed for use in the biological and health sciences, survival analysis has become commonly used in the social sciences for measuring and understanding other behaviours, such as criminal offending. The technique requires three basic data elements:

- an event or action which indicates the beginning of time
- a plausible and interpretable metric of time
- an event of interest, measurable against time.

The beginning of time

In the DUCO study offenders were asked to nominate the age at which they first committed five different property offence types – vandalism, stealing without break-in, break and enter, trading in stolen goods and fraud. An offender's first offence was calculated as the youngest age reported across each of these offence types. It is from this point – the beginning of the criminal career – that each offender was subsequently observed.

The metric of time

From the time of first offence, each offender was observed at intervals of one year. It was not possible to measure time in any smaller metric because the DUCO study only required offenders to report the age of their first offence to the nearest whole year. The number of observable years for each offender is equivalent to the number of years between their first offence and the year in which they completed the DUCO survey. For some offenders this may have been up to 30 years, while for others it may have been as few as five. This report examines the probability of property offence escalation for the first 10 years of an offender's criminal career: as a result each offender is observed for 10 yearly intervals subsequent to their first offence.

The event of interest

Having established both the beginning and metric of time, the event of escalation is now defined. Escalation is deemed to have occurred if an offender reported regularly committing either break and enter or trading in stolen goods. For the purposes of survival analysis, this event is tied to the metric of time so that *when* an offender escalated could also be determined. The number of years between an offender's first offence and their escalation to regular property offending was calculated as the time difference between the age of both events, plus one (age regular – age first +1). The additional year added to the time difference adjusts for the imprecision inherent in the data collection process and rounds each offender up to their nearest birthday. Two examples clarify the importance of this rounding procedure:

- Offender one reports the age of first offence at 13 years and regular offending at 16 years. Although regular offending is reported at 16 years, it is impossible to determine the precise moment during their 16th year that regular offending actually commenced. It is possible that regular offending commenced one day after their 16th birthday or one day prior to their 17th birthday. It is only when the offender turns 17 that it can be certain that regular offending has commenced (four years after the first offence).

- Offender two reports their first offence at 13 years and regular offending also at 13 years. It is impossible to determine at which point during the offender's 13th year that each event occurred, although regular offending could not have preceded first offending. Regular offending is thus taken to have occurred after the first offence and by the offender's 14th birthday (within one year after their first offence).

Discrete-time survival analysis

There are two commonly used methods for dealing with longitudinal survival data – continuous-time and discrete-time analysis. Continuous-time analysis is used when the measurement of time can be divided so that no two subjects can experience an event at the same time (known as the absence of ties). Discrete-time analysis is used when the observational units of time are aggregate intervals, and where the precise instance of the event is unknown. This study employed discrete-time survival where the discrete-time intervals were measured as units of one year from an offender's first offence until the end of the 10th year of their criminal career. There were 10 time periods (T_1 through T_{10}) measured in this study.

The reconstructed data

The DUCO study involved a one-off survey of offenders incarcerated in four Australian states. While these data were not collected in a true longitudinal format (i.e. multiple surveys conducted at each year of an offender's criminal career) it is possible to analyse it as such because the event data were measured on a metric of time. Earlier, this report introduced the conceptual importance of an offender's birthday in providing a 'change point' where the movement from one interval to the next could be indicated. Each birthday measured all events occurring in the previous 12 months, almost as if the offender was surveyed on each birthday and asked to recall all events occurring between this and the last survey. Each offender had as many observational periods as the number of birthdays observed prior to their current incarceration.

From person-level to person-period data

For discrete-time survival analysis, there are two types of data – a person-level and person-period dataset. The person-level dataset is constructed so that each offender has one observation, and each variable is measured against the metric of time. Table 1 illustrates the person-level dataset for four offenders. There are five variables:

- PersonID – the unique identification number for each offender
- StartAGE – the age at which each offender committed their first offence
- Escalation – a dichotomous event indicator coded as 1 for offenders who escalated and 0 for those who did not
- EscalationAGE – the age at which the event of escalation occurred
- TimeDIFF – the difference in years between StartAGE and EscalationAGE (plus one).

Note that for the one offender (PersonID=2) who did not escalate to regular property offending, TimeDIFF was coded as 10. This is because TimeDIFF actually measured the number of time periods that each offender was observed prior to their escalation. Offenders not escalating were still observed for the first 10 years of their criminal career.

Table 1: Sample person-level data

PersonID	StartAGE	Escalation	EscalationAGE	TimeDIFF
1	13	1	13	1
2	14	0	–	10
3	16	1	18	3
4	10	1	15	6

The person-period dataset transformed the number of observed time periods (TimeDIFF) into individual observations so that each offender had as many valid observations as the number of time periods for which they were observed. An event indictor was used to nominate the period in which escalation occurred, and the variables measuring age were no longer needed in the data. Table 2 illustrates the example person-period data. Note that the substantive information has not changed between the person-level and person-period data – offender one was observed for one time period, and in that period they escalated to regular property offending. Similarly, offender two did not escalate in any of the 10 time periods in which they were observed.

Table 2: Sample person-period data

PersonID	TimePERIOD	Escalation
1	1	1
2	1	0
2	2	0
2	3	0
2	4	0
2	5	0
2	6	0
2	7	0
2	8	0
2	9	0
2	10	0
3	1	0
3	2	0
3	3	1
4	1	0
4	2	0
4	3	0
4	4	0
4	5	0
4	6	1

The covariates

Having illustrated the development of the person-period data from the DUCO dataset, it was easy to add substantive predictors whose values were also measured against the metric of time. There were two types of covariates used in this study – time-variant and time-invariant. The value of a time-invariant predictor remains constant across all time periods. In the present study, two time-invariant predictors were estimated, measuring an offender's age at first offence and their Indigenous status. Table 3 illustrates how these predictors were included in the person-period dataset. ATSI, which measures Indigenous status, remained constant for each offender in all time periods because an offender's Indigenous status cannot vary over time. Offender two, for example is coded as Indigenous (ATSI=1) in all time periods.

A time-varying predictor is one whose values can change. In this study, CannabisEVER measured the onset and subsequent use of cannabis and was coded zero in all time periods prior to the initiation of its use, and one in the periods subsequent to and including the period of first use. According to Table 3, offender two did not commence using cannabis until the 6th time period after their first offence (equivalent to 19 years of age).

Table 3: Sample person-period data

PersonID	TimePERIOD	Escalation	ATSI	CannabisEVER
1	1	1	0	1
2	1	0	1	0
2	2	0	1	0
2	3	0	1	0
2	4	0	1	0
2	5	0	1	0
2	6	0	1	1
2	7	0	1	1
2	8	0	1	1
2	9	0	1	1
2	10	0	1	1
3	1	0	1	0
3	2	0	1	0
3	3	1	1	1
4	1	0	0	0
4	2	0	0	0
4	3	0	0	0
4	4	0	0	0
4	5	0	0	1
4	6	1	0	1

Descriptive statistics

Of the 1,500 incarcerated offenders whose criminal career commenced with a property offence, 25 percent were Indigenous. The average age of first offence was 13.7 years – the minimum was four and the maximum was 53 years. Within 10 years of their first offence, 694 offenders (46 percent) escalated to serious regular property offending with the average number of years to escalation being four.

In terms of drug use, 89 percent had used cannabis and 22 percent had used cannabis prior to their first offence. Of those who used cannabis after their first offence, the average number of years to first use was 4.5. Seventy-five percent of offenders (n=1,118) reported the use of other illicit drugs (heroin, amphetamines, cocaine or LSD) within an average of 4.7 years of their first offence.

Table 4: Descriptive offending indicators among property offenders

	Property offenders	
	%	n
Demographic		
Indigenous	25	362
Offending indicators		
Mean age of first property offence (min/max)	13.7 (4/53)	1,500
Escalation to regular offending within 10 years	46	694
Mean years to escalation (min/max)	4.1 (1/10)	
Drug use indicators		
Used cannabis	89	1,337
Used cannabis prior to first offence	22	325
Mean years to from first offence to first cannabis use (min/max)	4.5 (0/10)	
Used other illicit drugs	75	1,118
Used other illicit drugs prior to first offence	8	124
Mean years to from first offence to other illicit drug use (min/max)	4.7	
(Total)		**(1,500)**

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Results

Describing the data: the uncontrolled baseline hazard

Before examining the impact of illicit drug use initiation on the probability of property offence escalation, it is important to understand the uncontrolled baseline hazard and survivor functions. Within the context of event occurrence, hazard (h) is the conditional probability that an individual (i) will experience the event in a specified time period (j), given that they did not experience the event in any earlier time period. This principle can be expressed in notation (Singer & Willett 2003) as:

$$h(t_{ij})=\Pr\{T_i = j \mid T_i >= j\}$$

In this study, individual hazard can be defined as the likelihood that offender (i) would have escalated to serious regular property offending in time period (j) given that they did not escalate in any previous time period. The population hazard function is the proportion of offenders who had escalated by the end of time period (j) as a function of the number of offenders who were at risk of escalation at the beginning of that time period. The total number of offenders entering time period (j) was defined as the risk set, and therefore the population hazard in any time period can be shown as:

$$\text{population } h(t_j)= \text{n events}(_j) \text{ / n at risk}(_j)$$

The life-table (Table 5) illustrates the key components of the population hazard functions amongst this sample of property offenders. Each time period (T_n) is expressed as an interval of one year. Time period one (T_1) measures the occurrence of property offence escalation within one year of an offender's first offence. Similarly, time period six (T_6) measures the occurrence of escalation between the fifth and sixth year of the offender's criminal career. Population hazard in any time period is measured as the probability of escalation on the condition that the group of offenders at risk had not escalated in any previous time period. Given the conditionality of hazard, column 3 of the life-table indicates the number of offenders who have entered that time period (a). The number of offenders entering any time period is equal to the total sample of offenders (n=1,500) less the number of offenders who have escalated (b) or were censored (c) in any earlier time period. Censored individuals are those whose escalation could not be observed because the time they spent under observation ended prematurely (prior to the 10th year). In this study, censoring occurred when an individual was incarcerated (and interviewed for this study) prior to their escalation into regular property offending and prior to their 10th year of offending. Information about event occurrence for censored individuals can only be used in the periods for which they were observed. Survival analysis was specifically designed to deal with the problem of censoring.

The final two columns of the life-table present the uncontrolled population hazard and survivor functions for this sample of 1,500 incarcerated property offenders. The calculations indicate that in time period one (T_1) the population hazard was 0.0978, or 9.7 percent. That is, nearly 10 percent of those offenders at risk escalated to serious regular property offending within one year of their self-reported first offence. Similarly, 5.4 percent of offenders at risk in time period two (T_2) escalated to serious regular property offending.

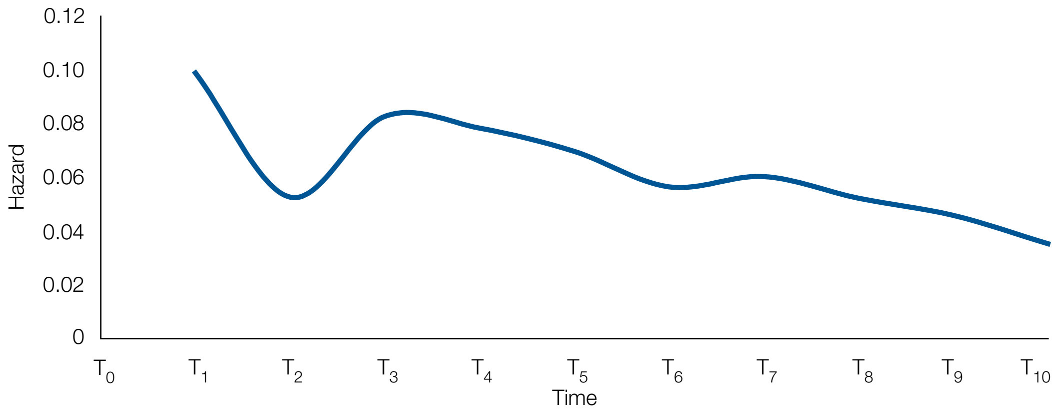
Plotting the population hazard function illustrates the hazard experienced by offenders at risk in each time period (Figure 1). The uncontrolled baseline hazard is monotonic, peaking at the beginning of the criminal career, and declining for each additional year. This suggests that should an offender not escalate within the first three years of their criminal career, the risk of escalation decreases to a hazard of just over 3.5 percent (hazard in T_{10}).

