KEEPING OFF THE GRASS? AN ECONOMETRIC MODEL OF CANNABIS CONSUMPTION BY YOUNG PEOPLE IN BRITAIN *

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ABSTRACT: This paper presents estimates of a dynamic individual-level model of cannabis consumption, using data from a 1998 survey of young people in Britain. The econometric model is a split-population generalisation of the non-stationary Poisson process, allowing for a separate dynamic process for initiation into cannabis use. The model allows for heterogeneity in consumption levels and behavioural shifts induced by leaving education and the parental home.

KEYWORDS: Cannabis; Illicit drugs; Transition modelling; Poisson processes; Demand analysis

JEL CLASSIFICATION: C43, C82, K42

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1 Introduction

The illicit drug cannabis is the focus of intense policy debate. In Britain, it is likely that cannabis will shortly be reclassified as a class C substance, implying that possession for one's own use will no longer be an arrestable offence. There is also growing support for more radical policies, ranging from the 'Dutch option' of retaining formal illegality of cannabis whilst allowing limited retail trading, through to complete legalisation with consumption controlled through excise taxes. Cannabis has been studied extensively as an element of the spectrum of illict substances, with an emphasis on contemporaneous cross-price effects and the possible gateway effect of cannabis use on the subsequent demand for harder drugs (see Yamaguchi *et. al.*, 1984a,b; Kandel *et. al.*, 1992; Pacula, 1997; DeSimone, 1998; Fergusson and Horwood, 2000; Kenkel *et. al.*, 2001; Pudney, 2001b; van Ours, 2001). However, the demand for cannabis has not been studied in the same degree of statistical detail as the demand for the legal 'vices' of alcohol and tobacco (for recent examples, see Labeaga, 1999 and Kenkel and Terza, 2001; see also Sohler Everingham and Rydell, 1994, for a broadly similar Markov model of cocaine). If policy on cannabis is to be soundly based, there is a need for detailed econometric analysis allowing for the complex dynamics of initiation and subsequent consumption against the background of changing social and economic circumstances. This paper is an attempt to study the demand for cannabis by young people in Britain taking account of a wide range of relevant factors, including:

- family background, locality, gender and ethnicity effects;

- cohort effects induced by the evolving drug culture and drug availability;

- changes in individual exposure and opportunity induced by leaving full-time education and leaving the parental home;

- the effect of age including the initial discovery phase and subsequent maturing out of drug use;

- the possibility of innate personal characteristics predisposing some individuals towards complete abstention or heavy use;

- the impact of early initiation into drug use on the subsequent rate of consumption;

- the influence of disposable income on current demand

- the impact of early and current experience of unemployment;

- unobservable individual-specific sources of heterogeneity in rates of consumption.

Econometric modelling of the demand for illicit drugs is inevitably based on weaker data than standard demand analysis. Because of the legal status of these goods, it is not feasible to collect family budget data in the usual way. As a result, special statistical methods must be developed to analyse the partial data that are available. The econometric approach used here combines transition modelling and generalisations of the Poisson process/count data model to incorporate both the qualitative and quantitative aspects of drug use. In addition to the main objective of providing an individual-level analysis of consumption behaviour, the econometric models also offer a means of estimating the aggregate level of cannabis consumption by particular demographic groups within the general population. This is potentially important for the purpose of setting policy targets and benchmarks (for example Bramley-Harker, 2001 and Pudney 2001a).

2 Trends in the UK cannabis market

2.1 Prices

An important objective of demand analysis is to estimate the magnitude of price responses. If price variation and the responses to it are large, then the failure to include price variables in the demand model will cause bias. Prices are also important for many policy purposes. For example, knowledge of cannabis price elasticities would, under certain assumptions, allow us to simulate the effect on consumption of the price falls that might follow legalisation of the drug. Several authors have tried to estimate own- and cross-price effects of illicit drugs (see Chaloupka *et. al.* (1998) and Kenkel *et. al.* (2001) for recent US evidence) but firm estimates of price elasticities remain elusive. A major additional problem is the paucity and unreliability of available UK

price data, compounded by the presence of largely unobservable variations in quality and purity of drugs at street level.

Our aim is to model recorded individual histories of cannabis use, so we would need a long time series of cannabis prices to capture price effects. In Britain, the National Criminal Intelligence Service (NCIS) is the only source of time-series price information with anything like official status. NCIS records street prices and produces (unpublished) regular summaries for a sample of cities. NCIS price data is hard to use because it is presented in the form of price ranges whose interpretation is unclear. Figure 1 plots these figures for London, Cardiff, Birmingham and Manchester.
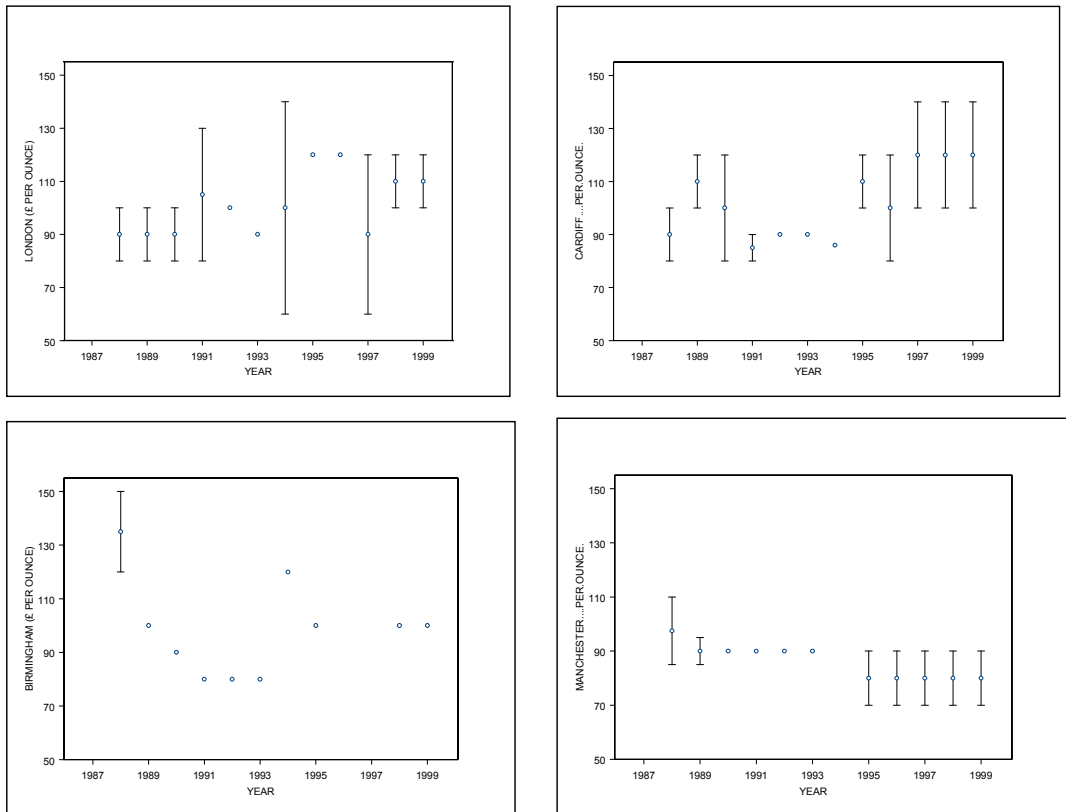

Figure 1   Street prices for cannabis resin in London, Cardiff, Birmingham and Manchester (source National Criminal Intelligence Service)

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There are two conclusions to be drawn from Figure 1. Firstly, the quality of the data is too low to be usable in a formal econometric analysis. There is no consistent policy underlying the reported price ranges: these can sometimes be very wide and sometimes a single point. For example, in Cardiff the price was apparently £86 per ounce exactly in 1994 but £100-120 in 1995 and £100-140 in 1997. The pattern of year-to-year and between-city variation appears too dramatic to be entirely believable. However, if we abstract from the short-term uncertainty in recorded prices, the second major conclusion must be that there is no clear long-term trend in prices. There is perhaps some weak evidence of an increase over time in London and Cardiff and a fall in Manchester but, given the uncertainties inherent in the data, the overall impression is that prices have been more or less constant throughout the 10-year period. This is disappointing in that the measurement of price responses is a practical impossibility, but reassuring in the sense that biases arising from the omission of price variables are likely to be small.

