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CANNABIS, COCAINE AND JOBS

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Cannabis, cocaine and jobs

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Abstract

This paper uses a dataset collected among inhabitants of Amsterdam, to study the employment effects of the use of cannabis and cocaine. For females no negative effects of drug use on the employment rate are found. For males there is a negative correlation between past cannabis and cocaine use and employment. However, after correcting for the effect of unobserved personal characteristics there is no negative effect of cannabis use or cocaine use on the employment status of males.

Keywords: drugs, employment, cannabis, cocaine
JEL codes: C41, D12, I19

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1 Introduction

The use of illicit drugs is often related to detrimental health effects. The damage to the health of an individual is thought to have a negative effect on the labor productivity of that individual. This negative effect on labor productivity may result in a bad labor market position. So, illicit drug use may have a negative effect on the employment status of individuals. Although this negative effect seems plausible, results from empirical research are inconclusive. Even though the number of available datasets is limited there is a wide variety of outcomes concerning the labor supply effects of illicit drug use. Based on identical datasets some studies find no effects, while other studies find strong negative effects. The common problem in these studies is that the use of illicit drugs may not be exogenous to the employment position. The traditional solution to this problem is to find suitable instrumental variables that affect the use of illicit drugs but have no direct effect on employment. As will be spelled out in more detail in the next section the use of different instrumental variables may be one reason of the range in outcomes.

The current paper is on the employment effects of the use of cannabis and cocaine in Amsterdam (the capital of the Netherlands). In the Netherlands cannabis use is quasi-legalized since cannabis can easily be bought. Within the Netherlands it is especially the capital Amsterdam that has a reputation as a drug users city. This reputation is partly based on the fact that most of the cannabis selling places are found in tourist areas so tourists are easily confronted with soft drug users. Nevertheless, Amsterdam's reputation is built on more than just tourists getting biased observations about drug use. Surveys indicate that actual drug use in Amsterdam is quite high. In 2001 38 % of the Amsterdam population of 12 years and older had ever used cannabis while 10 % had ever used cocaine. Average for the Netherlands this was 17 % for cannabis and 3 % for cocaine (Abraham et al., 2003).

The high proportion of illicit drugs users makes it interesting to investigate the employment effects. The analysis is based on drug use surveys in 1994, 1997 and 2001. The current study has a number of distinguishing features. Amsterdam is interesting from a drug research point of view since the Netherlands is one of the few countries with a liberal attitude towards the use of soft drugs. Furthermore, the data collected contain information about parental cannabis use, information which is rarely available but very important in explaining individual drug use. Finally, in addition to a traditional analysis this study also uses an alternative approach to account for selectivity in drug use. In this alternative approach the process by which individuals start consuming drugs in the past is related to current drug use and to the current employment status.

The paper is set up as follows. Section 2 gives an overview of previous studies concerning the effects of drug use on the employment status of individuals. Section 3 presents stylized facts about the use of cannabis and cocaine and about the labor market in Amsterdam. Section 4 analyzes the dynamics in the consumption of cannabis and cocaine. Section 5 presents the results of the empirical analysis of the employment effects of past cannabis and cocaine use. Section 7 concludes.

2 Previous studies on illicit drugs and employment

Although the negative relationship between illicit drug use and productivity seems plausible, it is not often found in empirical research.[1] Since the 1990s as many as five studies on the relationship between employment and illicit drug use are based on the same dataset, the U.S. National Longitudinal Survey on Youth (NLSY). The studies differ in terms of the specification of the dependent variable, the specification of drugs use, the specific NLSY waves used, the individuals of whom the behavior is analyzed, the estimation procedure and the instrumental variables used. And, perhaps most surprising, the studies differ a lot in terms of the conclusions concerning the relationship between drug use and employment.

Gill and Michaels (1992) use the 1980 and 1984 waves of the NLSY. They estimate employment equations accounting for potential selectivity in drug use using information on illegal activities, attitude towards drinking and frequency of going to bars as instrumental variables. They find that hard drug use does not have a negative effect on the employment probability but for the sample of all drug users (combining users of hard and soft drugs) there is a reduced employment probability. They hypothesize that on the demand side of the labor market drug use may be related to for example low productivity and increased absenteeism, which will lower the employment rate because drug users are less attractive for potential employers. On the supply side drug use may be complementary with leisure. Nevertheless, they conclude that the disparity in employment effects between the effects of soft drugs and hard drugs is difficult to explain. If anything hard drugs are thought to be more harmful than soft drugs.

Register and Williams (1992) who use the 1984 wave of the NLSY find similar results. In their analysis they use attendance of religious services, parental education and previous divorce as instrumental variables. Their results suggest that for young male workers cannabis

[1] There are also studies on wage effects of cannabis use and cocaine use. These studies are not discussed here. See Van Ours (2004) for an overview of this literature. The study by Terza and Vechnak (2001) is ignored because it considers a substance abuse indicator that includes not only cannabis and cocaine but also alcohol.

has negative employment effects while cocaine use is found not to be significantly related to employment status. They too mention the possibility that their analysis did not account for unobserved differences between users and nonusers correlated with both use and productivity.

Kaestner (1994) finds a negative association between cannabis or cocaine use and the hours of labor supplied by young males. He uses household composition at a young age, frequency of past religious attendance and a measure of perceived self-esteem as instrumental variables. He compares separate cross-sectional estimates based on the 1984 and 1988 waves of the NLSY with panel estimates based on these two waves. In the cross-sectional estimates he finds that illicit drug use a has large, negative effect on labor supply. However, the panel estimates indicate that illicit drug use does not have a significant negative effect on labor supply.

Burgess and Propper (1998) use the NLSY to study long-term effects of drug use for males. As instrumental variables they use parental attainment and work status, circumstances at age 14 (living with parents, religious upbringing, living in the south), and number of siblings. They find that soft drugs use has no harmful effects on labor market participation 10 years later. However, heavy substance use does have a negative effect on later labor market participation.

Finally, De Simone (2002) again uses the 1984 and 1988 waves of the NLSY to study the employment effects of cannabis and cocaine use. His main criticism on the previous concerns the instrumental variables used. It is possible that variables like past-year divorce, prior delinquency and parental education have a direct effect on the employment rate or are correlated with unobserved determinants of employment. De Simone uses drug price related variables and family background variables as instruments. The price variables are past-year local retail price of cocaine and an indicator of whether cannabis possession is decriminalized in the state of residence. The family background variables are an indicator that both the mother and father were present in the household when the respondent was 14 years old and an indicator of parental alcoholism or problem drinking. De Simone finds that cannabis use and cocaine use have substantial negative effects on the employment of males, while no such effects are found for females.[2] Since these effects are established in separate estimates and almost all cocaine users use cannabis it is not clear that cocaine use has a negative effect *in addition* to the negative effect of cannabis use. Or, alternatively since 30-40% of the cannabis users also use cocaine it is not clear whether the estimated effect of cannabis use is a mixture of cannabis use having no effect and cocaine use having a large negative effect or whether cannabis use has a negative

[2]In footnote 11 of his paper De Simone (2002) states that for females neither cannabis nor cocaine use affects female employment.

effect irrespective of cocaine use.[3] All in all, what is striking is that on the basis of the same NLSY dataset such a wide range of employment effects of the use of cannabis and cocaine are found. One would be tempted to conclude: anything goes.