Table 5: Life-table of years to escalation among property offenders

Year	Interval	Entered (a)	Escalated (b)	Censored (c)	Hazard (h) $h(t_j)= (b_j / a_j)$	Survival (s) $s(t_j)=s(t_j-1)[1-h(t_j)]$
Transition to regular property offending						
T_1	[0, 1)	1,500	148	3	0.0987	0.9013
T_2	[1, 2)	1,349	71	7	0.0526	0.8539
T_3	[2, 3)	1,271	105	15	0.0826	0.7834
T_4	[3, 4)	1,151	90	12	0.0782	0.7221
T_5	[4, 5)	1,049	73	19	0.0696	0.6718
T_6	[5, 6)	957	54	22	0.0564	0.6339
T_7	[6, 7)	881	53	24	0.0602	0.5958
T_8	[7, 8)	804	42	20	0.0522	0.5647
T_9	[8, 9)	742	34	29	0.0458	0.5388
T_{10}	[9, 10)	679	24	655	0.0353	0.5198

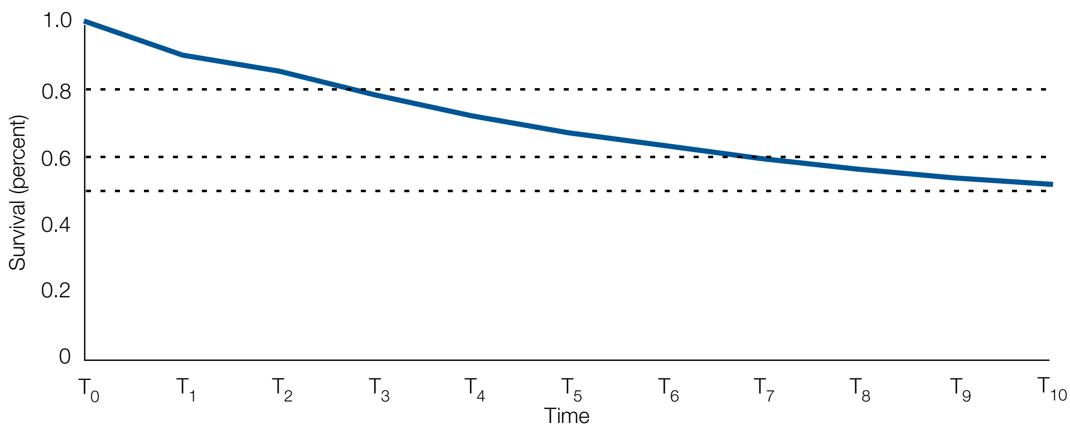
Source: AIC, Drug Use Careers of Offenders 2001 [computer file]. n=1,500; events=694

Figure 1: Uncontrolled hazard function of years to escalation among property offenders



Source: AIC, Drug Use Careers of Offenders 2001 [computer file]. n=1,500; events=694

Figure 2: Uncontrolled survivor function of years to escalation among property offenders



Source: AIC, Drug Use Careers of Offenders 2001 [computer file]. n=1,500; events=694

The survivor function provides another way of understanding and describing the distribution of event occurrence over time. Unlike the hazard function, which illustrates the unique period-by-period hazard rates, the survivor function cumulates these hazards to assess the probability that a randomly selected individual will experience the event by a specified period of time. Survival probability (s) is the probability that individual (i) will survive past time period (j) given that they survived the event in all earlier time periods (Singer & Willett 2003). The individual survival probability can be expressed as:

$$S(t_{ij}) = Pr[T_i > j]$$

In the absence of censoring, the population survival probability is calculated as the proportion of individuals who have survived past a specified time period. However, the presence of censoring complicates this calculation because there is no information about the event occurrence for individuals who could not be observed. In such cases, the estimated survival probability in time period j is calculated as the estimated survival probability for the previous time period ($s(t_{j-1})$) multiplied by one minus the estimated hazard probability for current period ($1-h(t_j)$). The estimated hazard function in any time period was the proportion of at risk offenders for whom the event occurred – otherwise known as the percent who failed. The survival probability is therefore the inverse of the hazard probability – the percentage of the population who survived. Population survival probabilities can be expressed as:

$$S(t_j) = S(t_{j-1})[1-h(t_j)]$$

The life-table (Table 5) illustrates the survival probabilities for the first 10 years of a property offender's criminal career. It illustrates that by the end of the first 12 months, nearly 10 percent of all offenders had escalated to regular property offending. This is opposed to the 90.2 percent of property offenders who survived. Figure 2 depicts the survivor function from first offence (entering a criminal career) until the end of the 10th year. It illustrates that within the first five years, approximately two thirds of property offenders had survived and not escalated to serious regular property offending. By the end of the 10th year, 51.6 percent of property offenders had survived, and 48.4 percent had escalated.

Modelling the data: the effect of age and Indigenous status

Moving from the uncontrolled baseline hazard to a statistical discrete-time model requires the transformation of the event occurrence data into a person-period dataset. Event occurrence in the person-period dataset is indicated by a dichotomous variable *EVENT*, whose value is one (1) in the observation corresponding to the period when the event occurred. Offenders escalating to regular property offending within the first 12 months of their criminal career had just one observation in the person-period dataset and *EVENT*=1. Offenders who did not escalate to regular property offending within 10 years had 10 observations, in all of which *EVENT*=0.

Finally, time is indicated in the discrete-time hazard model as a set of dichotomous dummy variables whose values indicate the time period of the observation. In the present study there are 10 time dummy variables (T_1 through T_{10}). Variable $T_1 = 1$ in all observations corresponding to the first year of the criminal career. Similarly, $T_{10} = 1$ for all observations corresponding to the 10th year of the criminal career.

The discrete-time hazard model uses a maximum likelihood (ML) function to estimate the parameter values that maximise the likelihood of observing the sample data. The exact calculation and mathematical components of the ML function can be found in Singer and Willett (2003: 381–384), but for the purposes of the present study, the ML estimates can be obtained using a logistic regression routine to regress the event indicator (EVENT) on the time indicators (T_1 through T_{10}). The discrete-time hazard model with no substantive predictors is expressed as:

$$\text{logit } h(t_j) = [\alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_{10} T_{10}]$$

The statistical model estimates the probability of event occurrence in each time period for all offenders who had valid observations. When no substantive predictors are included, the parameter estimates for each time period mirror the uncontrolled hazard function presented earlier in this report. To illustrate this, Table 6 provides the parameter estimates of the fitted discrete-time hazard model (column 2). Transforming the logit estimates yields both the odds and the probability of event occurrence in each time period. The probability of event occurrence is equal to the hazard estimates derived earlier in the life-table for uncontrolled hazard function (column 5). This result is not unexpected given that the uncontrolled baseline hazard function represented the proportion of at risk offenders who failed in each time period, and the discrete-time hazard model estimates the probability of event occurrence for all individuals with valid observations in each time period.

Table 6: Fitted discrete-time hazard model and uncontrolled baseline hazard model

	Model A1			
	Logit	Fitted odds e^{logit}	Fitted hazard $1 / (1+ e^{(-logit)})$	Uncontrolled hazard
Parameter estimates				
T_1	-2.2121**	0.1095	0.0987	0.0987
T_2	-2.8904**	0.0556	0.0526	0.0526
T_3	-2.4074**	0.0901	0.0826	0.0826
T_4	-2.4672**	0.0848	0.0782	0.0782
T_5	-2.5930**	0.0748	0.0696	0.0696
T_6	-2.8167**	0.0598	0.0564	0.0564
T_7	-2.7487**	0.0640	0.0602	0.0602
T_8	-2.8983**	0.0551	0.0522	0.0522
T_9	-3.0361**	0.0480	0.0458	0.0458
T_{10}	-3.3066**	0.0366	0.0353	0.0353

**statistically significant at $p < 0.01$. n=1,500; events=694

Note: Asymptotic standard errors omitted. Full model diagnostics provided in Table A1 of the Appendix

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

The literature review noted national and international studies linking a number of demographic variables to an increased likelihood of criminal offending and drug use. In this study, demographic variables were limited because appropriate variables must be measurable across the same time periods in which the criminal career was established. While variables on marital status, prior incarceration history and employment status were collected, their measurement was as at the time of interview and no conclusion can be made about their value during the first 10 years of each offender's criminal career. Two variables, Indigenous status (ATSI), and the age of first offence (AGE18) were examinable, however. ATSI is coded dichotomously (where 1=Indigenous and 0=non-Indigenous) while AGE18 is a continuous variable centred at 18 years. Both variables are time invariant, which means that their values do not change during the period of observation. Given the volume of literature which links younger offending onset to more serious lifetime criminal careers, it is hypothesised that the risk of escalation to regular property offending will decrease with an increase in the age of first offence. Although the literature on Indigenous status is not as conclusive, some Australian studies have noted that Indigenous offenders are more likely to engage in regular offending than their non-Indigenous counterparts (Putt, Payne & Milner 2005). For this reason, it is hypothesised that the risk of escalation will be greater for Indigenous offenders.

The statistical discrete-time models that give rise to an examination of the risk differential associated with each of these substantive predictors, and their combination are expressed as:

$$\text{Model A2: logit } h(t_j) = [\alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_{10} T_{10}] + \beta_1 AGE18$$
$$\text{Model A3: logit } h(t_j) = [\alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_{10} T_{10}] + \beta_2 ATSI$$
$$\text{Model A4: logit } h(tj\,) = [\alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_{10} T_{10}] + \beta_1 AGE18 + \alpha_2 ATSI$$

The results (parameter coefficients and asymptotic standard errors) of all three models are provided in Table A1 of the Appendix. In this statistical model building process, each predictor added to the discrete-time model is assessed for its capacity to improve (result in a statistically significant decrease in) the deviance statistic. The deviance statistic (otherwise termed the -2 Log Likelihood statistic) of nested models can be compared using the critical values calculated on a chi square distribution and based on n degrees of freedom, where the n degrees of freedom equal the number of additional parameters added to the model (see Singer & Willett 2003). When multiple predictors are added, nested model comparison allows the determination of which of the additional parameters contributed to the observed decrease in the deviance, and which did not.

Models A2 and A3 assess the independent, main effect of AGE18 and ATSI, while Model A4 includes both predictors. Model A4 performs significantly better than the completely general model but only slightly better than Model A2 which examines the main effect of AGE18 only. Further examination of the deviance statistic indicates that ATSI, when modelled independently, is a significant predictor of increased hazard (χ^2=4.48, df=1, $p<0.05$), but when modelled together with the AGE18 is insignificant (χ^2=3.38, df=1, $p>0.05$). AGE18, the predictor that examines the impact of an offender's age at first offence, is significant in both the independent (χ^2=41.94, df=1, $p<0.001$) and combined models (χ^2=40.83, df=1, $p<0.001$).

These results illustrate the importance of an offender's age at first offence in predicting an increased risk of escalation among property offenders. The parameter coefficient in the combined model indicates that each unit increase in age is significantly associated with a decrease in risk. The insignificance of Indigenous status in the combined model indicates that, when controlling for age at first offence, Indigenous offenders are no more or less likely to be at risk of escalation during the first 10 years of their criminal career than their non-Indigenous counterparts. This is probably because Indigenous offenders did not, on average, commence their criminal careers as early as their non-Indigenous counterparts (see Makkai & Payne 2003a).

Although insignificant, it is too early to dismiss the impact of Indigenous status on increasing or decreasing the risk of escalation. Recent research indicates significantly different drug use patterns between Indigenous and non-Indigenous offenders (Putt, Payne & Milner 2005) and thus, ATSI remains an important control variable despite its insignificance at this stage.

Building the model: the effect of drug use

Drug use in this study is measured using two main effects predictors, CannabisEVER and IllicitDrugEVER. The latter measures the use of four illicit drugs, heroin, amphetamines, cocaine and LSD. Both predictors are dichotomous time-varying predictors coded as zero (0) in the time period/s prior to the initiation of their use, and one (1) in the time period including and subsequent to the period of initiation. Reliable information about the cessation of drug use was not obtained in the present study, so these predictors can be conceptualised as group transition variables whose values change as an offender changes groups from a non-drug user to a drug user. As a time-varying predictor, the predictor's estimated coefficients are tied to the time period in which they are being interpreted. Hazard (h) for an individual offender (i) in any time period (j) can thus be re-expressed as:

$$\text{Model B1: logit } h(t_{ij}) = [\alpha_1 T_1 i + \alpha_2 T_2 i + \ldots + \alpha_{10} T_{10} i] + \beta_1 AGE18_i + \beta_2 ATSI_i + \beta_3 CannabisEVER_{ij} + \alpha_4 IllicitDrugEVER_{ij}$$

The addition of subscript j to the predictors CannabisEVER and IllicitDrugEVER indicates that an individual's hazard in each time period depends on their value of CannabisEVER and IllicitDrugEVER in that time period. This compares with time-invariant predictors (such as ATSI) whose values are constant across all time periods, and where subscript j is omitted.

As noted, this study measured drug use using two time-varying predictors – one for cannabis, and the other for other illicit drugs. The use of two drug use predictors allows the examination of the independent effects of other illicit drug use, while controlling for the effects of cannabis use. This is a necessary feature in the analysis of illicit drug use given that the majority of other illicit drug using offenders in this sample had also used cannabis, and cannabis use almost always preceded other illicit drug use. If modelled using a single drug-use predictor, the interpretation of its coefficients could only be made in the context of cannabis use, and would provide little information about the additional controlled effects of hard drug use.

The literature provides a wealth of evidence to support the association between the use of illicit drugs and increases in criminal offending. The discrete-time hazard model measured the impact of cannabis and illicit drug use on increasing an offender's risk of escalating to serious regular property offending within the first 10 years of their criminal career. It was hypothesised that the initiation of cannabis use would increase the risk of escalation, and that the initiation of other illicit drugs would further increase that risk. In short, it was expected that both cannabis use and other illicit drug use would have significant positive coefficients when added to the base demographic discrete-time model (Model A4).

Model B1 measures the main effects of the predictors for drug use – CannabisEVER and IllicitDrugEVER. The results indicate a significant improvement in the model's explanatory power (χ^2=176.75, df=2, p<0.001), with both cannabis use and other illicit drug use significantly increasing the risk of escalation to serious regular property offending. As a dichotomous time-varying predictor, the coefficients can be interpreted as the risk differential associated with the transition from being a non user of that drug to a user. By adding the drug use predictors, the variable measuring Indigenous status (ATSI), which was previously insignificant, becomes a significant predictor in the model and also contributes significantly to its improved explanatory power (χ^2=19.67, df=1, p<0.001). This result confirms that by controlling for both cannabis and other illicit drug use, Indigenous offenders are at a significantly greater risk of property offence escalation than non-Indigenous offenders.

Given that the majority of offenders had used cannabis prior to or concurrent with other illicit drug use, it was reasonable to assume an interaction effect between both drug types. The interaction term (as measured in Model B2) challenged the assumption that the coefficient for other illicit drug use was additive to the coefficient for cannabis. It tested the hypothesis that the risk associated with illicit drug use was reduced for offenders who were already actively using cannabis – or in other words, offenders already actively engaged in cannabis use would be less affected by the initiation and subsequent use of other illicit drugs. The results in Model B2 suggest that while the interaction between CannabisEVER and IllicitDrugEVER is significant (p<0.05), its addition to the model resulted in only a modest improvement in the deviance statistic, which did not achieve conventional levels of statistical significance (χ^2=3.55, df=1, p<0.10). The impact of the interaction term was twofold. First, it increased the hazard associated with other illicit drugs from five percent in Model B1 to over 12 percent in Model B2. This suggests that when occurring in isolation (without cannabis use), other illicit drug use was associated with a much greater increase in hazard than previously indicated. The second implication is that the interaction term itself was negative, confirming that when other illicit drug use occurred in conjunction with cannabis use (any time when CannabisEVER equals one), the resulting hazard estimate for other illicit drugs was not 11 percent, but decreased to around five percent (see Table 7).