2.2   Availability

Individual drug use cannot be understood in isolation from the general social and cultural context. Individuals make their own decisions against the backdrop of very strong growth in most aggregate indicators of the size of the UK cannabis market. Figure 2 makes this clear by plotting the number and volume of cannabis seizures made by Customs and Excise (C&E) and the police and the proportion of BCS respondents (males aged 16-29) who report use of cannabis within the 12 months preceding interview. Although there is a great deal of random variation in these indicators, there is a reasonably coherent picture of strong growth, approximately 300% during the 1990s and 500-600% over the 1980-1998 period. Given the roughly constant cannabis price and modest income growth over this period, simple microeconomic explanations like the Becker-Murphy (1988) rational addiction model can at best account for a small part of this very large growth. Explanations based on contagion-like social interactions have much to offer. Since social interactions tend to be strongest within birth cohorts, it is very important to allow for cohort-specific factors in cannabis demand.
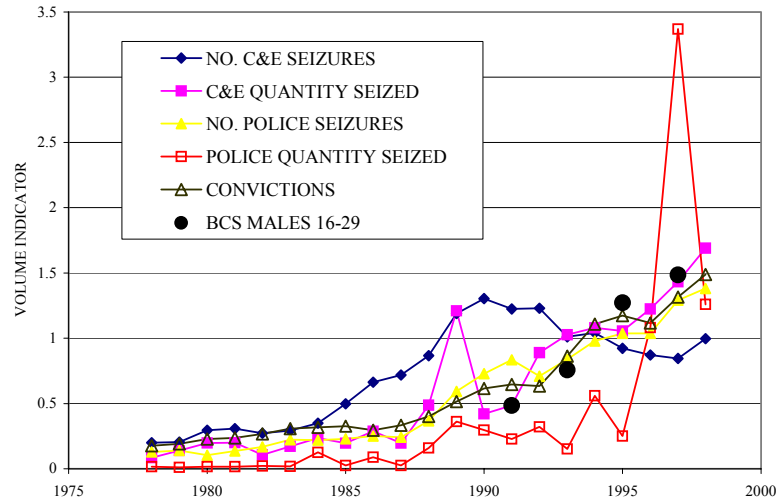
Figure 2   Time-series indicators of cannabis use

3   The 1998-9 Youth Lifestyles Survey

The Youth Lifestyles Survey (YLS) is an extended version of a youth survey first conducted in 1993. It covers the 12-30 age group, who were identified through one or other of two methods. A core sample of 3643 young people was identified from households participating in the 1998 British Crime Survey (BCS). This sample was then topped up by screening the occupants of addresses adjacent to those of the core sample to identify further subjects in the target age group. To ensure adequate coverage of high-crime areas, this top-up sample was deliberately biased towards areas identified by the BCS as having high victimisation rates. This over-sampling raised the coverage of high-crime areas from 27.5% in the core sample to 35.4% in the top-up sample.

Fieldwork took place between October 1998 and January 1999. Interviewing was subject to written consent from the parents of subjects aged under 16. Face-to-face computer assisted personal interviewing (CAPI) and computer assisted self interviewing (CASI) were used for different parts of

the data gathering process, with CASI employed for the sensitive topics of drug use and criminal activity. The response rate was 69.1%, yielding a final usable sample of 3821 respondents. Further detail on the design and conduct of the survey can be found in Stratford and Roth (1999) and Flood-Page *et. al.* (2000). The YLS questionnaire gives considerable detail on respondents' family circumstances, both currently and at age 15. Appendix Table A1 summarises the variables we use to describe individual characteristics and family background.

The principle questions about cannabis use are the following:

Q1 *Have you EVER taken CANNABIS (MARIJUANA, GRASS, HASH, GANJA, BLOW, DRAW, SKUNK), even if it was a long time ago?*
    1. Yes
    2. No
    3. Never heard of it
    4. Don't want to answer

Q2 *In the last 12 MONTHS have you taken CANNABIS (MARIJUANA, GRASS, HASH, GANJA, BLOW, DRAW, SKUNK)?*
    1. Yes
    2. No
    3. Don't want to answer

Q3 *How often have you taken CANNABIS (MARIJUANA, GRASS, HASH, GANJA, BLOW, DRAW, SKUNK) in the last 12 MONTHS?*
    1. Every day
    2. 3-5 days a week
    3. Once or twice a week
    4. Two or three times a month
    5. Once a month
    6. Once every couple of months
    7. Once or twice this year
    3. Don't want to answer

Q4 *How old were you when you first took CANNABIS (MARIJUANA, GRASS, HASH, GANJA, BLOW, DRAW, SKUNK)?*

Although the phrasing of question Q3 is reasonable in its use of everyday terms to describe rates of consumption, it is ambiguous since there is no specific definition of an episode of use. The question also does not specify precise limits on the range covered by each of the seven permitted responses. We have resolved this ambiguity by assuming that responses relate to the number of times a typical unit of cannabis has been consumed in the last year, rather than the number of days on which cannabis was taken. Thus there is no upper bound on the number of consumption episodes a respondent might have to report. We have translated the pre-specified responses into ranges of possible values for the number of consumption episodes per year in the following way. First we translate the seven responses into mid-point values: respectively 1.5, 6, 12, 30, 78, 208 and 365. The boundaries of the ranges are then taken by halving the intervals between these values and rounding appropriately. The resulting interpretation of the responses to question Q3 is given in Table 1.

Table 1 Interpretation of responses to the YLS usage question

Usage rate in last year	Assumed limits	
	L_i	U_i
Once or twice this year	1	3
Once every couple of months	4	8
Once a month	9	17
Two or three times a month	18	43
Once or twice a week	44	129
3-5 days a week	130	311
Every day	312	$+\infty$

The accuracy of self-reported data from voluntary surveys is always questionable and there is no direct check of accuracy available. However, there is some indirect evidence to suggest that mis-reporting might not be too serious. For sensitive topics like drug use, the CASI approach to interviewing has been found to give much better responses than traditional paper-based interviewing (Acquilino, 1994). The inclusion of a fictitious drug 'semeron' in the questionnaire gave rise to very few claims of its use - suggesting at least

that the 'false positives' problem is not too serious. There are a few surveys that use biological drug tests to confirm self-report data, mainly on groups like arrestees or prisoners. Whilst test results for the USA (and to a lesser extent for the UK) suggest very high levels of under-reporting for serious drugs like crack (Bennett, 1998; Lu *et. al.*, 2001), there is evidence that the magnitude of the problem is very much less for more socially acceptable drugs like cannabis. For example, 19% of arrestees testing positive for cannabis in 1999-2001 claimed not to have used the drug within the last 3 days, and only 3% denied ever having used the drug.[1] Note that NEW-ADAM uses face-to-face interviewing in a police custody area, rather than anonymous CASI in a private residence, so it seems more likely to understate drug use than the YLS. Note also that the comparison between drug test results and self-report data on use within the last 3 days is uncertain because the test for cannabis may have a longer detection window than the 3-day reference period for individuals with long-established patterns of drug use. It is certainly true that general-population surveys like the YLS will tend to under-sample certain high-consumption sections of the population. Nevertheless, for the great majority of the population, responses to the cannabis questions are probably no less reliable than the responses to many routinely-used survey income questions.

3.1   Cannabis histories from the YLS

The YLS data are summarised in Figures 3-5. The peak age of initiation into cannabis use is around 16 years (Figure 1).