A second U.S. dataset that has been used to study the relationship between drug use and employment status is the National Household Survey on Drug Abuse (NHSDA). Zarkin et al. (1998) use the 1991 and 1992 NHSDA data to study for young men (age 18 to 24) the relationship between hours worked and illicit drug use. They use respondents' assessment of the risk associated with using illicit drugs and their assessment of the difficulty in obtaining illicit substances as instrumental variables. Their main conclusion is that illicit drug use has little effect on the number of hours worked.[4] French et al. (2001) use 1997 NHSDA data to study the employment rate for different types of drug users. They use a composite religiosity indicator to test for exogeneity of drug use finding that exogeneity of chronic drug use is not rejected. They find that chronic drug use has a negative effect on employment, while non-chronic use has no effect. So also on the basis of two studies based on NHSDA data no clear conclusions can be drawn.

MacDonald and Pudney (2000) use the British Crime Survey to estimate a model covering drug use and unemployment. Instrumental variables used are religious attendance and housing tenure. They conclude that past use of soft drugs tends not to be significantly associated with current unemployment, but there is strong evidence of long-term damage to employment prospects from the use of hard drugs.[5]

3 Drugs and labor supply in Amsterdam

The Netherlands has a special type of drug policy. The main aim is to protect the health of individual users, the people around them and society as a whole.[6] There are clinics for the treatment of addicts and care services, which aim to reach as many addicts as possible to assist them in efforts to rehabilitate, or to limit the risks caused by their drug habit. Methadone

[3]The parameter estimates are also sensitive to the set of instruments used. If the parental background variables are not excluded from the employment equation no significant negative employment effect of drug use is found for the year 1988.

[4]With respect to the working hours effect of the use of 1 to 3 marijuana joints in the past month they find conflicting results depending on the dataset used. For 1991 they find a positive effect, for 1992 a negative effect.

[5]MacDonald and Pudney (2001) is very similar in many respects including the conclusions.

[6]See Ministry of Health, Welfare and Sport (1997) from which most of the information in this section is derived. An international perspective on Dutch drug policy is given in Boekhout van Solinge (1999).

programs enable addicts to lead reasonably normal lives without causing nuisance to their immediate environment, while needle exchange programs prevent the transmission of diseases such as AIDS and hepatitis B through infected needles. The services also provide counseling.

Regulations on drugs are laid down in the Opium Act, which draws a distinction between hard drugs and soft drugs. The distinction that is drawn relates to the health risks involved in drug use. Hard drugs are those substances which can seriously harm the health of the user and include heroin, cocaine an synthetic drugs such as ecstasy. Soft drugs, i.e. cannabis derivatives marijuana and hashish cause far fewer health problems. The possession of hard drugs is a crime. However, since 1976 the possession of a small quantity of soft drugs for personal use is a minor offence.

The data used in the analysis are collected in Amsterdam, which has a population of 700,000 inhabitants and has around 300 recognized retail outlets were soft drugs can be purchased. These are called 'coffee-shops' since one of the rules under which these shops can operate is prohibition of shop window advertisements for soft drugs. The data are from three surveys by CEDRO, the Center for Drug Research of the University of Amsterdam (see the Appendix A for a more detailed description). The surveys were carried out in 1994, 1997 and 2001. The data on drug use are based on self-reported information, which is the norm for analyses of drug consumption. To give an impression about the use of cannabis and cocaine and their relation with labor supply variables some stylized facts are presented in Tables 1 and 2. As will be shown in more detail below if an individual will start using cannabis (s)he will usually do so before age 26. Furthermore, most individuals have completed their full-time education before age 26. After age 50 individuals in the Netherlands employment participation rates start to decline due to inflow into disability benefits and early retirement schemes. Therefore, the focus of the analysis is on prime age males and females (age 26 to 50).

Table 1 shows prevalence indicators for cannabis and cocaine. As shown, of the prime age females in the sample 47.8% has ever used cannabis while 12.4% has ever used cocaine. For prime age males the lifetime prevalence numbers are 57.9% for cannabis and 17.3% for cocaine. There is a clear correlation in the use of cannabis and cocaine. As shown 52% of the female individuals in the sample have neither used cannabis nor cocaine. For males this number is about 42%. About 12% of the females in the sample have (ever) used both cannabis and cocaine, while this is the case for about 17% of the male individuals. As shown there are only a few individuals that have ever used cocaine but never used cannabis. The percentages of individuals that have ever used cannabis and never used cocaine are quite high. As shown the last year prevalence numbers are substantially smaller and last month prevalence numbers are substantially smaller than last year prevalence numbers. The difference between the last two indicators could suggest that many individuals have stopped using in the past year. However, it is also possible that some individuals use infrequently, i.e. less than once a month. Therefore, last year use is considered as recent use and last month use as current use (see also EMCDDA, 2002). Table 1 shows that of the recent cannabis users only a very small percentage is also current cocaine user. In fact more than half of the current cannabis users have never used cocaine. Many of the users have used cannabis and cocaine only a couple of times. The majority of users used the drugs less than 25 times. Of the frequent cannabis users only a very small part has also frequently used cocaine. Again, more than half of the frequent cannabis users have never used cocaine.

Table 2 shows how for prime age individuals the four groups of cannabis and cocaine users and the group of abstainers compare with each other in terms of average characteristics. As shown, in terms of average age there is not a lot of difference between the groups, except perhaps for the current cannabis users and recent cocaine users who are somewhat younger than the others. With respect to education there are clear differences. Individuals that have never used cannabis or cocaine are lower educated than average while individuals that ever used cannabis have the highest educational level. Of the male abstainers only about 38% has a higher education, while of the ever cannabis users almost 60% has a higher education. Of the female abstainers about 42% has higher education, while of the individuals that ever used cannabis about 53% has a higher education. Similar differences between the groups occur concerning marital status and the presence of children. Of the group of female abstainers about 34% is single, while of the group of recent cannabis users or recent cocaine users almost 60% is single. For males marital status has a similar effect. Furthermore, of the male abstainers 38% has one of more children while of the males that recently used cannabis the share with children is about 15% and of the recent cocaine users only 11% has children. Whether or not parents ever used cannabis has a large effect on the probability that their children also use cannabis or cocaine. Of the females that abstained from cannabis and cocaine only about 2% has parents that ever used cannabis, while of the frequent cocaine users 32% has parents that ever used cannabis. Of the females that recently used cannabis 22.2% have parents that ever used cannabis. Also for males there is this large effect of parental cannabis use. Of the abstainers 1.5% have parents that used cannabis, of the males that recently used cannabis this is 17.4%.

Table 2 also gives information about the employment rates of the individuals in the sample. Full-time jobs are defined as jobs that have regular working hours of more than 20 hours per week.[7] Total employment includes all jobs of at least 1 paid working hour per week. As shown for females in the sample the average full-time employment rate is 64%, while the total employment rate is 76%. For males the average full-time employment rate is 84%, while the total employment rate is 88%. To do a comparable analysis the focus is on the full-time employment rate. For females the full-time employment rate is lowest for frequent cocaine users (52.6%) and abstainers from cannabis and cocaine (58.5%), while the highest full-time employment rate is for recent cocaine users (70.4%). Of course the employment rates are influenced by differences in educational level and family situation. For males the highest full-time employment rate is for abstainers from cannabis and cocaine (87.4%). Frequent cocaine users have the lowest employment rate (61.2%), but note that this group also has the lowest share of individuals with higher education. Before discussing the analysis of the determinants of the employment rate the determinants of the starting rates for cannabis and cocaine are investigated. This will be helpful in the analysis when distinguishing between the causal effect from cannabis and cocaine use to employment and the effect caused by joint unobserved determinants.

4 Starting to use cannabis and cocaine

The datasets used in the analysis contain information about the ages of onset of cannabis use and cocaine use. This information is used to calculate age-specific starting rates and the related cumulative starting probabilities. As shown in Figure 1 for females the cumulative starting probability of cannabis increases from about 5% at age 15 up to 45% at age 25.[8] After that the cumulative starting probability hardly increases. For males the pattern is the same but the maximum cumulative probability is about 55%. As shown in Figure 2 the patterns for cocaine are similar although here the increase is only small after age 30 at a level of about 12% for females and 17% for males.

