Alcohol Consumption in Australia: An Application of the Ordered Generalised Extreme Value Model*

Mark N. Harris Preety Ramful
Xueyan Zhao
Department of Econometrics and Business Statistics
Monash University
Australia

March 2004

Abstract

The adverse effects of excessive alcohol consumption are well-known. Of great concern to policy makers is to understand the potentially different drivers for consumers of different levels of alcohol consumption. Using unit record data from the Australian Drug Strategy Household Surveys, this paper estimates an Ordered Generalised Extreme Value model to identify the factors that influence differing levels of alcohol consumption. Unlike previous studies using inflexible approaches such as Ordered Probits/Logits or Multinomial Logits, the OGEV model is both flexible and consistent with random utility maximization. The results suggest that important drivers are: age; income; education; gender; and own and cross-prices.

JEL Classification: C3, D1, I1

Keywords: Drug consumption, discrete ordered data, Ordered Generalised Extreme Value model, random utility maximisation, rational addiction.

*We wish to thank Ben Machado and Jennine Boughton of ABCI and Steve Whennan from ABS for supplying the data. Financial support from the Australian Research Council (ARC large grant # A00105073) and from Monash University (Faculty Grant, Faculty of Business and Economics) are also acknowledged.

1 Introduction and Background

The misuse of alcohol represents one of the leading causes of preventable death, illness and injury in many societies throughout the world. Murray and Lopez (1997) estimate that globally in 1990, alcohol contributed to 773,600 deaths, 19.3 million years of life lost and 47.7 million disability adjusted life years. Due to the broad range and severity of alcohol-related consequences, the monitoring of alcohol use and the formulation of effective policies constitute a major challenge to policy makers worldwide.

A great number of empirical studies have been published on alcohol consumption using unit-record data ranging from: price effects (for example, Manning, Blumberg, and Moulton 1995, Chaloupka and Wechsler 1996, Saffer and Chaloupka 1998, Farrell, Manning, and Finch 2003); to policies such as taxation and legal drinking age (Saffer and Grossman 1987, Coate and Grossman 1993, Laixuthai and Chaloupka 1993, Saffer and Chaloupka 1994, Kenkel 1996); to labour productivity (Berger and Leigh 1988, Mullahy and Sindelar 1993); and to individual social, economic and demographic characteristics (Cameron and Williams 2001, Lee 2003, Zhao and Harris 2003). Due to the nature of unit-record data, usually obtained from surveys where discrete levels rather than the actual quantities of consumption are available, discrete choice models are often used in these studies. Probit or Logit models are usually estimated when the focus is on an individual's decision to participate, or not, in the consumption of alcohol (see, for example, Cameron and Williams 2001).

Where data on multiple choices of levels of alcohol consumption are available, the discrete choices often exhibit a natural ordering representing increasing consumption levels. In these cases, the literature has predominantly quantified the effects of personal demographics and policy variables using Ordered Probit models. The choices of levels of consumption are modelled through a *single* latent variable that relates the propensity of alcohol consumption to the observed outcomes (see, for example, Chaloupka and Laixuthai 1997). It is well known that the Ordered Probit model is inflexible in specification and also inconsistent with a consumer preference framework of Random Utility Maximisation (RUM). A more flexible model is the frequently used Multinomial Logit (MNL) model, which allows for separate latent equations for alternative choices and which is consistent with the RUM (see, for example, Lee 2003) specification. However, the MNL model does not account for the fact that the discrete choices are ordered. Moreover, MNL models possess the undesirable property of “Independence from Irrelevant Alternatives” (IIA), which implies that the probability ratio of any two choices is independent of the probabilities of other choices (Greene 2003). This property follows from the assumption that the disturbances of different latent equations or the unobserved stochastic components of utility for alternative choices are independent.

The objective of this paper is to estimate an Ordered Generalised Extreme Value (OGEV) model to study the levels of alcohol consumption, using the Australian Drug Strategy Household Survey data. The OGEV model was proposed by Small (1987) to deal with ordered discrete data. It belongs to the class of the Generalised Extreme Value (GEV) models, as proposed by McFadden (1978), which embody the MNL model as a special case. The OGEV model allows for correlations between the random utility components of choices that are of close proximity in the ordering. Thus, it is a flexible RUM model that accounts for the ordered nature of the discrete choices. The OGEV model will be applied in this paper to study the impacts of own and related drug prices, income, and other individual social and demographic factors on an individual’s choice of the level of alcohol consumption. For policy purposes, the OGEV model is preferable than an Ordered Probit, as, for example, it allows variables to have differing effects and significance levels across the different levels of consumption. Therefore this is particularly apt for policy specifically targeted at “heavy” users.

According to a report by the World Health Organisation (1999), Europe reported the highest per capita consumption of alcohol (at 8.60 litres per year), followed by the Americas (6.98 litres) and the Western Pacific region (5.54 litres). Significant differences in patterns of alcohol consumption also exist within regions. In countries such as Italy or Spain, “heavy” drinkers tend to spread their consumption throughout the week, thereby reducing the risk of acute, but not of chronic, consequences of drinking. In contrast, in Ireland and the UK, drinkers are more likely to drink heavily once or twice per week, increasing the risk of acute consequences. Per capita alcohol consumption in Australia was 7.8 litres for the financial year 1999/2000 (World Drink Trends 2002), ranking 19th in the world, not far behind major European countries and higher than the US, Canada and New Zealand in terms of per capita consumption. The heaviest drinkers in Australia are those under 25 years of age, while in New Zealand nearly half the alcohol sold is consumed predominantly by the 10 percent heaviest male drinkers.

While it is widely recognised that excessive use of alcohol can be detrimental to health, in recent years a number of health benefits have been linked with a moderate and regular pattern of small amounts of consumption. Examples of this include reduced risks of heart disease and some preliminary evidence of protection against diabetes (National Health and Medical Research Council 2001). By including time dummies in the estimations, the current study involving nearly 40,000 individuals over the years of 1995 to 2001 will be able to identify any such shift in consumption patterns over time.

2 The OGEV Model

We start with the Generalised Extreme Value (McFadden 1978) class of the Random Utility Maximization (RUM) models, where indirect utility function for consumer i choosing alternative j is given by

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad (i = 1, \ldots N \text{ and } \ j = 1, \ldots J). \tag{1}$$

V_{ij} is the observable part of the utility that is typically assumed to be a linear (in the parameters) function of observable individual characteristics $\mathbf{x}_i$, such that[1] $V_{ij} = \mathbf{x}_i'\boldsymbol{\beta}_j$, or

$$U_{ij} = \mathbf{x}_i'\boldsymbol{\beta}_j + \varepsilon_{ij} \qquad (i = 1, \ldots N \text{ and } j = 1, \ldots J). \tag{2}$$

ε_{ij} is a random disturbance term accounting for unobserved individual tastes and preferences. Let Y_i $(j = 1, \ldots J)$ indicates the choice made by consumer i. The consumer is assumed to choose the choice with the maximum utility. That is, $Y_i = j$ if $U_{ij} > U_{ik}, \forall k \neq j$. When the marginal distributions for ε_{ij} are Extreme Value distributions, the class of GEV models results.