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[1]The analogous figures for cocaine are 34% and 7%. However, note that these figures are sensitive to the cutoff used for distinguishing positive and negative test results and that the probability of non-report amongst those testing positive is higher for those with relatively low test scores.
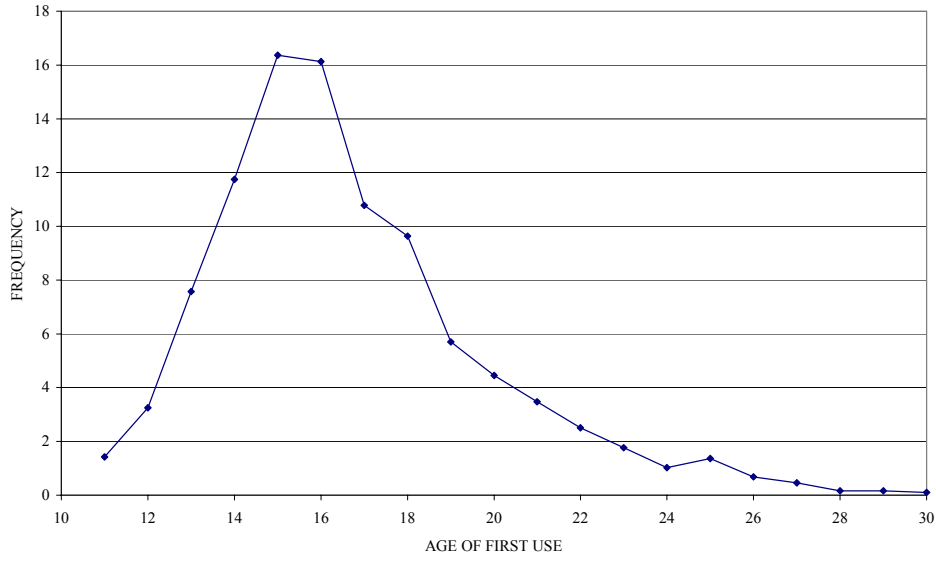
Figure 3   Age of first cannabis use (all respondents with some past use; YLS)
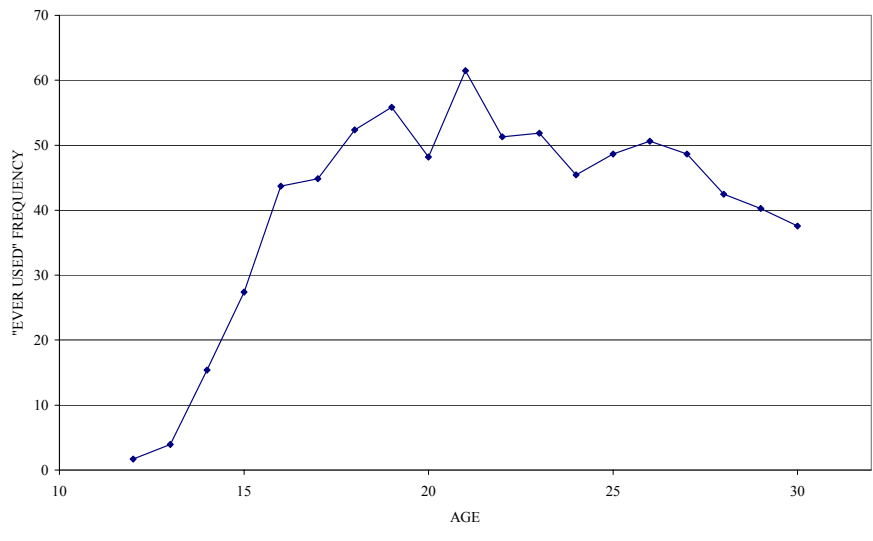

Figure 4   Experience of cannabis use by age
(all respondents; YLS)

Across the 12-30 age range covered by the YLS, experience of cannabis use rises to a peak of around 60% at 21 years, followed by a decline to around 40% for 30-year olds. This shape is a combination of two dynamic effects. There is a rising age profile for any given birth cohort, since the survivor function for transitions into drug use must be non-increasing.[2] Superimposed on the age profile is a declining birth cohort effect, resulting from the growth in 'drug culture' over time. The need to distinguish age and cohort effects is an important factor in the design of the econometric analysis. It has often been overlooked in the empirical literature on drug use.

For those who report consumption within the last year, the distribution of consumption levels is very dispersed with an ill-defined peak corresponding to regular daily use. This dispersion in consumption rates is another important feature to be captured in the model.
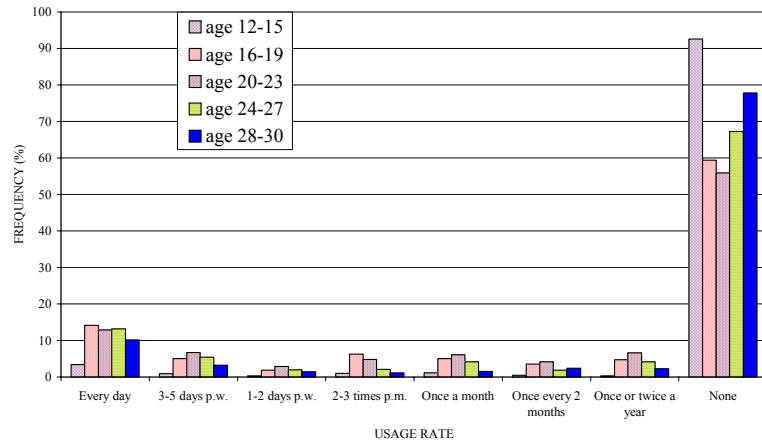
Figure 5   Self-declared cannabis usage rates by age group
(all respondents reporting use in the last year; YLS)

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[2]Differential mortality can in principle cause the age profile to be non-monotonic. This will happen if drug users have a sufficiently higher mortality rate than non-users, since we do not observe those who have died before the survey date. Any such effect is almost certain to be negligible in comparison to the cohort effect.

4 A generalised Poisson model of cannabis use

4.1 The nonstationary Poisson model

Let an individual's life be measured from an origin of $t = 0$. The number of episodes of drug use that have occurred up to time t is denoted $N(t)$ and follows a non-stationary counting process, which starts from the initial value $N(0) = 0$ and takes non-decreasing integer values. Make the following assumptions:

Independent increments: If (s,t) and (q,r) are non-overlapping time intervals, then $[N(t) - N(s)]$ and $[N(r) - N(q)]$ are statistically independent.

Proportionality: To first order, the distribution of the number of episodes occurring within any short time interval depends only on the length of the interval and the instantaneous intensity rate:

$$\Pr(N(t + dt) - N(t) \quad = \quad 1) = \lambda(t)dt + o(dt)$$
$$\Pr(N(t + dt) - N(t) \quad > \quad 1) = o(dt)$$

where $\lambda(t)$ is a positive quantity interpreted as the instantaneous intensity rate of the process and $o(dt)$ represents a residual term that goes to zero at least as fast as dt.

These assumptions define the non-stationary Poisson process. The basic result that derives from this is that the number of events occurring in any time interval (s,t) has the following Poisson distribution:

$$\Pr(N(t) - N(s) = k) = \frac{e^{-[m(t)-m(s)]} [m(t) - m(s)]^k}{k!} \quad , \qquad k = 0, 1, 2, ... \tag{1}$$

(see Ross, 2000, pages 284-285). Thus the mean usage over any period (s,t) is $E(k) = m(t) - m(s)$, where $m(t)$ is the integrated intensity rate:

$$m(t) = \int_0^t \lambda(s)ds \tag{2}$$

The nonstationary Poisson model is equivalent to the conventional hazard rate representation of counting processes. Let successive episodes of use occur

at times t_1 and t_2. Then the distribution of the interval $\delta = t_2 - t_1$ has density:

$$g(\delta|t_1) = \lambda(t_1 + \delta)\exp\left(-[m(t_2) - m(t_1)]\right) \tag{3}$$

The first term on the right hand side of (3) is the hazard rate at time $t_1 + \delta$, while the exponential term is the survivor function, expressible as the exponential of minus the integrated hazard. Since we do not observe individual episodes of use, the Poisson count representation is the more useful.

4.2 A split-population Poisson model

There are two implausible features of the Poisson model that prevent its direct use as a model of drug consumption. Firstly, there may be a structural change in the process initiated by the first use: in other words the process governing the transition from non-user to user may not be the same as the process governing the development of consumption over time for those who have become users. This suggests that we should think of drug histories as a compound process constructed as a consumption process following on from an initiation process. A second drawback of the Poisson model is the familiar over-dispersion problem. In general, even allowing for observable conditioning variables, Poisson processes frequently cannot capture the cross-section variation in consumption rates. One way of overcoming this is to think of the population as a mixture of a number of separate 'types' with different potential usage rates. For example, the self-declared YLS usage frequencies in Figures 1 and 2 suggest that there might be a mixture of at least three types: non-users, occasional users (or brief experimenters) and regular users. However, these are not clearly delineated, nor can individuals be unambiguously assigned to these categories, so we use a stochastic mixture model.

Suppose there are J distinct types of individual, each with a different expected rate of drug 'discovery', λ_j $(j = 1...J)$. Let Q_j be the probability of an individual being of type j. Then, if discovery is governed by a non-homogeneous Poisson process conditional on type, the probability of a randomly-drawn individual of type j commencing drug use whilst of age a is:

$$\Pr(\text{commences at age } a \mid \text{type } j) = e^{-m_j(a)} - e^{-m_j(a+1)} \tag{4}$$

where $m_j(a) = \int_0^a \lambda_j(t)dt$. We allow for conscientious non-users by taking type $j = 1$ as those with a zero discovery intensity, $\lambda_1(t) = 0, \forall\, t$.

After 'discovery' has occurred, the usage process is governed by intensity function $\lambda_j^*(d; a)$, where a is the age of onset and t is current age. Thus the probability that k drug use episodes occur in a period $[t, t + \Delta t]$ sometime after onset is:

$$\Pr(k \text{ episodes in } [t, t + \Delta t] \mid \text{onset at age } a)$$
$$= \frac{e^{-[m_j^*(d + \Delta t) - m_j^*(d)]} \left[m_j^*(d + \Delta t) - m_j^*(d)\right]^k}{k!} \qquad (5)$$

where $d = t - a$ is time since onset and $m_j^*(.)$ is the cumulative intensity corresponding to $\lambda_j^*(.)$.