To investigate the determinants of the starting rates of cannabis and cocaine a bivariate mixed proportional hazard model with a flexible baseline hazard is used. This type of models is frequently used in the analysis of labor market transitions i.e. unemployment durations (See Van den Berg (2001) for a recent overview of the state of the art of duration models). Differences between individuals in the rate by which they start using a particular drug are characterized by the observed characteristics x, the elapsed duration of time t they are exposed to potential

[7] As shown in appendix A this broad definition of a full-time job is driven by data availability.

[8] An individual who did not use cannabis or cocaine but is below age 50 is considered to have an incomplete duration of non-use, i.e. is assumed to be a 'right censored' non-user.

use and unobserved characteristics v. Age 12 is taken to be the time at which this potential exposure to drugs starts.

The starting rate for cannabis and cocaine, at time (age) t conditional on observed characteristics x and unobserved characteristics v is specified as.

$$\theta_j(t \mid x, v_j) = \lambda_j(t) \exp(x'\beta_j + v_j) \text{ for } j = a, b \tag{1}$$

where $\lambda(t)$ represents individual duration dependence, v represents individual specific unobserved heterogeneity, the subscript a refers to cannabis and the subscript b refers to cocaine. Flexible duration dependence is specified as a step function:

$$\lambda_j(t) = \exp(\Sigma_k \lambda_{jk} I_k(t)) \text{ for } j = a, b \tag{2}$$

where k (= 1,..,4) is a subscript for age-intervals and $I_{jk}(t)$ are time-varying dummy variables that are one in subsequent age-intervals. In line with the pattern in Figure 1 four age intervals are distinguished. For cannabis the age intervals are up to 15, 16-20, 21-25, and 25+ years; for cocaine the age intervals are up to 20, 21-25, 26-30, and 30+ years. For normalization, because also a constant term is estimated, $\lambda_{j1} = 0$.

The conditional density functions of the completed durations of non-use can be written as

$$f_j(t \mid x, v_j) = \theta_j(t \mid x, v_j) \exp(-\int_0^t \theta_j(s \mid x, v_j) ds) \text{ for } j = a, b \tag{3}$$

The possible correlation between the unobserved components is taken into account by specifying the joint density function of the two durations of non use t_a and t_b conditional on x as

$$f(t_a, t_b \mid x) = \int_{v_b} \int_{v_a} f_a(t_a \mid x, v_a) f_b(t_b \mid x, v_b) dG(v_a, v_b) \tag{4}$$

$G(v_a, v_b)$ is assumed to be a discrete distribution 4 points of support (v_{1a}, v_{1b}), (v_{1a}, v_{2b}), (v_{2a}, v_{1b}), (v_{2a}, v_{2b}). The associated probabilities are denoted as follows:

$$\begin{array}{ll} \Pr(v_a = v_{1a}, v_b = v_{1b}) = p_1 & \Pr(v_a = v_{1a}, v_b = v_{2b}) = p_2 \\ \Pr(v_a = v_{2a}, v_b = v_{1b}) = p_3 & \Pr(v_a = v_{2a}, v_b = v_{2b}) = p_4 \end{array}$$

where p_n $(n = 1, .., 4)$ is assumed to have a multinomial logit specification:

$$p_n = \frac{\exp(\alpha_n)}{\Sigma_n \exp(\alpha_n)} \tag{5}$$

and to normalize $a_4 = 0$. Instead of estimating the mass points v_{2a} and v_{2b} the differences between the two mass points are estimated: $\lambda_a = v_{2a} - v_{1a}$ and $\lambda_b = v_{2b} - v_{1b}$.[9]

To understand the dynamics of drug use backward looking information is necessary, i.e. characteristics that are valid at the time when the individual was potentially confronted first with the choice to use a particular drug. Ideally, this information indicates how relevant circumstances change over time. Information that could be important concerns family situation, experiences at school, changing supply conditions, prices of drugs, et cetera. Unfortunately, this type of information is not available. Variables that indicate the current situation, i.e. marital status and presence of children, are not very useful because they could be influenced by past drug use. The educational level attained is also problematic. Nevertheless, although the highest educational level may be attained long after the use of a particular drug started one might assume that this level represents ability rather than educational investment. Thus, a educational level that is attained eventually can be used to explain choice with respect to the use of drugs earlier on in life. Apart from educational level there is also information about parental cannabis use. This variable indicates whether or not cannabis use is 'family tradition'. Individuals may be more likely to start using a particular drug if the parents have experienced cannabis use.

The parameters are estimated using maximum likelihood. In the estimates observations of individuals that did not start to consume cannabis or cocaine are considered to be right censored durations. The parameter estimates for females are presented in the first two columns Table 3. As shown the starting rates are the same across the three survey years. Females with secondary or higher education have higher starting rates for both cannabis and cocaine than females with lower education. Recent birth cohorts also have higher starting rates for cannabis. Later generations are more likely to start using cannabis. And, cannabis use of parents has a positive effect on both starting rates. The parameter estimates also indicate clear evidence of age dependence. The starting rates for cannabis are highest in the age range 16-25, the highest starting rates for cocaine are in the age rage 21-30 years. Finally, there is presence of unobserved heterogeneity. Three groups are identified, which for unknown reasons behave differently. Conditional on age and observed characteristics there is a group of females of 26.1% that has both a high starting rate for cannabis and a high starting rate for cocaine. There is also a group of 63% that has low starting rates for both cannabis and cocaine. The remaining group (10.9%) has a high starting rate for cannabis and a low starting rate for cocaine. There

[9] Note that if $\lambda_a = \lambda_b = 0$ there is no unobserved heterogeneity but also note that in that case the probabilities p_n are not identified.

are big differences in starting rates due to unobserved heterogeneity. But, of the high starting rates categories not everyone will start using cannabis or cocaine. And, of the low starting rates not everyone will abstain from cannabis or cocaine.

The starting rates for males are influenced by similar characteristics, although education is less important than it is for females. The starting rate for cannabis is positively affected by birth year and cannabis use of parents is important for both starting rates. Also for males there is unobserved heterogeneity affecting the starting rates for cannabis and cocaine. For males there is conditional on age and observed characteristics a group of 31.9% that has both a high starting rate for cannabis and a high starting rate for cocaine. There is a group of 53% that has small starting rates for both cannabis and cocaine. The remaining group (15.1%) has a high starting rate for cannabis and a low starting rate for cocaine.

5 Cannabis, cocaine and jobs

5.1 Set-up of the analysis

To investigate the relationship between drug use and employment ideally there would be information about the dynamics in both drug use and employment, i.e. information about starting rates and quit rates. As shown in the previous section there is some information about drug dynamics. However, concerning employment only the situation at the date of the survey is available. To illustrate the way in which the limitation in information restricts the analysis this section first discusses how the ideal information could be used and then presents the set-up of the current analysis.

To ease the discussion assume that individuals start as non-drug users searching for a job, cocaine does not exist and employment is an absorbing state. So, the only relevant drug is cannabis and once individuals have found a job they keep it forever. Information about unemployment durations can be used to estimate job finding rate models similar to the ones on drug use starting rates presented in the previous section. The job finding rate may depend on the state of the labor market, on observed personal characteristics of the individual, and on unobserved characteristics. In terms of the relationship between cannabis use and job finding rate two situations can be distinguished. First, cannabis use has a negative effect on the job finding rate. As soon as someone starts using cannabis his or her job finding rate goes down. This will lead to the observation that those that use cannabis are less likely to have job. Second, there is no effect of cannabis use on the job finding rate but there is correlation through unobserved characteristics between the job finding rate and the cannabis starting rate, perhaps because people differ in attitude concerning career making. Anyway, for whatever reason there are individuals that are more likely to start using cannabis and less likely to find a job, while there are other individuals that are less likely to start using cannabis and more likely to find a job. This will also lead to the observation that those that use cannabis are less likely to have job. So, both situations are observationally equivalent.

