Analysing drug abuse with British Crime Survey data: modelling and questionnaire design issues *

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Abstract

We use the British Crime Survey (BCS) to analyse the demand for illicit drugs, and the implications of drug use for the probability of subsequent unemployment. We demonstrate that the BCS questionnaire has a serious design aw for this purpose, and propose some simple modi cations. We also develop a modelling technique suitable for existing BCS data, and apply it to the 1994/96 sample. We nd evidence that soft drug use is associated with a greatly increased probability of later hard drug use, and that past drug use is associated with increased probabilities of unemployment.

JEL classi cation: C51; I12; J24

Keywords: Illicit drugs; unemployment; questionnaire design; British Crime Survey

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1 Introduction

Drug abuse is an important social issue. It is also an issue on which there are strongly divergent opinions, particularly in terms of policy prescriptions. However, public policy on drug abuse raises very complex issues. We are still far from a full understanding of the dynamic process of the development over time of individuals drug use and dependency, and of the private and public consequences of this behaviour at each stage. Without such an understanding, it is difficult to develop a convincing policy stance. One would hope that careful analysis of survey data on drug use could make an important contribution to the debate on drugs, by elucidating both the process of drug use and its consequences. The only regular government source of survey data on drug abuse in the UK is the British Crime Survey (BCS), and we discuss in this paper the use of the BCS in this context.

We focus on two important research issues: one concerning the dynamics of drug use; the other concerning an important aspect of its social consequences, unemployment. Speci cally:

(i) Does the use of soft drugs tend to lead on to the use of hard drugs ?

Essentially, this question requires a comparison of two conditional probabilities. If the probability of hard drug use for an individual is greatly increased by previous exposure to soft drugs, then it reasonable (or at least feasible) to interpret soft drugs as a dangerous intermediate step on the path to hard drug dependence. This is the slippery slope hypothesis[1], which centres on the following probability difference:

$$\begin{aligned}\Delta_1 \;=\; & \Pr(\text{current use of hard drugs} \mid \text{previous use of soft drugs}) \\ & - \Pr(\text{current use of hard drugs} \mid \text{no previous drug use}) \qquad (1)\end{aligned}$$

The conditional probabilities involved in (1) can in principle be estimated from suitable individual-level survey data, conditioning also on relevant measured personal attributes.

(ii) How does the use of soft or hard drugs affect an individual s risk of unemployment ?

Again, this question relates to the size of certain probabilities conditioned on the pattern of drug use. For example, if we are interested in the additional unemployment risk generated by drug use, then the following probability difference should be estimated:

$$\begin{aligned}\Delta_2 \;=\; & \Pr(\text{unemployment} \mid \text{drug use}) \\ & - \Pr(\text{unemployment} \mid \text{no drug use}) \qquad (2)\end{aligned}$$

[1] Sometimes refered to as the stepping-stone hypothesis (Stenbacka *et al.*, 1993).

The two probabilities in (2) can again be estimated from survey data, conditional on personal characteristics and on particular classes of drug use, past and current.

These issues are particularly relevant to the current debate about the possibility of decriminalising soft drugs and refocussing anti-drugs policy on the more damaging hard drugs. If we find no convincing evidence of soft drugs leading on to hard drug use, nor a serious impact of drug use on labour market achievement, then permissive drugs policies become persuasive. If, on the other hand, we were to find that the probability differences (1) and (2) are large, then this could lend support to the argument against decriminalisation of soft drugs. However, it is important to be cautious in one's interpretation of the effects Δ_1 and Δ_2. If they are estimated to be large, it cannot automatically be concluded that illicit drugs have damaging unobservable characteristics that tend to persist over time and give rise to spurious associations. For example, an apparent link between past drug use and current unemployment might be partly attributable to a risk-loving personality or high subjective rate of utility discounting. If the individual was also less able in the past to afford hard drugs, then we might also observe a spurious link between soft drug use and later hard drug use. These issues are difficult to address without detailed panel data allowing individual-specific fixed effects to be estimated. Despite these interpretational *caveats,* large estimates of Δ_1 and Δ_2 would leave open the possibility of major causal adverse effects of drug use, and thus strengthen arguments for caution in attempts to reform drug policy.

Most previous research on these issues has been carried out with US data. Typically, this work has suggested a positive association between cocaine or marijuana use and wages for a young cohort of American workers (Kaestner 1991, Gill and Michaels 1992, Register and Williams 1992, Kaestner 1994b). Against this, however, it has been suggested that the detrimental effects of drug use tend to be more apparent in labour market participation rates than in earnings, and that there are important differences in the impact of soft and hard drugs (Burgess and Propper, 1998).

The major difficulty we face is the scarcity of survey data that is both reliable and in a suitable form for estimation of Δ_1 and Δ_2. Although far from ideal in this respect, recent waves of the BCS do offer an opportunity to address these issues empirically, and this paper presents the results of an attempt to do this. En route, we highlight a particularly serious problem for analysis generated by the design of the BCS questionnaire. We begin by giving a brief description of the BCS survey methodology. Then, in section 3, we set out the nature of the inferential problem induced by the BCS questionnaire design, and indicate how a very modest redesign of the questionnaire

would improve matters. In section 4 we introduce a modelling technique that can (with some difficulty) be used with the existing BCS. Section 5 presents the resulting estimates and analyses them in terms of the important probability contrasts (1) and (2).

2 The British Crime Survey

2.1 Survey methodology

The British Crime Survey (BCS) is a large representative household survey of people s experiences and perceptions of crime in England and Wales. The survey was rst administered in 1982, and repeated in 1984, 1988, 1992, 1994, 1996 and 1998. Face-to-face interviews are carried out by staff of Social and Community Planning Research in the rst few months of the survey year, and cover individuals experiences of crime and crime-related issues for the 12-14 months preceding the interview. Having previously used the electoral register as a sampling frame, this was changed to the postcode address le (PAF) in 1992, bringing the BCS in line with other major UK household surveys. Using the PAF typically yields a sample size of around 15,000 adults per survey year (for more details of the sampling procedure for the 1994 and 1996 surveys see White and Malbon (1995), and Hales and Stratford (1997), respectively). In 1992 a drug-use self-completion component was added to the survey, although previous surveys had included limited questions about cannabis use. The self-completion component of the survey is presented to respondents aged 16-59, and contains three questions about drug use that require simple yes-no responses. For the rst year, the self-completion form was paper based, but in 1994 the method changed to Computer-Assisted Personal Interviewing, with respondents being handed the laptop to complete the drug-use questions. The BCS drug-use questions are discussed in more detail below, however, we note here that they yield less detail about the extent of illicit drug use than do American surveys.