Table 7: Prototypical odds and hazard in time period one (T_1) – Models B1 and B2			
	Logit	**Fitted odds** e^{logit}	**Fitted hazard** $1 / (1+ e^{(-logit)})$
Model B1 (additive)			
Non drug user	-3.7063	0.0246	0.0240
Cannabis user	-2.4816	0.0836	0.0772
Illicit drug user	-2.9724	0.0512	0.0487
Combined user	-1.7478	0.1742	0.1483
Model B2 (interaction)			
Non drug user	-3.7366	0.0238	0.0233
Cannabis user	-2.4681	0.0847	0.0781
Illicit drug user	-2.0904	0.1236	0.1100
Combined user	-1.7603	0.1720	0.1468

Note: Asymptotic standard errors omitted. Full model diagnostics are provided in Table A2 of the Appendix

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

While the interaction term helped illustrate the isolated impact of other illicit drug use, this result was relatively uninterpretable for this sample of 1,500 offenders. As noted, few offenders reported using other illicit drugs prior to, or in the absence of cannabis and it is most likely for this reason that the addition of the interaction term failed to significantly improve Model B2's explanatory power. Moreover, the inclusion of the interaction term was to test the assumption that the parameter estimate for other illicit drug use is additive to the parameter estimate of cannabis use. The comparative prototypical hazard values for the combined drug use are provided for both Models B1 and B2 in Table 7. In Model B1, where additivity is assumed, the combined hazard estimate is 14.83 percent. This compares with 14.68 percent in Model B2, a difference of less than one quarter of one percent. Therefore, given that the vast majority of other illicit drug users in this sample were already using cannabis, and that the combined drug user estimate does not differ between the models, the interaction term is omitted from the model building process. Alternative explanations sought to further clarify the relationship between both drug types are presented later in this report.

The discrete-time hazard models presented so far have illustrated the significant impact of both cannabis and other illicit drug use in increasing the risk of escalation to serious regular property offending. The model's second assumption – that the estimated hazard is proportional across all time periods is now examined. To illustrate, the predictor CannabisEVER is coded dichotomously, and although time-variant, its estimated parameter value is interpreted as being equal in each time period for which its value is one. The implication is that cannabis users in time period one (T_1) are assumed to be at equal hazard with cannabis users in time period 10 (T_{10}). Like most model assumptions, validity can be tested and the results can provide valuable information for interpreting a predictor's effect on increasing or decreasing hazard.

The proportionality assumption can be tested using dummy interaction terms between the predictor variable and time (Singer & Willett 2003). CannabisEVER is replaced with 10 dummy variables ($CanT_1$ through $CanT_{10}$) whose values represent the interaction between CannabisEVER and time (T_1 through T_{10}). The value of $CanT_1$ is coded as one for offenders who were using cannabis in time period one and zero for offenders not using cannabis. By replacing CannabisEVER and IllicitDrugEVER with these dummy interaction variables the unique period-by-period risk experienced by those who became users can be observed. The proportionality assumption can be rejected if the new model significantly reduces the model deviance using a chi square distribution on n degrees of freedom. In this study, the additional period-by-period variables (resulting in 17 degrees of freedom) did not result in a significant improvement in the deviance (χ^2=24.41, df=17, p=0.1086), but did demonstrate volatility in the estimated period-by-period hazard values for both cannabis and other illicit drugs. This volatility, although not a formal criterion for rejecting the proportionality assumption raises questions about how an individual's hazard changes over the first 10 years of their criminal career.

Extending the model: the effect of drug use over time

In testing the proportionality assumption, volatility was revealed in the period-by-period hazard estimates for both cannabis and other illicit drugs, a result which required further investigation. To understand why the hazard associated with drug use might vary over the criminal career – variations which drive these period-by-period changes in hazard – two hypotheses are proposed:

1. If an offender survives (does not escalate to regular offending) in the year of drug use initiation, the hazard of escalation in subsequent years decreases due to resilience.
2. The hazard associated with drug use initiation varies as a function of time – that is, offenders who onset drug use at the beginning of their criminal career are at greater risk in that first year, than offenders who onset late in their criminal career.

The literature review noted three defining stages in both the criminal and drug use careers – onset, persistence and desistence. Although desistence was not measured in this study, these hypotheses seek to test the variation that occurs as a result of the interaction between the criminal and drug using careers. The first suggests that, while controlling for demographic variance, all drug using offenders are at equal risk of escalation during the year of drug use onset, but that offenders who demonstrate resilience to escalation in that year are less at risk in subsequent years. That is, cannabis exerts most pressure on an individual during the first year of use, and the impact of cannabis declines for each year the offender does not escalate to regular offending. For example, with both CannabisEVER and IllicitDrugEVER measured as a proportional hazard, the parameter estimates assume that long term drug using offenders in time period six (T_6) who have not yet escalated to regular property offending are at equal risk of escalation as those offenders who first started drug use in time period six. It is, however, possible to conceive that offenders who demonstrated some resilience to escalation would be at less risk than newly initiated drug users in that time period. This first hypothesis suggests that non-proportionality is not tied to each time period of the criminal career, but to the drug use career.

The second hypothesis suggests that the risk of regular serious property offence escalation associated with drug use onset is not constant for all offenders across all time periods, and that drug use onset will have the greatest impact during the developmental years of the criminal career, and less of an impact in later years when the criminal career is more established. In this, a discrete-time hazard model, drug use onset is measured as the risk differential in the first year of drug use. This second hypothesis suggests that the non-proportionality of drug use onset is tied to each time period of the criminal career.

In testing the first hypothesis, a similar interaction is assumed as in the earlier non-proportionality models, but this time the values of the interaction dummies are tied to the years since drug use onset. To simplify this process however, the 10 individual dummy variables are replaced with a linear function of time modelled in addition to the main effect of the original dichotomous variable. In this case, the linear function estimates the parameter coefficient associated with each unit increase in time (year) since drug use onset. In the year of onset, the time function dummy is coded zero, while in the first year after onset it is coded as one. The inclusion of a linear time function is again measured using a hypothesis-based deviance test. If its addition to the model significantly improves the model's explanatory power, the idea that hazard is proportional in each subsequent year of drug use can be rejected.

Model B3 is the model having the best fit for the data. It demonstrates the main effects of CannabisEVER and IllicitDrugEVER as well as the coefficients for the linear time functions that resulted in the best model fit. The results confirmed that the differentials for both cannabis and other illicit drugs are non-proportional – that is, hazard declines for each additional year of survival after the onset of each drug type. In other words, the impact of both cannabis and other illicit drug use was greatest in the year of onset – as measured by the main effect predictors – but declined for each year the offender did not escalate to regular property offending. The rate of the post-onset decrease differed between the drug types. The magnitude of the decline was greatest for other illicit drug use. Note also, that by including these non-proportionality controls, the interaction term, which was previously significant in the model, is now insignificant. This suggests that the interaction between both cannabis and other illicit drugs can be best explained by the declining hazard rates associated with post-onset survival.

The second hypothesis was that the parameter differential associated with the onset of each drug need not be constant across all time periods. That is, offenders commencing drug use in time period one may be at greater risk of escalation in the year of onset than offenders commencing drug use in time period six. To examine this, Models C1 through C3 use two additional dummy variables (CannabisYR and IlliicitDrugYR), both of which are coded zero if onset occurred in time period one, one if onset occurs in time period two, and so on. The resulting parameter estimate is interpreted as the change in hazard associated with each year of delay in drug use onset, and because these secondary dummies can only vary in the year an offender onsets their use of that drug, they are additive to the main effects variables of CannabisEVER or IllicitDrugEVER. For example, an offender who commences cannabis use in time period one, is taken to have an onset hazard value equal to the main effects variable only, because in time period one CannabisYR equals zero. Alternatively, an offender who does not onset cannabis until time period six is taken to have the combined onset value of CannabisEVER and CannabisYR*5, because onset occurs in the 5th time period after T_1.

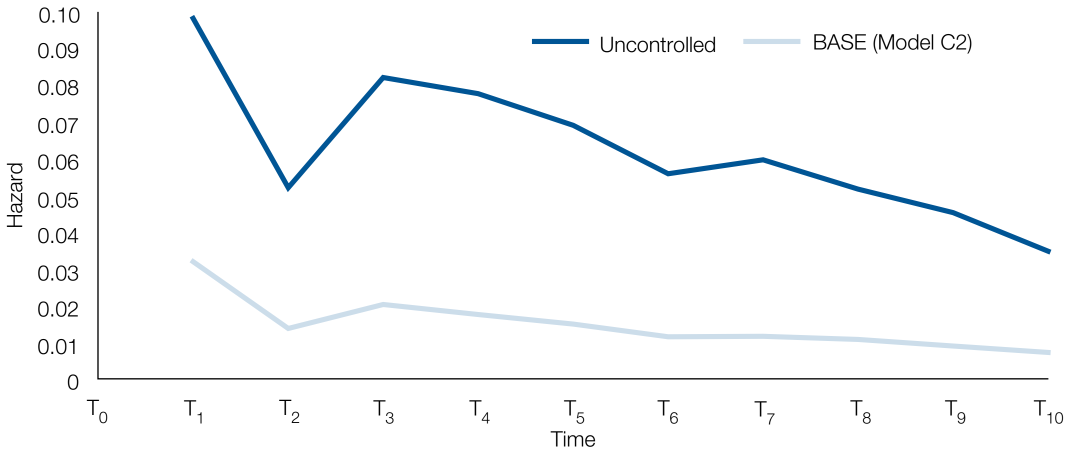
Models C1 though C3 test whether onset hazard is non-proportional. The model diagnostics suggest that the hazard differential associated with each year of delay for the onset of cannabis was proportional – that is, did not change over time. This is confirmed by the insignificance of the linear function measuring the year of cannabis onset (χ^2=0.03, df=1, p=0.54). The confirmation of proportionality suggests that, when controlling for other illicit drug use, the impact of cannabis onset remained constant, regardless of the year in which the offender commenced its use.

Although the hazard associated with cannabis onset was proportional across all time periods, the same cannot be said for other illicit drugs. Model C3 indicates that the hazard differential associated with other illicit drugs was non-proportional and, contrary to the hypothesised model the parameter coefficient was positive and significant (χ^2=7.04, df=1, p=0.01). This indicates that the onset hazard associated with other illicit drug use increased with each additional year that onset was delayed – in other words, holding all else constant, the onset hazard experienced by an offender who onset other illicit drugs in time period one was lower than the onset hazard differential experienced by an offender who onset in time period six. Taking the exponent of the parameter logit value (0.0859) yielded a fitted odds ratio of 1.090. On the odds scale, this indicates that hazard increased by approximately nine percent for each year that other illicit drug use was delayed. Holding all else constant, the onset hazard experienced by an offender who first used illicit drugs in time period six was 56 percent higher than an offender who onset in time period one.

Understanding the model: exploration through prototypes

Having uncovered the model that best describes the relationship between drug use and property offence escalation, the model's coefficients are now examined to understand the impact and effect of its predictors. It is possible to develop fitted hazard values for prototypical offenders who displayed the characteristics of interest. Figure 3 plots the baseline hazard function and the uncontrolled hazard function for these 1,500 incarcerated offenders. The baseline hazard function was derived from the final model (Model C2) and represents the sample of offenders whose values for all relevant predictors equal zero. In other words, the baseline hazard function is for non-Indigenous offenders whose first offence was at 18 years of age, and who did not use cannabis or other illicit drugs before or in first 10 years of their criminal career. In comparison, the uncontrolled hazard function represents the hazard experienced by all 1,500 offenders when values of the relevant predictors are unrestrained. The area observed between both hazard functions can be interpreted as the quantity of hazard explained by these predictors.

Figure 3: Fitted hazard functions – uncontrolled and baseline hazard



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]. n=1,500; events=694)

The first predictors added to the model were AGE18 and ATSI. ATSI measured the differential associated with an offender's Indigenous status, and the parameter coefficient (β=0.3978) can be interpreted as the increase in hazard experienced by Indigenous offenders, when holding all other predictors at zero (see Table 8). Anti-logging the coefficient yielded the comparative odds (1.488) that an Indigenous offender would escalate to regular property offending. The results indicated that in all time periods (T_1 through T_{10}) Indigenous offenders were 1.49 times more likely than non-Indigenous offenders to escalate to serious regular property offending (see Figure 4).

In terms of AGE18, the statistical model tested the hypothesis that the age of first offence was negatively associated with the hazard of escalation. The final model yielded a parameter coefficient of (β= -0.0828) and indicated that for each year younger an offender was at the time of their first offence, their escalation hazard in all time periods increased by an odds ratio of 1.086. The predictor AGE18 was centred at 18 years and therefore multiplying the coefficient by any number of years either side of 18 yielded the hazard probabilities experienced by prototypical offenders of those ages. Table 8 illustrates the odds and hazard values for three age groups, 18 years (as measured by the base hazard function), 23 years and 13 years. The results showed that if an offender first offended at 13 years of age, the odds of escalating to regular property offending were increased by 51 percent across all time periods. Figure 5 illustrates the fitted prototypical hazard functions for each of the three age groups.

The prototypical plots for age and Indigenous status illustrate the differential impact of each predictor on increasing or decreasing the hazard experienced by an offender in each of the 10 time periods. These plots, although informative, have limited practical bearing on understanding the 'real offender' because the prototypes do not represent the true values of these predictors from the sample. Additional analysis of the individual person-level data indicated that Indigenous offenders did, on average, commit their first criminal offence at the age of 13 years, and non-Indigenous offenders at 14 years (see also Makkai & Payne 2003a). This suggests that on average the hazard experienced by Indigenous offenders was compounded by the additional effect of age. Combining the adjusted coefficients and estimating their values across all time periods yielded the average hazard experienced by the average sample of incarcerated male offenders. Holding drug use constant at zero, Figure 6 illustrates the differences in survivorship between the average Indigenous and non-Indigenous offender. It shows that by the fifth year of the criminal career, more than 20 percent of non drug using Indigenous offenders had escalated to regular property offending, compared with only 14 percent of non-drug using non-Indigenous offenders.