One way to distinguish between the causal effect and the correlation through unobservables is to estimate a bivariate transition rate model in which the cannabis starting rate and the job finding rate are allowed to interact both through a possible "treatment" effect from cannabis use on the job finding rate and through correlated unobservables. Identification of the treatment effect depends on the timing of events, i.e. when individuals find a job and when they start to use cannabis.[10]

A extension of the simple model is to allow for job separations. Then, cannabis use may have a negative effect on the employment probability, both through a smaller job finding rate and a higher job separation rate. Here too, it is possible that an observational higher job separation rate among cannabis users is due to correlation through unobservables. A further extension is to allow the employment status to affect cannabis use. It could be that non-cannabis users are less likely to start using cannabis after they have found a job and cannabis users that find a job may be more likely to quit using.

If individual information is available about drug use dynamics and employment dynamics, it is possible to exploit this and study the interaction between cannabis use and employment in great detail. If there is information only on the current employment status and drug use dynamics the possibilities are limited. An instrumental variable approach is limited through the lack of suitable instruments.[11] Because of this, there is first an analysis of the relationship between recent cannabis use and current employment status where past cannabis and cocaine use are assumed to be exogenous to current employment status. Then, information about drug use dynamics are introduced in the analysis. In particular the possible correlation between

[10] Four situations are possible for individuals to occur up to the time of the survey: first start using cannabis and then find a job, first start using cannabis and not finding a job, no cannabis use before finding a job, no cannabis use and not finding a job; models like this have been used to estimate the effect of benefit sanctions on the job finding rate by for example Abbring, Van den Berg and Van Ours (1997) and Van den Berg, Van der Klaauw and Van Ours (2004). Van Ours (2003) uses a similar model to investigate the effect of cannabis use on the starting rate for cocaine. See for a general discussion on the identification of treatment effects in this type of models Abbring and Van den Berg (2003).

[11] See Appendix B2 for an attempt in the context of a bivariate probit model.

unobservable determinants of the current situation and past behavior are taken into account.

5.2 Preliminary results

The analysis of the employment effects of drug use starts with the relationship between recent cannabis use and employment. Here, e is the indicator of whether ($e = 1$) or not ($e = 0$) an individual has a (full-time) job and c as the indicator of whether ($c = 1$) or not ($c = 0$) an individual has recently used cannabis. Recent use refers to last year prevalence. And, we are interested in the effects of past drug use (more than 1 year ago) on the current employment status. In the presentation of the model only the potential effects of past cannabis use will be discussed. In the empirical analysis past cocaine use will also be taken into account. The following latent variable specifications represent the individual's unobserved propensity to have a job and to be a recent cannabis user

$$\begin{aligned} e^* &= x_e\beta_e + \delta_c c_p + \varepsilon_e, \qquad e = 1 \quad \text{if } e^* > 0\text{, and 0 otherwise} \\ c^* &= x_c\beta_c + \varepsilon_c, \qquad\qquad\quad c = 1 \quad \text{if } c^* > 0\text{, and 0 otherwise} \end{aligned} \tag{6}$$

where x_e is a vector of personal characteristics affecting the probability to have a job, β_e is a vector of parameters, c_p is a dummy variable indicating whether or not the individual used cannabis in the past, δ_c indicates whether past cannabis use affects current employment status and ε_e is an error term. In the same way x_c is a vector of personal characteristics affecting the probability to be a recent cannabis user, where x_c partly overlaps with x_e. Furthermore β_c is again a vector of parameters, and ε_c is an error term. The possible correlation between recent cannabis use and employment status through unobservable characteristics is taken into account by modelling the joint distribution of the two.

It turns out that when there is no past cannabis use there is no current cannabis use either, which has to do with the fact that individuals in our sample are above age 25 so not many individuals will start using drugs.[12] Therefore, when an individual has a full time job three situations are possible with respect to past and current cannabis use.[13] If there is past and current cannabis use: $\Pr(e^* > 0, c^* > 0|c_p = 1)$; if there is past but no current cannabis use: $\Pr(e^* > 0, c^* < 0|c_p = 1)$. Finally, if there is no past cannabis use: $\Pr(e^* > 0, c^* < 0|c_p = 0) = \Pr(e^* > 0|c_p = 0)$.[14]

[12]Note that this also prevents us from estimating the effect of past cannabis use on recent cannabis use.

[13]For individuals that do not have a job the specifications of the three situations are similar.

[14]Note that $\Pr(e^* > 0, c^* < 0|c_p = 0) = \Pr(e^* > 0|c^* < 0, c_p = 0) * \Pr(c^* < 0|c_p = 0)$ If there is no

To account for correlation through unobservables a bivariate logit specification with a 2 point discrete mixing distribution is used.[15] The possible observable outcomes in case the individual has a job are

1. past cannabis use, no current use: $\sum_{j=1}^{2} q_j \Lambda(x_e\beta_e + \delta_c + v_{je})\Lambda(-x_c\beta_c - v_{jc})$

2. past and current cannabis use: $\sum_{j=1}^{2} q_j \Lambda(x_e\beta_e + \delta_c + v_{je})\Lambda(x_c\beta_c + v_{jc})$

3. no past cannabis use: $\sum_{j=1}^{2} q_j \Lambda_j(x_e\beta_e + v_{je})$

where the v_{je} represent the mass points in the employment part while the v_{jc} represent the mass points in the current cannabis use part. Furthermore, the q_j have a binomial logit specification with $q_1 = \frac{exp(\alpha)}{1+\exp(\alpha)}$ and $q_2 = \frac{1}{1+\exp(\alpha)}$. Again, not the mass points itself are estimated but $\lambda_{je} = v_{je} - v_{1e}$ and $\lambda_{jc} = v_{jc} - v_{1c}$. Note that if for all j, $\lambda_{je} = \lambda_{jc} = 0$, there is no unobserved heterogeneity affecting employment status and recent cannabis use.[16]

The parameters are estimated with maximum likelihood and are shown in Table 4. For females recent use of cannabis was higher in 1997 than it was in 1994 and 2001. It is also higher if parents have used cannabis in the past and it is lower for females with higher education and females with children than it is for their counterparts. The probability to have a full-time job is higher in 1997 and 2001 than it was in 1994, which is consistent with the growth of employment in the Netherlands during the second half of the 1990s. Age initially has a positive effect on the probability to have to job but a negative one at higher age (the maximum job probability is around age 40, but note that this could also be a cohort effect). The probability to have a job increases with the level of education. And, females that are single or females with children have a smaller employment probability than their counterparts. Past cannabis use has a positive effect on the employment rate (significantly different from zero at a 10% level), while past cocaine use has a significant negative effect on the employment rate. Finally, conditional on the effect of the observed characteristics there is a significant negative correlation between the two probabilities. There is a group representing 24% of the individuals that have a high

past cannabis use, there is no current cannabis use, which implies that $\Pr(c^* < 0|c_p = 0) = 1$. Therefore $\Pr(e^* > 0|c^* < 0, c_p = 0) * \Pr(c^* < 0|c_p = 0) = \Pr(e^* > 0|c_p = 0)$

[15] A logit specification is used to ease the specification of a joint model including drug use dynamics. Alternatively a bivariate probit model could be used but as shown in Appendix B1, the results in this stage of the analysis are very similar.

[16] Also note that in this case q is not identified.

probability to be a cannabis user and a low probability to have a job; and there is a group of 76% of the individuals that have a low probability to be a cannabis user and a high probability to have a job. As indicated in the bottom two rows of the table we cannot reject the hypothesis that the unobservables are unrelated. And, we cannot reject the hypothesis that past cannabis use and past cocaine use have no significant effects on current employment status.