Note that, if there is a split population of this kind, a simple count data model of episodes of use in the last year conditional on age of first use will give biased results because of the endogeneity of the age of first use induced by the stochastic mixing.

4.3 Random variations in consumption

We have already generalised the Poisson model to some extent by assuming a mixture of three broad consumer types. However, the remaining assumption of homogeneity within types is questionable. A related limitation of the model is its assumption that the development of expected usage rates over time is essentially deterministic. A more general model would be one in which there are random individual departures from trend usage rates, of the form $\lambda_j^{**}(s) = \lambda_j^*(s)V_j(s)$ where $V_j(s)$ is a positive, continuous-time stochastic process, possibly with correlated increments, reflecting the random evolution of the individual's drug 'habit' over time. In general a model of this form is difficult to handle, given the observational scheme used in the YLS. However, under the plausible assumption that the process $V_j(s)$ typically exhibits a high degree of stability over time, an approximate approach should work well. To implement this, we assume that $V_j(s)$ is approximately constant over any 12-month observation period. Thus:

$$m_j^{**}(t, V_j(.)) = \int_0^t \lambda_j^*(s)V_j(s)ds$$

$$\approx \sum_{\tau=1}^{[t]} v_{j\tau} \int_{t-[t]+\tau-1}^{t-[t]+\tau} \lambda_j^*(s)ds + v_{j0} \int_0^{t-[t]} \lambda_j^*(s)ds \qquad (6)$$

where $[t]$ denotes the integer part of t and where the discrete variables $v_{j\tau}$ are:

$$v_{j\tau} = \int_{t-[t]+\tau-1}^{t-[t]+\tau} V_j(s)ds$$

Since we only observe drug use within the last year, only the current element in the sequence of random terms $v_{j[t]}$ is involved in the observation:

$$
\begin{aligned}
m_j^{**}(t, V_j(.)) - m_j^*(t-1, V_j(.)) &\approx v_{j[t]} \int_{t-1}^t \lambda_j^*(s)ds \\
&= v_{j[t]} \left[m_j^*(t) - m_j^*(t-1) \right] \qquad (7)
\end{aligned}
$$

A consequence of this is that we do not have to specify the autocorrelation structure of the $v_{j\tau}$, only their marginal distribution across individuals. Note that the structure (7) can be justified as an exact model if the $v_{j\tau}$ are random across individuals but fixed over time. For computational simplicity, the natural assumption to make about the $v_{j\tau}$ are that they have a gamma distribution with mean 1 and variance σ_j^2.

In the YLS, there are three observable regimes: (i) no previous use; (ii) some previous use but none in the last year; and (iii) k episodes of use in the last year. Provided we make no use of information on last year drug use for those who might be within one year of onset, the probabilities of the three regimes are as follows:

$$\Pr(\text{no previous use}) = Q_1 + \sum_{j=2}^J Q_j e^{-m_j(t)} \qquad (8)$$

$\Pr(\text{onset at age } a, \text{ none in last year})$

$$= \sum_{j=2}^J Q_j e^{-m_j(a)} \left\{ 1 - e^{-[m_j(a+1)-m_j(a)]} \right\} W_j^{-1/\sigma_j^2}$$

$$\qquad (9)$$

Pr(onset at age a, k episodes in last year)

$$= \sum_{j=2}^{J} Q_j e^{-m_j(a)} \left\{ 1 - e^{-[m_j(a+1) - m_j(a)]} \right\}$$

$$\times \frac{\Gamma(\sigma_j^{-2} + k)}{\Gamma(k+1)\Gamma(\sigma_j^{-2})} W_j^{-1/\sigma_j^2} \left(1 - W_j^{-1} \right)^k \qquad (10)$$

where $W_j = 1 + \sigma_j^2 \left[m_j^*(d; a) - m_j^*(d-1; a) \right]$

4.4   Time-varying explanatory variables

The YLS is not a full longitudinal study, but it does capture some past changes in personal circumstances. Suppose at time τ there is a change in the value of some explanatory variable, causing a shift in the intensity rates prevailing at that time. The effect will be to change the integrated intensity functions $m_j(.)$ or $m_j^*(.)$ in expressions (8)-(10). For example, if there is a shift from $\lambda_j(.)$ to $\lambda_j^0(.)$ from time $a = \tau$ onwards, the integrated intensity of cannabis initiation becomes:

$$\begin{aligned} \widetilde{m}_j(a) &= \int_0^\tau \lambda_j(s)ds + \int_\tau^a \lambda_j^0(s)ds \\ &= m_j(\tau) + m_j^0(a) - m_j^0(\tau) \end{aligned}$$

The most important changes in circumstances are likely to be the shift from full-time education into work or unemployemnt and the move away from the parental home.[3]

4.5   Functional forms

We need tractable specifications for the non-negative intensity functions $\lambda_j(t)$, $\lambda_j^*(t)$ and mixing probabilities Q_j. The intensity functions should

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[3]Education, domicile and unemployment are potentially endogenous since educational success and family harmony may both be threatened by drug use. We treat this problem by estimating models with and without the school-leaving and domicile variables. Income and unemployment are treated in the same way, since they are also possibly endogenous influences on demand.

be parsimoniously specified and sufficiently flexible to capture an inverted U-shaped profile, since we find in practice that drug use rises up to some critical age and then declines with further ageing. The usage rates and mixing probabilities should also be specified to vary across individuals to reflect their different observable characteristics, which are captured by a vector of observable variables $\mathbf{x}$. A simple specification is the following exponential-quadratic form:

$$\lambda_j(a) = \exp\left\{\alpha_{0j} + \mathbf{x}\boldsymbol{\alpha}_{1j} + \alpha_{2j}a - \alpha_{3j}a^2\right\} \tag{11}$$

$$\lambda_j^*(d) = \exp\left\{\beta_{0j} + \mathbf{x}\boldsymbol{\beta}_{1j} + \beta_{2j}d - \beta_{3j}d^2 + \beta_{4j}a + \beta_{5j}a^2\right\} \tag{12}$$

where d is the elapsed time since initiation and α_2, α_3, β_2 and β_3 are non-negative parameters. By completing the square and making a change of variable, the cumulative intensities can be expressed in terms of the distribution function $\Phi(.)$ of the standard normal distribution. Specifically:

$$m_j(a) = \begin{cases} \exp\left(\theta_{0j} + \mathbf{x}\boldsymbol{\alpha}_{1j}\right)\left\{\Phi\left(\theta_{2j}a - \theta_{3j}\right) - \Phi(-\theta_{3j})\right\} & \alpha_{2j}, \alpha_{3j} > 0 \\ \exp\left\{\alpha_{0j} + \mathbf{x}\boldsymbol{\alpha}_{1j}\right\}\alpha_{2j}^{-1}\left[\exp\left\{\alpha_{2j}a\right\} - 1\right] & \alpha_{2j} > 0; \alpha_{3j} = 0 \\ \exp\left\{\alpha_{0j} + \mathbf{x}\boldsymbol{\alpha}_{1j}\right\}a & \alpha_{2j}, \alpha_{3j} = 0 \end{cases}$$

$$\tag{13}$$

where $\theta_{0j} = \alpha_{0j} + \alpha_{2j}^2/4\alpha_{3j} + \ln(\sqrt{\pi/\alpha_{3j}})$, $\theta_{2j} = \sqrt{2\alpha_{3j}}$ and $\theta_{3j} = \alpha_{2j}/\sqrt{2\alpha_{3j}}$. A similar expression gives $m_j^*(d)$.

This functional form turns out to be restrictive, since the log intensity function is symmetrical about its maximum point, implying a similar rate of build-up and decay of drug use with age. This restriction can be relaxed by replacing a by $\psi_j(a)$ in (13), where $\psi_j(.)$ is an arbitrary increasing function. The implied intensity function is:

$$\lambda_j(a) = \psi_j'(a)\exp\left\{\alpha_{0j} + \mathbf{x}\boldsymbol{\alpha}_{1j} + \alpha_{2j}\psi_j(a) - \alpha_{3j}\psi_j(a)^2\right\} \tag{14}$$

In our application of this model, we specify $\psi_j(.)$ as:

$$\psi_j(a) = \frac{a^{1+\psi_j}}{1+\psi_j}$$

where ψ_j is now a constant parameter. A similar extension is made to (12)

The following multinomial logit specification is used for the mixing probabilities:

$$Q_j = \frac{\exp\left(\gamma_{0j} + \mathbf{x}\boldsymbol{\gamma}_{1j}\right)}{\sum_{r=1}^{J} \exp\left(\gamma_{0r} + \mathbf{x}\boldsymbol{\gamma}_{1r}\right)} \tag{15}$$

where the first of the J coefficient vectors $(\gamma_{01}, \boldsymbol{\gamma}_{11})$ is normalised at zero.