American research into the impact of illicit drug use on labour market outcomes has almost exclusively used the National Longitudinal Survey of Youth (Kaestner 1991, Gill and Michaels 1992, Register and Williams 1992, Kaestner 1994a 1994b, Kandel *et al.* 1995, Burgess and Propper 1998). There are other surveys available to researchers in the US (the Monitoring the Future Survey[2] and the National Household Survey on Drug Misuse), but

[2]The Monitoring the Future survey has been used by Grossman and Chaloupka (1998), in conjunction with data from the Drug Enforcement Administration s system for generating drug price series, to estimate the price elasticity of demand for cocaine in the US.

these tend not to be appropriate for analysing the relationship between illicit drug use and labour market outcomes. The National Longitudinal Survey of Youth (NLSY) is a longitudinal survey of the labour market experiences of young American adults. It started in 1979 and has been updated each year, with new question areas added a different points in time. On a number of occasions drug use questions have been introduced to the NLSY. Unlike the BCS, the NLSY drug use questions are restricted to mainly marijuana (cannabis) and cocaine, but respondents are asked about their lifetime and current (past 30 days) frequency of use (i.e. the number times the drug was taken in the reference period). Knowledge about the frequency of drug use is clearly more informative for policy determination, although it should be noted that neither the BCS nor the NLSY yield information about dosage. Having said this, to know that an individual has consumed cocaine 25 times in the past 30 days (NLSY) is far more revealing than knowing that a respondent has consumed cocaine in the past month (BCS).

2.2 Classi cation of drugs and drug use states

The BCS presents respondents with a list of 14 drugs about which they are required to answer a number of simple questions (the survey also includes 3 catchall questions to capture those drugs not listed). For the purpose of our analysis, we focus on only those drugs in the list that are classi ed under the 1971 Misuse of Drugs Act. Controlled drugs are listed in the Act as Class A, B, or C type depending on the magnitude of danger or harm that is associated with their use. This provides a natural distinction between hard drugs (Class A) and soft drugs (Class B or C). The BCS also asks about respondents use of unclassi ed drugs (such as glues or solvents), unknown substances consumed or smoked, and a ctitious drug Semeron , put in the survey to test for false claiming. In Table I we summarise the drugs in the BCS list that fall under the Misuse of Drugs Act classi cation. We also provide some of the alternative names for the drugs that are presented to respondents on the computer screen as they answer the drug use questions.

Table I
Drug Categories in the BCS

Drug	Class	Screen Alternative
Cocaine	A	Coke
Crack	A	Rock , Stone
Ecstasy/MDMA	A	E
Heroin	A	Smack , Scag , H
LSD	A	Acid
Magic Mushrooms	A	
Methadone/Physeptone	A	(not prescribed)
Amphetamines	B	Speed , Whizz , Uppers
Cannabis	B	Marijuana , Grass , Hash , Ganja , Blow , Draw , Skunk ,
Tranquillisers	C	Temazepam , Valium

The responses to questions about the drugs listed in Table 1 allow us to work with an ordered scale of drug use: none; soft drugs only; hard drugs (with or without simultaneous use of soft drugs). Arguably, we should separate hard drug use without soft drug use from hard drug use with soft drug use. However, the observed frequency of the former state is very small in the current sample. For example, of the 4112 individuals who report any drug use ever, 3.3% report hard drug use without soft drug use, whereas 32.1% report using both hard and soft drugs. The ratio of observed states is similar for drug use in the last year. Of the 1493 interviewees who report any drug use in the past twelve months, 1.9% use only hard drugs, compared to a rate of 20.3% for those who report use of both hard and soft drugs.

2.3 The incidence of drug use

In the current analysis we use data from the 1994 and 1996 sweeps of the BCS. Although drug use questions were introduced into the survey in 1992, the 1992 survey is generally considered not suitable for comparison with the 1994 and 1996 surveys (Ramsay and Percy, 1997). This is largely attributed to the change in interview technique (from paper-based to computer-aided), which in general terms, is likely to subject the data from 1994 onwards to totally different sources of error than the 1992 survey (O Muircheartaigh and Campanelli, 1998). We are not able to use the 1998 data as it has not been released into the public domain (and nor is it likely to be until later in 1999[3]).

[3]Although a summary of the main ndings from the 1998 survey (but excluding drug use) is given in Mirrlees-Black *et al.* (1998).

After losses for incomplete records, and exclusion of those aged over 50, our pooled sample consists of 13916 observations (6407 for 1994 and 7509 for 1996). We separate our sample into three age cohorts: those aged less than 25; those between 25 and 34; and those aged 35 to 50. This approach re ects a common nding in the literature that suggests individuals tend to mature out of drug use in their late twenties or early thirties (Gill and Michaels 1991, Kandel 1980, Labouvie 1996, MacDonald 1997, Ramsay and Percy 1996). In Table II we summarise the responses to the three BCS drug-use questions by age cohort. We separate the responses into hard and soft drug categories, and we present separate gures for 1994 and 1996.

Table II
Frequency of illicit drug use by age cohort(%)
(standard errors in parentheses)

	1994			1996		
	16-24	25-34	35-50	16-24	25-34	35-50
Soft drugs						
Ever used	35.78 (1.50)	32.15 (0.96)	21.35 (0.75)	41.06 (1.49)	33.42 (0.90)	22.80 (0.69)
Recently used	24.02 (1.34)	11.73 (0.663)	3.81 (0.35)	26.37 (1.33)	13.29 (0.65)	4.72 (0.35)
Used in last month	15.00 (1.120	6.37 (0.50)	1.86 (0.25)	17.06 (1.14)	7.21 (0.49)	2.65 (0.27)
Hard drugs						
Ever used	18.82 (1.22)	11.69 (0.66)	6.20 (0.44)	18.61 (1.18)	12.78 (0.64)	6.66 (0.41)
Used in past year	7.25 (0.81)	1.81 (0.27)	0.43 (0.12)	9.40 (0.88)	2.95 (0.32)	0.46 (0.11)
Used in last month	2.84 (0.52)	0.68 (0.17)	0.10 (0.06)	4.47 (0.62)	0.98 (0.19)	0.30 (0.09)
observations	1020	2370	3017	1096	2747	3666

Compared to the NLSY, the gures in Table II reveal lifetime prevalence of drug use to be lower in BCS for both hard and soft drugs, although the rates for use in the past month by the youngest cohort are comparable. In the current sample, soft drug use is far more prevalent than hard drug use, but the use of both diminishes across cohorts. In addition, we observe that across cohorts, the ratio of drug use in the past month to use in the past year also diminishes. This may indicate that as respondents get older, there is a tendency for the frequency of drug use to decline.

