Demand for Marijuana, Cocaine and Heroin: A Multivariate Probit Approach*

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Abstract

This paper investigates factors affecting the demand for marijuana, cocaine and heroin in Australia using micro-unit data from a national survey. Accounting for cross-commodity correlation potentially induced by unobserved personal characteristics such as tastes and addictive personalities, we estimate a trivariate probit model where the participation decisions for all drugs are jointly modelled as a system with correlated error terms. The estimated correlation coefficients are high across all three drugs. The multivariate approach allows us to predict joint and conditional probabilities, unavailable from univariate models. Such results offer extra insights in designing educational programs and drug policies within a multi-drug framework.

Key Words: Drug consumption, discrete choice models, univariate probit, multivariate probit.

JEL Classification: C3, D1, I1

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Demand for Marijuana, Cocaine and Heroin in Australia: A Multivariate Probit Approach

1. Introduction

The use of psychoactive substances is widespread around the globe. Excessive and chronic use of psychoactive drugs not only affects the users, with research evidence linking to psychiatric illnesses amongst other harms, but also imposes significant costs on the society through its impacts on health, criminal justice and social welfare systems. According to the United Nations Office on Drugs and Crime (UNODC 2003), about 15 million people in the world used opium and heroin and about 14 million people used cocaine in 2000-01. Medical treatment data consistently rank heroin and cocaine abuse as having the most severe consequences on drug abusers and medical systems. Marijuana is commonly considered a soft drug. However it has remained the most widely produced, trafficked and consumed illicit drug worldwide (UNODC, 2003).

In Australia, according to the most recent national survey on drug consumption, the National Drug Strategy Household Survey (2001), about 38 per cent of the population aged fourteen and over, or 5.9 million Australians, have used an illicit drug at some stage in their lives, and nearly 17 per cent have reported recent use of an illicit drug. According to a comprehensive Australian study (Collins and Lapsley 2002), illicit drug-related illness, death, and crime costed the Australian nation approximately $6.1 billion in 1998-99. This suggests that every man, woman, and child in Australia paid nearly $320 in a year to cover the expenses of unnecessary health care, extra law enforcement, auto accidents, crime, and lost productivity resulting from illicit substance abuse. Recently, a study on the Australian burden of diseases (Mathers et al. 1999) find that illicit drugs are direct causes of death as well as risk factors for conditions such as HIV/AIDS, hepatitis, low birth-weight, inflammatory heart disease, poisoning, suicide and self-inflicted injuries. They estimated that these account for nearly 2 per cent of all disability-adjusted life years (DALY)[1]. In particular, deaths from illicit drug use were found to be mainly associated with opiates, of which heroin is the refined product

[1] One DALY is a lost year of 'healthy' life and is calculated as a combination of years of life lost due to premature mortality and equivalent 'healthy' years of life lost due to disability.

form, with only 23 of the 4,658 deaths from illicit drug dependence, abuse or poisoning in the eleven years from 1986 to 1996 not related to opiates.

In late 2000 and early 2001, Australia experienced a “heroin drought” resulted in part from a shortage in world supply, mainly from opium production decline in Afghanistan, and the cracking down of a number of trafficking groups supplying the Australian market. The significant reduction in the availability of heroin led to declines in the number of drug related crimes and deaths, as well as increases in the number of heroin addicts seeking treatment. However, there have been reports that heroin originated or trafficked via North Korea took up the Australian market in 2003 (UNODC, 2003).

While there exists a vast economic literature on the consumption of legal recreational drugs such as alcohol and tobacco, research on the consumption of illegal drugs is limited due to the paucity of data on illicit drug usage and prices. Some important theoretical advances have been made into the understanding of consumer behaviour of drug addiction (Becker and Murphy 1988). However, scarcity in inter-temporal consumption data often restricts the empirical applications of the rational addiction model. The lack of reliable price data for illicit drugs also hinders empirical estimation of price responsiveness. Where price elasticities are estimated, results often vary widely across studies.

Among the illegal drugs, marijuana has attracted the most attention given its popularity and widespread use. Many economists have attempted to estimate its price elasticity using marijuana decriminalisation as a proxy for its price (Model 1993; Thies and Register 1993; Chaloupka *et al.* 1998; Saffer and Chaloupka 1998, 1999; Farrelly *et al.* 2001). Marijuana decriminalisation is a law that eliminates criminal sanctions for the possession of small amounts of marijuana. By lowering the penalties associated with the use of marijuana, decriminalisation usually increases its demand. Others have investigated the economic relationship between marijuana and alcohol (Chaloupka and Laixuthai 1997; Pacula 1998b; DiNardo and Lemieux 2001), tobacco (Farrelly et al. 2001), and cocaine (Chaloupka et al. 1998; Desimone and Farrelly 2003). The gateway effects of marijuana have also been a focus of some studies (Pacula 1998a). Limited number of studies, most of which have been conducted in the US, have investigated the demand for other psychoactive substances such as cocaine and heroin (DiNardo 1993; Saffer and Chaloupka 1995; Chaloupka et al. 1998; Grossman and Chaloupka 1998; Saffer and Chaloupka 1999; Petry 2001; Desimone and

Farrelly 2003; van Ours 2003). In Australia, despite the severity of illicit drugs abuse, very limited economic research has been undertaken on their consumption. Recently, using data from the National Drug Strategy Household Surveys (NDSHS), a few studies have investigated the demand for marijuana (Clements and Daryal 1999; Cameron and Williams 2001; Zhao and Harris 2003; Williams 2004), but to our knowledge there has not been economic analysis on the demand for cocaine and heroin in Australia.

Using unit-record data from the two most recent NDSHS surveys, we investigate the factors that influence the joint demand for marijuana, cocaine and heroin in Australia. The drug price data obtained from the Illicit Drug Reporting System (IDRS) enable us to study the own and cross price effects for the three related drugs. Additionally, the use of individual level data also allows us to investigate how drug consumption is related to various demographic factors characterising the users. Such findings can be useful to policy makers in designing and assessing the impacts of education programs and drug policies.

Survey data related to illicit drug consumption are mostly of categorical nature. Studies on drug participation decisions of several drugs based on such data often use a univariate probit framework. For example, Cameron and Williams (2001) estimated three univariate probit equations to study participation decisions for tobacco, alcohol and marijuana in Australia using the same dataset. The univariate approach ignores the potential cross-commodity correlations across the various drugs for the same individual that are not reflected in observable characteristics. Due to unobserved characteristics such as individual tastes and addictive personalities, an individual's decision for a variety of drugs can well be related through the error terms. As a consequence, vital cross-drug information is lost using a univariate approach.

In this paper, we estimate a trivariate probit model that accounts for potential correlation between the participation decisions for marijuana, cocaine and heroin. In addition to estimating marginal effects of individual explanatory variables on marginal probabilities available from univariate models, we also estimate joint and conditional probabilities of drug participation, and marginal effects on these probabilities. Prediction of such probabilities indeed provides valuable cross-drug information to policymakers. We also note that the proposed trivariate probit model and how results on joint and conditional probabilities are computed and presented in this paper are generally applicable to joint analysis of any three binary decisions of the same individuals.

2. Data

A pooled set of data from the 1998 and 2001 National Drug Strategy Household Surveys (NDSHS, 2001) comprising more than 36,000 observations is used in this study. The NDSHS is a nationally representative survey of the non-institutionalised civilian population of Australia aged fourteen and above. Individuals are personally interviewed about their awareness and attitude to both licit and illicit drugs while more sensitive and confidential questions about personal drug usage are answered by means such as self-completion drop-and-collect method. While these surveys have been conducted in Australia since 1985, our study is restricted to the two most recent surveys due to unavailability of some drug prices prior to 1998.

Questions on drug usage in the surveys are in the form of multiple choices referring to the respondents' frequencies of drug consumption. Table 1 depicts these consumption frequencies for marijuana, cocaine and heroin across the two surveys. The users represent individuals who have consumed the respective drugs at least once in the year before the survey. As shown in Table 1, while on average around 15% of the surveyed individuals participated in marijuana use, only 1.5% and 0.5% of the respondents used cocaine and heroin respectively.