When the disturbances ε_{ij} in equation (2) are assumed to *independently* and identically follow a Type I Extreme Value distribution, equation (2) leads to the familiar MNL model (Maddala 1983), where the probability of individual i choosing alternative j is given by[2]

[1] Note only the case where data for the explanatory variables are individual specific rather than choice specific is considered. The model applicable to data with choice-specific attributes is often termed Conditional Logit model (Greene 2003).

[2] For identification $\boldsymbol{\beta}_0 = \mathbf{0}$ (Maddala 1983)

$$P_{ij}^{MNL} = P(Y_i = j) = \frac{\exp(V_{ij})}{\sum_{j=1}^{J} \exp(V_{ij})} \qquad (i = 1, \ldots N \text{ and } j = 1, \ldots J). \tag{3}$$

Although the MNL has been applied to modelling discrete levels of alcohol consumption (Lee 2003), and indeed to other applications with *ordered* discrete data, it does not account for any inherent ordering in the discrete choice data. Related to this point is another unattractive feature, that of IIA, where the probability odd between any two choices is independent of other choices (Fry and Harris 1996).

Small (1987) proposed the Ordered Generalised Extreme Value (OGEV) model, from the GEV class, that is more suited for ordered discrete outcomes. While maintaining the flexibility of allowing the explanatory variables to have different coefficients and significance levels for the utility attached to respective choices (unlike the Ordered Probit), the OGEV model also relaxes the restriction of independence between the unobservable characteristics across different choices. Specifically, the OGEV model allows for correlations between the disturbances of outcomes that are "close to" each other in the ordering. The further the two outcomes j and k are located from one another, the smaller is the correlation between the two disturbances ε_j and ε_k $(j, k = 1, ..., J)$. When $|j - k|$ is greater than a pre-selected integer M, the correlation is zero. Such a pattern of correlation appears likely, especially for an addictive good such as alcohol, with heavy drinking likely to be highly correlated with moderate drinking, but much less correlated with the abstainers, and so on.

It is possible to allow the window of correlation M, across nearby outcomes to be arbitrarily large. However, this significantly increases the complexity of the model and the associated difficulties in the maximisation procedures used in the estimation (Small 1987). In this paper a standard OGEV model is considered with only the adjacent outcomes correlated ($M = 1$). It only involves one additional parameter ρ relative to the MNL model. Although it cannot be written explicitly in closed form, the correlation between the adjacent outcomes is *inversely* related to the parameter ρ (Small 1987).

The associated standard OGEV probabilities for $M = 1$ have the form

$$P_{ij}^{OGEV} = \exp\left(\rho^{-1}V_{ij}\right) \times \frac{\left[\left(\exp\left(\rho^{-1}V_{ij-1}\right)+\exp\left(\rho^{-1}V_{ij}\right)\right)^{\rho-1} + \left(\exp\left(\rho^{-1}V_{ij}\right)+\exp\left(\rho^{-1}V_{ij+1}\right)\right)^{\rho-1}\right]}{\sum_{r=1}^{J+1}\left(\exp\left(\rho^{-1}V_{ir-1}\right)+\exp\left(\rho^{-1}V_{ir}\right)\right)^{\rho}} \tag{4}$$

with the convention that $\exp(\rho^{-1}V_{i0}) = \exp(\rho^{-1}V_{iJ+1}) = 0$ and $0 < \rho \leq 1$.

As $\rho \to 1$, OGEV probabilities converge to MNL ones. Therefore a simple parameter restriction based test ($\rho = 1$) is one of the OGEV *versus* MNL, which is also implicitly a test of ordering versus non-ordering of the outcomes in the choice set. Note that as $\rho \to 0$, the associated cumulative distribution function is a degenerate one, but one still consistent with RUM (Small 1987).

3 The Data

The data used in this study are drawn from the three most recent Australian National Drug Strategy Household Surveys (NDSHS)(National Drug Strategy Household Survey 1995, 1998, 2001). These are nationally representative surveys of the Australian population aged 14 and above. While the 1995 and 1998 surveys covered around 4,000 and 10,000 individuals respectively, almost 27,000 people provided information in the 2001 survey on their drug use patterns, attitudes and behaviour. Individuals were personally interviewed about their general attitudes to both licit and illicit drugs, while more sensitive questions about personal drug usage were answered by means of self-completed "drop-and-collect", hence minimising the likelihood of any non-response bias. Data from these three surveys have been pooled in this analysis and year dummies used to capture any exogenous changes in tastes over time.

The summary in Table 1 shows that the proportion of individuals who consumed alcohol during the 12 months prior to the surveys rose progressively from 77.2 percent in 1995 to 79.2 percent in 1998, and further to 81.3 percent in 2001. Out of the total females interviewed, 78.9 percent consumed alcohol in 2001 as compared to 73.9 percent in 1995. The proportion of male respondents who consumed alcohol also went up from 77.2 percent in 1995 to 81.3 percent in 2001.

Table 1: Participation in Alcohol Use (Percent)

	Female	Male	Total
1995	73.9	80.9	77.2
1998	76.9	82.0	79.2
2001	78.9	84.2	81.3

Source: NDSHS (1995-2001).

Empirical studies that concentrate on the *participation* probabilities treat all alcohol users as a homogeneous group and hence cannot differentiate between occasional drinkers and heavy drinkers. It is the heavy users that tend to be associated with the majority of the ill effects associated with alcohol consumption. Therefore, often this is the more relevant target group for alcohol-related policies. While the actual amount of each individual's alcohol consumption (expenditure or quantity) is not available in the surveys, information on the frequency of use is provided. The frequency is used as a proxy for the intensity of consumption. In particular, the observed dependent variable is discrete and ordinal, taking the values of: 1 for an *abstainer* (no alcohol consumption in the previous 12 months); 2 for an *occasional* drinker (drinks 2 or 3 days a month); 3 for a *moderate* drinker (consumes alcohol more frequently than weekly but no more than 3 to 4 days a week); and 4 for a *frequent* drinker (consumes alcohol at least 4 days a week). Details on the definition of the dependent variable, together with that for the independent variables, are given in the Appendix.

Table 2: Pattern of Alcohol Use (Percent)

	1995	1998	2001
Frequent	16.7	16.9	23.7
Moderate	29.3	32.5	24.8
Occasional	34.0	33.4	34.5
Abstainer	19.9	17.3	17.0
Total	100	100	100

Source: NDSHS (1995-2001).