The second issue we address in this paper concerns the impact of drug use on the risk of unemployment. Kaestner (1994a) analyses the impact

of drug use on labour market participation, represented by the number of hours worked per week in the past 12 months. However, in this analysis we focus directly on employment status. In Table III we present a summary of the responses to the BCS drug use questions according to employment status: employed (including self-employed) and unemployed (de ned as not in work, but currently seeking employment). We exclude respondents in full-time education from the sample of those not in work. We also exclude respondents who do not participate in the labour market (such as individuals who are retired or are looking after the home or family).

Table III
Summary of drug use by employment status (%)
(Standard errors in parentheses)

	1994		1996	
	Employed	Unemployed	Employed	Unemployed
Soft drugs				
Ever used	26.38 (0.58)	38.83 (1.91)	28.40 (0.54)	40.83 (2.05)
Used in past year	8.49 (0.37)	22.96 (1.65)	10.04 (0.36)	22.66 (1.74)
Used in last month	4.53 (0.27)	15.25 (1.41)	5.55 (0.28)	16.78 (1.56)
Hard drugs				
Ever used	9.48 (0.39)	16.95 (1.47)	9.57 (0.35)	23.53 (1.77)
Used in past year	1.56 (0.16)	6.13 (0.94)	2.22 (0.18)	8.13 (1.14)
Used in last month	0.56 (0.10)	2.47 (0.61)	0.91 (0.11)	4.15 (0.83)
Observations	5758	649	6931	578

Unlike the data from the NLSY, where the mean prevalence of drug use for those in employment is not signi cantly different for those out of work (Kaestner, 1994a), in the current sample we observe a higher prevalence of hard and soft drug use for respondents who are unemployed. Indeed, in all cases, there is a greater prevalence of drug use in the past month for those out of work than there is drug use in the past year for those in employment. Moreover, individuals who are unemployed are four times more likely to have taken a hard drug in the past month than have respondents who are in work.

3 The implications of questionnaire design for statistical modelling

Consider an individual, interviewed at a particular date. Divide his or her life into three periods: a rst period nishing 12 months before the interview date; a second period lasting from 1-12 months prior to the interview, and a current period consisting of the month leading up to the interview. Thus the chronology underlying our data is as shown in Figure 1. Note that the de nition of the rst period is not constant, and its duration will be equal to the individual s age minus 1 year.

FIGURE 1 HERE

We consider a hierarchy of three levels of drug use: none; soft drugs only; and hard drugs. We are interested in four outcomes: drug use in periods 1, 2 and 3 (trichotomous indicators d_1, d_2 and d_3); and unemployment at the survey date (binary indicator u). If all four of these indicators were directly observable, we would wish to estimate the following probability structure:

$$\Pr(d_1, d_2, d_3, u|x) = \Pr(d_1|x) \Pr(d_2|d_1, x) \Pr(d_3, u = 1|d_1, d_2, x) \qquad (3)$$

where x is a vector of exogenous explanatory variables. Each d_t is equal to 0 for no drug use, 1 for soft drug use and 2 for hard drug use during period t.

3.1 The probability structure of observable outcomes

Unfortunately, there is a signi cant observational problem stemming from the design of the questionnaire used in the BCS. The question structure is set out in Figure 2, with the drug Ecstasy used as an example. Following a question about whether they have heard of the drug, each respondent is asked only whether or not he or she has ever used the drug in question, if so, whether during the last year, and if so, whether during the last month.

FIGURE 2 HERE

Concentrate for the moment on the two drug use variables, and de ne the 27 conditional probabilities $P_{ijk}(x) = \Pr(d_1 = i, d_2 = j, d_3 = k|x)$, for $i, j, k = 0..2$. However, the survey structure allows us only to observe the ten possible events set out in table III.

Table IV
Probabilities of drug use responses

Ever	**Last year**	**Last month**	**Probability**
None	-	-	P_{000}
Soft	None	-	P_{100}
Soft	Soft	None	$P_{010} + P_{110}$
Soft	Soft	Soft	$P_{001} + P_{011} + P_{101} + P_{111}$
Hard	None	-	P_{200}
Hard	Soft	None	P_{210}
Hard	Soft	Soft	$P_{201} + P_{211}$
Hard	Hard	None	$P_{020} + P_{120} + P_{220}$
Hard	Hard	Soft	$P_{021} + P_{121} + P_{221}$
Hard	Hard	Hard	$P_{002} + P_{012} + P_{022} + P_{102} + P_{112}$ $+P_{122} + P_{202} + P_{212} + P_{222}$

Thus, without imposing any structure on the underlying probabilities, it is possible to identify the probability of complete abstinence P_{000} and the probabilities of three chains of transition down the drug use hierarchy: P_{100}, P_{210} and P_{200}. The probabilities of certain other downward transitions (P_{110}, P_{211}, P_{220} and P_{221}), a constant position (P_{111} and P_{222}), any upward move in the hierarchy (P_{001}, P_{011}, P_{002}, P_{012}, P_{022}, P_{112}, and P_{122}), and any non-monotonic chain (P_{010}, P_{101}, P_{201}, P_{002}, P_{020}, P_{021}, P_{102}, P_{202} and P_{212}) are not separately identi able in this most general nonparametric sense.

One of our main objectives is to estimate the impact of soft drug use on the probability of subsequent hard drug use. If we de ne a hard drug user as (say) someone who has used hard drugs throughout the last year, then the probability difference (1), is $\Delta_1 = \{P_{122} - P_{022}\}$, which is clearly not identi able from the BCS questionnaire responses. The constraint on inference imposed by the BCS questionnaire is clearly serious, and there must be a strong case for some redesign.

3.2 Alternative questionnaire designs

One immediate and important conclusion of this paper is that the value of the BCS as a source of information on drug use is signi cantly reduced by

the structure of the self-completion questionnaire. Ideally, one would like to have a speci c drug-use survey comparable to the US National Longitudinal Survey of Youth, giving greater detail on the timing and intensity of drug use, together with some indication of changes over time in relevant personal characteristics (such as marital status, employment, etc.). However, we assume this is judged infeasible for cost reasons, and consider instead a modest redrafting of the existing BCS questionnaire. The BCS asks about fourteen different drugs. Two possible alternatives to the existing BCS question structure, both of which would avoid the type of identi cation difficulty outlined above, are given in gures 3 and 4.