Note also that participation in heroin showed a significant decline from 1.3% in 1998 to 0.2% in 2001 reflecting decreases in all categories of users. This is most likely the result of the heroin drought experienced all over Australia in late 2000 and early 2001. Weatherburn *et al.* (2001) also found that the heroin drought led to sharp falls in heroin consumption and the number of heroin overdoses across NSW, and also prompted some heroin users to seek methadone treatment and others to consume more of other drugs. The Australian Bureau of Criminal Intelligence (ABCI, 2002) also suggested that the reduction in heroin use may also be the outcome of increased law enforcement efficiency that may have disrupted heroin importation networks and thus reduced heroin availability in the country.

Table 1: Drug Consumption Frequencies[a]

	1998		2001		Combined	
	N	%	N	%	N	%
Marijuana						
Abstainer	8181	*80.90*	23086	*87.23*	31267	*85.48*
Every few months or less	906	*8.96*	1613	*6.09*	2519	*6.89*
Once a month	267	*2.64*	430	*1.62*	697	*1.91*
Once a week or more	759	*7.51*	1337	*5.05*	2096	*5.73*
Total	**10113**	***100.00***	**26466**	***100.00***	**36579**	***100.00***
Cocaine						
Abstainer	9899	*98.00*	26141	*98.89*	36040	*98.65*
Every few months or less	191	*1.89*	252	*0.95*	443	*1.21*
Once a month	8	*0.08*	27	*0.10*	35	*0.10*
Once a week or more	3	*0.03*	14	*0.05*	17	*0.05*
Total	**10101**	***100.00***	**26434**	***100.00***	**36535**	***100.00***
Heroin						
Abstainer	9982	*98.71*	26376	*99.81*	36358	*99.50*
Every few months or less	112	*1.11*	21	*0.08*	133	*0.36*
Once a month	8	*0.08*	7	*0.03*	15	*0.04*
Once a week or more	10	*0.10*	23	*0.09*	33	*0.09*
Total	**10112**	***100.00***	**26427**	***100.00***	**36539**	***100.00***

[a] Based on data from NDSHS (2001). Missing observations are excluded in calculations.

Due to the relatively few observations of users for the two harder drugs, particularly that for heroin, our study will focus on the decision of participation rather than the frequency of use. Thus, the dependent variables $Y_j\ (j = M, C, H)$ in this study are dichotomous measures for participation in the use of marijuana, cocaine and heroin, taking the value one for all those who have used the respective drugs at least once in the past year and zero otherwise.

Table 2: Joint and Marginal Participation Probabilities[a]

	Joint Probability	Marginal (Marijuana)	Marginal (Cocaine)	Marginal (Heroin)
Marijuana only	13.23	13.23		
Cocaine only	0.17		0.17	
Heroin only	0.03			0.03
Marijuana and Cocaine only	0.87	0.87	0.87	
Marijuana and Heroin only	0.15	0.15		0.15
Cocaine and Heroin only	0.02		0.02	0.02
Marijuana, Cocaine and Heroin	0.30	0.30	0.30	0.30
None	85.23			
Total	100.00	14.55	1.35	0.50

[a] Measured as percentages of total respondents, based on data from NDSHS (2001). Missing observations are excluded in calculations.

Based on the pooled sample data, the joint and marginal frequency distributions of participation are compiled in Table 2. As mentioned above, the rate of participation in marijuana is relatively higher (14.6%) than those of cocaine (1.4%) and heroin (0.5%). While these proportions appear small, when translated to the Australian population of around 15 million aged fourteen and over, they represent about 2 million marijuana users, 200,000 cocaine users and 74,000 heroin users.

While the marginal probabilities are useful, the conditional probabilities of participation given in Table 3 indicate how the consumptions of the three illicit drugs are related. For instance, among those who consume heroin, 90.1% use marijuana and 63.5% use cocaine, much higher than the unconditional probabilities of 14.6% and 1.4% respectively. As high as 86% of cocaine users consume marijuana and 23.3% of them use heroin. Among those who consume cocaine and heroin jointly, 94.8% are marijuana users. Thus, we see that the chance of an individual participating in a particular drug is much higher if he/she is known to be taking other drug(s). These sample statistics indicate strong correlation across the three drugs. A formal econometric model will allow the estimation of conditional correlations after observable explanatory factors are controlled.

Table 3: Sample Participation Probabilities[a]

	Marijuana	Cocaine	Heroin
P(.)	14.55	1.35	0.50
$P(.\|Y_M = 1)$	100.00	8.03	3.07
$P(.\|Y_C = 1)$	86.23	100.00	23.28
$P(.\|Y_H = 1)$	90.06	63.54	100.00
$P(.\|Y_C = 1, Y_H = 1)$	94.78	100.00	100.00
$P(.\|Y_M = 1, Y_H = 1)$	100.00	66.87	100.00
$P(.\|Y_M = 1, Y_C = 1)$	100.00	100.00	25.59

[a] Probabilities are calculated from Table 2.

Price series for marijuana, cocaine and heroin for individual years and states/territories are obtained mostly from the Illicit Drug Reporting System (IDRS, 2003). They correspond to prices per ounce of marijuana and per gram of cocaine and heroin. The IDRS drug prices are collected from interviewing injecting drug users and key informants who have regular contacts with illicit drug users. In occasional cases where a price report is missing for a particular state, we have constructed the price using information from the Australian Bureau of Criminal Intelligence (ABCI, 2002). The ABCI (2002) is an alternative source for drug prices, with information supplied by covert police units and police informants. We have opted to use the price data from IDRS which are provided with unified measures and fewer missing observations. Consumer Price Indexes by states for all groups come from the Australian Bureau of Statistics (ABS 2003) and are used to deflate all three price series as well as personal incomes of individuals.

In addition to information on drug use, the NDSHSs also contain details on personal characteristics of respondents such as gender, marital status, educational attainment, occupational status, household structure, income, etc. These are potential explanatory variables in the econometric model to account for heterogeneity in participation decisions. Details on definition of variables and sample statistics are outlined in the Appendix.

Table 4 highlights some cross statistics that provide information on how the participation in marijuana, cocaine and heroin relate to the various demographic groups. These figures represent proportions of individuals who consume the respective drugs in each population group. It appears that males are more likely to consume all three drugs than females. Single individuals have much higher chances of consuming all drugs than those who are married. In terms of main activity, the highest proportions of marijuana or heroin use are recorded for the unemployed individuals, followed by those whose main activity is studying. In fact, the highest proportion of cocaine use is observed in the student group. In terms of educational attainment, it appears that those with year-12 qualifications are more likely to use drugs than those with higher qualifications or those with less than year-12 qualifications.

Also noted is that Aboriginals/Torres Strait Islanders (ATSI) have almost twice the chances of using the drugs than non-aboriginals. Those who have pre-school children in the household have lower chances of using these drugs than the rest. However, in terms of household structure, single parents with dependent children have much higher chances to consume the three drugs than the rest. Correlation with personal income is not straightforward from the sample statistics. Marijuana use is highest among the low and middle income earners, while heroin prevalence is highest in low income or higher-middle income earners. Cocaine prevalence seems to fluctuate between one and two percent, with the highest percentages observed among middle and very high income earners.

Table 4: Observed Participation Proportions by User Type[a]

	Marijuana	Cocaine	Heroin
MALE	17.14	1.61	0.57
FEMALE	12.42	1.15	0.43
MARRIED	8.61	0.68	0.25
SINGLE	28.37	3.05	1.04
WORK	16.43	1.74	0.45
STUDY	24.93	2.05	0.68
UNEMPL	28.80	1.60	1.52
OTHERACT	5.87	0.40	0.39
DEGREE	13.35	1.76	0.33
DIPLOMA	14.49	1.38	0.36
YR12	19.14	1.79	0.75
LESSYR12	12.27	0.73	0.55
PRESCHOOL	12.98	1.27	0.32
NO-PRESCHOOL	14.75	1.36	0.52
ATSI	26.45	2.20	1.10
NON-ATSI	14.30	1.34	0.48
CAPITAL	15.57	1.70	0.57
NON-CAPITAL	12.09	0.54	0.33
SIN-PARENT	25.42	1.82	1.20
OTHERHHLD	13.72	1.32	0.44
INCOME:			
$0-$9,999	14.78	0.99	0.65
$10,000-$19,999	16.60	1.38	0.34
$20,000-$29,999	17.56	1.94	0.52
$30,000-$39,999	14.40	1.98	0.32
$40,000-$49,000	14.21	1.02	0.76
$50,000-$59,000	12.34	1.26	0.21
$60,000 or more	11.49	1.92	0.14

[a] Percentage of participation out of total for each demographic group.