Table 8: Fitted prototypical odds and hazard values in time period one (T_1)

	Logit Parameter (β)	Odds (vs. Base)	Fitted Odds in T_1 e^{logit}	Fitted Hazard in T_1 $1 / (1+ e^{(-logit)})$
Model C2				
BASE	-3.3956		0.0335	0.0324
Indigenous	0.3973	1.488	0.0499	0.0475
13 years at first offence	0.4142	1.513	0.0507	0.0483
23 years at first offence	-0.4142	0.661	0.0222	0.0217

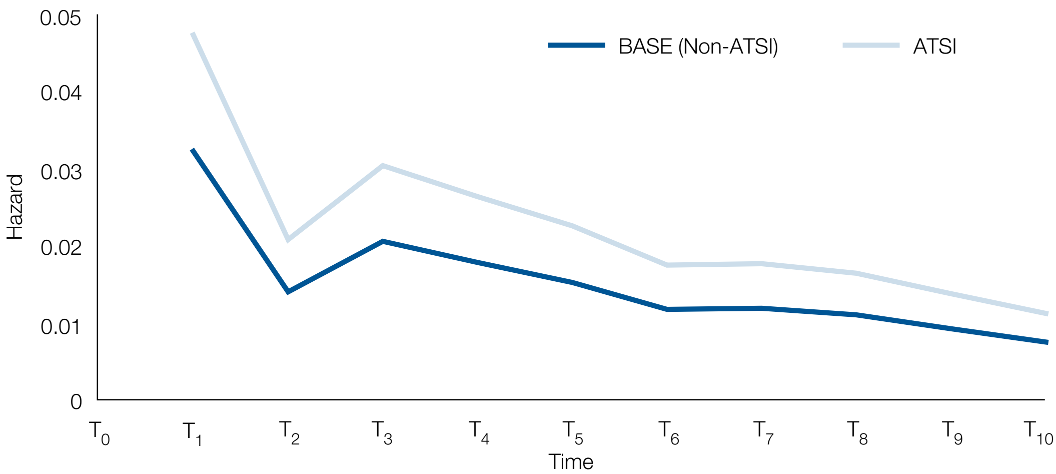
n=1,500; events=694

Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs

Note: Asymptotic standard errors omitted, full model diagnostics are provided in Table A1 of the Appendix

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

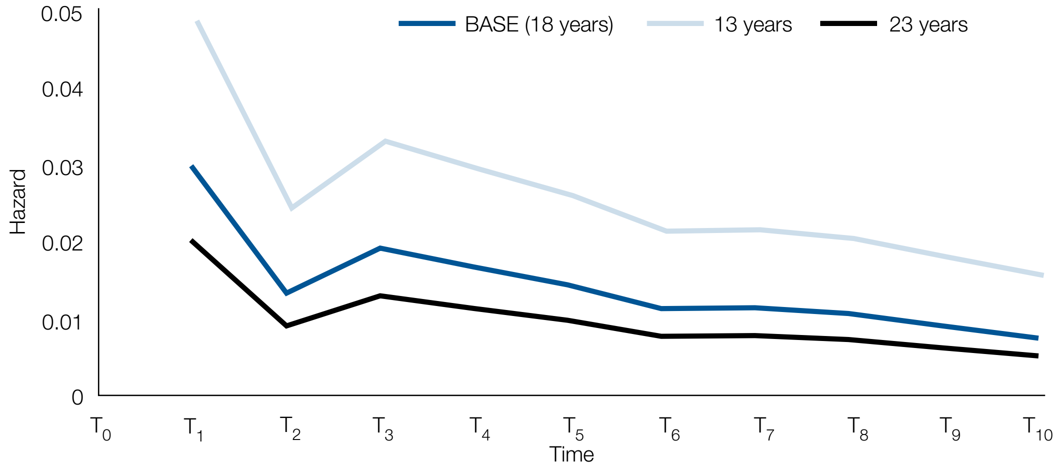
Figure 4: Fitted prototypical hazard function by Indigenous status



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

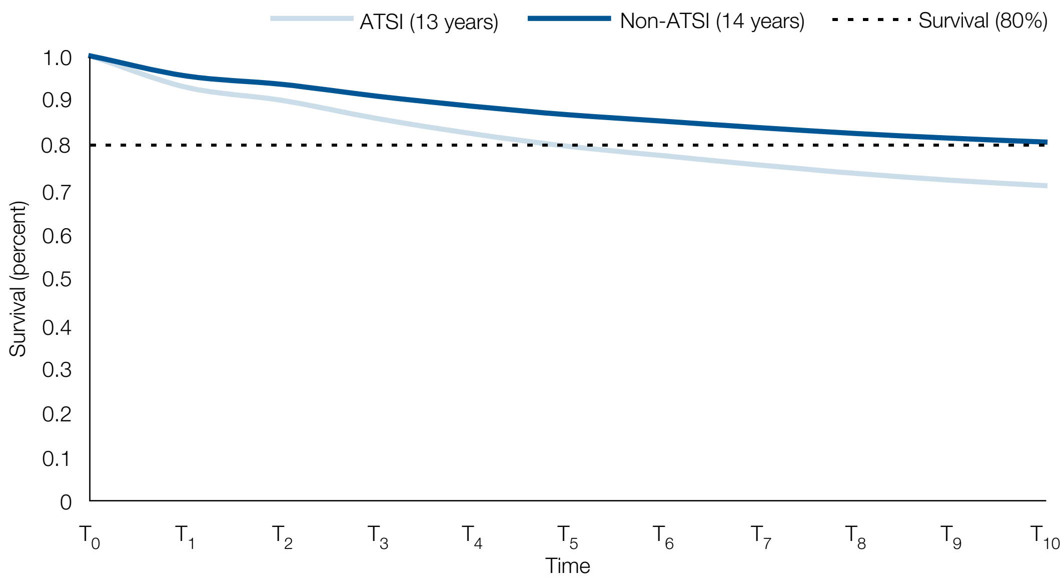
Figure 5: Fitted prototypical hazard function by age of first offence



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Figure 6: Fitted prototypical survivor function by age of first offence and Indigenous status



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

In examining the impact of drug use on the hazard of property offence escalation, the final statistical model led to a number of important conclusions:

- offenders using cannabis and/ or illicit drugs were a greater risk of escalation than offenders not using drugs
- the hazard differential associated with drug use was greatest in the year of drug use onset and decreased with each additional year of survival
- the hazard differential associated with the onset of other illicit drugs increased for each year that onset is delayed.

As time-varying predictors, it was possible for an offender to commence either cannabis or other illicit drugs at any time prior to or during the first 10 years of the criminal career, and the onset of both drug types did not need to coincide. Nonetheless, the final model indicates the parameter coefficient associated with the onset of cannabis use as $\beta=1.2355$. Transformation from the logit scale to an odds ratio reveals that in the year of onset, offenders commencing cannabis use were 3.44 times more likely to escalate to serious regular property offending than offenders not using cannabis in that time period. In terms of other illicit drug use, the final model revealed a positive and significant parameter coefficient of $\beta=0.9093$, which on the odds scale suggests that in the year of onset, offenders commencing other illicit drug use were 2.48 times more likely to escalate to regular property offending than those not using other illicit drugs.

As previously noted, other illicit drug use rarely occurred prior to, or in the absence of cannabis use and an examination of the interaction revealed that the individual coefficients for both cannabis and other illicit drug use were additive. Given this, the actual hazard differential experienced by offenders who onset both cannabis and other illicit drugs within the same year was $\beta=2.1448$, which is equivalent to an odds ratio of 8.54. In other words, offenders commencing both cannabis and other illicit drug use in the same year were 8.5 times more likely than their non drug using counterparts to escalate to regular serious property offending in that year.

These comparative odds ratios refer only to the increase in hazard experienced by offenders during the time period of drug use onset. The final model notes that this differential was non proportional – that is, it decreased for each year a drug using offender did not escalate (experience the event). For cannabis use, the risk of escalation decreased by approximately nine percent for each additional year of survival ($\beta= -0.0858$) while for other illicit drug use, the hazard decreased by approximately 11 percent each year ($\beta= -0.1128$).

To illustrate these differences, Figures 3.7 and 3.8 plot the fitted hazard and survivor functions for three offender groups:

- the base group of non-drug using offenders
- a group of offenders who commenced cannabis use in time period one, but did not commence other illicit drugs for any of the remaining time periods
- a group of offenders who commenced both cannabis and other illicit drugs in time period one.

Note the significant difference between the three prototypes in time period one (T_1). More than 22 percent of at risk offenders who commenced using both cannabis and other illicit drugs escalated to regular property offending within the first year of their criminal career, compared with only 10 percent of those using cannabis but not other illicit drugs, and three percent of non drug using offenders. For each additional year of survival, the relative hazard experienced by offenders in each prototypical group declined. This is for two reasons: first, the actual hazard experienced by all offenders decreased for each additional year (as noted in the uncontrolled hazard function); and second, the risk differential associated with drug use also declined. Figure 7 shows that the prototypical hazard functions for cannabis-only users and other illicit drug users converged after eight years. In fact, by the sixth year of a criminal career, the relative difference in hazard between non-drug users and other illicit drug users was only 2.5 percent (see Table 9).

Table 9: Fitted prototypical odds and hazard in time period one (T_1)

	Logit parameter (β)	Odds (vs. Base)	Fitted hazard in T_1 $1/(1+e^{(-logit)})$	Fitted hazard in T_6 $1/(1+e^{(-logit)})$
Model C2				
BASE	-3.3956	0.0335	0.0324	0.0120
Cannabis (onset)	1.2355	3.4399	0.1034	–
Cannabis (post-onset in T_2)	-0.0858	0.9177	–	0.0264
Other illicit (onset)	0.9093	2.4825	0.2225	–
Other illicit (post-onset in T_2)	-0.1128	0.8934	–	0.0369

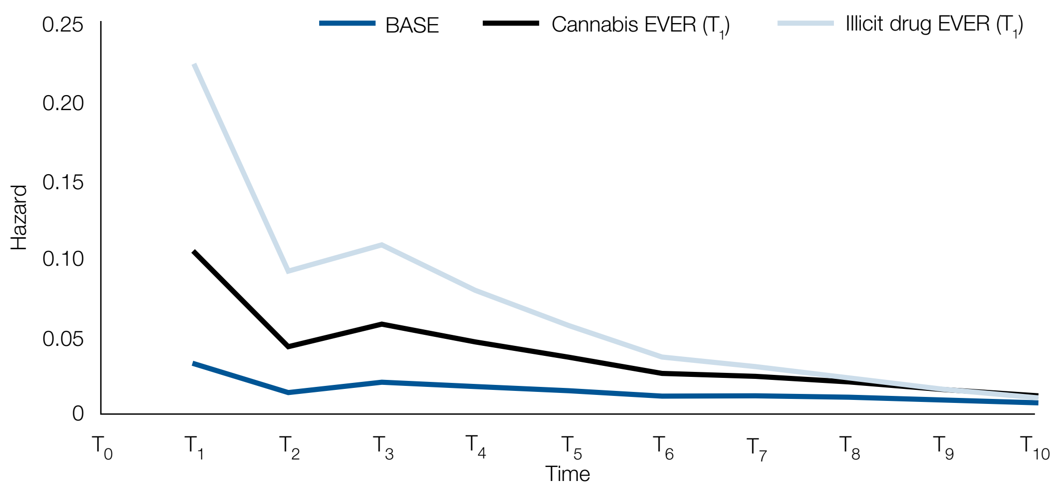
n=1,500; events=694

Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs

Note: Asymptotic standard errors omitted, full model diagnostics are provided in Table A3 of the Appendix

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

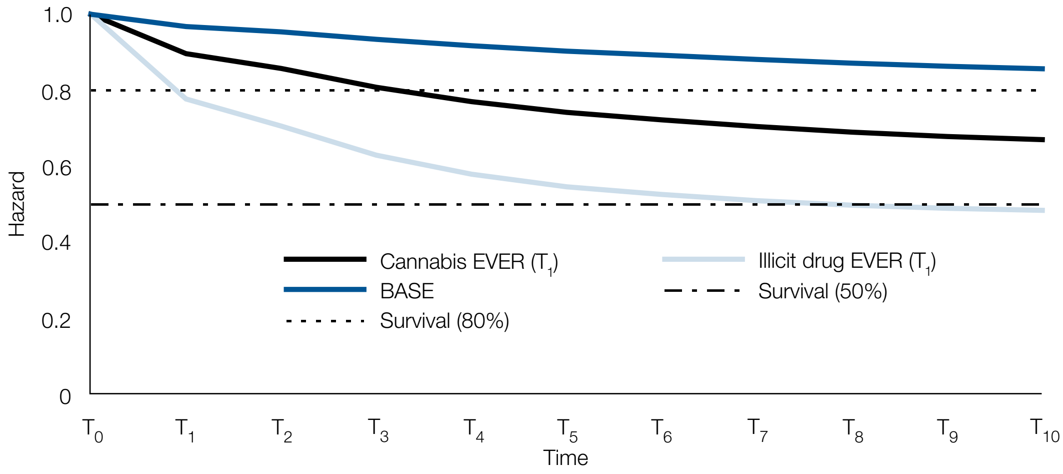
Figure 7: Fitted prototypical hazard functions by drug use in time period one (T_1)



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Figure 8: Fitted prototypical survivor functions by drug use in time period one (T_1)



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Although designed primarily for illustrative value, the prototypical constructions in Figures 3.7 and 3.8 are not unrealistic. Of the 1,500 offenders in this study, 105 had used cannabis in time period one, but did not use other illicit drugs within the next 10 years. Similarly, there were 210 offenders who commenced both cannabis and other illicit drugs in the first year of their criminal career and 218 offenders who did not use cannabis or other illicit drugs before or during these years. These prototypes account for one third of the offenders in this study.

However for the remaining 967 offenders, the order and sequence of drug use varied and in total, there are 220 possible temporal combinations of cannabis and other illicit drug use, but many of these are not of any real value in understanding the average or typical prototypes seen in this sample of incarcerated offenders. Instead, prototypes were constructed according to questions of interest to policy makers and practitioners:

- Assuming all offenders use cannabis in time period one, does the prevention of other illicit drug use decrease the risk of escalation to serious regular property offending in the first 10 years of the criminal career?
- In the absence of prevention, can the overall risk of escalation be reduced by *delaying* the onset of other illicit drugs?
- Can a decrease in risk be achieved by delaying the average onset of both cannabis and other illicit drugs?
- Are offenders who use drugs prior to their first offence at greater hazard than offenders who commence drug use after their first offence?

The first of these questions has already been partially answered – offenders not using other illicit drugs for the duration of their criminal career were spared the additional hazard associated with the onset of these drugs. Similarly, offenders not using any of the drug types measured in this study remained at lower risk in all time periods. Measured at time period one, the earlier prototypes illustrated the relative benefits in survival from the prevention of both cannabis and other illicit drug use.