Many of the parameter estimates for males are similar to those for females. Higher educated males and males with children have a lower probability to be a recent cannabis user while single males and males with parents that ever used cannabis have a higher probability to be a cannabis user than their counterparts. The growth in employment opportunities in the second half of the 1990s is also present for males. Age has a positive but diminishing effect on the employment rate (the calculated maximum is age 70), while higher educated and non-single males have a higher employment rate than their counterparts. The main variables of interest, past cannabis use and past cocaine use have significant negative effects on employment status. Conditional on the observed characteristics there is a negative correlation between recent cannabis use and employment rate through unobservables, but the Likelihood Ratio test for absence of unobserved heterogeneity is not significantly different from zero.

The parameter estimates in Table 4 differ from those in Table 3 in the sense that in the starting rate analysis it was possible to identify three mass points in the distribution of unobserved heterogeneity for both males and females while in the analyses presented in Table 4 only two mass points are identified for females[17] while for males the absence of unobserved heterogeneity could not be rejected.

5.3 Cannabis, cocaine and jobs reconsidered

The basic assumption so far is that past drug use is exogenous to current employment status. However, it could be that past cannabis use and past cocaine use are influenced by unobserved factors that also influence the employment status. To investigate the role of unobservables affecting both employment and drug use in more detail the bivariate starting rate model for cannabis and cocaine is combined with a bivariate analysis of employment rates and recent drug use. Thus information about past behavior is combined with information about the current

[17] It was not possible to identify a third mass point.

situation. In the joint model the associated probabilities are denoted as follows:

$$\begin{aligned}\Pr(v_a = v_{1a}, v_b = v_{1b}, v_e = v_{1e}, v_c = v_{1c}) = p_1 \\ \Pr(v_a = v_{1a}, v_b = v_{2b}, v_e = v_{2e}, v_c = v_{2c}) = p_2 \\ \Pr(v_a = v_{2a}, v_b = v_{2b}, v_e = v_{3e}, v_c = v_{3c}) = p_3\end{aligned} \tag{7}$$

The parameter estimates are shown in Table 5. Since the parameters of the starting rates and most of the parameters of the recent cannabis use probability and the employment status are very similar to those presented in previous tables the discussion is on the effects of past cannabis use, past cocaine use and the presence of unobserved heterogeneity.

For females the distribution of the unobserved heterogeneity is very similar to the one presented in Table 3. There are three points of support. There is a group of 23.6% that has a high starting rate for cannabis, a high starting rate for cocaine, a high probability to be a recent cannabis user and a low probability to have a job. There is also a group of 60.1% that has a low starting rate for cannabis, a low starting rate for cocaine, a low probability to be a recent cannabis user and a high probability to have a job. The third and smallest group has an intermediate position. What is obvious is that for 83.7% of the females there is a perfect negative correlation between on the one hand starting rates for cannabis and cocaine and current cannabis use and on the other hand the probability to have a full time job. Because of this strong negative correlation between drug use and employment probability the direct effect of past drug use on current employment rate changes. As shown in Table 5 past cannabis use has now a significant positive effect on the employment rate of females while past cocaine use has an insignificant positive effect. The Likelihood Ratio test statistics shown in the bottom part of the table indicate the presence of correlation through unobservables. And, the hypothesis that past cannabis use has a positive effect on the employment rate of females cannot be rejected. One can only speculate about the nature of this relationship. It is difficult to see how there could be a causal positive effect of cannabis use on employment status. Therefore, most likely there is still correlation through unobservables not accounted for in the analysis. It could be that females that were anxious to explore the drug scene in the past are more ambitious to find a job in the current situation.

For males there are similar estimation results as for females. For about 80% of the males there is a negative correlation between on the one hand starting rates for cannabis and cocaine and recent cannabis use and on the other hand the probability to have a full time job. Because of this the effects of past cannabis use and past cocaine use on the employment rate are no longer significantly different from zero. As shown by the Likelihood Ratio statistic in the bottom part of the table we cannot reject the hypothesis that there is no direct effect of past cannabis use and past cocaine use on the employment rate of males. All in all we no longer find detrimental employment effects of cannabis use and cocaine use, neither for females nor for males.

6 Conclusions

Previous empirical studies on the employment effects of cannabis and cocaine use are inconclusive. Some studies find that there are detrimental effects but other studies find no effects and some studies even find a positive employment effect of cannabis use. The main issue in all studies is how to correct for possible selectivity i.e. unobserved determinants that affect both drug use and employment status.Previous studies have used past family situation, parental education and local drug prices as instrumental variables. This study uses an alternative approach that combines information about drug use dynamics and current employment status. Unobserved components that affect starting rates of cannabis use and cocaine use are related to unobserved components affecting recent cannabis use and employment rates.

The analysis concerns prime age individuals living in Amsterdam. For females a positive causal effect of past cannabis use on the employment rate is found. For males past use of cannabis and cocaine is correlated with lower employment rates. However, after correcting for correlation through unobservables there is no negative effect of cannabis use or cocaine use on employment status of males. Apparently, neither for males nor for females drugs use has detrimental effects on the employment status.

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Appendix A. **Information about the dataset**

A.1 General set-up

The analysis is based on drug use data collected by CEDRO, the Center for Drug Research of the University of Amsterdam in 1994, 1997 and 2001 (see Abraham et al. (2003) for a detailed description). There are some differences between these surveys, but the information used in this paper is collected consistent through time. The data on drug use are based on self-reported information, which is the norm for analyses of drug consumption. The survey population is defined as all persons in the Municipal Population Registry of Amsterdam.

In 1994 two interview methods were used, a written and a computer assisted version (using laptop computers where the interviewer directly typed in the answers). The sample was randomly subdivided into two equal sized samples. It turns out that the interview method did not affect the answers to the questions. The 1997 survey was fully computer assisted. The 2001 survey was based on a mixture of methods. Respondents could choose between a paper questionnaire, a computer assisted face-to-face interview, an interview per telephone, via their own computer on the Internet or on a floppy disk (by mail). The non-response in 1994 was 49.2%, in 1997 48.1%, and in 2001 60%.

The available data refer to all inhabitants of Amsterdam of 12 years and older. The sample was reduced using a number of criteria. Because the focus of the paper is employment status only individuals who age 26 to 50 are considered. The individuals in this age category have finished their education and have made the choice about whether or not to participate in the labor market. Because some studies find individuals from ethnic minority groups to underreport drug consumption the focus is on individuals born in the Netherlands with a Dutch nationality. After removing observations with incomplete information the net samples contain 2308 females and 2057 males. Information with respect to working hours is available in categories. For the surveys of 1994 and 1997 the categories are (in weekly hours excluding overtime payments): < 8, 8-20, 20-32, >32. For the survey of 2001 the categories are: 1, 2-10, 11-20, >20. In the analysis a full-time job refers to a working time of more than 20 hours per week.