3. The Multivariate Probit Model for Illicit Drug Participation

We assume that there is an underlying latent propensity variable Y_j^* (where $Y_j^* \subset (-\infty, \infty)$) that is proportional to the unobserved level of demand for each of the three illicit drugs j $(j = M, C, H)$. The latent demand is determined by:

$$Y_j^* = X_j'\beta_j + \varepsilon_j \qquad (j = M, C, H), \tag{1}$$

where X_j represents a vector of observed personal characteristics and other economic variables that affect the consumption of drug j, β_j is a vector of unknown parameters, and ε_j is the error term. Equation (1) is mapped to an observable binary discrete variable Y_j indicating whether or not an individual consumes a particular drug:

$$Y_j = \begin{cases} 1 & \text{if } Y_j^* > 0 \\ 0 & \text{if } Y_j^* \le 0 \end{cases} \qquad (j = M, C, H). \tag{2}$$

If we assume that ε_j $(j = M, C, H)$ are independently and identically distributed with a standard normal distribution, equations (1) and (2) define three univariate probit (UVP) models. The assumption of independent error terms in the UVP means that information about an individual's participation in one drug does not alter the prediction of the participation probability of the same person for another drug.

A more general specification is to assume that the error terms in the three latent equations in (1) jointly follow a multivariate normal distribution, that is, $(\varepsilon_M, \varepsilon_C, \varepsilon_H)' \sim MVN(\underline{0}, \Sigma)$, where the variance-covariance matrix Σ is given by

$$\Sigma = \begin{pmatrix} 1 & \rho_{MC} & \rho_{MH} \\ \rho_{MC} & 1 & \rho_{CH} \\ \rho_{MH} & \rho_{CH} & 1 \end{pmatrix}, \tag{3}$$

and where ρ_{ij} is the correlation coefficient of ε_i and ε_j $(i, j = M, C, H;\ i \ne j)$. Under this assumption, equations (1) and (2) give a multivariate probit (MVP) model that jointly represents the participation decisions for the three drugs. The MVP specification with potentially non-zero off-diagonal elements in Σ allows for correlations across the disturbances of the three latent equations, which embody unobserved characteristics for the same individuals. While the MVP model has the UVP as a special case, it now allows for the knowledge on an individual's participation in one drug to help predicting his/her probability of participating in a related drug. Note that the assumption of unit variance for ε_j ensures that the β_j parameters can be identified separately from the variance of ε_j $(j = M, C, H)$.

The univariate marginal probability for participation in each drug is given:

$$P(Y_j = 1 \mid X_j) = \Phi_1(X_j^{'}\beta_j) \qquad (j = M, C, H), \tag{4}$$

where $\Phi_1(.)$ is the cumulative univariate distribution function for standard normal distribution.

The bivariate joint probabilities are given by $(i, j = M, C, H; i \neq j)$:

$$\begin{aligned}
&P(Y_i = 1, Y_j = 1 \mid X_i, X_j) = \Phi_2(X_i^{'}\beta_i, X_j^{'}\beta_j; \rho_{ij}),\\
&P(Y_i = 1, Y_j = 0 \mid X_i, X_j) = \Phi_2(X_i^{'}\beta_i, -X_j^{'}\beta_j; -\rho_{ij}),\\
&P(Y_i = 0, Y_j = 0 \mid X_i, X_j) = \Phi_2(-X_i^{'}\beta_i, -X_j^{'}\beta_j; \rho_{ij}).
\end{aligned} \tag{5}$$

where $\Phi_2(z_1, z_2; \gamma_{12})$ denotes the cumulative distribution function of standard bivariate normal distribution with γ_{12} as the correlation coefficient between the two univariate random elements Z_1 and Z_2.

The multivariate joint probabilities are given by $(i, j, k = M, C, H; i \neq j, i \neq k; j \neq k)$:

$$\begin{aligned}
&P(Y_i = 1, Y_j = 1, Y_k = 1 \mid X_i, X_j, X_k) = \Phi_3(X_i^{'}\beta_i, X_j^{'}\beta_j, X_k^{'}\beta_k;\ \rho_{ij}, \rho_{ik}, \rho_{jk}),\\
&P(Y_i = 1, Y_j = 1, Y_k = 0 \mid X_i, X_j, X_k) = \Phi_3(X_i^{'}\beta_i, X_j^{'}\beta_j, -X_k^{'}\beta_k;\ \rho_{ij}, -\rho_{ik}, -\rho_{jk}),\\
&P(Y_i = 1, Y_j = 0, Y_k = 0 \mid X_i, X_j, X_k) = \Phi_3(X_i^{'}\beta_i, -X_j^{'}\beta_j, -X_k^{'}\beta_k; -\rho_{ij}, -\rho_{ik}, \rho_{jk}),\\
&P(Y_i = 0, Y_j = 0, Y_k = 0 \mid X_i, X_j, X_k) = \Phi_3(-X_i^{'}\beta_i, -X_j^{'}\beta_j, -X_k^{'}\beta_k;\ \rho_{ij}, \rho_{ik}, \rho_{jk}), \text{ etc.}
\end{aligned} \tag{6}$$

where $\Phi_3(z_1, z_2, z_3; \gamma_{12}, \gamma_{13}, \gamma_{23})$ denotes the cumulative distribution function of standard trivariate normal distribution with γ_{st} as the correlation coefficient between two of the three univariate random elements Z_s and Z_t $(s,t = 1,2,3; s \neq t)$.

Various conditional probabilities can also be similarly defined. Below are a few such conditional probabilities:

$$
\begin{aligned}
&P(Y_i = 1 \mid Y_j = 1, Y_k = 1; X_i, X_j, X_k) = \frac{\Phi_3(X_i'\beta_i, X_j'\beta_j, X_k'\beta_k; \rho_{ij}, \rho_{ik}, \rho_{jk})}{\Phi_2(X_j'\beta_j, X_k'\beta_k; \rho_{jk})}, \\
&P(Y_i = 1 \mid Y_j = 0, Y_k = 0; X_i, X_j, X_k) = \frac{\Phi_3(X_i'\beta_i, -X_j'\beta_j, -X_k'\beta_k; -\rho_{ij}, -\rho_{ik}, \rho_{jk})}{\Phi_2(-X_j'\beta_j, -X_k'\beta_k; \rho_{jk})}, \\
&P(Y_i = 0, Y_j = 0 \mid Y_k = 1; X_i, X_j, X_k) = \frac{\Phi_3(-X_i'\beta_i, -X_j'\beta_j, X_k'\beta_k; \rho_{ij}, -\rho_{ik}, -\rho_{jk})}{\Phi_1(X_k'\beta_k)}, \\
&P(Y_i = 1 \mid Y_j = 1; X_i, X_j) = \frac{\Phi_2(X_i'\beta_i, X_j'\beta_j; \rho_{ij})}{\Phi_1(X_j'\beta_j)}, \text{etc.}
\end{aligned}
\tag{7}
$$

Given an *i.i.d.* sample of *N* individuals and conditional on observed personal heterogeneity, the MVP model can be estimated by maximising the following log-likelihood function:

$$
\log(L) = \sum_{n=1}^{N} \sum_{i=0}^{1} \sum_{j=0}^{1} \sum_{k=0}^{1} h_n(i,j,k) \log(P(Y_M = i, Y_C = j, Y_H = k \mid X_{Mn}, X_{Cn}, X_{Hn})),
$$

where

$$
h_n(i,j,k) = \begin{cases} 1 & \text{if individual } n \text{ chooses } (Y_M = i, Y_C = j, Y_H = k) \\ 0 & \text{if otherwise.} \end{cases} \qquad (i,j,k = 0 \text{ or } 1).
$$

4. Results

4.1 Results on Marginal Probabilities

The MVP model is estimated using the pooled sample of around 36,000 individuals from the 1998 and 2001 NDSHS surveys. We have used the same set of explanatory variables for all three drug equations, so $X_M = X_C = X_H \equiv X$. Table 5 gives estimates of the multivariate probit model for marijuana, cocaine and heroin. Marginal effects (MEs) reported in this table correspond to those of univariate marginal probabilities. For each continuous explanatory variable the MEs relate to the absolute change in the unconditional probability of participation for a particular drug in response to a unit change in the explanatory variable, while for a dummy variable it represents the change in the probability when the dummy variable changes from 0 to 1, all evaluated at the sample means of the other explanatory variables[2]. Standard errors are reported in parentheses.