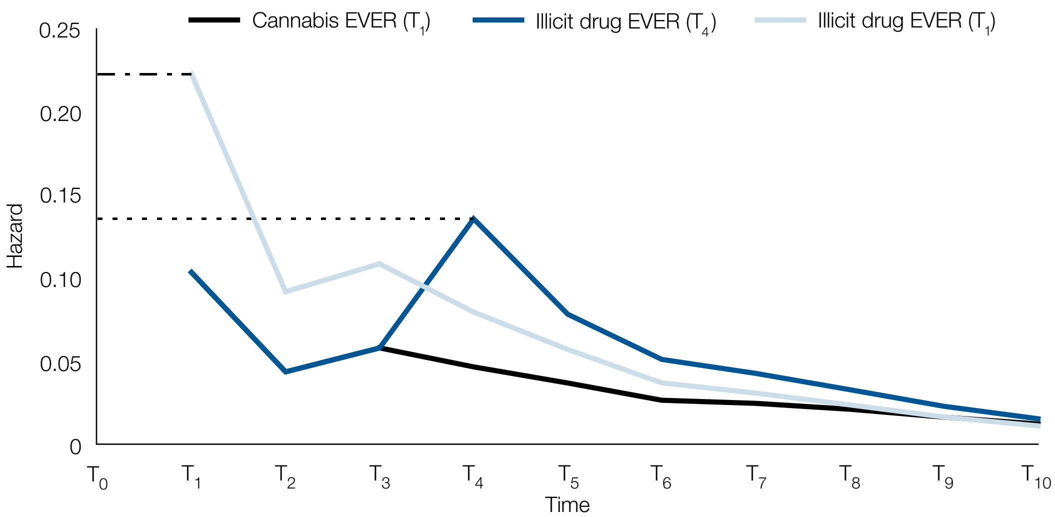
While the prevention of cannabis and other illicit drug use is presumably the key policy aim for primary prevention programs, absolute prevention itself may not be a realistic goal. Instead, programs may aim to delay illicit drug use onset in the hope that other maturation effects will counteract the impact of their use. Figure 9 plots the comparative hazard functions for offenders who used cannabis in time period one, but did not commence other illicit drug use until sometime in the fourth time period (equivalent to a three year delay). It shows that the maximum hazard experienced by these offenders in time period four was equivalent to a 14 percent probability of escalation (h_4=0.14). This compared with those offenders who used both cannabis and other illicit drugs in time period one and whose maximum lifetime hazard was 22 percent (h_1=0.22).

For all time periods beyond (and including) T_4, offenders whose onset of other illicit drugs was delayed were in fact at greater risk of escalation than offenders who used both drug types in T_1. This result is the byproduct of the declining hazard associated with each year of survival, but should not be interpreted as a less favourable outcome. To illustrate, the cumulative hazard function, which cumulates the period-by-period hazard experienced by offenders who survive through each time period is introduced. The cumulative hazard function differs only slightly from the survival function in that it demonstrates the total amount of hazard experience by a surviving offender, rather than the overall failure (or survival) of a group of offenders. Recall that the survivor function is calculated to account for individuals within the group who did not fail, but were censored. An offender's cumulative hazard is equivalent to the sum of the hazard they experienced for as many time periods in which they survived.

Figure 10 depicts the cumulative hazard function for offenders whose other illicit drug use was delayed by three years and indicates that despite being at slightly higher risk in time period four and onwards, offenders within this group had still not experienced the magnitude of hazard equivalent to that experienced by offenders who used both cannabis and other illicit drugs in the first time period. This result remained consistent up to, and presumably beyond, the 10th year of their criminal career – confirming that a three-year delay in the use of other illicit drugs can decrease overall probability of escalation into regular offending.

Figure 11 extends this analysis by plotting an additional prototype – offenders whose cannabis use and illicit drug use were delayed by an additional two years. Unlike the previous prototypes, where cannabis occurred in time period one, the delay in cannabis use, and therefore the subsequent delay in other illicit drug use resulted in a further decrease in the cumulative hazard and therefore a further reduction in lifetime hazard.

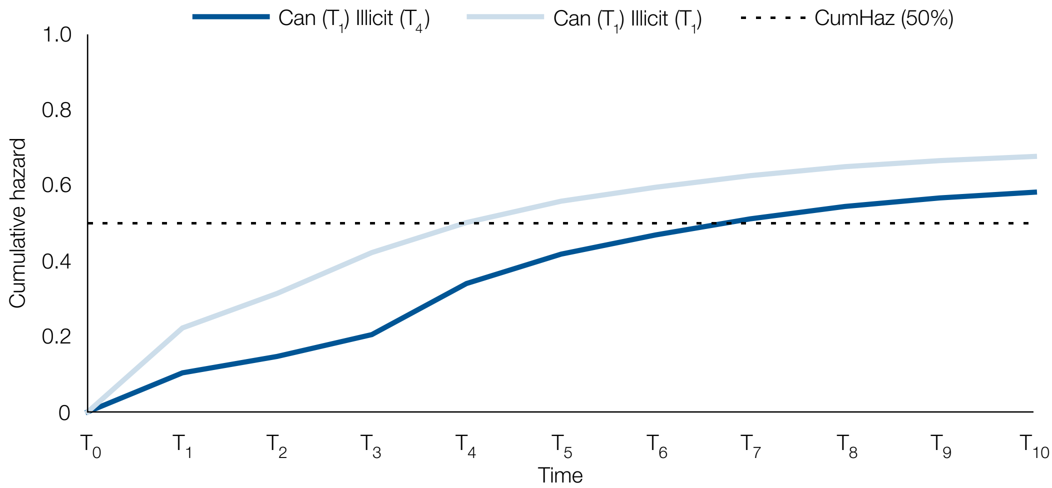
Figure 9: Fitted prototypical hazard functions by drug use delay



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

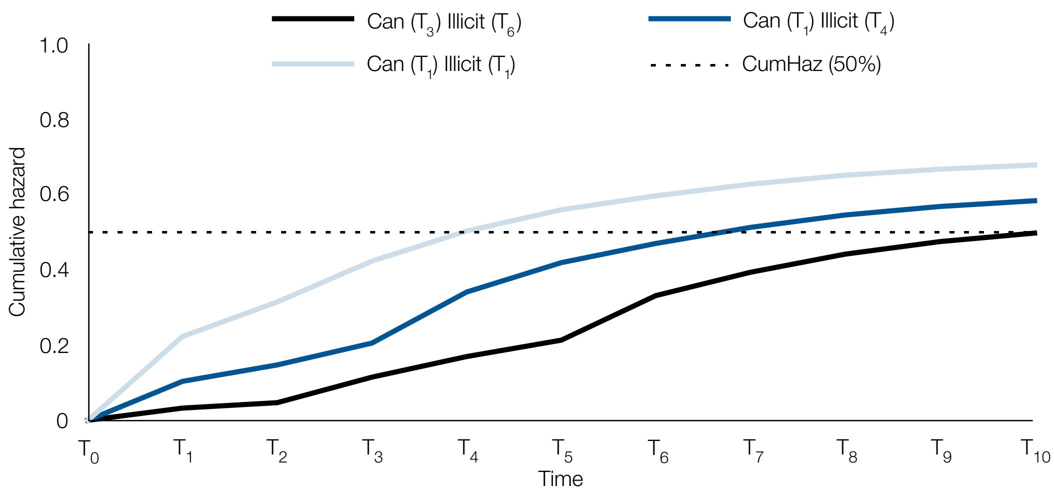
Figure 10: Fitted prototypical cumulative hazard functions by drug use delay



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Figure 11: Fitted prototypical cumulative hazard functions by drug use delay



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

The final question of interest is whether offenders who commenced drug use prior to their offending career were at greater risk of escalation than offenders who commenced drug use concurrent with, or subsequent to their first offence. Recall that the final statistical model uses a linear function to represent the number of years since drug use onset. This function is coded as zero in the year of onset and increases by one unit for each year an offender survived (did not escalate to regular property offending). For those commencing drug use in the first year of their criminal career, the linear function is coded zero in T_1, one in T_2 and so forth. For offenders who used drugs prior to their first offence, the linear function in T_1 is coded according to the number of years they had already been using drugs. For example, an offender having already used cannabis for five years prior to their first reported offence was coded as five in T_1, six in T_2 and so forth.

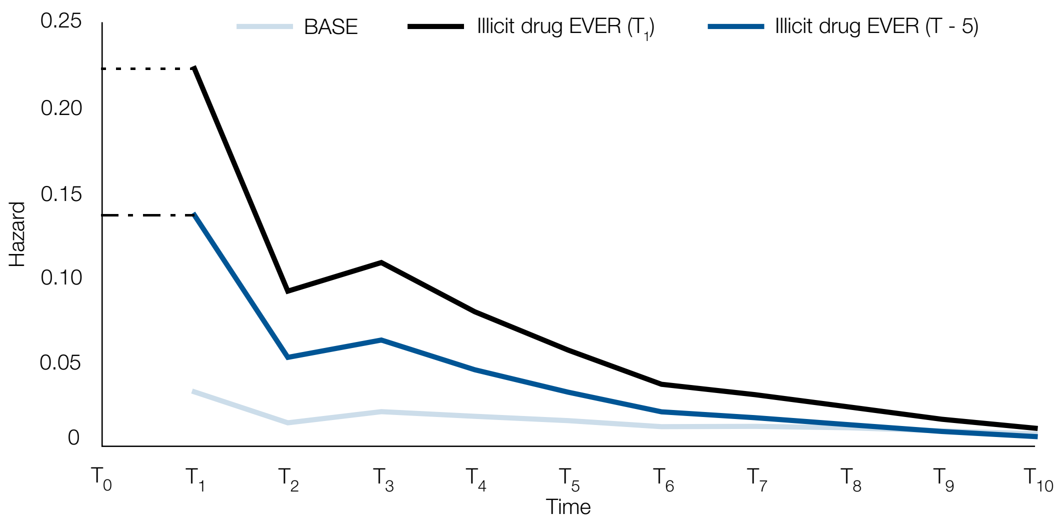
The negative parameter values estimated for these linear functions have so far been used to illustrate the decreasing hazard values associated with resilience beyond the year of onset but for the 338 offenders who had used illicit drugs prior to their first offence, this function also illustrates their comparative hazard in time period one compared with offenders who commenced drug use after their first criminal offence. Figure 12 plots the fitted hazard values for offenders who were using cannabis and other illicit drugs five years prior to their first offence, and compares these values with those experienced by offenders who onset cannabis and other illicit drugs in the first year of their criminal career. The fitted hazard functions confirm that offenders who had used illicit drugs prior to their first offence were less at risk of escalation than offenders whose drug use occurred within one year of their first offence. The cumulative hazard function (Figure 13) similarly illustrates the reductions in overall lifetime hazard experienced by offenders who were using drugs prior to the commencement of their criminal career.

Finally, as a linear function, the results suggest that the earlier an offender used drugs prior to their criminal career, the less at risk they were of escalating to regular property offending. That is, an offender who first used drugs 10 years prior to their first offence was at less risk of escalation than an offender using drugs only one year prior to their first offence.

Given these somewhat surprising results, additional analyses were conducted to confirm that these observed differences were real. Two reduced models were estimated – the first, which replaced the linear function of time since drug use onset with two dichotomous predictors – CannabisPRIOR and IllicitDrugPRIOR. These predictors are coded as one for offenders who had used each drug type prior to their first offence, and zero for offenders who did not use that drug until sometime after their first offence. Their estimated parameter values are interpreted as the proportional decrease in hazard experienced by offenders who had used cannabis or other illicit drugs prior to their first offence. Reduced Model 1 (see Table A4 of the Appendix) illustrates that offenders who had used drugs prior to their first offence were indeed less likely to escalate to regular offending than offenders using drugs after their first offence.

The second reduced model replaces the dichotomous predictors with a linear function predictor. For each offender having used drugs prior to their first offence, the linear function measures the number of years that drug use commenced prior to offending. This reduced model is used to confirm that offenders using drugs many years prior to their first offence experienced lower hazard values than offenders using drugs only a few years prior. The parameter estimate (β= -0.1201) is significant (p=0.002) and confirms this declining risk.

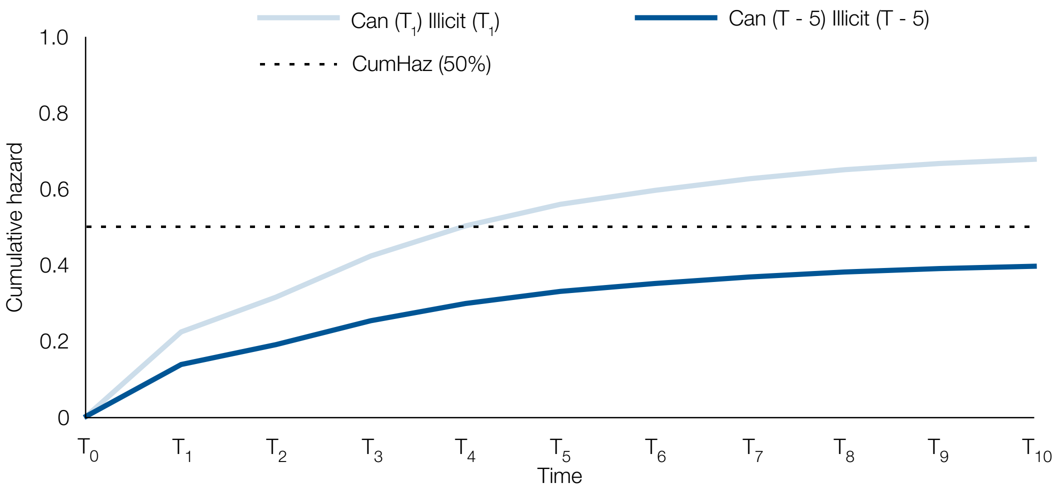
Figure 12: Fitted prototypical hazard functions by previous drug use status



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Figure 13: Fitted prototypical cumulative hazard functions by previous drug use status



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Finally, the statistical discrete-time hazard model found that the onset hazard associated with other illicit drug use increased by approximately nine percent for each additional year that onset was delayed (β= -0.0862). That is, offenders who commenced illicit drugs later in their criminal career were at greater hazard than offenders using other illicit drugs earlier in their criminal career. To illustrate this, consider the comparative hazard values between two prototypical offenders, one who commenced cannabis and other illicit drugs in time period one and the other who commenced cannabis in time period one, but other illicit drug use in time period four. Table 10 illustrates the prototypical hazards for both offender groups as indicated by the combined user in each prototype. The value of interest here is not the maximum hazard experienced by each prototype, but rather the percentage increase in hazard when compared with a cannabis only user. This percentage increase (115 percent vs. 191 percent) is illustrative of the relative hazard associated with the onset of other illicit drugs when delayed by three years (until time period four).