Table 2 shows the average consumption pattern of individuals. The proportion of frequent drinkers has increased quite significantly from 16.7 percent in 1995 to 23.7 percent in 2001. It is not unreasonable to speculate that the media coverage of research on the potential health benefits of daily intake of moderate amount of alcohol, in particular red wine, may be partly responsible. This rise is accompanied by a fall in the proportions of moderate drinkers and abstainers. On the other hand, the proportion of individuals who

Table 3: Percentage Descriptive Statistics on the Frequency of Use

	Abstainer	*Occasional*	*Moderate*	*Frequent*	*Total*
Female	19.7	40.2	25.0	15.1	100
Male	14.4	26.8	29.7	29.1	100
Married	15.6	32.8	26.9	24.6	100
Divorced	16.4	34.0	25.7	23.9	100
Widowed	34.5	29.8	15.4	20.3	100
$Non-Partnered$	17.7	37.9	30.3	14.1	100
Work	10.1	32.2	33.0	24.7	100
Study	26.6	43.1	24.3	6.0	100
Unemployed	18.3	36.7	26.2	18.8	100
OtherAct	25.6	34.1	18.6	21.7	100
Degree	11.8	29.2	32.0	27.0	100
Diploma	12.9	32.5	28.7	25.9	100
$Yr12Qual$	14.9	36.3	31.0	17.9	100
$LessYr12$	25.5	38.7	20.0	15.7	100
Capital	18.6	34.6	25.0	21.8	100

Source: National Drug Strategy Household Survey (1995, 1998, 2001).

consumed alcohol occasionally has remained more or less constant at around 34 percent over the years.

The surveys also provide comprehensive information on individual social, economic and demographic characteristics of the respondents. These are used as part of the explanatory variables $\mathbf{x}_i$ in equation (2), detailed in the Appendix, to explain an individual's choice of the level of alcohol consumption.

Table 3 highlights the sample proportions of various population groups for each of the four categories of drinkers. It appears that males are more likely to be frequent drinkers, whereas females are more likely to be occasional drinkers. As much as 29.1 percent of males consume alcohol at least 4 days a week as compared to 15.1 percent of females. On the other hand, 40.2 percent of females drink occasionally as compared to 26.8 percent of males. Out of those who are married, 24.6 percent are frequent drinkers as compared to 14.1 percent of single people. Among divorcees, the highest proportion drinks occasionally but a fairly high percentage are moderate to frequent drinkers.

Occasional to moderate drinking is more popular among those individuals who are employed. However, a significant percentage (24.7 percent) of workers consume alcohol frequently. Students are mostly occasional drinkers (43.1 percent) or abstainers (26.6 percent) with very few consuming alcohol frequently (6 percent). Unemployed people are mostly occasional to moderate drinkers although as much as 18.8 percent drink alcohol at least 4 days a week. There appears to be a high proportion of abstainers (25.6 percent) and occasional drinkers (34.1 percent) among those who are pensioners, retirees or primarily engaged in home duties. There appears to be a pattern within each drinking category with respect to educational attainment. For the abstainer and occasional drinking groups, the higher the level of education, the lower is the participation probability while for the moderate and frequent drinking categories, the more educated individuals have higher drinking probabilities.

Obviously these descriptive observations for the effects of individual explanatory factors could be misleading when other factors are not controlled for (*Simpson's Paradox*). More formal econometric models such as the one estimated in this study are needed to isolate the partial effects due to each individual explanatory factor. This is discussed in the next section.

Alcohol prices by states of residence, as well as prices of tobacco and marijuana are also used as explanatory variables. Empirical evidence indicates that alcohol is closely related to other addictive drugs such as tobacco and marijuana (see, for example Cameron and Williams 2001, Zhao and Harris 2003). Data on the prices of alcohol and tobacco by states are obtained from the Australian Bureau of Statistics (ABS 2003b). The price of alcoholic drinks is a weighted average price index for sub-categories of beer, wine and spirits. Yearly prices of marijuana by states are constructed from quarterly data published in the Australian Illicit Drug Report by the Australian Bureau of Criminal Intelligence (ABCI) and the Australian Crime Commission (Australian Bureau of Criminal Intelligence 2002, Australian Crime Commission 2003). All three price series are deflated using the all-items CPI for individuals' respective state of residence (ABS 2003a).

4 Results

Table 4 reports the estimated coefficients and their associated standard errors (SE) of the OGEV model for three of the four random utility equations, along with the implied marginal effects (ME), on the probabilities for all four consumption levels (the normalisation is on the parameter vector corresponding to *abstainers*). The marginal effects represent the absolute changes in the probabilities for the respective levels of consumption in response to unit change in each individual explanatory variable. For each continuous explanatory

Table 4: Results of OGEV Model for Alcohol Consumption [a]

	Abstainer	*Occasional*			*Moderate*			*Frequent*		
	ME	Coeff.	SE	ME	Coeff.	SE	ME	Coeff.	SE	ME
Constant	-1.358	12.600	4.28**	2.665	9.131	4.77**	ME	-1.374	5.28	-2.115
P_{ALC}	0.195	-1.585	0.55**	-0.277	-1.422	0.62**	0.808	-0.038	0.67	0.261
P_{MAR}	0.021	-0.120	0.08	0.000	-0.185	0.09**	-0.179	-0.103	0.10	0.007
P_{TOB}	0.147	-0.779	0.49	0.011	-0.937	0.56*	-0.028	-1.458	0.63**	-0.147
Income	-0.052	0.180	0.02**	-0.064	0.438	0.03**	-0.011	0.649	0.04**	0.076
1998 × 1	-0.040	0.147	0.10	-0.009	0.233	0.11**	0.041	0.343	0.12**	0.029
2001 × 1	-0.090	0.475	0.20**	0.037	0.394	0.22*	0.020	0.846	0.26**	0.092
Capital	0.006	-0.015	0.03	0.009	-0.045	0.04	-0.038	-0.085	0.04**	-0.012
Age	0.036	-0.519	0.08**	-0.174	-0.274	0.08**	-0.003	0.668	0.08**	0.208
Male	-0.024	-0.098	0.04**	-0.134	0.299	0.03**	-0.070	0.689	0.05**	0.121
Married	0.015	-0.019	0.05	0.038	-0.149	0.05**	0.037	-0.248	0.06**	-0.035
Divorced	-0.020	0.146	0.06**	0.010	0.152	0.07**	-0.018	0.145	0.07**	0.003
Widowed	0.035	-0.129	0.07*	0.031	-0.283	0.09**	0.007	-0.358	0.10**	-0.036
Work	-0.061	0.335	0.04**	-0.014	0.541	0.06**	-0.030	0.416	0.05**	0.005
Study	0.080	-0.294	0.07**	-0.006	-0.323	0.08**	0.070	-0.739	0.11**	-0.085
Unemployed	-0.045	0.204	0.09**	-0.021	0.336	0.10**	0.011	0.424	0.11**	0.042
#Depchild	0.006	-0.001	0.02	0.019	-0.066	0.02**	0.024	-0.107	0.02**	-0.015
Degree	-0.053	0.174	0.04**	-0.059	0.462	0.06**	-0.010	0.541	0.06**	0.051
Diploma	-0.060	0.274	0.04**	-0.027	0.471	0.05**	0.061	0.525	0.05**	0.039
Yr12Qual	-0.061	0.277	0.05**	-0.026	0.474	0.06**	0.049	0.518	0.06**	0.037
ρ		0.516	0.12**				0.050			

[a] SE: standard errors; ME: marginal effect on probabilities; *significant at 10% level; **significant at 5% level. The reference individual is non-partnered, undertakes "other" activities, has less than Year 12 education and is surveyed in 1995.

variable this relates to one unit increase in the explanatory variable, while for dummy variables it represents the change in probabilities when the variable changes from 0 to 1, all evaluated at the means of all of the other explanatory variables.