Table 5: Results of the MVP Model[a]

	Marijuana		Cocaine		Heroin	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
CONSTANT	-16.966 (1.088)**	-2.862 (0.153)**	-22.999 (2.771)**	-0.248 (0.026)**	-22.477 (5.314)**	-0.109 (0.022)**
PRH	0.162 (0.045)**	0.027 (0.009)**	-0.221 (0.112)**	-0.002 (0.001)**	0.048 (0.177)	0.000 (0.000)
PRC	0.233 (0.051)**	0.039 (0.013)**	0.032 (0.158)	0.000 (0.002)	0.081 (0.170)	0.000 (0.001)
PRM	-0.121 (0.079)	-0.020 (0.013)	0.387 (0.197)**	0.004 (0.002)*	0.757 (0.510)	0.004 (0.002)*
INCOME	0.038 (0.016)**	0.006 (0.001)**	0.153 (0.039)**	0.002 (0.000)**	-0.044 (0.060)	0.000 (0.000)
CAPITAL	0.020 (0.025)	0.003 (0.002)*	0.341 (0.064)**	0.004 (0.001)**	0.128 (0.093)	0.001 (0.000)
YR01	-0.065 (0.032)**	-0.011 (0.006)*	0.126 (0.075)*	0.001 (0.001)	-0.255 (0.163)	-0.001 (0.001)*
AGE	9.563 (0.555)**	1.614 (0.045)**	11.546 (1.387)**	0.125 (0.010)**	9.857 (2.303)*	0.048 (0.007)**
AGESQ	-1.550 (0.079)**	-0.261 (0.006)**	-1.809 (0.200)**	-0.020 (0.002)**	-1.499 (0.341)**	-0.007 (0.001)**
MALE	0.279 (0.022)**	0.047 (0.002)**	0.113 (0.046)**	0.001 (0.000)**	0.222 (0.083)**	0.001 (0.000)**
MARRIED	-0.410 (0.025)**	-0.069 (0.004)**	-0.457 (0.057)**	-0.005 (0.001)**	-0.418 (0.094)**	-0.002 (0.001)**
WORK	-0.047 (0.037)	-0.008 (0.005)*	0.014 (0.094)	0.000 (0.001)	-0.236 (0.118)**	-0.001 (0.000)**
STUDY	-0.051 (0.046)	-0.009 (0.009)	0.134 (0.104)	0.001 (0.001)	-0.268 (0.129)**	-0.001 (0.000)**
UNEMP	0.290 (0.058)**	0.049 (0.004)**	0.058 (0.138)	0.001 (0.002)	0.036 (0.150)	0.000 (0.001)
PRESCHOOL	-0.106 (0.031)**	-0.018 (0.005)**	-0.122 (0.073)*	-0.001 (0.001)*	0.111 (0.111)	0.001 (0.000)
ATSI	0.208 (0.072)**	0.035 (0.018)*	0.108 (0.171)	0.001 (0.002)	-0.101 (0.303)	0.000 (0.002)
DEGREE	-0.080 (0.034)**	-0.013 (0.005)**	0.020 (0.074)	0.000 (0.001)	-0.403 (0.115)**	-0.002 (0.000)**
DIPLOMA	0.033 (0.031)	0.006 (0.004)	0.051 (0.070)	0.001 (0.001)	-0.287 (0.095)**	-0.001 (0.000)**
YR12	0.008 (0.032)	0.001 (0.004)	-0.001 (0.072)	0.000 (0.001)	-0.235 (0.097)**	-0.001 (0.000)**
SIN-PARENT	0.133 (0.038)**	0.023 (0.010)**	-0.027 (0.082)	0.000 (0.001)	0.178 (0.096)*	0.001 (0.000)**
ρ_{MC}	0.651 (0.023)**					
ρ_{MH}	0.590 (0.044)**					
ρ_{CH}	0.835 (0.026)**					

[2] Alternatively, we can compute the average MEs over all individuals. Harris et al. (2004) estimated MEs for a different discrete choice model using both approaches and found that the difference between them was trivial.

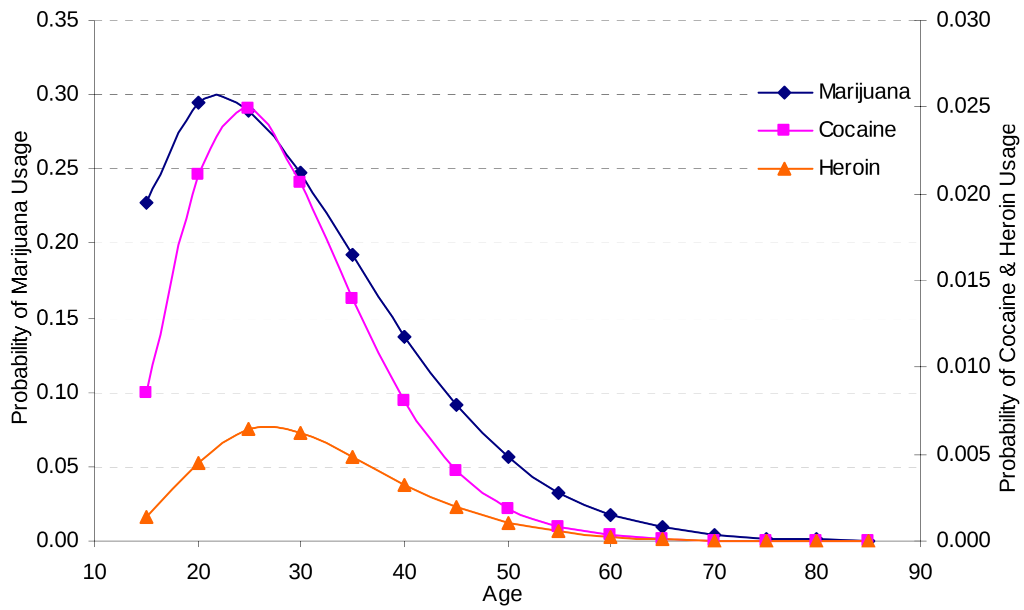
a. Standard errors are given in parentheses. * indicates significance at 10% level. **indicates significance at 5% level.

The last three rows of Table 5 show the estimated correlation coefficients ρ_{ij}'s $(i, j = M, C, H; i \neq j)$. As expected, after accounting for impacts of observable individual heterogeneity and economic factors, there still remains a strong positive correlation among the participation decisions of the three drugs for the same individual. This correlation is likely to be induced by unobservable personal characteristics such as taste and addiction that have similar effects on individuals' consumption of the three drugs. All three correlation coefficients are statistically significant at the 1% level. This suggests that the null hypothesis of three UVP models, or the hypothesis of independence across the error terms of the three latent equations, can be rejected, and the MVP model is a better model for the observed data. In particular, a correlation coefficient of 0.65 is estimated between the error terms for marijuana and cocaine, 0.59 between those for marijuana and heroin, and the highest correlation of 0.84 is observed between cocaine and heroin. It appears that being hard drugs, cocaine and heroin are more strongly related in consumption.

Turning to the effects of observed explanatory factors, we start with the impacts of personal characteristics. The knowledge of the vulnerable population segments for drugs can be useful to policy makers in designing effective anti-drug programs. Prior studies have shown that participation probabilities for recreational drugs are highest among young adults as compared to teenagers and elderly people. To allow for this non-linear relationship, we have entered a "squared" variable for age in the model. In all three equations, we obtain significant effects for both the linear and quadratic age terms. To illustrate the combined effect of the two age-related variables we estimate participation probabilities for a range of different age values as plotted in Figure 1, holding all other explanatory variables fixed at mean values. In particular, holding other factors at the same values, we find that the highest rate of participation for marijuana is predicted among users who are in their early twenties. Cocaine is more popular among individuals who are in their mid-twenties, while the highest participation in heroin usage is observed among users in their late twenties. Overall, individuals in the age group 20-30 years are mostly likely to be drug users.