Table 10: Fitted prototypical odds and hazards by time period of illicit drug use onset

	Logit	Fitted odds e^{logit}	Fitted hazard $1 / (1+ e^{(-logit)})$
Offender ONE – Cannabis (T_1), Other illicit drugs (T_1)			
Non user	-3.3956	0.0335	0.0324
Cannabis only user (a)	-2.1602	0.1153	0.1034
Combined user (b)	-1.2509	0.2862	0.2225
Difference (b-a)			0.1192
Percent increase from (a) to (b)			115.26
Offender TWO – Cannabis (T_1), Other illicit drugs (T_4)			
Non user	-3.9983	0.0183	0.0180
Cannabis only user (c)	-3.0204	0.0488	0.0465
Combined user (d)	-1.8525	0.1568	0.1356
Difference (d-c)			0.0891
Percent increase from (c) to (d)			191.49

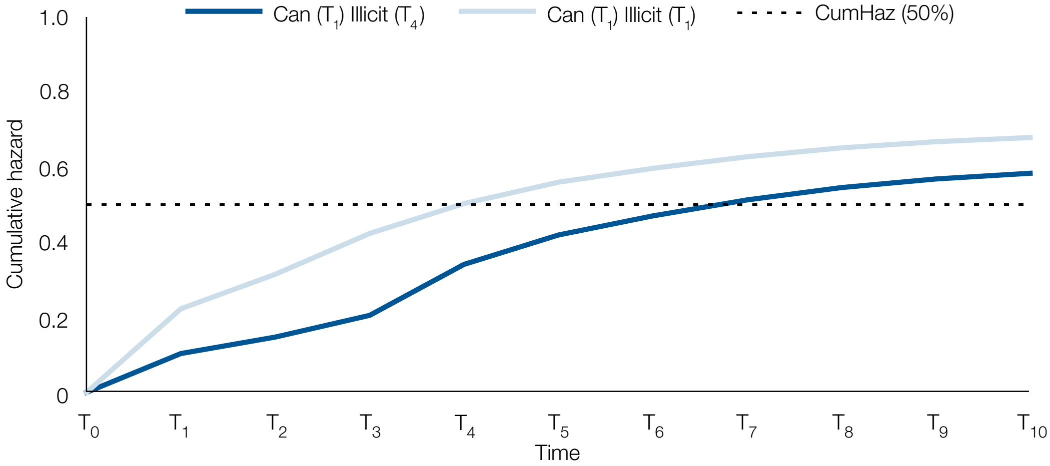
n=1,500; events=694

Note: Asymptotic standard errors omitted, full model diagnostics are provided in Table A3 of the Appendix

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

While the statistical model indicates that onset hazard for other illicit drug use increased for each year in which it is delayed, this result does not mean that lifetime risk was necessarily increased. The parameter estimate of a time-varying predictor is tied to the time period in which it occurred (changed from zero to one), and as such can be interpreted only in connection with the base logit hazard for that time period. Recall that the base hazard function decreased from T_1 through T_{10} so that in T_{10} the relative base hazard was only one quarter of its original value in T_1. Because of this, the actual maximum hazard value experienced by each prototypical offender at the time of illicit drug use onset decreased for each year onset was delayed, despite the increasing onset hazard estimated in the model. Figure 14 illustrates the cumulative hazard function for both of the prototypical offender groups from Table 10 and demonstrates that despite the increasing onset hazard differential for other illicit drug use, delayed use still resulted in improved lifetime survival outcomes. Although difficult to discern from Figure 14, the relative hazard in time period one for offenders who onset both drugs was 22.25 percent. By drug type, 10.33 percent was attributable to the onset of cannabis and 11.92 percent attributable to onset of other illicit drugs. Since hazard was equal to zero (h=0) in time period zero (T_0), the proportion of the increase in hazard that was attributable to other illicit drugs was 53.6 percent (11.92/22.25). Applying the same calculation to the proportional increase in time period four illustrates that the onset of other illicit drugs accounted for 65.8 percent of the relative increase in hazard for those who did not onset other illicit drugs until time period four. This difference can be re-expressed as a proportional increase in hazard from cannabis to other illicit drug use yielding the 115 percent and 191 percent illustrated in Table 10.

Figure 14: Fitted prototypical cumulative hazard function by time period of illicit drug use onset



Base = non-Indigenous, 18 years old at first offence and non user of cannabis or other illicit drugs. n=1,500; events=694

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Understanding the model: implications for the theories

The literature review for this report examined some of the theoretical approaches used to explain the link between drug use and crime. This study has demonstrated that in the year of drug use initiation, offenders were at the greatest risk of escalating to serious regular property offending. The final model also suggests that the earlier an offender used illicit drugs, the greater the overall lifetime risk, except if first use preceded the first offence, in which case hazard was in fact decreased. To understand why this might be the case, Goldstein's (1985) theories of drug use and crime are examined to determine whether the relationship can be explained either in terms of economic compulsive motives or psychopharmacological effects. The DUCO study noted in 2003 that motives need not be the same for all offenders, and motives will inevitably differ by offender type (Makkai & Payne 2003a).

Using the discrete-time analysis model, it was possible to identify any number of offenders by their escalation status, but for illustrative purposes, two groups are compared. Group 1 (early escalation offenders), consists of those offenders who escalated to serious regular property within the first five years of their criminal career and who also used cannabis or other illicit drugs during this time. Group 2 (late escalation offenders) consists of those offenders who escalated between six and 10 years after their first criminal offence, and who also first used drugs during this time.

To examine the theories of drugs and crime, the DUCO study asked offenders to describe in their own words, 'what has been the effect of your personal alcohol or drug use history on your criminal activities'. This question, collected in a qualitative form was subsequently re-coded into a number of categories – including economic compulsive, psychopharmacological or drug use led to crime (but where a financial motive was not noted). The bivariate results (see Table 11) indicate that:

- economic compulsive motives were most likely to be reported by offenders escalating through drug use and into regular offending within the first five years of the criminal career
- offenders who escalated through drugs to regular offending later in the criminal career were primarily driven by psychopharmacological motives (49 percent).

These results provide an interesting dimension to understanding how drugs can impact upon different offenders at different times in their criminal career. It suggests that at the time when offenders were most at risk of escalating to serious regular property offending, the relationship between drug use and escalation was more likely to be driven by the need to obtain money to support the drug use habit.

On the other hand, offenders who did not escalate until some time later in their criminal career (after six but before 10 years) were more likely to report that the lifetime offending was driven by the biological and physiological effects of drugs on their behaviour.

Table 11: Descriptive offending indicators among property offenders (percent)

	Property offenders	
	Early escalation	Late escalation
Self-perceived effect of drugs on the criminal career		
Economic compulsive*	35	19
Psychopharmacological*	29	49
Drugs and alcohol led to crime*	27	17
Other	9	15
(n)	(495)	(80)

* statistically significant at $p < 0.05$

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Assessing the model: exploring the limitations

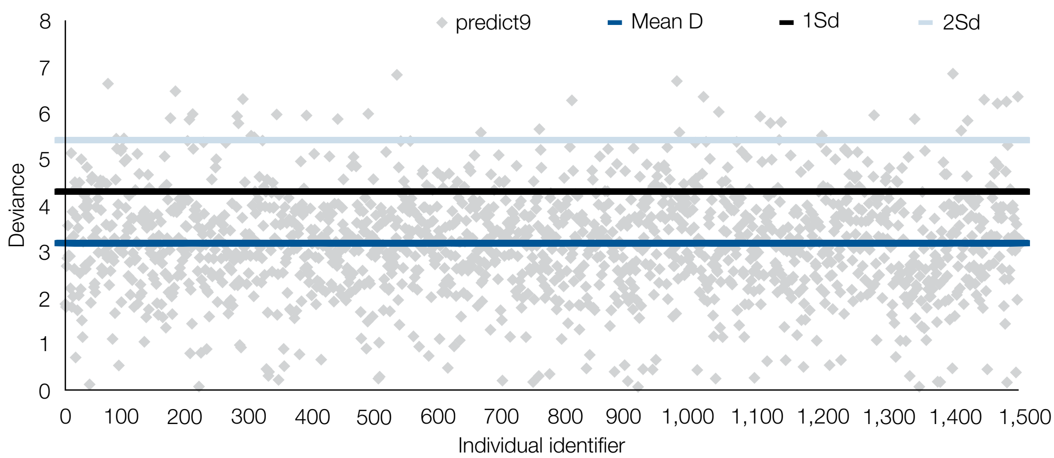
No statistical model is complete without an examination of its soundness and a discussion of its limitations. To do so, the model's deviance statistic – the quantification of error resulting from the model's inability to explain every outcome perfectly – is examined. It is this quantification that allows exploration of the assumption in all statistical regression models – that there is no unobserved heterogeneity.

In the case of this discrete-time survival model, each of the 1,500 offenders had a deviance residual for each time period in which they were observed. The residual is the difference between the predicted probability of escalation and the actual observed value. Taking the square of the deviance residual and its sum across each offender in all time periods yields that individual's deviance statistic. The sum of the deviance statistics from all offenders determines the overall model deviance, which in the final model is 4639.16. A perfect model that predicts all outcomes perfectly will have a total deviance statistic of zero. The further from zero the model deviance statistic, the greater the prediction error. It will be recalled from the discussion of the model building process that an improvement (measured as a reduction) in the deviance statistic was used as the method for determining whether each additional variable improved the model's explanatory power. This was because any variable that significantly reduced the model's deviance was seen as bringing the model closer to perfect prediction.

In a discrete-time survival model, there is no systematic way of determining what constitutes an acceptable or unacceptable deviance statistic (see Singer & Willet 2003). As such, the deviance of the model is examined not in terms of its absolute value, but by whether the model performs 'equally' well for all offenders within it. Should one offender's deviance be disproportionate to the sample average, it suggests that the model itself was particularly problematic for predicting that offender's outcome. Should this be the case for a number of offenders, it suggests that additional predictors are needed to account for what appears to be additional heterogeneity not already explained by the model. Figure 15 plots the sum of the squared deviance residuals for each of the 1,500 offenders. Figure 15 also indicates the mean deviance value across all offenders (3.18) and the standard deviation (1.12). Because a deviance value of zero indicates perfect prediction, analysis of the deviance statistic is focused on those offenders whose deviance exceeded the mean value for the total sample. Higher values indicate poor model prediction, and the presence of offenders whose deviance value was situated more than two standard deviations away from the mean indicates a particularly poor prediction. In this study, the maximum deviance value for any one offender was 6.8, and there were no obvious outliers whose deviance was extremely large.

This suggests that for this sample, the final statistical model is reasonable in explaining escalation to serious regular property offending (see Singer & Willett 2003).

Figure 15: Fitted deviance residuals by ID (sum of squared deviance residual)



Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Despite the deviance plot in Figure 15 indicating that there were no significant outliers, an examination of those offenders for whom the model did not fit particularly well provides additional information about the value of illicit drug use initiation as a predictor of escalation. Additional bivariate analysis indicates some important findings for those offenders whose deviance statistic was greater than two standard deviations above the mean (n=39). They were more likely to have started their criminal career at a younger age (9 years), equally likely to have used cannabis and other illicit drugs, but less likely to have escalated to regular property offending within the first 10 years of their criminal career. Moreover, these offenders were significantly more likely to report regularly engaging in both the buying and selling of illegal drugs, suggesting that drug use initiation for these offenders may have been linked to a different pathway resulting in heavy engagement in the drug market. For these offenders, illicit income was more likely to be produced from sources within the drug market, rather than requiring regular involvement in serious regular property offending.

Finally, this study found that the hazard associated with both cannabis and other illicit drug use declined for each year that an offender used that drug, provided that they had not yet escalated to regular offending. This decline was estimated at between nine and 11 percent for each year of survival and suggests that resilience to regular offending mitigated the impact of drug use so that offenders who did not escalate were subsequently at less risk, despite their use of drugs. While this conclusion is plausible, it is limited because the predictors used to measure drug use assumed that from the year of onset, each offender continued to use that drug until escalation or until the 10th year of their criminal career, whichever came first. The DUCO study did not collect information about an offender's cessation of each drug so it was not possible to measure if and when an offender stopped their drug use. Because of this, the drug use variables were conceptualised as transition indicators to illustrate the point in time at which an offender transited from never having been a user to having been a user.

Given that drug use desistence could not be measured in this study, the decline in hazard associated with each year of survival after onset might be the byproduct of an offender's cessation of drug use rather than resilience to escalation. In any case, the result still confirms that for the population of drug users in any time period, risk was highest at the time of drug use onset, and regardless of the mechanism driving the decline, risk decreased for each year after onset.

Conclusion

This report posed seven important questions:

- Does an offender's initiation and subsequent use of illicit drugs increase the probability of escalation to serious regular property offending?
- Does the initiation of hard illicit drugs (heroin, speed, cocaine or LSD) increase the probability of escalation above that which is attributable to cannabis use?
- At what point in an offender's criminal career does drug use initiation exert most pressure for escalation?
- Is the resulting increase in hazard proportional for every year an offender uses illicit drugs, or does the hazard of escalation increase (or decrease) over time?
- Are offenders who use drugs prior to their first offence at greater hazard of escalation than offenders who use illicit drugs after their first offence?
- Can the lifetime probability of escalation be mitigated through policies aimed at preventing drug use or, in the absence of prevention, can a delay in drug use initiation result in a decrease in the lifetime hazard of escalation to regular property offending?
- Are the self-reported motives for engagement in offending different according to the timing of drug use initiation and escalation to regular offending?