The first result to note in Table 4 is that the parameter ρ is estimated to be 0.52 and is statistically significantly different from zero at 1% level. ρ is also significantly different from 1 at 1% level. Although the correlation coefficient between categories cannot be written explicitly in closed form (Small 1987), an estimate of 0.52 for the parameter ρ implies a fairly strong correlation between categories that are neighbours in the choice ordering. Small (1987) performed some numerical integrations for the standard OGEV model and showed that an estimate of $\rho = 0.5$ implies a correlation of about 0.354 between adjacent categories when $M = 1$. Also note that the majority of the explanatory variables

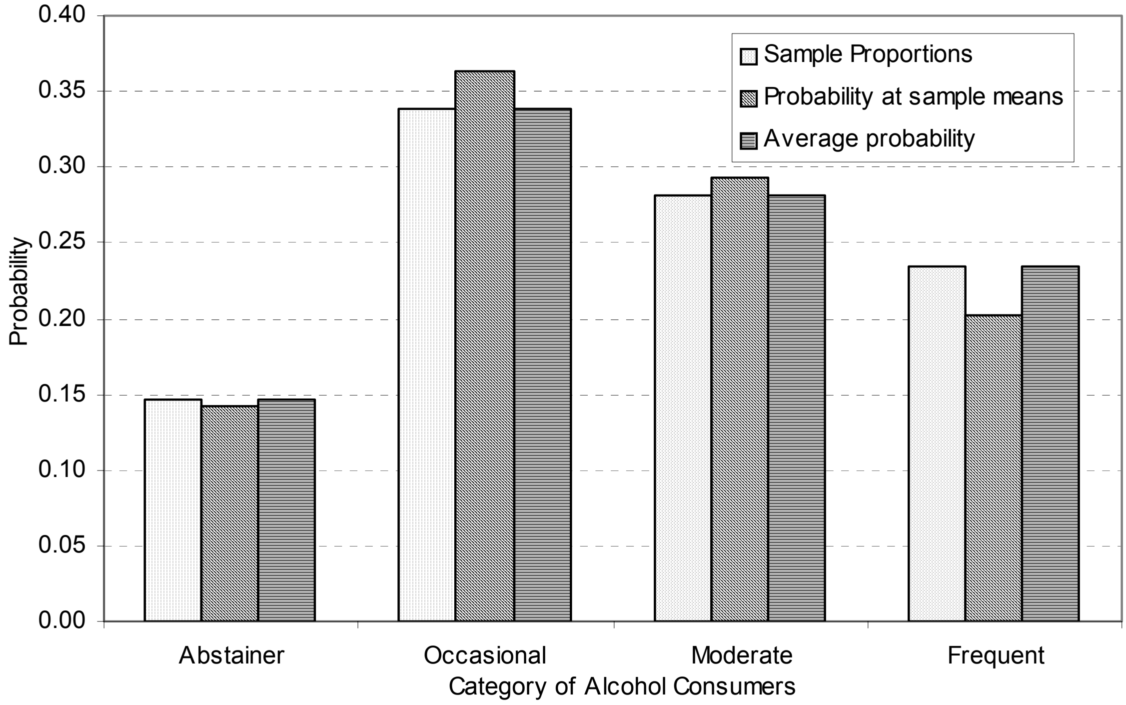

Figure 1: Sample Proportions, Average Predicted Probabilities and Predicted Probabilities at Average Covariate Values

are statistically significant at either 5% or 10% levels.

Before turning to the effects of individual covariates, the observed sample proportions along with the predicted probabilities (evaluated at sample means) and the average predicted probabilities from the OGEV model are presented in Figure 1. Both of these predicted probabilities closely mimic the observed sample proportions, thereby giving a clear indication as to the adequacy of the estimated model.

So what do the results tell us about the impacts of individual explanatory factors on a typical Australian's probabilities of consuming differing levels of alcohol? Starting with prices, via excise duty predominantly a (potential) policy variable, an increase in own price causes reductions in utilities for all three drinking categories, but the impact on the frequent drinkers is not statistically significant. This result of price insensitivity for the heavy drinkers is interesting, especially for policy makers, as it indicates that a change in alcohol price is not important for people who are already drinking frequently: an indication of demand being price inelastic for possibly addicted users.

However, the *probability* of frequent drinking can still change significantly in response to an alcohol price rise, due to the significant reductions in utilities for the other groups and therefore a change in the ranking of the four utilities. Related, it may be worthwhile to point out that the sign of the coefficient for each choice category only indicates the direction of marginal change in *utility* for that category from a unit change of a particular explanatory variable, but not necessarily the direction of change in the *probability* for that category. This is evident from the opposite signs observed for the estimated β coefficient and the marginal effect on the probability in some cases in Table 4. For example, the utilities for all categories/levels of consumption can be increased due to a price reduction, but changes in probabilities can be either positive or negative, depending on the relative sizes of the utility changes, with the total probability changes summing to zero. Thus, in response to a 10% increase in alcohol price, the marginal effects in Table 4 indicate reductions in *probabilities* for the occasional and moderate drinking by 0.028 and 0.018 respectively, but increases the probabilities of being an abstainer and a frequent drinker by 0.020 and 0.026, respectively. Note all prices and income variables enter the equations in natural logarithmic form (see Appendix).

It is also interesting to see how an individual's participation decision is affected by the prices of related drugs such as marijuana and tobacco. For instance, an increase in the price of marijuana results in a lower probability for moderate drinking and increases the chances of being an abstainer. However, it also slightly increases the probability for frequent drinking. These mixed findings may suggest that in response to a rise in the price of marijuana, for some individuals there is a substitution effect towards more alcohol consumption, increasing the probability of frequent drinking, while those individuals for whom alcohol is a complement for marijuana, may choose to quit alcohol along with marijuana (increasing the probability of abstention).

On the other hand, an increase in tobacco price results in lower probabilities for the moderate and frequent drinking groups, but increases the probability of being an abstainer or occasional drinker. This tends to suggest that alcohol is a complement for tobacco such that when the price of tobacco goes up individuals choose to consume less alcohol thus shifting towards occasional drinking or abstention. The marginal probability indicates that a 10% increase in the price of marijuana leads to a higher participation probability of 0.002 for the abstainer and 0.001 for the frequent drinker while it lowers the drinking probability by 0.003 for moderate drinking. A 10% increase in tobacco price increases the chances of being an abstainer or an occasional drinker by 0.015 and 0.001 respectively but reduces the drinking probabilities by 0.001 and 0.015 for the moderate and frequent drinking groups. For an Australian population of 20 million, these marginal effects are non-trivial implying, for example a 10% increase in the price of marijuana (is estimated to result) in: 55,800 fewer moderate drinkers; an increase of 41,400 in the number of abstainers; a marginal 200 more individuals being occasional drinkers; and 14,200 more frequent drinkers. Similarly, a 10% rise in the tobacco price translates into 293,400 less frequent drinkers and 22,400 fewer moderate drinkers (who thereby shift their drinking patterns towards less frequent drinking or abstention, increasing the number of occasional drinkers by 22,200 and the number of abstainers by 293,600).