Looking at the marginal effects of other demographic factors, other factors being constant, we find that males are 4.7% more likely to use marijuana and 0.1% more likely to engage in cocaine or heroin consumption than females. As compared to single individuals, married or partnered individuals are 6.9%, 0.5% and 0.2% less likely to use marijuana, cocaine and heroin respectively. With respect to individuals' main occupation, relative to the group of individuals who are pensioners or retired or who mainly perform home duties ('OTHERACT'=1), it appears that those who work have 0.8% and 0.1% less chances to consume marijuana and heroin respectively, those who study are 0.1% less likely to consume heroin, and those who are unemployed have 4.9% more chances of engaging in marijuana consumption. Controlling for all other factors, it appears that main activity of individuals has no significant partial effect on cocaine consumption.

Figure 1: Participation Probabilities by Age



The presence of pre-school children in the household decreases the chances of consuming marijuana and cocaine by 1.8% and 0.1% respectively. Aboriginals/Torres Strait Islanders (ATSI) have 3.5% higher chances of using marijuana than non-aboriginals. Those living in capital cities have 0.3% and 0.4% more chances in participating in marijuana and cocaine consumption respectively. While there appears to be no correlation between education and the use of cocaine, those who hold a degree have 1.3% less chances of using marijuana than those with less than year-12 education. As for heroin, it appears that all other education groups are significantly less likely to participate than the less than year-12 group. In particular, degree holders are 0.2% less likely and those with a diploma or year-12 have 0.1% less chances to use heroin than those in the lowest education band. People who did not finish year-12 seem to be the most vulnerable group for heroin. Finally, being a single parent increases the chances of using marijuana and heroin by 2.3% and 0.1% respectively. The predicted probabilities for some of the demographic groups, holding other factors at mean values, are illustrated in Figures 2-4.

In terms of personal income, we find that at the 5% significance level, it is positively related to marijuana and cocaine participation when other factors are held constant. In particular, a 10% increase in income on average seems to increase the participation probabilities for marijuana and cocaine by 0.06 and 0.02 percentage points respectively. For a total population of 15 million aged 14 and above in Australia, these marginal effects translate into about 9,500 and 2,500 more marijuana and cocaine users respectively. However, we do not observe any significant effect of income on heroin usage.

Finally, the drug price effects indicate that neither cocaine nor heroin participation is responsive to their own prices, while there appears to be some evidence (with a *p*-value of 0.13) of own price response for marijuana. To the extent the price data are representative of the true drug prices facing each individual, the cross price results provide some indication about the economic relationships across the drugs. In particular, we find that marijuana demand seems to respond to changes in the prices of harder drugs, such that a 10% increase in the respective prices of cocaine and heroin increases the prevalence of marijuana use by 0.39 and 0.27 percentage points. However, there seems to be only weak evidence that an increase in the price of marijuana will lead to an increased participation in cocaine and heroin usage. Lastly, we find that an increase in the price of heroin decreases the participation probability for cocaine. However, we recognise the lack of variation in our price data, given that they vary by years and states, and deem individual level prices more appropriate.

Figure 2. Predicted Probabilities by Groups - Marijuana

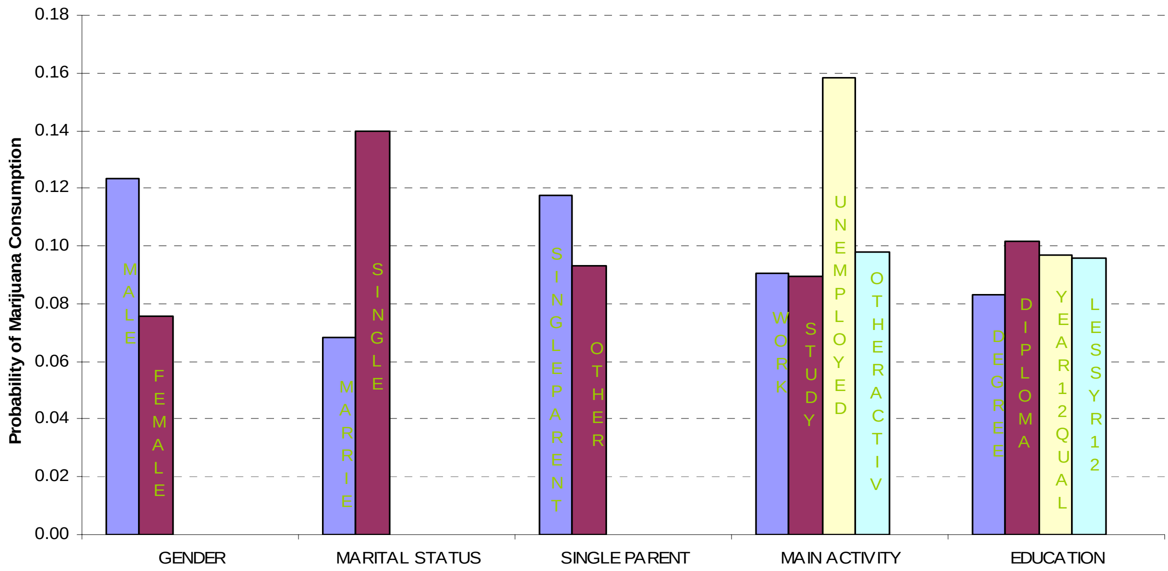


Figure 3. Predicted Probabilities by Groups - Cocaine

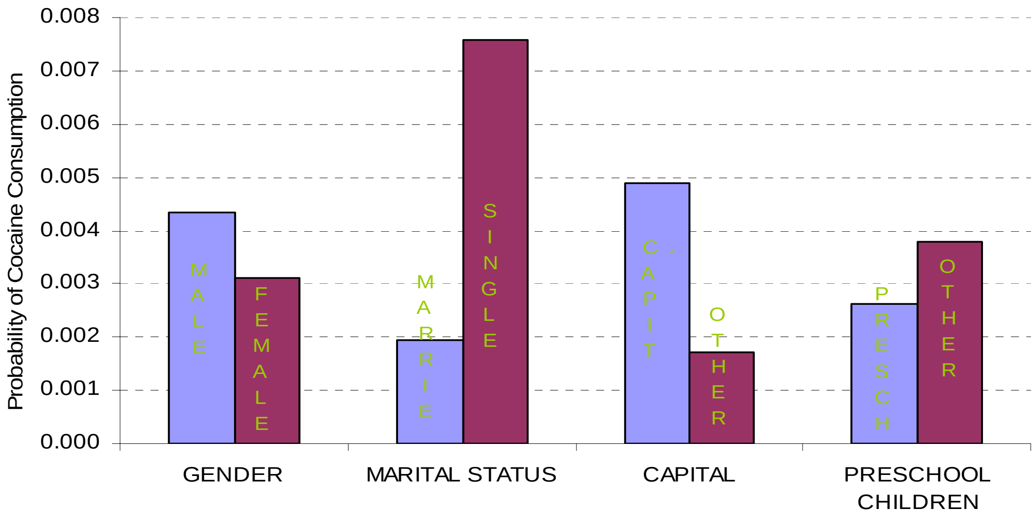
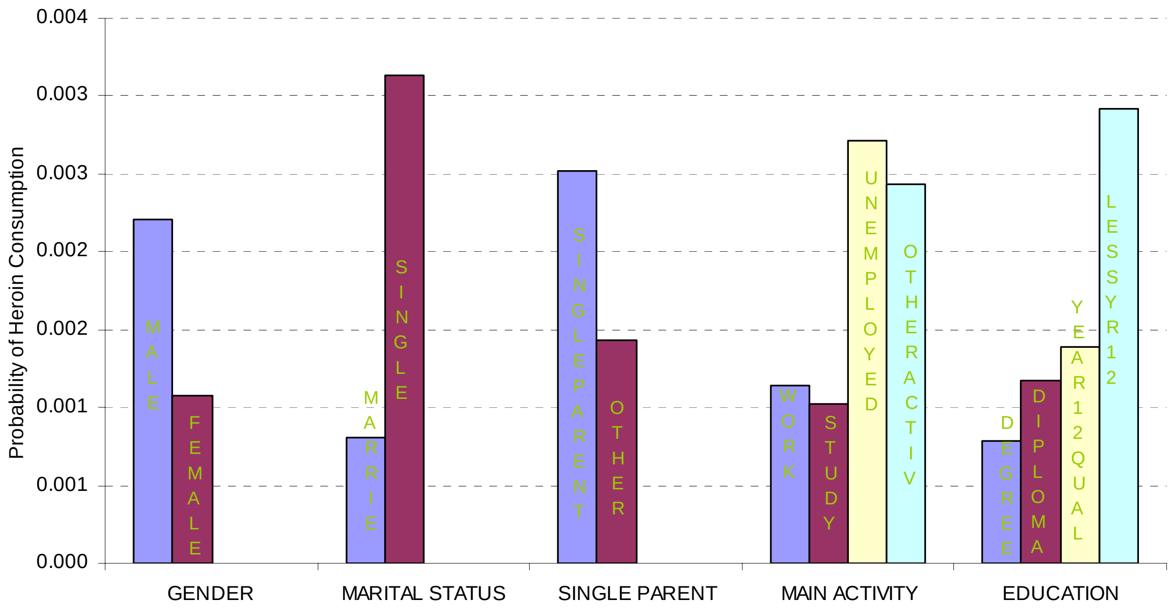