The extended model allows for structural shifts caused by the events of leaving full-time education and leaving the parental home, with allowance for interaction between the two. This is equivalent to including three time-varying covariates in the intensity functions $\lambda_j(a)$ and $\lambda_j^*(d)$: dummy variables for being out of full-time education, living away from home and a third for their joint occurrence. A fourth time-varying dummy is used to capture the 'scarring' effect of early unemployment. For all individuals, this takes the value 0 during the period before leaving education. During the period after leaving education, it takes the value 1 if unemployment (of at least 6 months duration) was the first destination or 0 if there was a smooth school-work transition.

A set of time-invariant variables describes basic individual characteristics, including age, gender, ethnicity, family background, area type and birth cohort.[4] In addition, the following seven variables are used to allow for income, education and domicile effects:

- (i)   current disposable income, defined as normal weekly spending money available after meeting basic living costs;
- (ii)   a dummy variable for those with no regular disposable income;
- (iii)   a dummy variable for current unemployment
- (iv)   a time-varying dummy variable for being in full-time education and living away from home;
- (v)   a time-varying dummy variable for having left full-time education but still living at the parental home;
- (vi)   a time-varying dummy variable for having left both full-time education and the parental home.
- (vii)   a time-varying dummy variable for having left full-time education and been unemployed for at least 6 months before finding a first job

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[4]We also included a dummy variable for inner-city location, but this was always insignificant in every part of the model and has been omitted from the final specification.

The two income variables are only observable at the time of interview and are included in the consumption part of the model (λ_j) but excluded from the initiation element (λ_j^*). Note that cannabis is cheap (roughly £1 per 'joint') and it is unlikely that lack of available money is a significant reason for not experimenting at least once. The enforced exclusion of income from λ_j seems unlikely to be a significant source of bias. The explanatory variables are summarised in Table A1 of Appendix 2.

5 Results

5.1 Estimation

Estimation of the model is carried out using maximum likelihood. Details of the log-likelihood function are given in Appendix 1; the full parameter estimates appear in Appendix 2, Table A2.

Attempts to fit the gamma-Poisson model in full generality led to a corner solution in the likelihood maximisation. The optimisation algorithm drove the expected rate of consumption by type 2 individuals to zero, with the parameter β_{0j} diverging towards $-\infty$ for $j = 2$.[5] This implies an interpretation of type 2 individuals as people who may briefly experiment with cannabis but then not take it up. Our split population model therefore partitions the population into three classes: abstainers ($j = 1$), one-time experimenters ($j = 2$) and potential longer-term users ($j = 3$). This empirical division of the population into potential user types seems theoretically fruitful and plausible. It is also consistent with the distinction between regular recreational drug 'users' and experimental drug 'triers' which is emphasised by Aldridge *et. al.* (1999) in their longitudinal study of young people in the north of England.

A second notable feature of the fitted model is that no significant duration effect could be found in the consumption process, so the final estimates have $\beta_{2j} = \beta_{3j} = 0$ imposed. Age of first use of cannabis turns out to be the dominant influence on the current rate of consumption.

A number of summary measures are presented in Table 2 to illustrate the properties of the fitted models. The sample means of the estimated mixing

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[5]Note that the recorded consumption intensity is not used in estimation for those who, at interview, are within a year of their first use of cannabis.

probabilities $\widehat{Q}_1 \ldots \widehat{Q}_3$ are calculated by evaluating (15) at each data point using the estimated parameter values and then averaging. Also included in Table 2 are mean consumption and the probability of abstention up to age 30. These are approximated by the following expressions:[6]

$$n^{-1} \sum_{i=1}^{n} \sum_{j=2}^{3} \widehat{Q}_{ij} \left\{ \sum_{a \leq 29} \left[e^{-\widehat{m}_{ij}(a-1)} - e^{-\widehat{m}_{ij}(a)} \right] \left[\widehat{m}_{ij}^{*}(30-a) \right] \right\} \qquad (16)$$

$$\Pr(\text{no use to age } 30) = n^{-1} \sum_{i=1}^{n} \left\{ \widehat{Q}_{i1} + \sum_{j=2}^{3} \widehat{Q}_{ij} e^{-\widehat{m}_{ij}(30)} \right\} \qquad (17)$$

where n is sample size.

Table 2 Properties of estimated cannabis consumption models

$\Pr(\text{abstainer}) = \overline{Q}_1$	0.29
$\Pr(\text{potential experimenter}) = \overline{Q}_2$	0.23
$\Pr(\text{potential user}) = \overline{Q}_3$	0.48
Mean cumulated use to age 30	379
Mean cumulated use to age 30 (1970 cohort)	144
Mean cumulated use to age 30 (1985 cohort)	508
$\Pr(\text{no use by age } 30)$	0.41

Around a half of all people are classified as potential regular users and a further quarter as potential brief experimenters. Of course, not all of these potential users will become actual users. The most striking feature of Table 2 is the ubiquity of cannabis use among the cohorts covered by the YLS.

---

[6]Note that (16)-(17) require a full trajectory for the time-varying covariates up to age 30. These trajectories are incomplete for most respondents, and we impute the missing components by using age-specific sample means. For example, a 17-year old respondent who is still at school when interviewed is assigned an age of leaving education equal to the sample mean for all those observed to leave education at or after age 17.

Almost 60% of the sample are predicted to have used cannabis by the time they reach age 30. The predicted average total episodes of use up to age 30 is 379. The strong and significant cohort effects in the discovery stage of the consumption process implies that this figure is rising rapidly over time. Comparing predictions of cumulated use to age 30 for the sampled individuals born in 1970 with those for the individuals born in 1985, the model predicts more than a 350% increase in long-term cannabis use. This finding is broadly in line with the time series information summarised in Figure 2 (see also Pudney, 2001c).

5.2   Robustness to alternative assumptions about time, cohort and age effects

To understand the consumption process at the individual level, it is necessary to separate the effects of aging from the general cultural effects linked to birth cohort and the passage of time. Cohort and time effects are subtly different. The former relates to the effect of cultural differences between successive generations and implies some insulation between generations. The latter relates to general trends over time, which have some influence on the members of all generations simultaneously. Of course, if the age profile is sufficiently compressed there is little difference between cohort and time effects. In the extreme case, if all drug use takes place one particular age, then cohort and time effects are essentially the same thing, since one and only one birth cohort is exposed to influence at any time. The issues involved in separating time and cohort effects are slightly different for the two component processes of initiation into drug use and consumption by the initiates.

Consider first the initiation process. Write the true transition intensity in general terms as $\Lambda(a, y, t)$ where a is age, y is year of birth and t is calendar time. As time passes from the point of origin y, these variables are related by the identity $y + a \equiv t$ and their effects cannot be separated. We have resolved this indeterminacy by estimating a model of the general form $\lambda(a, y) \equiv \Lambda(a, y, y + a)$. In general, the effect of excluding time is likely to be an upward bias in the estimated age and cohort effects (in differential terms: $\lambda_a = \Lambda_a + \Lambda_t$ and $\lambda_y = \Lambda_y + \Lambda_t$), since we expect a predominantly rising time profile if there is a time profile at all. It is useful to indicate robustness by considering two extreme cases. If the true intensity function

Λ is invariant to t then the estimated model can be interpreted directly. On the other hand, if Λ is in fact invariant to y, we have $\Lambda(a,t) = \lambda(a, t-a)$ suggesting a downward bias in the apparent age effect. Using the estimated model coefficients and concentrating on the implied age profile, this would imply:

$$\Lambda_1(a,t) = K_1(t,\mathbf{x})\exp\left\{-0.168a + 7.278\psi_1(a) - 0.538\psi_1(a)^2\right\} \quad (18)$$

$$\Lambda_2(a,t) = K_2(t,\mathbf{x})\exp\left\{-0.072a + 4.639\psi_2(a) - 0.344\psi_2(a)^2\right\} \quad (19)$$

where $K_j(t,\mathbf{x})$ is the remaining component of Λ_j. We have plotted in figure 6, these age profiles together with those of the original model. For $j = 3$ (the potential regular users) there is only a slight forward shift in the profile when the estimated year-of-birth coefficient is reinterpreted as a time effect. For the experimenters ($j = 2$), there is a larger shift, but this is of little consequence in terms of the health or aggregate demand implications. Thus our inability to separate time and cohort effects is unimportant for the estimation of the age profile of initiation into cannabis use.[7] There remains a question about the interpretation of the rise in prevalence as a cohort or time effect, but this requires long-term panel or pseudo-panel data for a complete resolution.