Using a discrete-time survival analysis model building process, answers were found to these seven questions, and more:

- Holding drug use constant, Indigenous offenders were more at risk of escalating to regular property offending than non-Indigenous offenders.
- The younger an offender at the time of their first offence, the more at risk they were of escalation to regular property offending.
- An offender's initiation and subsequent use of illicit drugs increased the probability of escalation to regular property offending.
- The initiation of hard illicit drugs (heroin, speed, cocaine or LSD) increased the probability of escalation above that attributable to cannabis use.
- The maximum hazard was experienced by offenders who initiated both cannabis and other illicit drugs in the same year.
- Despite the increasing hazard of illicit drug onset and the proportional hazard of cannabis onset, initiation of drug use exerted most pressure on lifetime offending if it occurred within the first three years of the criminal career.
- The increased probability of escalation associated with both cannabis and other illicit drugs decreased for each additional year after first use.
- Offenders who had used drugs prior to their first offence were more at risk of escalation than non-drug users, but less at risk than offenders who commenced drugs after their first offence.
- The self-reported reasons for how drugs affected criminal behaviour differed between offenders who escalated to regular offending early in their criminal career and those who did not escalate until later in their criminal career.
- Not all offending behaviour could be explained by drug use, and some offenders might not have escalated to regular property offending because of other possible criminal pathways such as engagement in the drug market.

Early intervention and prevention policy aims to prevent both illicit drug use and criminal offending during the early years. This research study presents a unique approach to the analysis of the impact of illicit drugs on the criminal career. It moves beyond the prevalence studies that have dominated the Australian literature base and provides important information for the development and implementation of targeted early intervention programs. Its policy implications are:

- preventing drug use will reduce the probability of escalation to regular property offending
- in the absence of prevention, delaying drug use will result in a tangible improvement in lifetime offending outcomes
- offenders are most at risk of escalation in the year of their first use of drugs
- the treatment needs of offenders will differ depending on when in the criminal career they use drugs
- prevention policies should target younger offenders
- policies should target offenders who commence drug use subsequent to or concurrent with their first offence, as it is in this time period that offenders are most at risk of escalating to regular offending.

This research demonstrates the importance of drug use initiation as a risk marker for escalation to regular income generating crimes. It suggests that should an offender onset illicit drugs after their first offence, they will be no less than four times more likely to escalate to regular offending than those not using drugs in that same year. It also demonstrates that offenders are most at risk in the year of initiation – a risk that decreases over time.

The Australian Government's Illicit Drug Diversion Initiatives rely primarily on the apprehension and identification of drug using offenders at the point of arrest by police. To be eligible for this front end early intervention program, offenders need to have been apprehended for a minor drug possession offence: substantiation of use of illicit drugs justifies the diversion. Should offenders not be apprehended until some years after their first use of drugs (the most probable scenario), diversion schemes such as those operating under the IDDI will target offenders whose drug use is already well established. This research suggests that these offenders will have already passed the point where drug use has exerted maximum hazard for becoming a regular offender. This is supported by Health Outcomes International's evaluation of IDDI which noted that the majority of participants diverted under this program were well established in the criminal and drug use careers (HOI 2002).

Clearly there are still significant criminal justice and public health benefits in diverting drug using offenders away from the criminal justice system and into treatment. This research suggests that greater benefit may be derived from more innovative drug prevention and early intervention campaigns that do not wait until an offender is apprehended for a drug charge, but see first apprehension on any charge as a possible point of identification for program delivery. Moreover, this research has demonstrated that drug use exerts a greater risk differential on those offenders who become drug users, than on those drug users who become offenders.

Should early intervention and treatment programs be appropriately targeted, it is also important that they meet the diverse needs of offenders. This research has demonstrated that offenders engaging in drug use and regular offending during the early years of their criminal career are more likely to report that their offending (also including the escalation of their offending) was related to economic compulsive motives. That is, their offending was primarily the result of the need for money to support their drug use. In contrast, a greater proportion of offenders escalating to regular offending in the later years of their criminal career reported that the main effect of drugs on their criminal offending was psychopharmacological, that is, behaviour altering. If, as this research suggests, the relationship between drugs and crime differs depending on when in the criminal career the offender uses drugs, the treatment needs of these offenders are also likely to be different.

At the other end of the policy spectrum, a considerable financial investment is made by each of the states and territories in the development and implementation of drug court programs for drug dependent offenders. These programs are run at significant cost, and recent Australian evaluations have noted that they are no more cost effective than imprisonment (Lind et al. 2002). This research illustrates the importance of identifying and preventing illicit drug use before it happens. It is this developmental period that appears most significantly linked to poorer lifetime offending outcomes. While policies and programs are still needed at the harder end – when offenders have become drug dependent or when drug dependants have become offenders – this report indicates that expenditure might be more appropriately directed at preventing and delaying the onset of illicit drug use, than at dealing with its consequences.

Finally, many drug diversion and treatment initiatives operating from within the criminal justice system fail to target sub-populations of disadvantaged offender groups – in particular Indigenous offenders. This is primarily for two reasons. First, disadvantaged offender groups are less inclined to voluntarily participate and second, treatment and education services are relatively unavailable in rural and regional areas. This report uncovered a seemingly consistent research finding – that Indigenous offenders are at greater risk of offence escalation than non-Indigenous offenders. In light of this, efforts should be made to increase the accessibility of drug treatment and crime reduction initiatives to populations who are at significant risk, but do not currently have access to these services.

Appendix

Model parameters and diagnostics

Table A1: Fitted discrete-time hazard model to the age of transition to regular property offending

	Model A1	Model A2	Model A3	Model A4
Parameter estimates and asymptotic standard errors				
T_1	-2.2121**	-2.4858**	-2.2544**	-2.5198**
	(0.0866)	(0.0995)	0.0906	(0.1030)
T_2	-2.8904**	-3.1746**	-2.9318**	-3.2079**
	(0.1219)	(0.1322)	0.1247	(0.1347)
T_3	-2.4074**	-2.6940**	-2.4481**	-2.7266**
	(0.1019)	(0.1141)	0.1052	(0.1169)
T_4	-2.4672**	-2.7618**	-2.5081**	-2.7947**
	(0.1098)	(0.1217)	0.1128	(0.1244)
T_5	-2.5930**	-2.8923**	-2.6341**	-2.9250**
	(0.1213)	(0.1326)	0.1242	(0.1351)
T_6	-2.8167**	-3.1200**	-2.8563**	-3.1515**
	(0.1401)	(0.1502)	0.1424	(0.1523)
T_7	-2.7487**	-3.0522**	-2.7884**	-3.0841**
	(0.1417)	(0.1516)	0.1440	(0.1538)
T_8	-2.8983**	-3.1968**	-2.9349**	-3.2256**
	(0.1585)	(0.1672)	0.1604	(0.1690)
T_9	-3.0361**	-3.3321**	-3.0707**	-3.3588**
	(0.1756)	(0.1834)	0.1772	(0.1849)
T_{10}	-3.3066**	-3.5991**	-3.3404**	-3.6251**
	(0.2078)	(0.2143)	0.2092	(0.2156)
Age18		-0.0550**		-0.0544**
		(0.0088)		(0.0088)
ATSI			0.1929*	0.1670^
			0.0903	(0.0905)
Goodness of fit				
LL	-2519.16	-2495.92	-2516.32	-2493.77
Deviance	5038.33	4991.83	5032.63	4987.54
n parameters	10	11	12	13
AIC	5058.33	5013.83	5056.63	5013.54
BIC	5130.81	5093.56	5143.61	5107.76
Deviance-based hypothesis tests (df)				
H_0: $\beta_{Age18} = 0$		46.50** (1)		45.10** (1)
H_0: $\beta_{ATSI} = 0$			5.69^ (2)	4.29 (2)

Statistical significance: ^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Sample: n=1,500; events=694

Note: Models including ATSI also control for missing values using a dummy variable ATST_M

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Table A2: Fitted discrete-time hazard model to the age of transition to regular property offending

	Model A4	Model B1	Model B2	Model B3
Parameter estimates and asymptotic standard errors				
Age18	-0.0544**	-0.1323**	-0.1334**	-0.0866**
	(0.0088)	(0.0123)	(0.0124)	(0.0135)
ATSI	0.1670^	0.4238**	0.4229**	0.3986**
	(0.0905)	(0.0952)	(0.0952)	(0.0957)
Cannabis EVER		1.2246**	1.2684**	1.2491**
		(0.1138)	(0.1160)	(0.1187)
Illicit drug EVER		0.7338**	1.6462**	1.6906**
		(0.1007)	(0.4450)	(0.4488)
Cannabis * illicit drug EVER			-0.9383*	-0.6308
			(0.4507)	(0.4554)
Cannabis EVER (time - 1)				-0.0800**
				(0.0266)
Illicit drug EVER (time - 1)				-0.1614**
				(0.0366)
Goodness of fit				
LL	-2493.77	-2353.52	-2351.76	-2322.24
Deviance	4987.54	4707.04	4703.52	4644.49
n parameters	13	15	16	18
AIC	5013.54	4737.04	4735.53	4680.49
BIC	5107.76	4845.76	4851.49	4810.95
Deviance-based hypothesis tests (df)				
H_0: $\beta_{ATSI} = 0$		19.70** (2)		
H_0: $\beta_{Cannabis\ EVER} = 0$		121.25** (1)		
H_0: $\beta_{Illicit\ Drug\ EVER} = 0$		54.50** (1)		
H_0: $\beta_{Cannabis\ *\ Illicit\ Drug\ EVER} = 0$			3.51^ (1)	1.67 (1)
H_0: $\beta_{Cannabis\ EVER\ (time\ -\ 1)}{}^3 = 0$				9.40** (1)
H_0: $\beta_{Illicit\ Drug\ EVER\ (time\ -\ 1)} = 0$				21.02** (1)

Statistical significance: ^ p < 0.10, * p < 0.05, ** p < 0.01

Sample: n=1,500; events=694

Note: Time dummies have been omitted from table

Note: Models including ATSI also control for missing values using a dummy variable ATST_M

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Table A3: Fitted discrete-time hazard model to the age of transition to regular property offending

	Model B4	Model C1	Model C2	Model C3
Parameter estimates and asymptotic standard errors				
Age18	-0.0852**	-0.0836**	-0.0828**	-0.0828**
	(0.0134)	(0.0137)	(0.0134)	(0.0134)
ATSI	(0.3985**	0.4064**	0.3973**	0.3968**
	(0.0957)	(0.0960)	(0.0958)	(0.0958)
Cannabis EVER	1.2213**	1.2665**	1.2355**	1.2536**
	(0.1167)	(0.1275)	(0.1167)	(0.1242)
Illicit drug EVER	1.0823**	1.0912**	0.9093**	0.9000**
	(0.1084)	(0.1116)	(0.1269)	(0.1287)
Cannabis EVER (time - 1)	-0.0835**	-0.0899**	-0.0858**	-0.0906**
	(0.0266)	(0.0298)	(0.0266)	(0.0290)
Illicit drug EVER (time -1)	-0.1604**	-0.1574**	-0.1128**	-0.1101**
	(0.0369)	(0.0376)	(0.0398)	(0.0403)
Cannabis EVER (yr onset - 1)		-0.0190**		-0.0163
		(0.0395)		(0.0385)
Illicit drug EVER (yr onset - 1)			0.0862**	0.0875**
			(0.0320)	(0.0322)
Goodness of fit				
LL	-2323.081	-2323.06	-2319.58	-2319.4906
Deviance	4646.16	4646.13	4639.16	4638.9812
n parameters	17	18	18	19
AIC	4680.16	4682.13	4675.16	4676.98
BIC	4803.38	4812.59	4805.63	4814.69
Deviance-based hypothesis tests (df)				
H_0: $\beta_{\text{Cannabis EVER (tyr onset - 1)}} = 0$		0.03 (1)		0.18 (1)
H_0: $\beta_{\text{Illicit Drug EVER (tyr onset - 1)}} = 0$			7.00** (1)	7.15** (1)

Statistical significance: ^ p < 0.10, * p < 0.05, ** p < 0.01

Sample: n=1,500; events=694

Note: Time dummies have been omitted from table

Note: Models including ATSI also control for missing values using a dummy variable ATST_M

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Table A4: Fitted discrete-time hazard model to the age of transition to regular property offending

	Final model	Reduced model 1	Reduced model 2
Parameter estimates and asymptotic standard errors			
Age18	-0.0828**	-0.1076**	-0.1108**
	(0.0134)	(0.0133)	(0.0140)
ATSI	0.3973**	0.4124**	0.4201**
	(0.0958)	(0.0954)	(0.0953)
Cannabis EVER	1.2355**	1.2503**	1.2318**
	(0.1167)	(0.1150)	(0.1135)
Illicit drug EVER	0.9093**	0.8448**	0.7726**
	(0.1269)	(0.1020)	(0.1011)
Cannabis EVER (time - 1)	-0.0858**		
	(0.0266)		
Illicit drug EVER (time - 1)	-0.1128**		
	(0.0398)		
Cannabis EVER (yr onset - 1)			
Illicit drug EVER (yr onset - 1)	0.0862**		
	(0.0320)		
Cannabis PRIOR		-0.2973**	
		(0.1244)	
Illicit drug PRIOR		-0.6591**	
		(0.2086)	
Years PRIOR (any drug)			-0.1201**
			(0.0383)
Goodness of fit			
LL	-2319.58	-2341.33	-2347.98
Deviance	4639.16	4682.66	4695.96
n parameters	18	17	16
AIC	4675.16	4716.66	4727.96
BIC	4805.63	4839.88	4843.93

Statistical significance: ^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Sample: n=1,500; events=694

Note: Time dummies have been omitted from table

Note: Models including ATSI also control for missing values using a dummy variable ATST_M

Source: AIC, Drug Use Careers of Offenders 2001 [computer file]

Bibliography

All URLs were correct at 20 September 2006

Andrews G et al. 1999. *The mental health of Australians*. Canberra: Department of Health and Aged Care

Anglin MD & Speckart G 1988. Narcotic use and crime: a multisample, multimethod analysis. *Criminology* 26(2): 197–233

Armstrong T & Britt C 2002. Exploration of the correlates of specialization and escalation: final report. Report to the US National Institute of Justice 197053

Australian Bureau of Statistics (ABS) 2004. *Recorded crime, victims, Australia, 2003.* ABS cat. no. 4510.0. Canberra: Australian Bureau of Statistics

Australian Bureau of Statistics (ABS) 2003. *Crime and safety.* ABS cat. no. 4509.0. Canberra: Australian Bureau of Statistics

Australian Institute of Health and Welfare 2005. *2004 National Drug Strategy household survey: first results.* Canberra: Australian Institute of Health and Welfare