Figure 4. Predicted Probabilities for Groups - Heroin



4.2 Results on Joint and Conditional Probabilities

Now we turn to the multivariate part of the analysis. One advantage of the multivariate probit (MVP) model over the univariate probit (UVP) model is that it allows us to evaluate joint and conditional probabilities taking into account the correlation across the three participation decisions. Given the high and significant correlation coefficients ρ's estimated, some probabilities predicted by the MVP are expected to be substantially different from those predicted by the UVP. To illustrate such differences, we estimate the UVP models restricting the correlation coefficients ρ's to be zero. Using each set of the UVP and MVP results, we calculate some predicted joint, conditional and marginal probabilities which are presented in Table 6. These probabilities are evaluated at the mean values of the explanatory variables and in loose terms correspond to an 'average' Australian.

Table 6: Predicted Probabilities[a]

	Marijuana			Cocaine	
	MVP	**UVP**		**MVP**	**UVP**
$P(Y_M = 1 \| \bar{X})$	0.0948	0.0950	$P(Y_C = 1 \| \bar{X})$	0.0036	0.0043
	(0.0025)	(0.0083)		(0.0006)	(0.0006)
$P(Y_M = 1 \| Y_C = 0, Y_H = 0, \bar{X})$	0.0918	0.0950	$P(Y_C = 1 \| Y_M = 0, Y_H = 0, \bar{X})$	0.0007	0.0043
	(0.0027)	(0.0083)		(0.0002)	(0.0006)
$P(Y_M = 1 \| Y_C = 1, Y_H = 1, \bar{X})$	0.8697	0.0950	$P(Y_C = 1 \| Y_M = 1, Y_H = 1, \bar{X})$	0.5692	0.0043
	(0.0087)	(0.0083)		(0.0598)	(0.0006)
$P(Y_M = 1 \| Y_C = 1, \bar{X})$	0.7943	0.0950	$P(Y_C = 1 \| Y_M = 1, \bar{X})$	0.0302	0.0043
	(0.0119)	(0.0083)		(0.0040)	(0.0006)
$P(Y_M = 1 \| Y_H = 1, \bar{X})$	0.7785	0.0950	$P(Y_C = 1 \| Y_H = 1, \bar{X})$	0.5095	0.0043
	(0.0204)	(0.0083)		(0.0582)	(0.0006)
	Heroin			**Joint**	
	MVP	**UVP**		**MVP**	**UVP**
$P(Y_H = 1 \| \bar{X})$	0.0015	0.0016	$P(Y_M = 1, Y_C = 1, Y_H = 1 \| \bar{X})$	0.0007	0.0000
	(0.0005)	(0.0003)		(0.0001)	(0.0000)
$P(Y_H = 1 \| Y_M = 0, Y_C = 0, \bar{X})$	0.0003	0.0016	$P(Y_M = 0, Y_C = 0, Y_H = 0 \| \bar{X})$	0.9043	0.8997
	(0.0001)	(0.0003)		(0.0029)	(0.0083)
$P(Y_H = 1 \| Y_M = 1, Y_C = 1, \bar{X})$	0.2308	0.0016	$P(Y_M = 1, Y_C = 0, Y_H = 0 \| \bar{X})$	0.0919	0.0945
	(0.0537)	(0.0003)		(0.0028)	(0.0083)
$P(Y_H = 1 \| Y_M = 1, \bar{X})$	0.0122	0.0016	$P(Y_M = 0, Y_C = 1, Y_H = 0 \| \bar{X})$	0.0007	0.0039
	(0.0037)	(0.0003)		(0.0002)	(0.0006)
$P(Y_H = 1 \| Y_C = 1, \bar{X})$	0.2108	0.0016	$P(Y_M = 0, Y_C = 0, Y_H = 1 \| \bar{X})$	0.0002	0.0014
	(0.0469)	(0.0003)		(0.0001)	(0.0003)

[a] Probabilities calculated at sample means of explanatory variables.

As shown in Table 6, with the UVP model, conditional and unconditional probabilities are exactly the same given that participation decisions for the various drugs are independent. For instance, even if an individual is known to be participating in both cocaine and heroin, his/her probability for marijuana usage will be predicted by the UVP model as 9.5%, same as that if the extra information is not available. However, taking into account the cross-equation correlations, the individual's marijuana participation probability is predicted by the MVP model as high as 87%. Also, if an individual is known to be a heroin user, his/her participation probability for cocaine is predicted to be 51% by the MVP model as against 0.4% by the UVP model. Using the UVP model, whether or not an individual is known to be engaged in other drugs' consumption, his/her probability of heroin consumption is predicted as 0.2%. However, given that an individual consumes both cocaine and marijuana, his chances of being a heroin user is higher at 23% using the MVP model. Similarly, joint probabilities in the UVP model are obtained from multiplying the relevant marginal probabilities, ignoring the positive links across uses of different drugs. Once the association of the various choices are taken into account in the MVP, the predicted joint probabilities for participating in all three drugs as well as for abstaining from all three drugs are higher than those from the UVP.

To further highlight the extra insight provided by the MVP model, we show in Tables 7(I)-(III) that the marginal effects of an explanatory factor can also be very different on conditional and unconditional probabilities. Marginal effects on some conditional and unconditional probabilities of all explanatory variables are presented in Tables 7(I)-(III), with standard errors of the marginal effects presented in the parentheses. It is interesting to see how the signs, the magnitudes, and the statistical significance levels of the marginal effects for unconditional participation probabilities can differ significantly from those of the conditional participation probabilities when an individual is known to be consuming or abstaining from other drugs. If the UVP model is used, all the marginal effects in each row will be the same.

For instance, from Table 7(I) we see that there are marked differences in the marginal effects of some demographic factors on marijuana participation probabilities. Other factors being equal, males are 4.7% more likely to use marijuana than females, but among the cocaine users, males are 7.7% more likely to use marijuana. Unemployed individuals are about 5% more likely to participate in marijuana consumption than the group of retirees, pensioners or homemakers in general, but among the harder drug users, they are about 10% more likely to use marijuana. In addition, while an increase in the price of marijuana appears to have less significant effect on the unconditional probability of marijuana participation, it does however have more significant effects in reducing the conditional probabilities for marijuana for individuals who consume other drugs.