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[7]The inverse U-shape of the estimated age profile of initiation suggests that we are finding a true age effect. If, for example, there were no true age effect, the estimate would imply that the intensity rate is a non-monotonic function of $t - y$ and thus of t. In view of the aggregate trend, it is hard to see why the time effect should turn down strongly in this way.
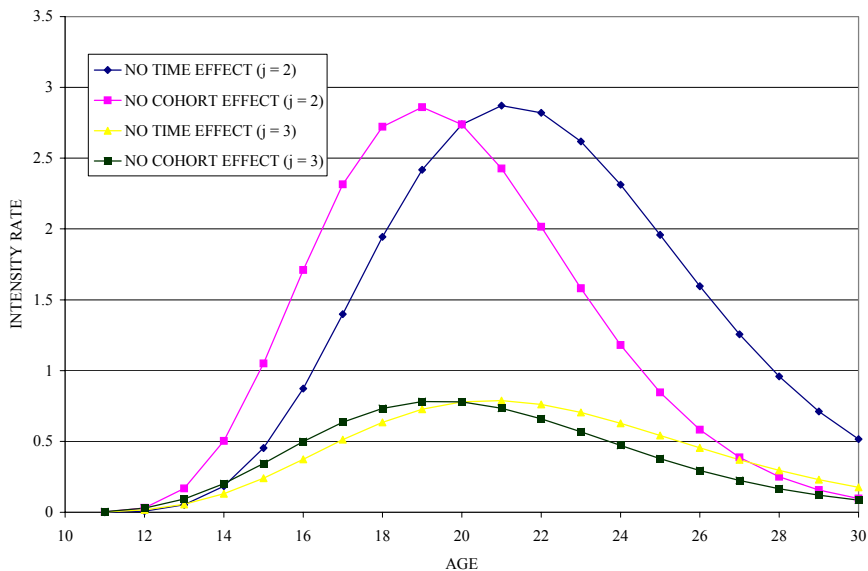
Figure 6 Sensitivity of the estimated cannabis hazard to alternative cohort-time assumptions

Consider now the consumption process. Expressing the intensity rate λ^* as a function of time since initiation (d) and age of initiation (a) is equivalent to writing it as a function of t and a, so we lose no generality by excluding t from the specification. However, the exclusion of y is an unavoidable restriction: since observed consumption relates to the same period for all respondents, we have the identity $y + a + d \equiv T$, where T is the interview date. This does give some possibility of bias. Let $\Lambda^*(d, a, y)$ be the true intensity of use at the time of interview. Empirically, we have found that $\ln \lambda^*$ is invariant to d but quadratic in $\psi(a)$. Thus the estimated model gives a U-shaped function $\lambda^*(a) = \Lambda^*(d, a, T - d - a)$. For λ^* to be invariant to d, if $\Lambda_y > 0$, we will require $\Lambda_d > 0$; but this is extremely implausible, since personal use of cannabis is generally observed to decline eventually with time. Conditional on age of onset, any cohort effect on the rate of consumption by a consumer therefore seems unlikely to be important.

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5.3 The influence of personal characteristics

There is no significant evidence of an impact of current disposable income (or its absence) on the current rate of consumption. On this evidence, economic factors seem to play a very minor role in comparison to personal and social influences. We now summarise these influences.

There is little doubt that cannabis is a harmful substance. It is believed to be physically at least as damaging as tobacco (Joy *et. al.*, 1999); its use raises the risk of accidental injury (Smiley, 1999); it is occasionally associated with temporary acute psychiatric difficulties[8]; and there is at least a possibility that its long-term use causes impairment of brain function (Joy *et. al.*, 1999). Whatever the true scale of these health effects, cumulated lifetime consumption is likely to be a good indicator of exposure to risk, perhaps with particular emphasis on use occurring at an early age. Given the characteristics that describe a hypothetical individual, we can compute an estimate of the expected number of times that he or she will use cannabis prior to age 30 as follows:

$$\widehat{C}_1 = \sum_{j=2}^{3} \widehat{Q}_j \int_{10}^{30} \widehat{\lambda}_j(a) \exp\left(-\widehat{m}_j(a)\right) \widehat{m}_j^*(30 - a|a) da \qquad (20)$$

The integral is computed using Gauss-Hermite quadrature. A similar approach is used to compute the probability of consumption exceeding 3600 episodes (roughly equivalent to 1 use per day for 10 years) and the probability that any use will occur before age 16. The results of these calculations are given in Table 3, where the top panel is based on the the estimated model interpreted directly and the lower panel corresponds to the alternative interpretation in which the apparent cohort effect on initiation is reinterpreted as a time effect.[9]

The baseline case is a white male, born in 1983, educated to age 18, with a working father and non-working mother and living in a non-deprived area. Consider first the top panel of Table 3. Almost 40% of such individuals are

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[8]See also Andreasson et.al. (1987) and Linszen et. al. (1990) on the possibility of an association with schizophrenia.

[9]Note that, for these models, the predicted cumulative consumption for type 2 individuals, $\widehat{m}_2^*$, is essentially zero. These are interpreted as one-time experimenters who use the drug briefly and then never again. In calculating (20) we have assumed a single episode of use and substituted the value 1 for the term $\widehat{m}_2^*(30 - a|a)$.

predicted to have used cannabis by age 16. Fewer than 10% of them will develop into very heavy users (3,600 episodes by age 30). The average level of use cumulated to age 30 is almost 1600 episodes and for one who does become a user, over 1,900 episodes are predicted.[10]

Changes in the attributes of this baseline individual generate large changes in the predicted level of use. The most important differences are birth cohort, gender, social deprivation and disadvantaged family background. Changing the year of birth from 1983 to 1968 reduces the mean rate of consumption by 86% and cuts the rate of early (pre-16) use from 40% to 6%. Comparing otherwise similar individuals, there is a reduction of almost 55% in mean cumulated consumption for females relative to males. Switching from a childhood spent in a 'normal' neighbourhood to one spent in a deprived area raises the predicted level of consumption by 65% and increases the rate of early initiation to nearly 50%. Family background, and particularly the father's status, appears the most important influence on cannabis use. If the baseline individual is raised in a family with no father and a working mother, expected consumption rises by 220% and the rate of early initiation to over a third. Having a father who is present but unemployed raises baseline expected consumption by over a third. Experience of prolonged unemployment as the first post-education destination generates a 90% increase in expected consumption. Leaving the parental home and leaving full-time education tend to reduce expected consumption, but are.quantitaively less important effects, despite being statistically significant.

Now interpret the year-of-birth coefficient as the consequence of a time effect. The simulation results are given in the lower panel of Table 3, with time (in other words the general social culture) held fixed at its 1983 level. The pattern of effects of varying personal characteristics remains largely unchanged.

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[10]Omitting the education, income,domicile and unemployment variables (which may be endogenous) makes little difference to these results.

Table 3 Simulation results: Gamma-Poisson model with income, education, domicile and unemployment variables

	Mean usage	Mean usage by users	% use exceeds 3600	% using by age 16
No time effect assumed				
Baseline white male 1983 birth cohort	1382	1933	9.8	39.5
1968 cohort	191	965	1.3	6.4
Female	640	1120	1.3	27.3
Black	1274	3385	8.6	37.5
Deprived inner-city	2277	2922	15.2	49.7
Fatherless, working mother	3060	4012	18.5	58.0
Unemployed father	1874	2488	12.4	31.7
Leave school at 16	1343	1878	8.8	34.2
Unemployed after leaving school	2629	3676	15.4	35.8
Leave home 19, leave education 21	1247	1744	8.9	39.5
Cohort effect reinterpreted as time effect				
Baseline white male under social conditions prevailing in 1983	990	1385	6.9	26.8
Conditions prevailing in 1968	129	650	9.0	3.9
Female	448	783	3.2	17.7
Black	996	2644	6.6	27.4
Deprived inner-city	1659	2129	10.8	34.3
Fatherless, working mother	2254	2956	13.2	39.2
Unemployed father	1315	1745	8.4	21.7
Leave school at 15	969	1355	6.3	23.8
Unemployed after leaving school	1882	2632	10.6	24.9
Leave home 19, leave education 21	892	1248	6.3	26.8