A.2 Explanatory variables

In the analysis the following explanatory variables are used:

- Age: Age of individuals at the time of the survey.
- Secondary education: Dummy variable with a value of 1 if the individual attended secondary general or vocational education, and a value of 0 otherwise. Secondary education refers to intermediate vocational or secondary general education.
- Higher education: Dummy variable with a value of 1 if the individual attended higher vocational or academic education, and a value of 0 otherwise. Since there are two dummy variables for education the overall reference group consists of individuals with basic or primary education.
- Single: Dummy variable with a value of 1 if the individual is living alone and a value of 0 if the individual is part of a multi-person household.
- Children: Dummy variable with a value of 1 if the individual has children and a value of 0 otherwise.
- Full-time: Dummy variable with a value of 1 if the individual has a regular job of at least 20 hours per week and a value of 0 otherwise.
- Year 1997 (year 2001): Dummy variable with a value of 1 if the individual participated in the survey of 1997 (2001) and a value of 0 otherwise.
- Birth year: Year of birth, calculated as (year of survey $-$ age $-$ 1950)/10
- Cannabis use parents: Dummy variable with a value of 1 if one or both parents have ever used cannabis and a value of 0 otherwise
- Past use of cannabis (cocaine): Dummy variable with a value of 1 if life time prevalence cannabis (cocaine) $= 1$ and a value of 0 otherwise
- Recent use of cannabis (cocaine): Dummy variable with a value of 1 if last year prevalence cannabis (cocaine) $= 1$ and a value of 0 otherwise

Appendix B. **Bivariate probit estimates**

B.1 Past drugs use

An alternative to the bivariate logit specification used in Section 5 is the bivariate probit specification. Then, for individuals with a job the possible outcomes are

$$\text{past cannabis use, no current use} \quad : \quad \Phi_2(x_e\beta_e + \delta_c, -x\beta_c; -\rho) \tag{B.1}$$

$$\text{past and current cannabis use} \quad : \quad \Phi_2(x_e\beta_e + \delta_c, x\beta_c; \rho) \tag{B.2}$$

$$\text{no past cannabis use:} \quad \Phi(x_e\beta_e) \tag{B.3}$$

where Φ_2 refers to a bivariate probit specification and ρ represents the correlation between the two error terms. The situations where the individual has no job are equivalent. The parameters are estimated with maximum likelihood and are shown in Table B1. They are very similar to those presented in Table 4 where a bivariate logit specification is used. Higher educated individuals, non-single individuals, individuals with children and individuals who do not have parents that used cannabis have a lower cannabis use than their counterparts. Conditional in their observed and unobserved characteristics, the employment rate is higher in 1997 and 2001 than in 1994. Age has a nonlinear effect on the employment rate. Education has a significant positive effect on the employment rate and both male and female singles have a smaller probability to have a (full-time) job. For females the presence of children also reduces the employment rate. Furthermore, for prime age females there is a positive employment effect of past cannabis use and a negative employment effect of past cocaine use. For prime age males past cannabis use and past cocaine use both have a negative effect on the employment rate. Finally, conditional on the effects of the observed characteristics there is a significant negative correlation through unobserved determinants between recent cannabis use and employment rate. Those that use cannabis have a smaller probability to have a job; or in other words those that have a small probability to have a job have a high probability to use cannabis. If there is causality, it is not possible to draw conclusions concerning the direction of causality.

B.2 Current drugs use

Ignoring the effect of past drugs use and introducing the effect of current cannabis use the bivariate probit specification for a person with a job is simply: $\Phi_2(x_e\beta_e, -x\beta_c; -\rho)$ in case of a non user and $\Phi_2(x_e\beta_e + \delta_c, x\beta_c; \rho)$ in case of a user. Again the specifications for a person without a job are equivalent. For the identification of the effect of recent cannabis use no exclusion restriction is necessary; the functional form assumption is sufficient. However, in addition to that, cannabis use of parents can be thought of as an instrumental variable under the assumption that parental cannabis use does not directly affect the employment status. Table B2 shows the parameter estimates for both recent cannabis use and for recent cocaine use. Most of the parameter estimates are very similar to those presented in Table B1. As shown for females neither the effect of recent cannabis use nor the correlation between the error terms are significantly different from zero. If the correlation is imposed to be zero there is a significant negative employment effect of recent cannabis use, if the employment effect of recent cannabis use is imposed to be zero a significant negative correlation between the error terms is found. The LR-test statistics indicate that both restrictions cannot be rejected. Apparently, it is not possible to distinguish between the causal employment effect of recent cannabis use and the correlation between unobserved components that affect both current cannabis use and employment status. For males a significant negative employment effect of recent cannabis use and an insignificant positive correlation between the error terms are found. Here, we the hypothesis that there is a negative employment effect of cannabis use cannot be rejected. Nevertheless, the positive correlation between the error terms does not seem very plausible.

Table 1 The use of cannabis and cocaine (%)[a)]

Cannabis	Cocaine	Females	Males
Ever	–	47.8	57.9
–	Ever	12.4	17.3
Ever	Ever	12.2	16.7
Ever	Never	35.6	41.1
Never	Ever	0.2	0.6
Never	Never	52.0	41.6
		100.0	100.0
Last year	Last year	1.5	3.6
Last year	Past	2.8	6.4
Last year	Never	6.2	10.9
Last year	–	10.5	20.9
–	Last year	2.3	4.3
$\geq$ 25 times	$\geq$ 25 times	1.9	4.7
$\geq$ 25 times	$\geq$25 times	5.5	7.8
$\geq$ 25 times	Never	10.0	15.2
$\geq$ 25 times		17.4	27.7
	$\geq$ 25 times	2.5	5.6
Last month	–	6.2	12.8
–	Last month	1.0	1.8

[a)] Sample of 2308 females and 2057 males age 26-50

Table 2 Characteristics different types of drug users[a)]

	Age	High educ (%)	Single (%)	Child (%)	Parents cannabis (%)	Employment full-time (%)	Employment total (%)	N
Females								
All	36.7	48.5	41.5	41.4	7.8	63.9	76.2	2308
No cannabis no cocaine	37.6	38.2	33.7	47.5	1.8	58.5	72.8	1199
Cannabis ever	35.6	59.6	50.0	34.8	14.5	69.8	79.8	1103
Cannabis frequent	35.8	56.6	54.6	34.4	23.7	67.1	77.3	401
Cannabis recent	34.2	52.2	60.5	21.3	22.2	62.1	72.0	243
Cocaine ever	36.2	55.7	56.8	36.6	20.6	62.7	74.6	287
Cocaine frequent	36.7	38.6	52.6	42.1	31.6	52.6	61.4	57
Cocaine recent	34.7	46.3	61.1	29.6	25.9	70.4	81.5	54
Males								
All	36.6	48.9	38.1	30.5	7.2	83.6	87.9	2057
No cannabis no cocaine	37.3	42.4	30.2	38.2	1.5	87.4	90.1	855
Cannabis ever	36.0	53.2	43.3	25.0	11.4	81.0	86.4	1190
Cannabis frequent	36.0	44.6	49.0	24.8	16.9	76.6	82.4	569
Cannabis recent	34.7	45.5	57.1	14.9	17.4	73.8	80.2	429
Cocaine ever	37.0	45.5	50.8	20.2	18.3	71.3	76.4	356
Cocaine frequent	36.9	30.2	60.3	25.0	22.4	61.2	67.2	116
Cocaine recent	35.2	38.2	66.3	11.2	20.2	65.2	70.8	89

[a)] Sample of 2308 females and 2057 males age 26-50

Table 3 Parameter estimates starting rates cannabis and cocaine[a)]

	Females		Males	
	Cannabis	Cocaine	Cannabis	Cocaine
Year 1997	0.06 (0.4)	-0.06 (0.3)	0.29 (2.4)*	0.26 (1.5)
Year 2001	-0.03 (0.2)	-0.02 (0.1)	-0.01 (0.1)	-0.20 (1.1)
Secondary education	1.02 (4.4)*	0.88 (3.2)*	0.52 (3.2)*	0.18 (0.8)
Higher education	1.19 (7.1)*	0.75 (3.1)*	0.19 (1.2)	-0.31 (1.5)
Birth year	0.45 (5.3)*	0.16 (1.1)	0.41 (5.5)*	-0.04 (0.4)
Cannabis use parents	1.93 (5.5)*	1.51 (5.1)*	1.69 (5.3)*	1.86 (5.7)*
Period 2	2.02 (12.1)*	1.11 (6.3)*	2.17 (18.4)*	1.37 (9.2)*
Period 3	1.98 (7.3)*	0.93 (4.3)*	2.17 (12.2)*	1.11 (5.8)*
Period 4	0.39 (1.0)	-0.75 (2.8)*	0.77 (2.7)*	-0.06 (0.3)
Mass points λ_a, λ_b	-2.75 (7.3)*	-5.73 (25.8)*	-2.78 (11.3)*	-5.24 (19.2)*
Probability α_1	-0.88 (3.4)*		-0.68 (4.1)*	
Probability α_2	-1.75(2.5)*		-1.43 (3.9)*	
-Loglikelihood	5904.6		6284.8	