Table 7(I): Marginal Effects on Selected Probabilities - Marijuana

	P(M=1)		P(M=1|C=0,H=0)		P(M=1|C=1,H=1)		P(M=1|C=1)		P(M=1|H=1)	
	ME	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**
Constant	-2.862	(0.153)**	-2.667	(0.173)**	-0.713	(0.544)	-1.096	(0.728)	-1.604	(1.200)
PRH	0.027	(0.009)**	0.028	(0.008)**	0.064	(0.020)**	0.109	(0.027)**	0.049	(0.038)
PRC	0.039	(0.013)**	0.039	(0.010)**	0.055	(0.024)**	0.078	(0.035)**	0.068	(0.038)*
PRM	-0.020	(0.013)	-0.024	(0.014)*	-0.126	(0.047)**	-0.131	(0.048)**	-0.198	(0.105)*
INCOME	0.006	(0.001)**	0.006	(0.003)**	-0.002	(0.007)	-0.020	(0.010)**	0.023	(0.013)*
CAPITAL	0.003	(0.002)*	0.001	(0.004)	-0.038	(0.011)**	-0.069	(0.016)**	-0.019	(0.020)
YR01	-0.011	(0.006)*	-0.011	(0.006)**	-0.013	(0.017)	-0.052	(0.018)**	0.028	(0.035)
AGE	1.614	(0.045)**	1.517	(0.085)**	0.743	(0.268)**	0.934	(0.362)**	1.477	(0.570)**

AGESQ	-0.261	(0.006)**	-0.246	(0.012)**	-0.134	(0.040)**	-0.165	(0.053)**	-0.259	(0.086)**
MALE	0.047	(0.002)**	0.046	(0.004)**	0.049	(0.010)**	0.077	(0.012)**	0.056	(0.018)**
MARRIED	-0.069	(0.004)**	-0.065	(0.004)**	-0.036	(0.011)**	-0.049	(0.014)**	-0.064	(0.022)**
WORK	-0.008	(0.005)*	-0.008	(0.006)	0.002	(0.015)	-0.020	(0.022)	0.031	(0.026)
STUDY	-0.009	(0.009)	-0.009	(0.008)	-0.009	(0.018)	-0.048	(0.025)*	0.036	(0.028)
UNEMP	0.049	(0.004)**	0.048	(0.009)**	0.071	(0.024)**	0.094	(0.035)**	0.098	(0.033)**
PRESCHOOL	-0.018	(0.005)**	-0.017	(0.005)**	-0.024	(0.013)*	-0.012	(0.017)	-0.061	(0.024)**
ATSI	0.035	(0.018)*	0.034	(0.013)**	0.053	(0.031)*	0.052	(0.042)	0.096	(0.064)
DEGREE	-0.013	(0.005)**	-0.013	(0.006)**	0.004	(0.014)	-0.034	(0.018)*	0.053	(0.026)**
DIPLOMA	0.006	(0.004)	0.006	(0.005)	0.024	(0.013)*	0.001	(0.017)	0.070	(0.023)**
YR12	0.001	(0.004)	0.002	(0.006)	0.019	(0.013)	0.003	(0.018)	0.051	(0.022)**
SIN-PARENT	0.023	(0.010)**	0.022	(0.006)**	0.027	(0.014)*	0.055	(0.020)**	0.012	(0.022)

Standard errors are given in parentheses. * indicates significance at 10% level. **indicates significance at 5% level.

Table 7(II): Marginal Effects on Selected Probabilities - Cocaine

	P(C=1)		P(C=1|M=0,H=0)		P(C=1|M=1,H=1)		P(C=1|M=1)		P(C=1|H=1)	
	ME	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**
Constant	-0.248	(0.026)**	-0.046	(0.010)**	-3.448	(3.027)	-1.209	(0.193)**	-3.719	(3.135)
PRP	-0.002	(0.001)**	-0.001	(0.000)**	-0.189	(0.092)**	-0.025	(0.009)**	-0.174	(0.100)*
PRC	0.000	(0.002)	0.000	(0.001)	-0.038	(0.118)	-0.007	(0.011)	-0.021	(0.114)
PRM	0.004	(0.002)*	0.001	(0.001)	-0.089	(0.255)	0.037	(0.016)**	-0.136	(0.275)
INCOME	0.002	(0.000)**	0.000	(0.000)**	0.123	(0.033)**	0.011	(0.004)**	0.126	(0.038)**
CAPITAL	0.004	(0.001)**	0.001	(0.000)**	0.170	(0.055)**	0.027	(0.006)**	0.162	(0.055)**
YR01	0.001	(0.001)	0.001	(0.000)**	0.215	(0.082)**	0.013	(0.006)**	0.219	(0.090)**
AGE	0.125	(0.010)**	0.022	(0.004)**	2.326	(1.381)*	0.565	(0.094)**	2.613	(1.401)*
AGESQ	-0.020	(0.002)**	-0.003	(0.001)**	-0.382	(0.206)*	-0.087	(0.013)**	-0.433	(0.207)**
MALE	0.001	(0.000)**	0.000	(0.000)	-0.054	(0.044)	-0.002	(0.004)	-0.040	(0.044)
MARRIED	-0.005	(0.001)**	-0.001	(0.000)**	-0.076	(0.055)	-0.021	(0.005)**	-0.089	(0.055)*
WORK	0.000	(0.001)	0.000	(0.000)	0.127	(0.077)*	0.003	(0.008)	0.133	(0.078)*
STUDY	0.001	(0.001)	0.001	(0.000)	0.225	(0.078)**	0.013	(0.008)	0.230	(0.085)**
UNEMP	0.001	(0.002)	0.000	(0.000)	-0.003	(0.095)	-0.007	(0.012)	0.020	(0.096)
PRESCHOOL	-0.001	(0.001)*	0.000	(0.000)	-0.127	(0.063)**	-0.006	(0.006)	-0.140	(0.064)**
ATSI	0.001	(0.002)	0.000	(0.001)	0.105	(0.187)	0.001	(0.014)	0.126	(0.204)
DEGREE	0.000	(0.001)	0.000	(0.000)	0.215	(0.062)**	0.005	(0.006)	0.225	(0.066)**
DIPLOMA	0.001	(0.001)	0.000	(0.000)	0.170	(0.057)**	0.003	(0.005)	0.184	(0.058)**
YR12	0.000	(0.001)	0.000	(0.000)	0.112	(0.055)**	0.000	(0.006)	0.122	(0.060)**
SIN-PARENT	0.000	(0.001)	0.000	(0.000)	-0.116	(0.058)**	-0.008	(0.007)	-0.111	(0.060)*

Standard errors are given in parentheses. * indicates significance at 10% level. **indicates significance at 5% level.

From Table 7(II), we also see that those who are married or partnered have 0.5% less chances of consuming cocaine than single individuals, but are 0.1% less likely to do so if they are abstainers of other drugs and 7.6% less likely to do so if they use both of other two drugs. Other factors controlled, individuals who study have as much chances to use cocaine as the base group of retirees, pensioners and homemakers but are about 23% more likely to do so given that they consume marijuana and heroin. In Table 7(III), we see that while educational attainment seems to have only negligible effect on heroin consumption, holders of a degree, diploma and year-12 qualifications are, respectively, 20%, 16% and 12% less likely to use heroin than the less than year-12 educated individuals among those who consume both marijuana and cocaine.