FIGURES 3 AND 4 HERE

The BCS questionnaire is a simple sequence of questions which can be administered very quickly for the overwhelming majority of respondents, who have little or no experience of drug-taking. The problem with this structure is that for current drug-users, no information is provided about past drug use. The re-design laid out in Figure 3 preserves the simplicity of the sequential structure, but avoids the observational difficulty by asking speci cally about the timing of rst and most recent use of the drug. The quantitative nature of the question would also give a much more informative sample than the multiple choice approach. Figure 4 displays an alternative question structure that also avoids the observational problem by asking about the rst and the most recent use of the drug, but sticks to the use of multiple choice questions.

In order to assess the implications for interview costs, we make the following illustrative assumptions:
(i) Interview costs are proportional to interview time.
(ii) A question involving a choice between m alternative responses (including a residual don t know/won t answer category) requires $5m$ seconds to answer.
(iii) A question requiring a quantitative answer (such as specifying the age at which the respondent took some action) takes nT seconds to answer (and is therefore as time-consuming as an n-option multiple choice question).
(iv) On average, 90% of respondents have heard of the drug in question, of whom 6% have taken it at some time. Of these, 70% last took it over a year ago, 15% last took it 1-12 months ago, and 15% have taken it within the last month.

On these assumptions, it is possible to evaluate the average questionnaire completion time, and also the time that a current drug-user would require. These times are given in Table V.

Table V
Projected questionnaire completion times
(increase over current BCS questionnaire in parentheses)

Questionnaire Design	**Average Completion Time**	**Completion Time for a Current Drug user**
Current BCS	4.94	11.0
Figure 3 re-design (n=4)	5.13 (+15%)	13.0 (+18%)
Figure 3 re-design (n=6)	5.35 (+28%)	17.0 (+55%)
Figure 4 re-design	5.09 (+13%)	13.0 (+18%)

Re-design clearly entails some increase in cost. Under our assumptions, the re-design displayed in Figure 4 entails a 13% rise in the average cost of the drug questionnaire, with a rise of 18% for respondents who are current drug users and who therefore answer all questions. The alternative reformulation (Figure 3), which asks for ages of first and last use, entails a roughly similar rise in questionnaire costs if the quantitative questions are judged equivalent to 4-option multiple choice questions, but a much larger increase if they are comparable to 6-option questions. To avoid the major inferential problems inherent in the current BCS design, it seems worthwhile to consider at least a minimal redesign along the lines suggested in figures 3 and 4. The additional cost is not excessive, and could in any case be offset by asking questions about a slightly smaller set of drugs (perhaps just those drugs that are classified under the Misuse of Drugs Act).

4 A parametric modelling approach

We have shown that there is a basic identification problem induced by the structure of the BCS questionnaire. Nevertheless, it would be unduly pessimistic to conclude from this that no useful inferences can be drawn from the BCS data. Indeed, it is probably true to say that the majority of statistical relationships estimated by researchers from survey and time series data are unidentified in this general non-parametric sense. In most realistic statistical applications a completely general model with flexible functional form and no restriction on the interactions between explanatory variables would be impossible to estimate with any useful degree of precision. Usually we feel able to resolve this problem by assuming that the underlying relationships are

sufficiently smooth to allow adequate approximation by simple forms - typically linear apart from a few speci c nonlinearities or other modi cations. We adopt the same strategy in this section, where we develop a modelling approach that offers a partial solution to this identi cation problem.

Since drug use forms a naturally ordered hierarchy from non-use to soft drugs to hard drugs, we use the conventional ordered probit model as a description of individual behaviour. We use separate equations to represent past and current drug use, and then allow for conventional lag effects to carry the in uence of past behaviour on the present. This approach provides a natural and convincing solution to the difficulties raised by the BCS questionnaire design. Consider rst the determination of past drug use. De ne a latent variable d_1^* representing an individual s past propensity to consume drugs. This drives the observed indicator of actual drug use, d_1, through a 3-outcome ordered probit mechanism:

$$\begin{aligned} d_1^* &= x_1\beta_1 + \varepsilon_1 \\ d_1 &= r \text{ if } \alpha_{1r} \square\ d_1^* < \alpha_{1r+1} \qquad r = 0,1,2 \end{aligned} \tag{4}$$

where x_1 is a row vector of personal and demographic attributes; β_1 is the corresponding vector of coefficients; the α_{1r} are unknown threshold parameters (with α_{10} and α_{13} normalised to $-\infty$ and $+\infty$ respectively); and ε_1 is a random error distributed as N(0,1) conditional on x.

The second stage of the model determines drug use in the second period (1-12 months before the interview), conditional on previous drug use. Again, this is an ordered probit, but involving lagged effects. If we de ne the two dummy variables $D_{11} = 1$ iff $d_1 = 1$ and $D_{12} = 1$ iff $d_1 = 2$, the second stage model is:

$$\begin{aligned} d_2^* &= x_2\beta_2 + D_{11}\delta_{21} + D_{12}\delta_{22} + \varepsilon_2 \\ d_2 &= r \text{ if } \alpha_{2r-1} \square\ d_2^* < \alpha_{2r} \qquad r = 0,1,2 \end{aligned} \tag{5}$$

The third stage of the model determines drug use in the month prior to interview jointly with unemployment at the time of the interview. This involves another ordered probit for drug use and a binary probit for the unemployment/employment distinction. These relationships are mutually correlated and conditional on previous drug use. Thus we have a system of two latent variables, assumed to be generated by the following multivariate regression structure:

$$d_3^* = x_3\beta_3 + D_{11}\lambda_{11} + D_{12}\lambda_{12} + D_{21}\lambda_{21} + D_{22}\lambda_{22} + \varepsilon_3 \tag{6}$$

$$u^* = z\gamma + D_{11}\mu_{11} + D_{12}\mu_{12} + D_{21}\mu_{21} + D_{22}\mu_{22} + \eta \tag{7}$$

where $D_{tj} = 1$ if $d_t = j$ and $D_{tj} = 0$ otherwise $(j = 1, 2)$; x_3 and z are row vectors of personal and demographic attributes, β_3 and γ are the corresponding vectors of coefficients, and ε_3 and η are errors with a bivariate normal distribution with zero means, unit variances and correlation ρ, conditional on $\{x_3, z, d_1, d_2\}$. The coefficients λ_{tj} and μ_{tj} are lag coefficients capturing the dynamic effect of past behaviour on current drug use and employment.