Table 5: Probability Elasticities

	Abstainer	*Occasional*	*Moderate*	*Frequent*
P_{ALC}	1.327	-0.819	-0.636	1.114
P_{MAR}	0.141	0.000	-0.099	0.030
P_{TOB}	1.001	0.033	-0.040	-0.626
Income	-0.354	-0.191	0.145	0.323

The marginal price effects are also converted into participation elasticities as given in Table 5. These elasticities show percentage changes, rather than absolute changes, in the participation probabilities in response to a 1% change in the explanatory variable. For example, a cross-price elasticity of -0.626 for the frequent drinkers indicates that a 1% increase in tobacco price will result in a 0.626% relative reduction in the probability value of frequent drinking.

Attention is next turned to income. From Table 4, an increase in annual household income reduces the utilities of all three categories. However, this translates into negative marginal probability effects for abstainers and occasional drinkers but positive effects for the moderate and frequent drinking groups. Thus, a 10% rise in real annual household income decreases probabilities of abstention and being an occasional drinker, by 0.005 and 0.006, but increases those of moderate and frequent drinkers by 0.004 and 0.008 respectively. The last row in Table 5 shows the corresponding income elasticities for all four drinking categories, which relate to *relative* changes in probabilities. For illustrative

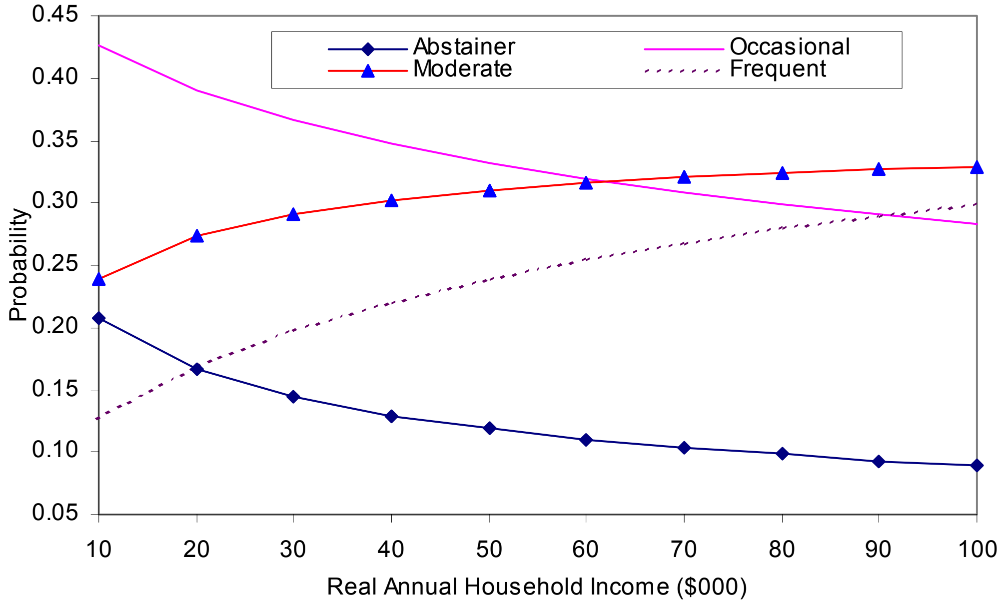

Figure 2: Predicted Probabilities: Effect of Income

purpose, the effects of income on consumption probabilities are plotted in Figure 2. The most significant effect is clearly the sharp rise in the probability of frequent consumption as income rises.

Consumption probabilities are also significantly related to demographic variables. The effects of age are depicted in Figure 3. While the probability of being an abstainer remains more-or-less constant across age groups, the participation probabilities for all other categories are clearly sensitive to an individual's age. It is interesting to see how the probability of being an occasional drinker decreases rather steeply for older individuals while the odds of being a moderate drinker changes only slightly with age. On the other hand, the probability for frequent drinking increases significantly for older individuals. This seems to point out that older individuals tend to be more frequent drinkers but the younger ones are rather occasional and moderately frequent drinkers. A high probability of frequent drinking among older individuals can well be a consequence of addiction where individuals' consumption of alcohol gradually increases over time because of the addictive nature of alcohol (Becker and Murphy 1988).

Figure 4 shows the relationship between gender and participation probabilities. Fe-