Table 7(III): Marginal Effects on Selected Probabilities - Heroin

	P(H=1)		P(H=1|M=0,C=0)		P(H=1|M=1,C=1)		P(H=1|M=1)		P(H=1|C=1)	
	ME	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**	**ME**	**SE**
Constant	-0.109	(0.022)**	-0.017	(0.006)**	-2.548	(2.510)	-0.551	(0.154)**	-2.445	(2.420)
PRH	0.000	(0.000)	0.000	(0.000)	0.095	(0.082)	-0.001	(0.007)	0.101	(0.078)
PRC	0.000	(0.001)	0.000	(0.000)	0.021	(0.083)	-0.001	(0.007)	0.027	(0.081)
PRM	0.004	(0.002)*	0.001	(0.001)	0.245	(0.233)	0.030	(0.019)	0.219	(0.234)
INCOME	0.000	(0.000)	0.000	(0.000)	-0.076	(0.031)**	-0.002	(0.002)	-0.075	(0.028)**
CAPITAL	0.001	(0.000)	0.000	(0.000)	-0.056	(0.048)	0.004	(0.004)	-0.060	(0.047)
YR01	-0.001	(0.001)*	0.000	(0.000)	-0.168	(0.086)**	-0.008	(0.007)	-0.164	(0.084)**
AGE	0.048	(0.007)**	0.006	(0.003)**	0.536	(1.135)	0.208	(0.073)**	0.557	(1.091)
AGESQ	-0.007	(0.001)**	-0.001	(0.000)**	-0.060	(0.172)	-0.030	(0.011)**	-0.066	(0.163)
MALE	0.001	(0.000)**	0.000	(0.000)	0.061	(0.044)	0.004	(0.003)	0.065	(0.039)*
MARRIED	-0.002	(0.001)**	0.000	(0.000)*	-0.034	(0.045)	-0.009	(0.004)**	-0.035	(0.046)
WORK	-0.001	(0.000)**	0.000	(0.000)	-0.120	(0.068)*	-0.008	(0.005)	-0.116	(0.066)*
STUDY	-0.001	(0.000)**	0.000	(0.000)	-0.178	(0.070)**	-0.009	(0.005)*	-0.173	(0.073)**
UNEMP	0.000	(0.001)	0.000	(0.000)	-0.012	(0.075)	-0.003	(0.006)	-0.004	(0.072)
PRESCHOOL	0.001	(0.000)	0.000	(0.000)	0.101	(0.057)*	0.006	(0.005)	0.095	(0.052)*
ATSI	0.000	(0.002)	0.000	(0.000)	-0.095	(0.153)	-0.007	(0.012)	-0.086	(0.167)
DEGREE	-0.002	(0.000)**	0.000	(0.000)**	-0.204	(0.061)**	-0.013	(0.005)**	-0.196	(0.056)**
DIPLOMA	-0.001	(0.000)**	0.000	(0.000)*	-0.161	(0.052)**	-0.011	(0.004)**	-0.153	(0.053)**
YR12	-0.001	(0.000)**	0.000	(0.000)*	-0.117	(0.049)**	-0.009	(0.004)**	-0.110	(0.045)**
SIN-PARENT	0.001	(0.000)**	0.000	(0.000)	0.093	(0.049)*	0.004	(0.004)	0.093	(0.047)**

Standard errors are given in parentheses. * indicates significance at 10% level. **indicates significance at 5% level.

Finally, as a technical note, the standard errors for the predicted probabilities and marginal effects presented in the brackets in Tables 6 and 7(I)-(III) are calculated using simulation and numerical gradients. As presented in the model section, conditional and joint probabilities are highly non-linear in both parameters and *X* variables, which prevent tractable analytical solution of marginal effects and standard errors. In particular, for the case of standard errors for the marginal effects on various joint and conditional probabilities, we simulate 500 sets of parameters $\Theta = (\beta'_M, \beta'_C, \beta'_H, \rho_{MC}, \rho_{MH}, \rho_{CH})'$ from an asymptotic multivariate normal distribution, each time calculate the numerical derivatives of the probability with respect to the relevant *X* variables evaluated at the means of all covariates, and thereby obtain 500 sets of marginal effects. Sample standard errors are then calculated as estimates of the standard errors for the marginal effects.

5. Conclusions

We investigate factors that influence the consumption of marijuana, cocaine and heroin in Australia using unit-record data from national representative surveys involving more than 36,000 individuals. Recognising the potential association between the demands for the three closely related drugs due to unobserved personal characteristics such as taste and addictive personality, we estimate a multivariate probit (MVP) model where the three participation equations are jointly estimated as a system with correlated error terms. The estimated correlation coefficients between the three drugs are found to be very high and statistically significant. The highest correlation is found between the two harder drugs, cocaine and heroin, which are more similar in nature as compared to marijuana.

To highlight the advantages of the MVP model over the typically used univariate probit (UVP) model where correlations across drug equations are restricted to zero, we compare the predicted marginal, conditional and joint probabilities using the two approaches. The results show that the MVP model provides better predictions than the UVP model in terms of conditional and joint probabilities. The additional knowledge of an individual's participation (or abstention) in other drugs can significantly alter his or her probability of consuming a particular drug.

We also estimate the marginal effects of individual explanatory factors on marginal, joint and conditional probabilities. They shed important insights on the effects of prices and other demographic factors on participation probabilities when the user is known to be consuming or abstaining from related drugs. The results indicate that the marginal effect of a particular independent variable and their statistical significance can be very different for conditional and unconditional participation probabilities. These extra insights on cross commodity relationships provided by the MVP model are important to policy makers.

The study provides valuable empirical information on the consumer behaviour of illicit drugs. While there are a range of studies on legal recreational drugs, illegal drug studies are much fewer due to data scarcity. We investigate the effects of price, income and other demographic factors on the demand for all three drugs. While acknowledging potential lack of variation in the drug price data used, we find no significant own price responsiveness for cocaine and heroin but some weak evidence of own price response for marijuana. Interestingly, the negative own-price effect on marijuana participation is much larger and statistically significant among users of other drugs. We also find some significant cross-price effects on the demand for the three drugs. There is also some evidence of a positive income effect on the use of marijuana and cocaine. Additionally, participation in the consumption of the three drugs is shown to be related to social and demographic factors. Marijuana is most popular among young adults in their early twenties and, other factors being equal, is more likely to be consumed by individuals who are male, single, unemployed, aboriginals and single parents. Cocaine is more associated with individuals in their mid twenties, male, single and who reside in capital cities. The highest participation in heroin usage is observed among individuals in their late twenties, less educated, male, and single, while lower participation probability is found among individuals who work or study, other factors equal. The empirical application indicates that important cross-drug information will be lost using a univariate approach.

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Appendix

Table A-1 Definition of Variables

Y_M = 1 if consuming marijuana at least once in the year prior to survey, 0 otherwise.

Y_C = 1 if consuming cocaine at least once in the year prior to survey, 0 otherwise.

Y_H = 1 if consuming heroin at least once in the year prior to survey, 0 otherwise.

PRM = natural logarithm of real price for marijuana measured in dollars per ounce.

PRC = natural logarithm of real price for cocaine measured in dollars per gram.

PRH = natural logarithm of real price for heroin measured in dollars per gram.

INCOME = natural logarithm of real personal annual income before tax measured in thousands of Australian dollars.

YR01 =1 for year 2001, 0 otherwise

CAPITAL = If the respondent lives in a capital city, 0 otherwise

AGE = Natural logarithm of age of respondent

AGESQ = Square of AGE variable

MALE = 1 if male, 0 for female

MARRIED = 1 if married or *de facto*, 0 otherwise

WORK = 1 if mainly employed, 0 otherwise

STUDY = 1 if mainly study, 0 otherwise

UNEMP = 1 if mainly unemployed, 0 otherwise

OTHERACT = 1 if retired, on pension or home duty, 0 otherwise (used as the reference category)

ATSI = 1 if respondent is of Aboriginal or Torres Strait Islander origin, 0 otherwise

PRESCHOOL = 1 if the respondent had pre-school child/children in the household, 0 otherwise.

DEGREE = 1 if highest qualification is a tertiary degree, 0 otherwise

DIPLOMA = 1 if highest qualification is a non-tertiary diploma or trade certificate, 0 otherwise

YR12 = if highest qualification is year 12, 0 otherwise

LESSYR12 = if respondent has no qualification, is still at school or highest qualification is less than year 12, 0 otherwise (used as the reference category)

SIN-PARENT = If respondent is a single parent with dependent child/children, 0 otherwise.

Table A-2 Summary Statistics

	Mean	Std. Dev.	Minimum	Maximum	Cases
Dependent Variables					
Y_M	0.145	0.352	0	1	36579
Y_C	0.014	0.116	0	1	36535
Y_H	0.005	0.070	0	1	36539
Explanatory Variables					
PRH	5.750	0.263	5.439	6.348	37081
PRC	5.169	0.238	4.818	5.824	37081
PRM	5.408	0.178	4.996	5.662	37081
INCOME	9.661	0.976	6.654	11.42	29141
CAPITAL	0.699	0.459	0	1	37084
YR01	0.721	0.448	0	1	37084
AGE	3.633	0.455	2.639	4.585	37080
AGESQ	13.41	3.252	6.965	21.02	37080
MALE	0.445	0.497	0	1	37084
MARRIED	0.565	0.496	0	1	36864
WORK	0.527	0.499	0	1	36230
STUDY	0.115	0.319	0	1	36230
UNEMP	0.037	0.188	0	1	36230
PRESCHOOL	0.138	0.345	0	1	36365
ATSI	0.018	0.132	0	1	36750
DEGREE	0.208	0.406	0	1	36390
DIPLOMA	0.276	0.447	0	1	36390
YR12	0.214	0.410	0	1	36006
SIN-PARENT	0.067	0.250	0	1	36293