The observable counterparts of these latent variables are the trichotomous indicator of current drug use, d_3 and the binary indicator of unemployment, u. The latent variables are then assumed to generate the observed states by means of the following relationships:

$$\begin{aligned} d_3 &= r \text{ if } \alpha_{3r} \square\, d_3^* < \alpha_{3r+1} \,, \qquad r = 0, 1, 2 \qquad (8) \\ u &= 0 \text{ if } u^* \square\, 0 \\ &= 1 \text{ if } u^* > 0 \qquad (9) \end{aligned}$$

where α_{30} ... α_{33} are unknown threshold parameters and α_{30} and α_{33} are normalised as before.

From this structure, it is possible to derive the conditional probabilities of the 20 possible observational outcomes (the ten outcomes listed in table III multiplied by the two possible unemployment states). These probabilities are extremely tedious, and are relegated to appendix 2. In general they require the evaluation of only bivariate normal probabilities, so the computational difficulty of maximum likelihood estimation is signi cant but not insuperable. We use the GAUSS Maxlik module to maximise the log-likelihood function numerically.

5 Results

5.1 Identi cation and estimation difficulties: the dynamics of drug use

The most important variables in any analysis of drug use are age and birth cohort. Age is important because of a well-established tendency for the young to experiment with drugs, and for people to mature out of drug-taking. Cohort effects are likely to be positive, with the growth in the drug culture over time (Parker and Measham, 1994). Given the nature of the BCS, and the typical age and cohort pro le of drug abuse, we can expect to nd three features present in BCS data.

(i) As we consider older individuals, the length of period 1 increases. Since older individuals will have had more elapsed time in which to discover

drugs, the effect of age *per se* must be to increase the probability of drug use during period 1.

(ii) However, since we are essentially dealing with a cross-section in the 1994/96 BCS data set, age effects cannot be distinguished from cohort effects. In general, the older groups will have had less exposure to drug culture , and will thus tend to have smaller probabilities of drug use, at any given age. The net effect of the age and cohort effects is likely to be a peaked pro le, with an increasing drug use probability for the very young, followed by steady decline for older groups.

(iii) Lag effects are also likely to vary with age. If the habit persistence effects of drug use in the distant past are small, and if drug use tends to happen early in life, then one can expect the effect of drug use during period 1 on the probability of drug use in later periods to decline with age. The same is not necessarily true of the effect of early drug abuse on later labour market achievement, since there is considerable evidence that labour market setbacks (such as career breaks and unemployment spells) tend to be cumulative.

To check on these expectations and allow exibility in the age pro le, we rst attempted to t separate models for the three age groups 16-24, 25-34 and 35-50. We encountered two difficulties.

(i) Convergence could not be obtained for the iterative algorithm used to maximise numerically the log likelihood function for the 35-50 age group, because the log-likelihood was virtually at over a wide range of values for the lag coefficients δ_{ij} and λ_{rs}. There are two contributory factors here: the fragile identi cation entailed by the BCS questionnaire structure; and the low frequencies of observed drug use in this older group.

(ii) Although convergence was achieved for the two younger groups, the lag coefficients capturing the partial effect of period 1 drug use on that of period 3 (λ_{11} and λ_{12}) were grossly insigni cant in both cases, and were therefore restricted to be zero. Several explanatory variables (notably ethnicity dummies and family structure dummies) also had insigni cant coefficients and were deleted from the period 3 ordered probit.

After imposing these restrictions, we estimated separate models for the 18-24 and 25-34 age groups. The estimates are given in appendix Tables A2.1-A2.5. In these models, age effects are captured using age in reciprocal form, since this gives a considerably better t than a speci cation involving age itself. The estimated lag coefficients for these two models are reproduced in Table VI. As anticipated, the lag effect of period 1 drug use on that of period 2 is signi cantly weaker for the older group.

TABLE VI

Estimated lagged drug use effects
(Standard errors in parenthesis)

Parameter estimate	**Age group**		
	16-34	**16-24**	**25-34**
Soft: δ_{21}	-1.069 (0.777) $+44.60/\text{age}$ (1.515)	0.797 (0.420)	0.504 (0.365)
Hard: δ_{22}	0.143 (0.349) $+ 44.86/\text{age}$ (0.841)	2.289 (0.196)	1.666 (0.157)
Soft: λ_{21}	1.868 (0.178)	1.667 (0.246)	2.002 (0.248)
Hard: λ_{22}	3.260 (0.148)	3.193 (0.194)	3.257 (0.219)

We also estimated a single combined model for the 16-34 group, and it is this latter model that we use in the analysis that follows. It captures the age-related declining lag effects by specifying δ_{21} and δ_{22} as linear functions of the reciprocal of age. Appendix Table A2.5 gives log likelihoods and the Akaike Information Criterion (AIC) for this model and also for the composite of the models tted separately to the 16-24 and 25-34 sub-samples. These are not nested, but the AIC suggests that the single model covering both groups does achieve as good a sample t, after allowing for the difference in the number of parameters.

The estimated dynamic effect of past drug use on current drug use is summarised in Table VII, using a set of illustrative hypothetical individuals. The base case is a 25-year old unmarried white male with educational attainment at the high GCSE level, and living alone in an inner city location. The gures quoted in the rst three columns of table VII are the estimated probabilities that the highest level of drug use attained to date (in other words $\max\{d_1, d_2, d_3\}$) is either none; soft drugs only; or hard drugs (with or without soft drugs also). Column 4 gives estimates of the hazard rate from the state of non-drug use into hard drug use, where this is de ned as $\Pr(\max\{d_2, d_3\} = 2 | d_1 = 0) = \sum \Pr(d_3 | d_1 = 0, d_2) \Pr(d_2 | d_1 = 0)$, where the sum is over the ve combinations of d_2, d_3 such that $\max\{d_2, d_3\} = 2$. Column 5 then gives the estimated difference between this and the hazard rate for transitions from soft to hard drugs, where the latter is de ned as $\Pr(\max\{d_2, d_3\} = 2 | d_1 = 1) = \sum \Pr(d_3 | d_1 = 1, d_2) \Pr(d_2 | d_1 = 1)$. The components of these expressions can all be constructed from the c.d.f. of the univariate standard normal distribution. The difference in column 5 of Table VII is an estimate of the slippery slope effect Δ_1 de ned in (1) above. The base case individual has a relatively high predicted probability of drug use, with over a fth predicted to have some experience of hard drugs by the age

of 25. For those with no previous experience of drug use, the conditional probability of starting hard drug use in the current month is around 1%, but this rises to roughly 4.5% for those who have previously used soft drugs. Thus the slippery slope effect is 3.44 percentage points, or a 3-fold increase in the risk of taking up hard drugs.