[a)] 2308 females and 2057 males; absolute t-values in parentheses; * indicates that the coefficient is at a 5% level significantly different from zero. The implied probabilities are (%)

		p_1	p_2	p_3
Starting rate	Cannabis	High	High	Low
	Cocaine	High	Low	Low
	Females	26.1	10.9	63.0
	Males	31.9	15.1	53.0

Table 4 Parameter estimates bivariate logits drug use - employment rates[a)]

	Females		Males	
	Cannabis recently	Full-time job	Cannabis recently	Full-time job
Year 1997	1.61 (2.2)*	0.68 (5.8)*	-0.37 (1.1)	0.70 (4.6)*
Year 2001	0.32 (0.5)	0.56 (4.9)*	-0.51 (1.3)	0.89 (5.7)*
Age	0.23 (0.5)	0.20 (2.4)*	-0.14 (0.5)	0.26 (2.4)*
$\text{Age}^2/100$	-0.44 (0.7)	-0.26 (2.3)*	0.09 (0.3)	-0.38 (2.7)*
Secondary education	-0.95 (1.1)	1.03 (7.8)*	0.01 (0.0)	0.10 (0.6)
Higher education	-3.00 (2.1)*	1.56 (12.8)*	-0.89 (1.8)	0.68 (4.2)*
Single	0.67 (1.1)	-0.32 (3.1)*	1.41 (2.5)*	-0.64 (4.5)*
Children	-3.17 (2.9)*	-0.93 (8.6)*	-0.91 (2.8)*	0.09 (0.5)
Cannabis use parents	2.73 (1.9)	-	1.54 (1.9)	-
Past cannabis	-	0.21 (1.9)	-	-0.39 (2.6)*
Past cocaine	-	-0.39 (2.3)*	-	-0.65 (3.9)*
Mass points λ_c, λ_e	-8.31 (3.3)*	0.48 (2.4)*	-4.40 (2.5)*	0.43 (1.7)
Probability α	-1.16 (9.1)*		-0.12 (0.3)	
-Loglikelihood	1856.1		1557.8	
LR test				
$\lambda_c = \lambda_e = 0$	14.2*		6.0	
$\delta_{ca} = \delta_{co} = 0$	6.8*		29.4*	

[a)] 2308 females and 2057 males; absolute t-values in parentheses; * indicates that the coefficient is at a 5% level significantly different from zero. The implied probabilities are (%)

	p_1	p_2
Recent cannabis use	High	Low
Employment probability	Low	High
Females	23.9	76.1
Males	47.0	53.0

Table 5 Parameter estimates joint model[a)]

	Females		Males	
Bivariate logit	**Cannabis**	**Full-time**	**Cannabis**	**Full-time**
Year 1997	0.48 (2.3)*	0.72 (5.6)*	-0.29 (1.4)	0.69 (4.6)*
Year 2001	0.18 (0.9)	0.57 (4.7)*	-0.28 (1.3)	0.89 (5.6)*
Age	-0.06 (0.4)	-0.06 (0.4)	-0.20 (1.4)	0.26 (2.4)*
$\text{Age}^2/100$	0.03 (0.2)	-0.28 (2.4)*	0.18 (1.0)	-0.38 (2.7)*
Secondary education	-0.30 (1.1)	0.96 (6.7)*	0.18 (0.7)	0.08 (0.5)
Higher education	-0.66 (2.6)*	1.51 (11.3)*	-0.48 (2.1)	0.68 (4.2)*
Single	0.36 (2.1)*	-0.31 (2.9)*	0.75 (4.3)*	-0.63 (4.4)*
Children	-0.87 (4.3)*	-0.95 (8.2)*	-0.58 (2.8)*	0.10 (0.6)
Cannabis use parents	0.61 (2.5)*	-	0.96 (3.3)*	-
Past cannabis	-	0.52 (2.1)*	-	-0.34 (1.2)
Past cocaine	-	0.41 (1.0)	-	-0.44 (1.6)
Mass points $\lambda_{2c}, \lambda_{2e}$	-2.83 (1.6)	1.59 (2.3)*	-3.54 (3.0)*	0.56 (1.3)
Mass points $\lambda_{3c}, \lambda_{3e}$	-0.77 (2.6)*	1.31 (2.7)*	-1.32 (4.7)*	0.36 (0.9)
Starting rates	**Cannabis**	**Cocaine**	**Cannabis**	**Cocaine**
Year 1997	0.02 (0.1)	-0.15 (0.7)	0.29 (2.4)*	0.25 (1.4)
Year 2001	-0.05 (0.4)	-0.08 (0.3)	0.03 (0.2)	0.23 (1.1)
Secondary education	1.07 (5.0)*	0.94 (3.4)*	0.29 (2.4)*	0.22 (1.0)
Higher education	1.21 (7.1)*	0.80 (3.4)*	0.51 (3.2)*	-0.29 (1.4)
Birth year	0.47 (6.4)*	0.17 (1.2)	0.40 (4.9)*	-0.06 (0.5)
Cannabis use parents	2.01 (6.9)*	1.43 (5.6)*	1.70 (5.7)*	1.75 (5.5)*
Period 2	2.06 (14.1)*	1.14 (6.8)*	2.18 (19.0)*	1.40 (9.8)*
Period 3	2.05 (9.2)*	0.99 (4.8)*	2.18 (12.2)*	1.19 (6.6)*
Period 4	0.49 (1.5)	-0.67 (2.5)*	0.77 (2.6)*	0.07 (0.3)
λ_a, λ_b	-2.87 (9.0)*	-3.78 (10.2)*	-2.77 (10.8)*	-3.59 (10.7)*
Probability α_1	-0.98 (4.6)*[b)]		-0.84 (5.6)*	
Probability α_2	-1.35 (3.8)*		-1.20 (4.4)*	
-Loglikelihood	7745.5		7795.8	
LR tests				
$\lambda_{2c} = \lambda_{2e} = \lambda_{3c} = \lambda_{3e} = 0$	22.3*		79.6*	
$\delta_{ca} = \delta_{co} = 0$	7.2*		4.4	

[a)] 2308 females and 2057 males; absolute t-values in parentheses; * indicates that the coefficient is at a 5% level significantly different from zero. The implied probabilities are (%)

		p_1	p_2	p_3
Starting rate	Cannabis	High	High	Low
	Cocaine	High	Low	Low
Current cannabis use		High	Low	Low
Full time job		Low	High	High
	Females	23.6	16.3	60.1
	Males	27.2	19.0	53.9

Table B1 Parameter estimates bivariate probits recent cannabis use - employment rates[a)]