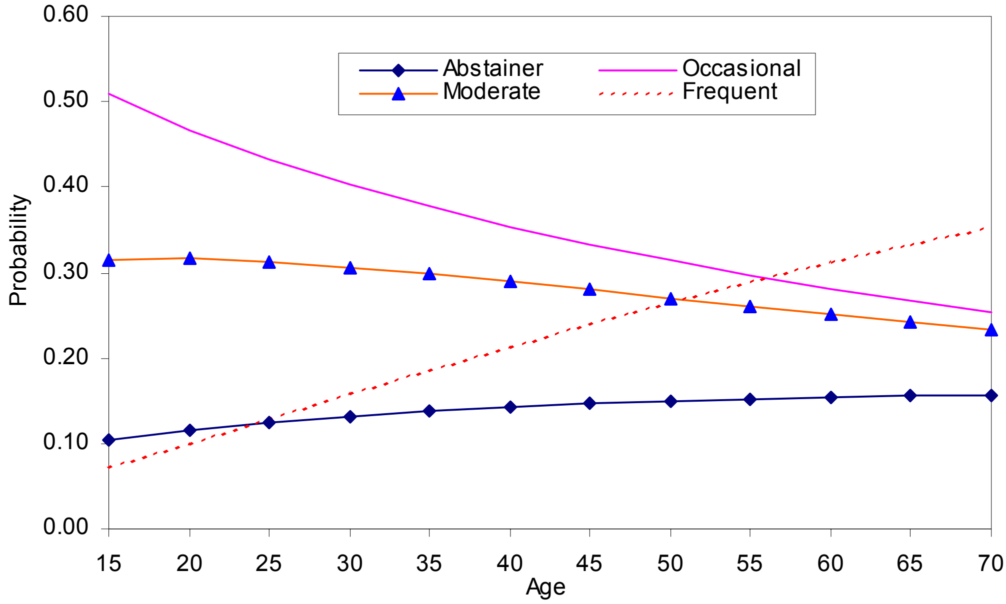

Figure 3: Predicted Probabilities: Effect of Age

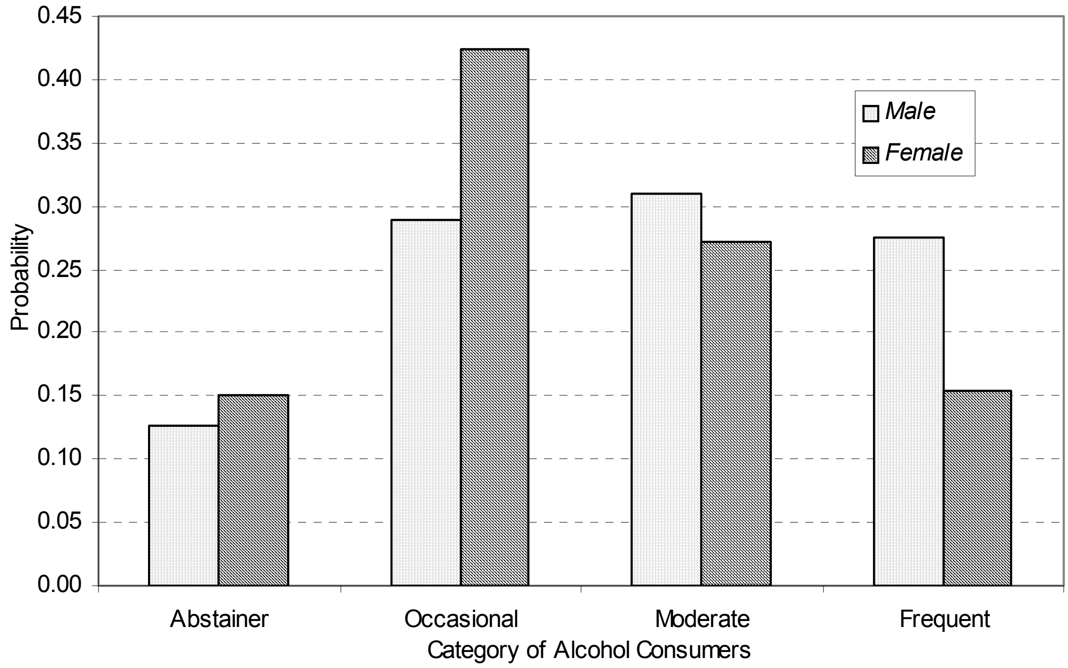

Figure 4: Predicted Probabilities: Effect of Gender

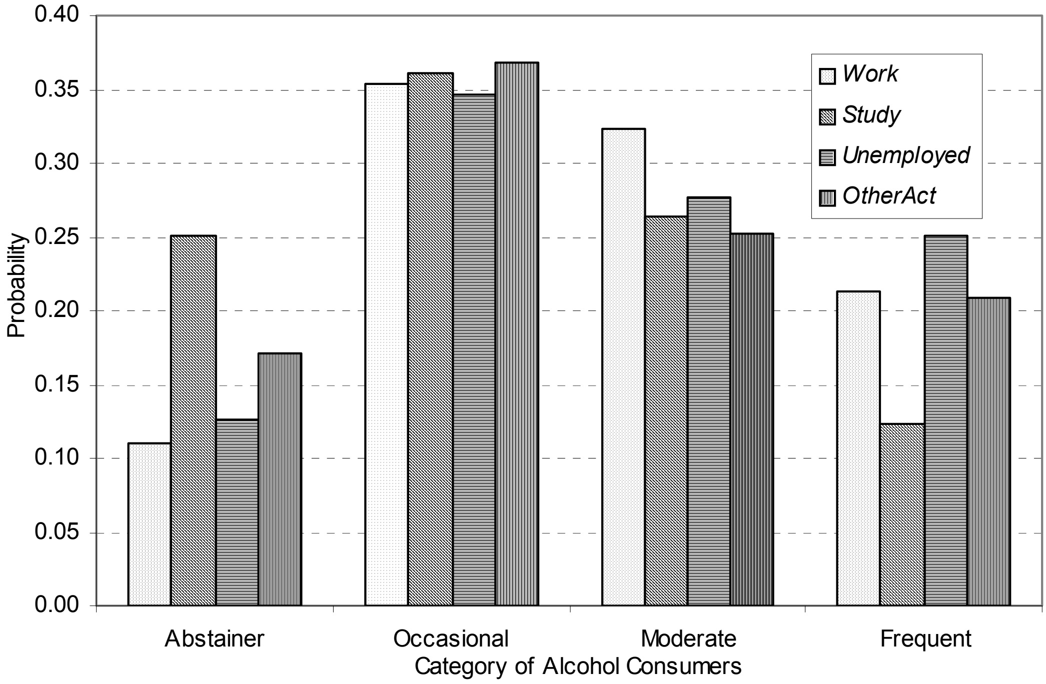

Figure 5: Predicted Probabilities: Main Activity

males are 2.4% more likely to be abstainers but 13.4% more likely to be occasional drinkers. However, males are 3.7% more likely to be moderate drinkers and have almost twice the probability of being a frequent drinker than females.

In terms of an individual's main activity, the probability of being an abstainer is distinctly higher for students relative to those who work, are unemployed or are primarily engaged in home duties (Figure 5). For the occasional drinking group, the probabilities do not seem to be much related to individuals' main activities such that an individual has about a 35% chance of drinking alcohol irrespective of what his/her main occupation is. Individuals who work have the highest chances of being in the moderate drinking group. For the heavy drinkers, other factors controlled being equal, the highest participation relates to unemployed individuals, while those who work are equally likely to drink as individuals who are engaged in home duties. However, those who study have markedly low chances of drinking frequently.

It is interesting to compare the observed sample proportions in Table 3 for the work status categories, which we plot in Figure 6, with the predicted probabilities in Figure