The remaining five rows of Table VII explore the effects of changing the characteristics of the hypothetical individual. Females have a considerably smaller probability of drug-taking and a smaller absolute increase in the hard drug hazard induced by previous soft drug use. The same is true to varying degrees for blacks and Asians and those living outside the inner city areas. There is a widely-held public perception of a high rate of drug abuse among young blacks, but the evidence here is to the contrary. Drug abuse is especially uncommon among the Asian community relative to whites (see Pearson and Patel (1998) for confirmation and discussion of this result). However, there is one widespread belief that does receive some support from these findings. People with a university education are found to have the highest probability of both soft and hard drug use among the hypothetical groups considered here. They are also found to show the largest slippery slope effect, at least in absolute terms. Students do indeed seem to be a high-risk group.

TABLE VII
Estimated dynamic pattern of drug use
(% probabilities)

Individual type	Pr(highest ever level of drug use) = ...			none → hard hazard rate	Δ_1
	None	Soft	Hard		
Base case	51.16	27.05	21.79	1.03	3.44
Female	64.32	22.57	13.10	0.64	2.54
Black	55.34	26.19	18.46	1.03	3.44
Asian	69.49	21.56	8.96	1.03	3.44
Not inner-city	53.02	25.71	21.27	0.63	2.50
University degree	43.36	28.38	28.26	1.30	4.10

Age effects are shown in Figures 5 and 6. Figure 5 plots the probabilities of a base case individual having reached each of the three drug use levels by ages 16-34. The anticipated peaked profile generated by an increasing age effect superimposed on a decreasing cohort effect is evident for the soft and hard drug consumption profile. The slippery slope effect is plotted

against age in gure 6. It is evidently particularly large for the very young (around 27 percentage points for our hypothetical 16 year-old), and declines sufficiently fast to become almost negligible by the early thirties. There is evidence here to generate a serious worry about the effects that any increase in soft drug use by the young might have on their welfare in later life. Seen from this viewpoint, the legalisation of soft drugs appears to be a risky social policy.

FIGURES 5 & 6 HERE

5.2 The impact of drug use on unemployment probabilities

We may be more prepared to take the risk of legalising soft drugs if it can be shown that drug use has no serious social consequences. One important dimension of this issue is the effect of drug use on subsequent employment prospects. We have again used a set of hypothetical individuals to illustrate the impact of drug use on the risk of unemployment. Using the same base case as above, we estimate the probability of unemployment conditional on no previous drug use, on past soft drug use, and past hard drug use. These probabilities are de ned respectively as $\Pr(u = 1|d_1 = d_2 = 0)$, $\Pr(u = 1|\max\{d_1, d_2\} = 1)$ and $\Pr(u = 1|\max\{d_1, d_2\} = 2)$, and their estimates are summarised in Table VIII. Columns 3 and 4 of Table VIII give the estimated difference in probability of unemployment for a given individual with a history of drug use and the same individual who has no past drug use (Δ_2 de ned in (2) above).

TABLE VIII
Estimated impact of past drug use on the probability of unemployment (%)

Individual type	Unemployment probability (no past drug use)	Δ_2 for past drug use = ...	
		Soft	Hard
Base case	19.09	5.83	12.10
Female	11.72	4.31	9.05
Black	29.76	7.17	14.27
Asian	28.10	7.33	14.24
Not inner-city	11.26	4.06	8.71
University degree	11.76	4.52	9.79

The predicted probability of unemployment for our base case with no past drug use is relatively high, as a consequence of his characteristics (low educational achievement, inner city residence, etc.). It rises to almost a one in three chance if he is black or Asian, but is much lower for females, those living outside the inner city, and for individuals with a degree. In all cases, however, the estimated impact of past drug use is to increase the probability of unemployment by 4 to 7 percentage points (for soft drugs) and 9 to 14 percentage points for hard drug use. We thus con rm the US ndings of Burgess and Propper (1998) for the UK, in the sense that hard drugs have a signi cantly more serious impact on unemployment than do soft drugs. However, we do nd a signi cant association between soft drugs and unemployment, so there is again evidence here to cast some doubt on the wisdom of decriminalisation of soft drugs.

The relationship between current drug use (d_3) and current unemployment (u) is relatively weak, and positive, albeit of marginal statistical significance (see appendix Table A2.4). The correlation between the underlying latent variables (d_3^*, u^*) is estimated at only 0.07.

6 Concluding Remarks

We began this paper by highlighting two important issues concerning the process of drug use and its consequences: does soft drug use present a pathway to hard drug use, and what impact does drug use have on unemployment?

To address these issues we used data from the British Crime Survey (BCS), the only available survey data for the UK that provides information on illicit drug use. We have shown that the current BCS questionnaire design generates an identi cation problem which makes it difficult to draw reliable inferences about the dynamics of drug use. The order in which the current BCS drug use questions are presented make it impossible to observe current drug use separately from past drug use in all cases. These problematic features are shared by a number of other surveys of drug use, including the US Monitoring the Future survey. We suggest a modest redesign of the questionnaire that would overcome this observational problem at little extra cost to survey administration.

Taking account of this identi cation problem, we develop a model of escalating drug use that allows for the lag effect of drug use in a previous period on drug use in the following period. Our results suggest that past consumption of soft and hard drugs have a positive impact on the probability of drug use in the following period. Thus, our results are consistent with the slippery slope hypothesis. With respect to a hypothetical individual (25

year old unmarried white male, with good GCSE grades, living alone in an inner city location), we estimate the probability difference Δ_1 (given in (1) above) to be 3.44. In other words, the impact of past soft drug use over no past drug use is a threefold increase in the risk of hard drug use in the current period. Of particular concern is the impact of past soft drug use for the young: although the slippery slope effect rapidly declines with age, past soft drug use increases the probability of current hard drug use by some 27 percentage points for a 16 year-old with base characteristics.