The impact of age and cohort effects can be seen in Figure 7. This plots expected annual consumption against age for the 1970, 1975, 1980 and 1985 birth cohorts, for the baseline white male case. Define a as age and y as year of birth. The age-cohort curves are defined in general as follows (note that

$\widehat{\lambda}_j^*(t|a)$ is identically zero for $j = 2$ in the gamma-Poisson model):

$$\widehat{C}_2(a,y) = \widehat{Q}_3 \int\limits_a^{a+1} \widehat{\lambda}_3(s|y) \exp\left(-\widehat{m}_3(s|y)\right) \left[\widehat{m}_3^*(a+1|t) - \widehat{m}_3^*(\widetilde{a}(t)|t)\right] ds \quad (21)$$

where $\widetilde{a}(t) = \max\{t, a\}$. These cohort effects are clearly important and represent the rapidly developing drug culture over the 1980s and 90s. It corresponds remarkably closely to the rising trend of most macro-level indicators of cannabis use (see Pudney 2001c).
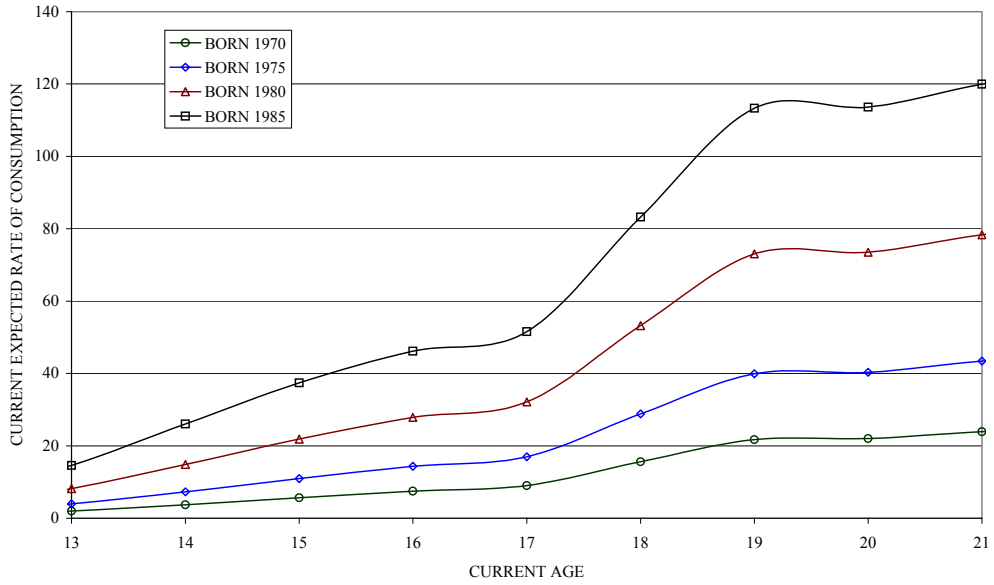
Figure 7 The effect of birth cohort on the consumption age profile

Figure 8 illustrates the predicted impact of age of initiation on cumulative consumption to age 30. This is an important issue, since government policy is heavily directed towards drugs awareness programmes operating in schools and through parents. These programmes are designed to educate schoolchildren alert parents to the potentially damaging effects of drug use

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and there is some evidence to suggest that they may be effective in postponing the onset of drug use (Caulkins *et. al.*, 1999; Velleman et. al., 2000; Evans *et. al.*, 2001). Under specific assumptions, our model can evaluate the likely impact on cumulated consumption of an intervention that succeeds in postponing first use. Assume that the policy intervention does nothing to alter the probabilities of the underlying user 'types', $Q_1...Q_3$, but rather acts in the same way as the purely random elements embedded in the initiation process. Then a good indicator of the scope for reduction in drug use achievable by such interventions is the following expectation of cumulated cannabis use, conditional on initiation ocurring at age a:[11]

$$\widehat{C}_3(a) = \sum_{j=2}^{3} \widehat{Q}_j \int\limits_{a}^{a+1} \left[\frac{\widehat{\lambda}_j(s) \exp\left(-\widehat{m}_j(s)\right)}{e^{-\widehat{m}_j(a)} - e^{-\widehat{m}_j(a+1)}} \right] \widehat{m}_j^*(30 - s|s)\, ds \qquad (22)$$

This is plotted in Figure 8 for a number of the hypothetical individual types defined in Table 3. The predicted effect of age of initiation into cannabis consumption emerges as an extremely important influence on cumulated consumption and therefore presumably on the scale of damage caused by consumption. School-based policies designed to delay onset seem an attractive policy option given these results.

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[11]This assumption about the way that policy interventions might work within the structure of this model is unlikely to be critical. The strong effects depicted in Figure 5 are driven by the large and highly significant age of onset coefficients in the consumption process. Expression (22) can be interpreted in a less specific way as a summary of their magnitude.
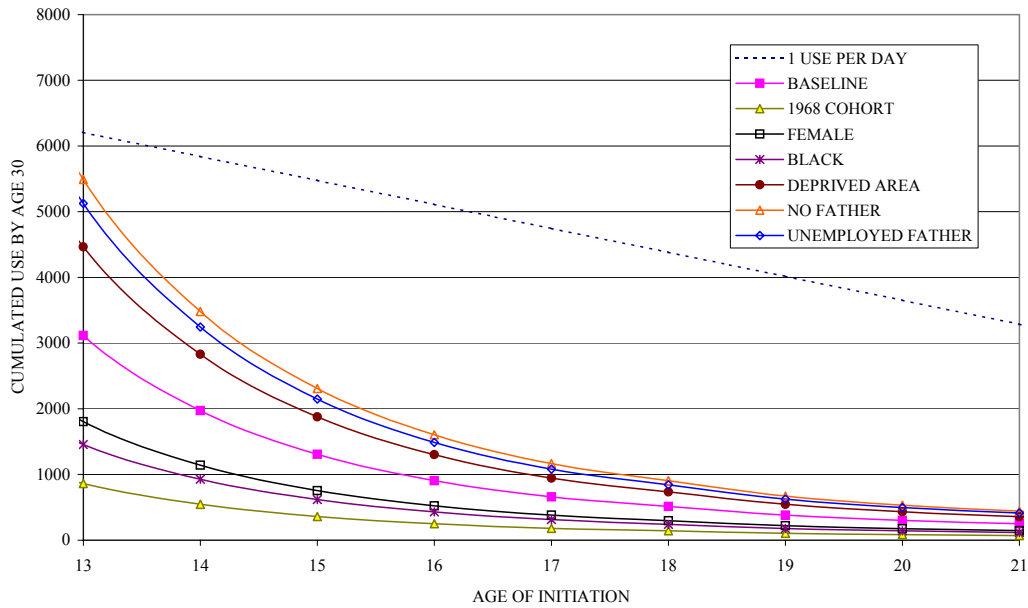
Figure 8 The effect of age of first use on cumulated consumption to age 30

6   Conclusions

This study of the consumption of cannabis by young people in the UK is based on a statistical model fitted to individual-level data from the 1998 Youth Lifestyles Survey. The model allows for a wide range of possible influences on cannabis demand including: family background, locality, gender and ethnicity effects; cohort effects induced by the evolving drug culture; changes in individual exposure and opportunity induced by leaving education and leaving the parental home; the effect of age including the initial discovery phase and subsequent maturing out of drug use; the possibility of innate personal characteristics predisposing some individuals towards complete abstention or heavy use; the impact of early initiation into drug use on the subsequent rate of consumption; the influence of disposable income and unemployment on demand; and individual-specific random variation in rates of consumption.

The main findings are the following:

- There is no significant evidence of a contemporaneous influence of income on demand.

- Early onset of cannabis use raises subsequent rates of consumption very substantially. In early adolesence, the effect of delaying onset by a year may be a reduction of a third or more in consumption cumulated to age 30.

- Heavy cannabis consumption is strongly related to family background. For example, a fatherless male cannabis user with a working mother has an expected level of cumulated consumption more than double that of an otherwise similar cannabis user from a 'normal' family background.

- Adverse early experience in the labour market is found to have a large impact. An individual who leaves full-time education to enter a long (above 6 months) spell of unemployment has an 80-90% increase in his or her expected level of cumulated consumption of cannabis.

- Social deprivation in the geographical sense is very important. A young person living in one of the (roughly) 10% most deprived areas has an expected cumulative consumption raised by around 65%.

- Trend effects apparently linked to birth cohorts are very strong. There is an autonomous trend towards early initiation and heavy use in successive birth cohorts. For example, cumulative consumption by early-onset users born in the mid 1980s is predicted to be more than six times that for similar users born in the late 1960s.