	Females		Males	
	Cannabis recently	Full-time job	Cannabis recently	Full-time job
Year 1997	0.26 (2.4)*	0.40 (5.8)*	-0.11 (1.2)	0.39 (4.7)*
Year 2001	0.12 (1.2)	0.33 (4.9)*	-0.14 (1.5)	0.49 (5.8)*
Age	0.02 (0.3)	0.12 (2.5)*	-0.02 (0.3)	0.14 (2.4)*
Age^2/100	-0.05 (0.5)	-0.16 (2.4)*	-0.02 (0.2)	-0.21 (2.7)*
Secondary education	-0.22 (1.6)	0.63 (8.0)*	0.03 (0.3)	0.05 (0.6)
Higher education	-0.40 (3.1)*	0.94 (13.0)*	-0.25 (2.4)*	0.37 (4.2)*
Single	0.23 (2.5)*	-0.20 (3.2)*	0.41 (4.9)*	-0.37 (4.2)*
Children	-0.44 (4.3)*	-0.44 (4.3)*	-0.33 (3.2)*	-0.04 (0.4)
Cannabis use parents	0.34 (2.9)*	-	0.43 (3.6)*	-
Past cannabis (δ_{ca})	-	0.12 (1.8)	-	-0.22 (2.7)*
Past cocaine (δ_{co})	-	-0.22 (2.3)*	-	-0.35 (3.7)*
ρ	-0.15 (2.5)*		-0.13 (2.2)*	
-Loglikelihood	1859.8		1558.6	
LR tests				
$\rho = 0$	6.0*		4.6*	
$\delta_{ca} = \delta_{co} = 0$	6.6*		33.8*	

[a)] 2308 females and 2057 males; absolute t-values in parentheses; * indicates that the coefficient is at a 5% level significantly different from zero.

Table B2 Parameter estimates bivariate probits recent cannabis use - employment rates[a)]

	Females		Males	
	Cannabis recently	Full-time job	Cannabis recently	Full-time job
I. Full estimates				
Year 1997	0.27 (2.9)*	0.41 (5.5)*	0.04 (0.5)	0.36 (4.4)*
Year 2001	0.13 (1.4)	0.33 (4.7)*	-0.02 (0.3)	0.46 (5.5)*
Age	0.08 (1.1)	0.12 (2.3)*	0.03 (0.5)	0.11 (1.8)
$\text{Age}^2/100$	-0.13 (1.4)	-0.15 (2.3)*	-0.07 (0.9)	-0.17 (2.2)*
Secondary education	0.07 (0.6)	0.64 (8.0)*	0.16 (0.8)	0.05 (0.6)
Higher education	0.02 (0.2)	0.96 (13.5)*	-0.05 (0.6)	0.33 (3.7)*
Single	0.32 (4.1)*	-0.20 (2.9)*	0.41 (5.7)*	-0.29 (3.2)*
Children	-0.40 (4.3)*	-0.56 (7.8)*	-0.36 (4.0)*	0.03 (0.3)
Cannabis use parents	0.71 (6.4)*	-	0.81 (7.3)*	-
Recent cannabis	-	-0.03 (0.1)	-	-0.80 (2.4)*
ρ	-0.13 (0.6)		0.22 (1.1)	
-Loglikelihood	2020.2		1805.0	
II. $\rho = 0, \delta$	-	-0.27 (2.9)*	-	-0.42 (5.2)*
LR test	0.2		1.0	
III. $\delta = 0, \rho$	-0.15 (3.0)*		-0.23 (4.9)*	
LR test	0.0		4.4*	

[a)] 2308 females and 2057 males; absolute t-values in parentheses; * indicates that the coefficient is at a 5% level significantly different from zero.

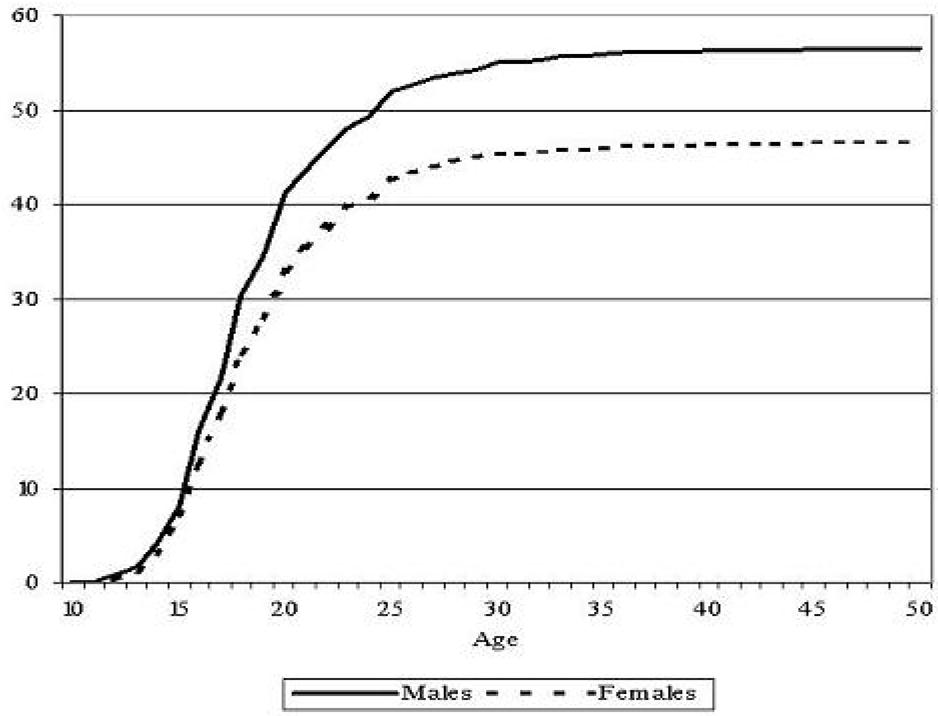

Figure 1: Cumulative starting probability cannabis by age (%)

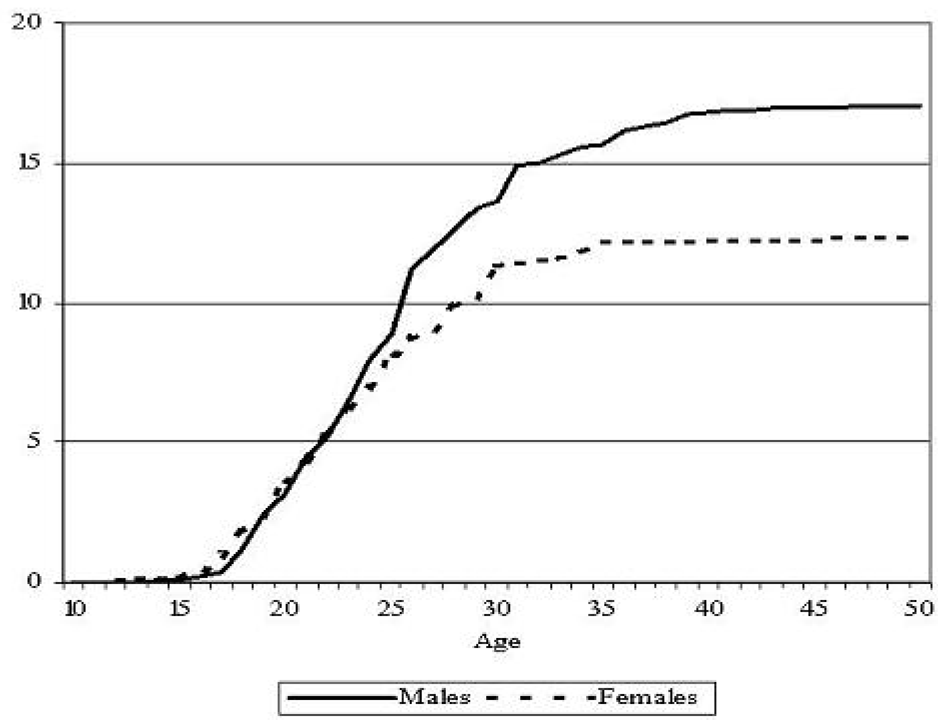

Figure 2: Cumulative starting probability cocaine by age (%)