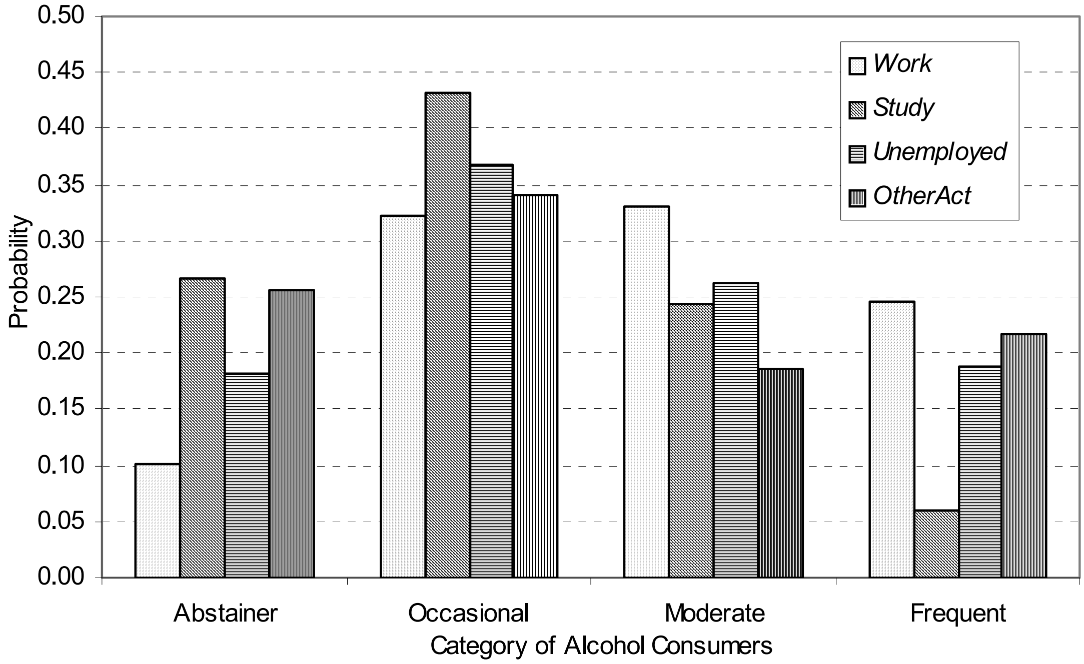

Figure 6: Observed Proportions: Main Activity

5; the latter controls for the effects of all other explanatory variables. They show some marked differences; for example, for the abstainer category, while the predicted probabilities are rather close to the observed probabilities for those who work and study, the model predicts much lower probabilities for those who are unemployed (12.6% compared to an observed 18.3%) or who are engaged in home duties (17.1 and 25.6%). Once again, for the frequent drinkers, while people who work are shown to have the highest *observed* sample proportion of 24.7% among the four activity groups as shown in Figure 6, the unemployed group is *predicted* to have the highest probability for frequent drinking once the other explanatory variables have been controlled for. This suggests that while we observe the highest proportion of frequent drinking in the working group, it might be more due to the fact that these people are also more likely to have higher incomes and education. Once the income and education levels have been controlled for, an unemployed person is, in fact, more likely to drink frequently than a working person. This highlights the fact that, while simple descriptive statistics such as the observed probabilities can be an indication of how the participation in alcohol consumption varies across different

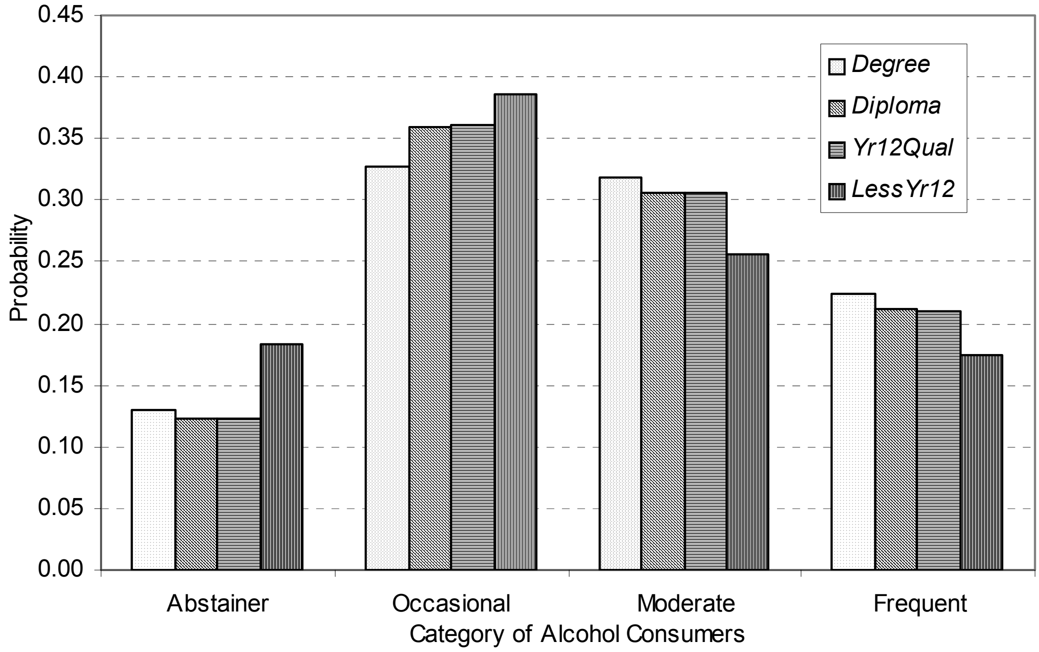

Figure 7: Predicted Probabilities: Educational Attainment

demographic groups, an econometric model is more appropriate in isolating the partial effect of a particular factor when other variables are controlled at the same levels.

Finally, Figure 7 shows the probability of consumption with respect to educational attainment. It seems that the more educated, the more likely a person is to be drinking more frequently. For the abstainers, those with less than year-12 qualifications have a relatively higher probability (of about 18%). Similarly, for the occasional drinking group the probabilities are highest for those with less than year-12 qualifications, while degree holders have the lowest probability. On the other hand, the converse is found for the moderate and frequent drinking groups, where the more educated individuals have higher chances than those with lower education. The marginal effects indicate that for the moderate drinking category, those who have a degree have 6.1% more chances and those with a diploma or year-12 qualifications have about 5% more chances of drinking than individuals with less than year-12 education. In the frequent drinking category, degree holders are 5.1% more likely and those with diploma or year-12 qualifications are about 4% more likely to drink than the less educated individuals. Once again, if we compare the predicted probabilities to the observed ones (in Table 3), we find that the model predicts significantly differences from the observed sample probabilities for certain groups.

5 Conclusion

This study investigates the intensity of alcohol consumption of Australian individuals. Here, the intensity of use, as measured by the frequency of consumption, is observed as the result of a discrete choice problem where the individuals' preferred choice is obtained by maximising random utilities from alternative choices. As is common in survey data, these discrete choices of consumption levels exhibit a natural ordering. Previous studies have mostly used Ordered Probit or Logit formulations to model such outcomes. While such models provide an ease of estimation, they require restrictive assumptions about the nature of the observed dependent variable. In particularly, these models are inflexible due to the specification of a single latent and also that they are inconsistent with RUM.

An alternative choice of model would be the Multinomial Logit (MNL) model which is more flexible and consistent with RUM. Much as this specification looks attractive in terms of its computational properties, it embodies the undesirable property of IIA. In this paper the preferred model is the OGEV one (Small 1987), that overcomes the drawbacks of the Ordered Probit/Logit and the MNL models.

Nearly 40,000 observations from surveys between 1995 and 2001 are used to study the effects of prices, income, and other social and demographic characteristics on an individual's choice of the frequency of alcohol consumption. Four categories are considered: abstention, occasional drinking, moderate drinking and frequent drinking. It is found that an increase in alcohol price reduces the probabilities for occasional and moderate drinking and increases the probabilities for abstaining and frequent drinking, although the utility of frequent drinkers does not change significantly. The cross-price effects indicate that marijuana is essentially a complement for alcohol such that in response to price rises in marijuana individuals shift from moderate drinking to occasional drinking or abstention, although a small proportion substitute marijuana by drinking alcohol more frequently. However, tobacco appears to be a complement for alcohol such that a rise in its prices reduces the probabilities of moderate and frequent drinking and increases those of occasional drinking and abstainer categories.

Significant demographic differences are observed across the four categories of drinkers. One interesting finding is that individuals' drinking patterns shift from occasional and moderate drinking to heavy drinking as they grow older; consistent with Becker and Murphy's (1988) theory of rational addiction. Income levels also significantly influence drinking behaviour: the chances of frequent drinking increases as income grows. Unemployed individuals have relatively higher chances of being a frequent drinker. Males are more likely to be moderate and frequent drinkers than females. The more educated individuals are, the more likely they are to consume alcohol frequently and moderately. These findings can be useful inputs when designing anti-alcohol campaigns and education programs as they indicate the potential target groups. In terms of variables amenable to policies, price and income effects are illustrative as they indicate how much of a change in price or income affect the probabilities of frequent use. The cross-price effects, on the other hand, can be useful to gauge the cross-industry effects of any changes in the related drugs.