Bachman J, O'Malley P & Johnston L 1984. Drug use among young adults: the impacts of role status and social environment. *Journal of personality and social psychology* 47(3): 629–645

Best D et al. 2000. Drinking and smoking as concurrent predictors of illicit drug use and positive drug attitudes in adolescents. *Drug and alcohol dependence* 60(3): 319–321

Blaze-Temple D & Lo SK 1992. Stages of drug use: a community survey of Perth teenagers. *British journal of addiction* 87(2): 215–225

Blumstein A & Cohen J 1979. Estimation of individual crime rates from arrest rates. *Journal of law and criminology* 70: 561–585

Blumstein A et al. (eds) 1986. *Criminal careers and career criminals, vol 1*. Washington, DC: National Academy Press

Britt C 1999. *Correlates of specialization and escalation in the criminal career: final report*. Washington DC: National Institute of Justice

Brook JS, Kessler RC & Cohen P 1999. The onset of marijuana use from preadolescence and early adolescence to young adulthood. *Development and psychopathology* 11(4): 901–914

Bursik R 1980. The dynamics of specialization in juvenile offenses. *Social forces* 58: 851–864

Campo A & Rohner P 1992. Relationships between perceived parental acceptance rejection: psychological adjustment, and substance abuse among young adults. *Child abuse and neglect* 1992 16: 429–440

Chen K & Kandel DB 1995. The natural history of drug use from adolescence to the mid-thirties in a general population sample. *American journal of public health* 85(1): 41–47

Coffey C et al. 2000. Initiation and progression of cannabis use in a population-based Australian adolescent longitudinal study. *Addiction* 95(11): 1679–1690

Cohen J 1986. Research on criminal careers: individual frequency rates and offense seriousness, in Blumstein A et al. (eds), *Criminal careers and career criminals* vol. 1. Washington DC: National Academy Press

Darke S et al. 2000. *Illicit drug use in Australia: epidemiology, use patterns and associated harm.* National Drug Strategy monograph series no. 43. Canberra: Department of Health and Aged Care

Dobinson I & Ward P 1985. *Drugs and crime: a survey of NSW prison property offenders.* Sydney: NSW Bureau of Crime Statistics and Research

Ellickson PL, Hays RD & Bell RM 1992. Stepping through the drug use sequence: longitudinal scalogram analysis of initiation and regular use. *Journal of abnormal psychology* 101(3): 441–451

Ellison C 2004. Grassroots funding for communities to fight crime locally. *Media release (Minister for Justice and Customs)* 15 September http://www.ag.gov.au/agd/WWW/justiceministerHome.nsf/Page/Media_Releases_2004_3rd_Quarter_15_September_2004_-_Grassroots_funding_for_communities_to_fight_crime_locally

Fagan J 1990. Social processes of delinquency and drug use among urban gangs, in Huff C (ed), *Gangs in America*. Newbury Park CA: Sage: 183–219

Farabee D, Joshi V & Anglin MD 2001. Addiction careers and criminal specialization. *Crime and delinquency* 47(2): 196–220

Farrell G 1998. Routine activities and drug trafficking: the case of the Netherlands. *International journal of drug policy* 9(1): 21–32

Farrington D 1989. Early predictors of adolescent aggression and adult violence. *Violence and victims* 4: 79–100

Farrington D, Snyder H & Finegan T 1986. Specialization in juvenile court careers. *Criminology* 26: 461–487

Fergusson D, Horwood L & Lynskey M 1994. The childhoods of multiple problem adolescents: a 15-year longitudinal study. *Journal of child psychology and psychiatry* 35(6): 1123–1140

Fergusson D, Horwood L & Lynskey M 1995. The prevalence and risk factors associated with abusive or hazardous alcohol consumption in 16-year-olds. *Addiction* 90: 935–946

Fergusson D, Lynskey M & Horwood L 1994. Childhood exposure to alcohol and adolescent drinking patterns. *Addiction* 89: 1007–1016

Gloub A & Johnson B 1994. The shifting importance of alcohol and marijuana as gateway substances among serious drug abusers. *Journal of studies on alcohol* September: 607–614

Goldstein J 1985. *Aggression and crimes of violence*. New York: Oxford University Press

Goldstein J 1995. The drugs/violence nexus: a tripartite conceptual framework, in Inciardi J & McElrath K (eds), *The American drug scene: an anthology*. Los Angeles: Roxbury

Goode E 1997. *Between politics and reason.* Contemporary social issues series. New York: St. Martin's Press

Hawkins D, Catalano R & Miller J 1992. Risk and protective factors for alcohol and other drug problems in adolescence and early adulthood: implications for substance abuse prevention. *Psychological bulletin* 112(1): 64–105

Health Outcomes International (HOI) 2002. *Evaluation of Council of Australian Governments' initiatives on illicit drugs, vol 1: executive summary.* St Peters SA: HOI

Hindelang M, Gottfredson M & Garfalo J 1978. *Victims of personal crime: an empirical foundation for the theory of personal victimization.* Cambridge MA: Ballinger

Hindelang MJ, Hirschi T & Weis JG 1979. Correlates of delinquency: the illusion of discrepancy between self-report and official measures. *American sociological review* 44: 995–1014

Hosmer D & Lemeshow S 1999. *Applied survival analysis: regression modeling of time to event data.* New York: John Wiley and Sons

Huiginga D, Mehanr S & Elliott D 1989. Delinquency and drug use: temporal and developmental patterns. *Justice quarterly* 6(3): 419–455

Inciardi J 1980. Youth, drugs and street crime, in Scarpatti F & Datesman S (eds), *Drugs and youth culture*. Beverly Hills CA: Sage: 175–204

Indermaur D 1995. *Violent property crime in Western Australia.* Australian studies in criminology. Annandale: Federation Press

Jackson K, Sher K & Wood P 2000. Trajectories of concurrent substance use disorders: a developmental, typological approach to comorbidity. *Alcoholism: clinical and experimental research* 24(6): 902–913

Johnson D 2001. Age of illicit drug initiation. *Trends & issues in crime and criminal justice* no. 201 http://www.aic.gov.au/publications/tandi/tandi201.html

Kandel D, Simcha-Fagan O & Davies M 1986. Risk factors for delinquency and illicit drug use from adolescence to young adulthood. *Journal of drug issues* 1986 16(1): 67–90

Kandel D, Yamaguchi K & Chen K 1992. Stages of progression in drug involvement from adolescence to adulthood: further evidence for the gateway theory. *Journal of alcohol studies* 53(5): 447–457

Lind B et al. 2002. *New South Wales drug court evaluation: cost effectiveness.* Sydney: Bureau of Crime Statistics and Research

Loeber R & Snyder H 1990. Rate of offending in juvenile careers: findings of constancy and change in Lambada. *Criminology* 28: 97–110

Lowencamp C & Presser L 2001. Cocaine use and violent arrest: a regression model with micro-level factors. *Journal of crime and justice* 24(2): 1–27

Makkai T 2001. Alcohol and disorder in the Australian community: some results from the National Drug Strategy household survey, in Williams P (ed), *Alcohol, young persons and violence*. Research and public policy series no. 35. Canberra: Australian Institute of Criminology: 85–111 http://www.aic.gov.au/publications/rpp/35/paper5.pdf

Makkai T & Payne J 2003a. *Drugs and crime: a study of incarcerated male offenders.* Research and public policy series no. 52. Canberra: Australian Institute of Criminology http://www.aic.gov.au/publications/rpp/52

Makkai T & Payne J 2003b. Key findings from the Drug Use Careers of Offenders study. *Trends & issues in crime and criminal justice* no. 267 http://www.aic.gov.au/publications/tandi/tandi267.html

Mayhew P 2003. Counting the costs of crime in Australia. *Trends & issues in crime and criminal justice* no. 247 http://www.aic.gov.au/publications/tandi/tandi247.html

McAllister I & Makkai T 2003. Antisocial behaviour among young Australians while under the influence of illicit drugs. *Australian and New Zealand journal of criminology* 36(2): 211–222

McAllister I & Makkai T 2001. The prevalence and characteristics of injecting drug users in Australia. *Drug and alcohol review* 20(1): 29–36

McCord J 2000. Developmental trajectories and intentional actions. *Journal of quantitative criminology* 16(2): 237–253

McGregor K & Makkai T 2003. Self-reported drug use: how prevalent is under-reporting? *Trends & issues in crime and criminal justice* no. 260 http://www.aic.gov.au/publications/tandi/tandi260.html

McGue M et al. 2001. Origins and consequences of age at first drink, II: familial risk and heritabilty. *Alcoholism: clinical and experimental research* 25(8): 1166–1173

Menard S 2001. The tripartite conceptual framework in adolescence and adulthood: evidence from a national sample. *Journal of drug issues* 31(4): 905–939

Milner L, Mouzos J & Makkai T 2004. *Drug use monitoring in Australia: 2003 annual report on drug use among police detainees.* Research and public policy series no. 58. Canberra: Australian Institute of Criminology http://www.aic.gov.au/publications/rpp/58/

Moffit T & Silva P 1988. Self-report delinquency: results from an instrument for New Zealand. *Australian and New Zealand journal of criminology* 21: 227–240

Moscato B et al. 1997. Gender differences in the relation between depressive symptoms and alcohol problems: a longitudinal perspective. *American journal of epidemiology* 146(11): 966–974

Mouzos J 2002. Homicide, in Graycar A & Grabosky P (eds), *The Cambridge handbook of Australian criminology.* Cambridge: Cambridge University Press: 157–195

Nagin D & Farrington DP 1992. The onset and persistence of offending. *Criminology* 30(4): 501–523

Nagin DS, Farrington DP & Moffit TE 1995. Life-course trajectories of different types of offenders. *Criminology* 33(1): 111–139

National Crime Prevention 1999. *Pathways to prevention: developmental and early intervention approaches to crime in Australia.* Canberra: Attorney-General's Department

Nevares D, Wolfgang ME & Tracy P 1990. *Delinquency in Puerto Rico: the 1970 birth cohort study.* New York: Greenwood Press

Nurco DN 1998. A long-term program of research on drug use and crime. *Substance use and misuse* 33(9): 1817–1837

Parker R 1993. The effects of context on alcohol and violence. *Alcohol health and research world* 17(2): 117–122

Parker R & Auerhahn K 1998. Alcohol, drugs and violence. *Annual review of sociology* 24: 291–311

Peterson M & Braiker H 1980. *Doing crime: a survey of California prison inmates.* Rand Publications Series R-2200DOJ. Santa Monica CA: RAND

Piquero A, Farrington D and Blumstein A 2003. Criminal career paradigm: background, recent developments and the way forward. *Annales internationales de criminologie* 41(1/2): 243–269

Pulkkinen L & Pitkanen T 1994. A prospective study of the precursors to problem drinking in young adulthood. *Journal of studies on alcohol* 55: 578–587

Putt J, Payne J & Milner L 2005. Indigenous male offending and substance abuse. *Trends & issues in crime and criminal justice* no. 293 http://www.aic.gov.au/publications/tandi/tandi293.html

Rojek DG & Erickson ML 1982. *Delinquent careers: a test of the career escalation model*. Criminology 20: 5–28

Salmelainen P 1995. *The correlates of offending frequency: a study of juvenile theft offenders in detention.* Sydney: NSW Bureau of Crime Statistics and Research

Sampson R & Lauritsen J 1990. Deviant lifestyles, proximity to crime, and the offender-victim link in personal violence. *Journal of research in crime and delinquency* 27(2): 110–139

Sampson R & Laub J 1993. *Crime in the making: pathways and turning points through life*. Cambridge MA: Harvard University Press

Shaw V et al. 1999. Sequences of powder cocaine and crack use among arrestees in Los Angeles County. *American journal of drug and alcohol abuse* 25(1): 47–66

Schulte C, Mouzos J & Makkai T 2005. *Drug use monitoring in Australia: 2004 annual report on drug use among police detainees.* Research and public policy series no. 65. Canberra: Australian Institute of Criminology http://www.aic.gov.au/publications/rpp/65/

Silburn S et al. 1996. *Western Australian child health survey: family and community health.* Perth: Australian Bureau of Statistics and TVW Telethon Institute for Child Health Research

Singer J & Willett J 2003. *Applied longitudinal data analysis: modeling change and event occurrence.* New York: Oxford University Press

Smith D & Smith W 1984. Patterns of delinquent careers: an assessment of three perspectives. *Social science research* 13: 129–158

Stockwell T et al. 2004. Risk and protection factors for different intensities of adolescent substance abuse: when does the prevention paradox apply? *Drug and alcohol review* 23: 67–77

Taylor N & Mayhew P 2002. Financial and psychological costs of crime for small retail businesses. *Trends & issues in crime and criminal justice* no. 229 http://www.aic.gov.au/publications/tandi/tandi229.html

Tinklenberg J 1973. Drugs and crime, in National Commission on Marijuana and Drug Abuse, *Drug use in America: problem in perspective*, Appendix, vol. 1. Washington DC: U.S. Government Printing Office: 242–267

van Kammen W & Loeber R 1994. Are fluctuations in delinquent activities related to the onset and offset in juvenile illegal drug use and drug dealing? *Journal of drug issues* 24(1): 9–24

van Kesteren J, Mayhew P & Nieuwbeerta P 2000. *Criminal victimisation in seventeen industrialised countries.* The Hague: Wetenschappelijk Onderzoek en Documentatiecentrum

Weatherburn D & Lind B 1997. *Social and economic stress, child neglect and juvenile delinquency.* Sydney: NSW Bureau of Crime Statistics and Research

White H & Gorman DM 2000. Dynamics of the drug crime relationship, in Lafree G (ed), *Criminal justice 2000*, vol 1: the nature of crime, continuity and change. Washington DC: National Institute of Justice: 151–218

Wilczynski A & Piggot R 2004. *The relationship between drugs and crime*. Canberra: Attorney-General's Department

Williams B et al. 2000. *Patterns and predictors of teenagers' use of licit and illicit substances in the Australian Temperament Project cohort 2000*: report commissioned by the Ross Trust. Melbourne: Australian Temperament Project

Willis K & Rushforth C 2003. The female criminal: an overview of women's drug use and offending behaviour. *Trends & issues in crime and criminal* justice no. 264 http://www.aic.gov.au/publications/tandi/tandi264.html

Wolfgang ME, Figlio RM & Sellin T 1972. *Delinquency in a birth cohort*. Chicago: University of Chicago Press