Finally, our results suggest that both soft and hard drug use have a signi cant association with an individual s risk of unemployment. We estimate that although the risk of unemployment is high for our hypothetical case even without any history of drug use, the use of soft drugs in the past increases the probability of unemployment by almost 6 percentage points. If this individual has used hard drugs in the past, the probability difference Δ_2 (given in (2) above) is 12 percentage points. Such results should of course be viewed with some caution. Survey data of this kind may be subject to response and measurement error, and the estimated associations may be at least partly attributed to persistent unobservable attributes rather than causal effects. Moreover, there might be compelling arguments for the legalisation of soft drugs even if these estimates of the adverse effects of their use are accepted at face value. However, our tentative estimates have serious implications for policy determination, and we would argue that any weakening of the Misuse of Drugs Act should be approached with considerable caution.

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Appendix 1 Probabilities of observational outcomes

Under the model speci cation outlined in section 4, there are 20 possible observational outcomes. To save space, we give only the probabilities of the rst six of these (corresponding to the rst three rows of table IV) below. These should suffice to make clear how the likelihood function is computed. The omitted 14 probabilities are considerably more complex. The full set of probabilities (in the form of a GAUSS procedure) are available from the authors on request. The symbols $\Phi(.)$ and $\Phi(.,.;\rho)$ refer to the distribution functions of the standard univariate and bivariate normal distributions, the latter with correlation ρ.

(i) Never a drug user, currently unemployed

$$\begin{aligned}\Pr(d_1^* \;<\; & \alpha_{11}, d_2^* < \alpha_{21}, d_3^* < \alpha_{31}, u^* > 0) = \Phi(\alpha_{11} - x_1\beta_1) \\ & \times\Phi(\alpha_{21} - x_2\beta_2)\Phi\left(\alpha_{31} - x_3\beta_3, z\gamma; -\rho\right)\end{aligned}$$

(ii) Never a drug user, not currently unemployed

$$\begin{aligned}\Pr(d_1^* \;<\; & \alpha_{11}, d_2^* < \alpha_{21}, d_3^* < \alpha_{31}, u^* \leqslant 0) = \Phi(\alpha_{11} - x_1\beta_1) \\ & \times\Phi(\alpha_{21} - x_2\beta_2)\Phi\left(\alpha_{31} - x_3\beta_3, -z\gamma; \rho\right)\end{aligned}$$

(iii) Past use of soft drugs, no drug use within last year, currently unemployed

$$\begin{aligned}\Pr(\alpha_{11} \;\square\; & d_1^* < \alpha_{12}, d_2^* < \alpha_{21}, d_3^* < \alpha_{31}, u^* > 0) = \\ & [\Phi(\alpha_{12} - x_1\beta_1) - \Phi(\alpha_{11} - x_1\beta_1)] \\ & \times\Phi(\alpha_{21} - x_2\beta_2 - \delta_{21})\Phi\alpha_{31} - x_3\beta_3 - \lambda_{11}, x_3\beta_3 + \mu_{11}; -\rho)\end{aligned}$$

(iv) Past use of soft drugs, no drug use within last year, not currently unemployed

$$\begin{aligned}\Pr(\alpha_{11} \;\square\; & d_1^* < \alpha_{12}, d_2^* < \alpha_{21}, d_3^* < \alpha_{31}, u^* > 0) = \\ & [\Phi(\alpha_{12} - x_1\beta_1) - \Phi(\alpha_{11} - x_1\beta_1)] \\ & \times\Phi(\alpha_{21} - x_2\beta_2 - \delta_{21})\Phi\left(\alpha_{31} - x_3\beta_3 - \lambda_{11}, -z\gamma - \mu_{11}; \rho\right)\end{aligned}$$

(v) No hard drug use, soft drugs used within last year but not last month; currently unemployed

$$\begin{aligned}\Pr(d_1^* \;<\; & \alpha_{12}, \alpha_{21} \,\square\, d_2^* < \alpha_{22}, d_3^* < \alpha_{31}, u^* > 0) = \Phi(\alpha_{11} - x_1\beta_1) \\ & \times \left[\Phi(\alpha_{22} - x_2\beta_2) - \Phi(\alpha_{21} - x_2\beta_2)\right] \Phi(\alpha_{31} - x_3\beta_3 - \lambda_{21}, z\gamma + \mu_{21}; -\rho) \\ & + \quad \left[\Phi(\alpha_{12} - x_1\beta_1) - \Phi(\alpha_{11} - x_1\beta_1)\right] \\ & \times \left[\Phi(\alpha_{22} - x_2\beta_2 - \delta_{21}) - \Phi(\alpha_{21} - x_2\beta_2 - \delta_{21})\right] \\ & \times \Phi(\alpha_{31} - x_3\beta_3 - \lambda_{11} - \lambda_{21}, z\gamma + \mu_{11} + \mu_{21}; -\rho)\end{aligned}$$

(vi) No hard drug use, soft drugs used within last year but not last month; currently unemployed

$$\begin{aligned}\Pr(d_1^* \;<\; & \alpha_{12}, \alpha_{21} \,\square\, d_2^* < \alpha_{22}, d_3^* < \alpha_{31}, u^* \,\square\, 0) = \Phi(\alpha_{11} - x_1\beta_1) \\ & \times \left[\Phi(\alpha_{22} - x_2\beta_2) - \Phi(\alpha_{21} - x_2\beta_2)\right] \Phi(\alpha_{31} - x_3\beta_3 - \lambda_{21}, -z\gamma - \mu_{21}; \rho) \\ & + \quad \left[\Phi(\alpha_{12} - x_1\beta_1) - \Phi(\alpha_{11} - x_1\beta_1)\right] \\ & \times \left[\Phi(\alpha_{22} - x_2\beta_2 - \delta_{21}) - \Phi(\alpha_{21} - x_2\beta_2 - \delta_{21})\right] \\ & \times \Phi(\alpha_{31} - x_3\beta_3 - \lambda_{11} - \lambda_{21}, -z\gamma - \mu_{11} - \mu_{21}; \rho)\end{aligned}$$

Appendix 2 Parameter Estimates

TABLE A2.1
Parameters of ordered probit for drug use in period 1

Parameter	**Age group**		
estimate	**16-34**	**16-24**	**25-34**
Male	0.336	0.333	0.346
	(0.032)	(0.060)	(0.038)
1/(age/10)	8.022	26.517	1.716
	(1.822)	(8.560)	(0.581)
$1/(\text{age}/10)^2$	−7.878	−26.842	-
	(2.117)	(8.424)	
Degree	0.180	0.138	0.184
	(0.061)	(0.138)	(0.070)
Sub-degree	−0.021	−0.003	−0.037
	(0.050)	(0.093)	(0.059)
Black	−0.124	−0.106	−0.120
	(0.057)	(0.123)	(0.065)
Asian	−0.603	−0.652	−0.565
	(0.067)	(0.113)	(0.084)
Religious	−0.311	−0.211	−0.353
	(0.066)	(0.126)	(0.079)
1996	−0.011	0.029	−0.030
	(0.033)	(0.062)	(0.039)
α_{11}	2.472	7.013	1.219
	(0.381)	(2.151)	(0.204)
α_{12}	3.097	7.483	1.896
	(0.383)	(2.154)	(0.211)