References

ABS (2003a): "Consumer Price Index 14th Series: By Region, All Groups," Australian Bureau of Statistics, Cat. No. 640101b.

——— (2003b): "Consumer Price Index 14th Series: By Region by Group, Sub-Group and Expenditure Class - Alcohol and Tabacco," Australian Bureau of Statistics, Cat. No. 6455.0.40.001.

Australian Bureau of Criminal Intelligence (2002): Australian Illicit Drug Report.

Australian Crime Commission (2003): Australian Illicit Drug Report 2001-02.

Becker, G., and K. Murphy (1988): "A Theory of Rational Addiction," *Journal of Political Economy*, 96(4), 675–700.

Berger, M., and J. Leigh (1988): "The Effect of Alcohol Use on Wages," *Applied Economics*, 20, 1343–51.

Cameron, L., and J. Williams (2001): "Cannabis, Alcohol and Cigarettes: Substitutes or Compliments," *The Economic Record*, 77(236), 19–34.

Chaloupka, F., and A. Laixuthai (1997): "Do Youths Substitute Alcohol and Marijuana? Some Econometric Evidence," *Eastern Economic Journal*, 23(3), 253–76.

Chaloupka, F., and W. Wechsler (1996): "Binge Drinking in College: The Impact of Price Availability and Alcohol Control Policies," *Contemporary Economic Policy*, 14(4), 112–24.

Coate, D., and M. Grossman (1993): "Effects of Alcoholic Beverage Prices and Legal Drinking Ages on Youth Alcohol Use," *Journal of Law and Economics*, 31, 145–71.

Farrell, S., W. Manning, and M. Finch (2003): "Alcohol Dependence and the Price of Alcoholic Beverages," *Journal of Health Economics*, 22, 117–47.

Fry, T., and M. Harris (1996): "A Monte Carlo Study of Tests for the Independence of Irrelevant Alternatives Property," *Transportation Research - Part B*, 30B, 19–30.

Greene, W. (2003): *Econometric Analysis*. Prentice Hall, New Jersey, USA, fifth edn.

Kenkel, D. (1996): "New Estimates of the Optimal Tax on Alcohol," *Economic Enquiry*, 34(2), 296–319.

Laixuthai, A., and F. Chaloupka (1993): "Youth Alcohol Use and Public Policy," *Contemporary Policy Issues*, 11(4), 90–81.

Lee, Y. (2003): "Wage Effects of Drinking in Australia," *Australian Economic Review*, 36(3), 265–82.

Maddala, G. S. (1983): *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge University Press, Cambridge, U.K.

Manning, W., L. Blumberg, and L. Moulton (1995): "The Demand for Alcohol: The Differential Response to Price," *Journal of Health Economics*, 14, 123–48.

McFadden, D. (1978): "Modeling the Choice of Residential Location," in *Spatial Interaction Theory and Planning Models*, ed. by A. Karlqvist, L. Lundqvist, and J. Weibull, pp. 75–96. North Holland Publishing Company, Amsterdam.

Mullahy, J., and J. Sindelar (1993): "Alcoholism, Work and Income," *Journal of Labour Economics*, 11, 494–520.

Murray, C., and A. Lopez (1997): "The Global Burden of Disease: A Comprehensive Assessment of Mortality and Disability from Diseases, Injuries, and Risk Factors in 1990/1996," Discussion paper, Harvard School of Public Health Cambridge, MA, for the World Health Organisation.

National Drug Strategy Household Survey (1995, 1998, 2001): Social Science Data Archives, the Australian National University, Canberra.

National Health and Medical Research Council (2001): Australian Alcohol Guidelines: Health Risks and Benefits.

Saffer, H., and F. Chaloupka (1994): "Alcohol Tax Equalisation and Social Costs," *Eastern Economic Journal, Winter*, pp. 33–43.

——— (1998): "Demographics Differentials in the Demand for Alcohol and Illicit Drugs," in *Economic Analysis of Substance Use and Abuse: An Integration of Econometric and Behavioral*, pp. 187–211. Chaloupka F., Bickel, W., Saffer, H., Grossman, M. (Eds.), Economic Research, University of Chicago Press, Chicago.

Saffer, H., and M. Grossman (1987): "Beer Taxes, the Legal Drinking Age and Youth Motor Vehicle," *Journal of Legal Studies*, 26, 351–74.

Small, K. (1987): "A Discrete Choice Model for Ordered Alternatives," *Econometrica*, 55, 409–424.

World Drink Trends (2002): "International Beverage Consumption and Production Trends," NTC Publications, Henley-on-Thames.

World Health Organisation (1999): Global Status Report on Alcohol.

Zhao, X., and M. Harris (2003): "Demand for Marijuana, Alcohol and Tobacco: Participation, Frequency and Cross-Equation Correlations," paper presented at the Australasian Meeting of the Econometrics Society, July, Sydney.

Appendix

- Y: frequency of alcohol consumption for the whole sample; $Y = 1$ if not current drinker, $Y = 2$ if drinking 2 to 3 days a month or less, $Y = 3$ if drinking more than weekly but no more than 3 to 4 days a week, and $Y = 4$ if drinking more than 4 days a week.

- P_{ALC} : natural logarithm of real price index of alcoholic drinks.

- P_{MAR} : natural logarithm of real price of marijuana measured in dollars per ounce.

- P_{TOB} : natural logarithm of real price index of tobacco.

- $Income$: natural logarithm of real household annual income before tax measured in Australian Dollars.

- 1995×1 : 1 for year 1995. This variable is the reference category for time-effect dummies and is dropped in the estimation.

- 1998×1 : 1 for year 1998.
- 2001×1 : 1 for year 2001.
- $Capital$: 1 if the respondent resides in a capital city.
- Age : natural logarithm of individual's actual age.
- $Male$: 1 for male.
- $Married$: 1 if married or *de facto*.
- $Divorced$: 1 if divorced.
- $Widowed$: 1 if widowed.
- $Non-partnered$: 1 if single. This variable is the reference category for marital status dummies and is dropped in the estimation.
- $Work$: 1 if employed part-time or full-time.
- $Study$: 1 if mainly study.
- $Unemployed$: 1 if unemployed.
- $OtherAct$: 1 if retired, on pension or perform home duties. This variable is used as the base of comparison for work status dummies and is dropped in the estimation.
- $Degree$: 1 if the highest qualification is a tertiary degree.
- $Diploma$: 1 if the highest qualification is a non-tertiary diploma or trade certificate.
- $Yr12Qual$: 1 if the highest qualification is year 12.
- $LessYr12$: 1 if respondent has no qualification, is still at school or highest qualification is less than year 12. This variable is the reference category for educational attainment dummies and is dropped in the estimation.
- $\#Depchild$: number of dependent children aged 14 or below in the household.