The policy implications of these findings are important. They give strong support for drug awareness programmes and similar interventions aimed at postponing school children's experimentation with drugs. They also emphasise the importance of indirect drug policies. Labour market programmes directed at reducing unemployment among school-leavers and urban planning initiatives intended to improve the condition of deprived neighbourhoods may be at least as effective as other more direct enforcement options.

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Appendix 1: the log-likelihood function

The log-likelihood function for the most general version of the model set out in section 3 of the paper is as follows.

$$
\ln L = \sum_{i \in S_1} \ln \left\{ Q_{i1} + \sum_{j=2}^{J} Q_{ij} e^{-m_j(t_i)} \right\}
$$

$$
+ \sum_{i \in S_2} \ln \left\{ \sum_{j=2}^{J} Q_{ji} e^{-m_j(a_i)} \left[1 - e^{-m_j(a_i+1)+m_j(a_i)} \right] P_i(0; t_i - a_i - 1) \right\}
$$

$$
+ \sum_{i \in S_3} \ln \left\{ \sum_{j=2}^{J} Q_{ji} e^{-m_j(a_i)} \left[1 - e^{-m_j(a_i+1)+m_j(a_i)} \right] \right\}
$$

$$
+ \sum_{i \in S_4} \ln \left\{ \sum_{j=2}^{J} Q_{ji} e^{-m_j(a_i)} \left[1 - e^{-m_j(a_i+1)+m_j(a_i)} \right] \sum_{k=A_i}^{B_i} P_i(k; t_i - a_i) \right\}
$$

$$(23)$$

where $P_i(k; s)$ is the probability of k episodes of cannabis use in a 1-year period starting at time s (measured from the time of first use)

$$
P_i(k; s) = \frac{\Gamma(\sigma_j^{-2} + k)}{\Gamma(k+1)\Gamma(\sigma_j^{-2})} W_{ij}^{-1/\sigma_j^2} \left(1 - W_{ij}^{-1} \right)^k
$$

and

$$
W_{ij} = 1 + \sigma_j^2 \left[m_{ij}^*(s+1; a_i) - m_{ij}^*(s; a_i) \right]
$$

Any time-varying explanatory variables are taken account of appropriately in the construction of the integrated intensity functions $m_j(.)$ and $m_j^*(.)$.

In expression (23) the sample of n individuals is partitioned into four subsets:

$$
\begin{aligned}
S_1 &= \{i : \text{ no cannabis use}\} \\
S_2 &= \{i : a_i < t_i - 1; k_i = 0\} \\
S_3 &= \{i : t_i \geq a_i \geq t_i - 1\} \\
S_4 &= \{i : a_i < t_i - 1; k_i \in [A_i, B_i]\}
\end{aligned}
$$

where: a_i is recorded age of first use of cannabis; t_i is age at interview;[12] k_i is the number of episodes of cannabis use within the last year, recorded either as zero or as a range of values $[A_i, B_i]$. The quantities $m_j(t_i)$, $m_j^*(t_i - a_i; a_i)$ and Q_{ji} are given by expressions of the type (13) and (15).

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[12]Both a_i and t_i are constructed as the relevant age, reported as an integer, plus 0.5. This adjustment converts the recorded age to an expected age, given the assumption of a uniform distribution of birth dates. We make no use of information on k_i for $i \in S_3$ since, for these people may have commenced use within the last year and thus have had an unknown period of 'exposure' lasting less than a year. By ignoring this information, we are marginalising the distribution with respect to it. Both a_i and t_i are measured from an origin of 10 years.

Appendix 2: data summary and parameter estimates

Table A1 Explanatory variables used in the analysis

Variable	Mean
Female	0.528
Age (years of age at last birthday[1])	21.13
Deprived area (one of the 8 most deprived BCS sampling areas)	0.098
Inner city	0.252
Black (self-described as Afro-Caribbean, black African or other black)	0.027
Other non-white (self-described as other than white or black)	0.063
Absent father (had no-one considered to be father[2])	0.075
Absent mother (had no-one considered to be mother[2])	0.026
Father managerial (father had managerial profession[2])	0.201
Father supervisor	0.156
(father was foreman/supervisor or self-employed with no employees[2])	
Father jobless (father was not employed, self-employed or retired[2])	0.047
Working mother (mother was employed or self-employed[2])	0.433
Cohort (year of birth (measured from origin of 1958)	18.87
Income	0.647
(money available after housing and regular outgoings (£'00 per week))	
No income (dummy variable = 1 if no regular spending money available)	0.347
Currently unemployed (dummy variable = 1 if unemployed at survey date)	0.046
At home, left education	0.211
(dummy = 1 if living with parents & completed full time education[1])	
In education, at home	0.021
(dummy = 1 if still in education & has left the parental home[1])	
Left education & home	0.394
(dummy = 1 if education completed and left the parental home[1])	
Unemployed after education	0.066
(dummy = 1 if has left education and was unemployed for at least	
6 months on leaving education[1])	

[1]Time-varying: the sample mean refers to time of interview

[2]For those aged 16 and over, refers to circumstances at the time respondent
was aged 15; for others, refers to current circumstances

Table A2(a) Heterogeneous model with income, education
and domicile covariates: estimates of the mixing probabilities

Parameter	$j = 2$ (light user)		$j = 3$ (heavy user)	
	Estimate	Std.err.	Estimate	Std.err.
Intercept	0.076	(0.048)	-2.383	(0.503)
Female	0.007	(0.001)	-0.736	(0.206)
Deprived area	0.288	(0.297)	0.448	(0.302)
Black	-1.922	(0.731)	-1.772	(0.453)
Other non-white	-1.627	(0.385)	-1.175	(0.543)
Absent father	0.650	(0.280)	0.054	(0.287)
Absent mother	0.320	(0.400)	0.245	(0.106)
Father managerial	0.604	(0.301)	0.227	(0.007)
Father supervisor	0.452	(0.344)	-0.092	(0.282)
Father jobless	-0.754	(0.470)	-0.004	(0.659)
Working mother	1.005	(0.334)	1.091	(0.312)
Cohort	-0.015	(0.035)	0.149	(0.028)

Table A2(b) Heterogeneous model with income, education
and domicile covariates: estimates of the initiation process

	$j = 2$ (light user)		$j = 3$ (heavy user)	
Parameter	Estimate	Std.err.	Estimate	Std.err.
Intercept	-26.336	(9.855)	-16.361	(5.153)
Female	-0.014	(0.176)	-0.383	(0.153)
Deprived area	0.191	(0.255)	0.261	(0.212)
Black	-0.170	(1.017)	1.436	(0.509)
Other non-white	0.965	(0.499)	-0.852	(0.486)
Absent father	-0.007	(0.226)	0.846	(0.240)
Absent mother	1.007	(0.319)	0.468	(0.297)
Father managerial	-0.299	(0.240)	-0.222	(0.169)
Father supervisor	-0.753	(0.245)	0.493	(0.191)
Father jobless	1.010	(0.479)	-0.334	(0.485)
Working mother	-0.076	(0.237)	-0.412	(0.152)
Cohort	0.168	(0.032)	0.072	(0.016)
At home, left education	-0.953	(0.166)	-1.059	(0.163)
In education, left home	-0.164	(0.272)	0.011	(0.292)
Left home & education	-1.120	(0.217)	-1.149	(0.251)
Unemployed before 1st job	-0.982	(0.443)	0.607	(0.383)
Time	7.278	(2.999)	4.639	(1.678)
Time^2	0.538	(0.226)	0.344	(0.132)
ψ_j	-0.580	(0.113)	-0.543	(0.116)

Table A2(c) heterogeneous model with income, education
and domicile covariates: estimates of the demand process

Parameter	Estimate	Std.err.
Intercept	6.904	(0.708)
Female	-0.318	(0.217)
Deprived area	0.277	(0.403)
Black	-0.138	(0.912)
Other non-white	-0.412	(0.564)
Absent father	0.313	(0.422)
Absent mother	0.382	(0.527)
Father managerial	-0.254	(0.215)
Father supervisor	-0.355	(0.279)
Father jobless	0.451	(0.825)
Working mother	0.173	(0.272)
Income	0.058	(0.133)
No income	-0.464	(0.446)
Currently unemployed	0.221	(0.424)
Age of onset	-0.647	(0.185)
Age of onset^2	0.026	(0.009)
At home, left education	0.733	(0.391)
In education, left home	0.044	(0.727)
Left home & education	0.823	(0.449)
Unemployed before first job	0.630	(0.390)
σ^2	3.707	(0.286)