TABLE A2.2
Parameters of ordered probit for drug use in period 2

Parameter estimate	**Age group**		
	16-34	**16-24**	**25-34**
1/(age/10)	0.132 (0.704)	3.709 (0.744)	4.912 (0.879)
Inner city	0.125 (0.050)	−0.058 (0.088)	0.211 (0.061)
Degree	0.045 (0.087)	0.285 (0.178)	−0.047 (0.104)
Sub-degree	−0.053 (0.071)	0.165 (0.128)	−0.141 (0.088)
Household structure:			
1 adult	0.107 (0.081)	−0.200 (0.156)	0.115 (0.106)
2 adults	0.329 (0.082)	0.327 (0.135)	0.275 (0.110)
3+ adults	0.110 (0.085)	0.177 (0.111)	−0.035 (0.140)
lone parent	0.071 (0.085)	0.392 (0.183)	−0.022 (0.105)
2 adults +children	0.070 (0.094)	0.141 (0.177)	0.037 (0.116)
Marital status			
single male	0.455 (0.080)	0.352 (0.162)	0.506 (0.101)
single female	0.344 (0.087)	0.252 (0.171)	0.374 (0.107)
married female	−0.293 (0.075)	−0.411 (0.181)	−0.252 (0.085)
Religious	−0.151 (0.106)	−0.338 (0.175)	−0.064 (0.136)
1996	0.107 (0.051)	0.116 (0.082)	0.101 (0.065)
δ_{21}	$-1.299 + 49.34/\text{age}$ (0.782) (15.25)	0.796 (0.420)	0.504 (0.365)
δ_{22}	$0.039 + 4.712/\text{age}$ (0.343) (0.848)	2.289 (0.196)	1.666 (0.157)
α_{21}	2.035 (0.300)	3.817 (0.526)	3.605 (0.362)
α_{22}	3.177 (0.303)	4.934 (0.544)	4.735 (0.374)

TABLE A2.3
Parameters of ordered probit for drug use in period 3

Parameter	**Age group**		
estimate	**16-34**	**16-24**	**25-34**
1/(age/10)	1.319	−0.198	3.270
	(0.381)	(0.784)	(1.243)
Inner city	0.232	0.250	0.211
	(0.063)	(0.103)	(0.084)
Degree	−0.206	−0.488	−0.194
	(0.108)	(0.214)	(0.133)
Sub-degree	−0.209	−0.203	−0.247
	(0.087)	(0.135)	(0.116)
Single male	0.182	0.270	0.141
	(0.085)	(0.165)	(0.107)
Single female	−0.087	−0.028	−0.095
	(0.090)	(0.171)	(0.117)
Married female	−0.189	−0.320	−0.145
	(0.104)	(0.226)	(0.123)
Religious	−0.160	−0.345	−0.081
	(0.139)	(0.282)	(0.169)
1996	−0.007	0.066	−0.063
	(0.061)	(0.089)	(0.085)
λ_{21}	1.873	1.667	2.002
	(0.179)	(0.246)	(0.248)
λ_{22}	3.265	3.193	3.257
	(0.148)	(0.194)	(0.219)
α_{31}	2.520	1.718	3.208
	(0.194)	(0.400)	(0.437)
α_{32}	4.285	3.458	5.013
	(0.223)	(0.544)	(0.458)

TABLE A2.4 Probit model for unemployment

Estimate	**16-34**	**16-24**	**25-34**
Intercept	−3.909 (0.549)	−10.033 (2.716)	−3.332 (3.374)
1/(age/10)	13.132 (2.613)	38.11 (10.85)	11.64 (19.65)
$1/(age/10)^2$	−14.536 (3.014)	−37.58 (10.68)	−13.87 (28.47)
Inner city	0.338 (0.047)	0.355 (0.077)	0.312 (0.061)
Degree	−0.887 (0.086)	−0.853 (0.174)	−0.825 (0.102)
HND, BTEC	−0.833 (0.084)	−0.829 (0.145)	−0.820 (0.107)
A-levels, ONC	−0.674 (0.084)	−0.805 (0.132)	−0.599 (0.105)
High GCE/GCSE	−0.574 (0.081)	−0.830 (0.108)	−0.413 (0.083)
Low GCE/GCSE	−0.369 (0.065)	−0.409 (0.129)	−0.355 (0.105)
Other quali cation	−0.331 (0.080)	−0.307 (0.205)	−0.373 (0.150)
Black	0.343 (0.068)	0.386 (0.131)	0.328 (0.081)
Asian	0.295 (0.074)	0.340 (0.104)	0.286 (0.110)
1 adult	−0.033 (0.076)	0.097 (0.140)	−0.206 (0.100)
2 adults	−0.119 (0.074)	−0.008 (0.119)	−0.251 (0.102)
3+ adults	−0.276 (0.080)	−0.188 (0.104)	−0.389 (0.136)
lone parent	−0.012 (0.079)	0.214 (0.151)	−0.136 (0.102)
2 adults +children	0.175 (0.077)	0.301 (0.156)	0.085 (0.095)
single male	0.458 (0.076)	0.078 (0.154)	0.652 (0.101)
single female	0.143 (0.080)	−0.137 (0.162)	0.220 (0.104)
married female	−0.399 (0.073)	−0.540 (0.181)	−0.400 (0.083)
1996	−0.248 (0.045)	−0.247 (0.075)	−0.267 (0.060)
μ_{11}	0.120 (0.064)	0.221 (0.116)	0.093 (0.079)
μ_{12}	0.132 (0.079)	0.248 (0.139)	0.064 (0.101)
μ_{21}	0.243 (0.076)	0.074 (0.136)	0.367 (0.096)
μ_{22}	0.414 (0.107)	0.366 (0.170)	0.390 (0.158)

TABLE A2.5
Summary statistics

	Age group		
	16-34	**16-24**	**25-34**
$\widehat{\rho}$	0.070 (0.046)	−0.032 (0.071)	0.148 (0.065)
log likelihood	−11330.1	−3878.6	−7388.0
No. observations	7233	2116	5117
No. parameters	70	68	67
Akaike Criterion	3.1523	3.1527	