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Recreational Drug Consumption

An Economic Perspective

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Chapter 1
Introduction

1.1 Background and Motivation

The use of psychoactive drugs—licit and illicit—is associated with a range of adverse effects on both physical and mental health. Such health consequences range from short-term effects such as insomnia and abdominal pain to long-term effects such as seizures, strokes, paranoia, liver cirrhosis and heart disease (IHME 2013). Other than health effects, drug use is also associated with an array of adverse consequences on the user, his family and the community at large. Such consequences include injuries or loss of life, family disruptions, poor job performance, road accidents, violence, crime and suicide. To put this into perspective, tobacco kills nearly 6 million people each year, including more than 600,000 non-smokers who die from exposure to tobacco smoke and up to half of the world's one billion smokers will eventually die of a tobacco-related disease. Approximately 2.3 million people worldwide died in 2004, from the use of alcohol. Between 153 and 300 million individuals aged 15–64 had used illicit drugs in 2010, out of which 15.5–38.6 million were problem drug users (UNODC 2012; WHO 2011a,b). Drug abuse imposes a high economic cost on society[1] and has been a major concern to policymakers worldwide. A range of strategies, campaigns and rehabilitation programs have been undertaken in a number of countries, to treat and prevent drug-related harms. Such harms (to the user and to society) range from drug-related morbidity and mortality, motor vehicle fatalities, to violence, crime, and suicide.

In Australia, recreational drugs have a long-standing popularity despite the government's commitment to discourage the uptake and supply of harmful drugs. It has one of the highest levels of alcohol consumption in the world (WHO 2011a). Over the last two decades, the National Drug Strategy (a cooperative venture

[1]Economic cost of drug abuse relates to external costs arising from lost productivity, health care expenditures, law enforcement and criminal justice expenditures, etc.

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between the Australian Commonwealth, State and Territory Governments and the Non Government sector) has developed a wide range of strategies towards harm reduction arising from drug consumption; produced and disseminated research for policy development and public awareness; and conducted national surveys to monitor the consumption of drugs. In 2004, nearly half of the Australian population, aged 14 or older, consumed alcohol and about one fifth smoked tobacco at least once weekly (NDSHS 2005a). More than 15 % reported the use of illicit drugs in the past year, and more than a third had used them at some stage in their life. While marijuana remains the most widely used illicit drug, mainly due to low price (AIC 2013), synthetic drugs such as speed, ice and ecstasy, which belong to the class of amphetamines, have become increasingly popular in the last decade, in particular, among young users (Ransley et al. 2011).

Drug abuse results in significant social and economic costs to the Australian society. In 2004–2005, drug misuse was estimated to cost Australians more than AUD56 billion (around 8.6 % of GDP), of which AUD48 billion was attributed to licit drugs and AUD8 billion to illicit drugs (Collins and Lapsley 2008). These costs relate to resources used to address crime, health care, accidents and loss of potential productivity from disability, drug-attributed death and withdrawal from the workforce. They also include intangible costs resulting from psychological stress or loss of life. Such a significant waste of resources (resulting from negative externalities) can only be minimised with a well-designed set of cost-effective policies and strategies. Thus, from a policy perspective, it is very important to have a thorough understanding of drug users and their economic behaviour.

The criminal status of illicit drugs is a topic of heated debate across the world. It is argued that drug prohibition imposes a heavy economic cost on society in terms of legal and health care expenses when those resources could be released to better protect society from more serious crimes. On the other hand, opponents of drug decriminalisation or legalisation advocate that such policies only result in an increased use of drugs without bringing any social benefits to society. A few countries, or jurisdictions within some countries, have decriminalised or legalised the use of drugs. In Australia, the decriminalisation of marijuana has stirred a lot of controversy. South Australia was the first jurisdiction to implement an expiation system for minor marijuana offences known as the Cannabis Expiation Notice (CEN) system, in 1987. Under this scheme, simple marijuana offences such as possessing, or cultivating small amounts for personal use are subject to minor penalties although the sanctions for commercial dealings are rather significant. Similar expiation systems have since been introduced in a few other Australian states and territories and yet others have been gradually easing their laws against marijuana consumption in recent years. Given Australia's fairly recent experience with decriminalisation, there is not much empirical evidence in support of the policy and its intended effect.

Research on drug use and its consequences has arisen from several disciplines. Drug users' behaviour has been studied extensively in psychology, sociology and medical arenas. In the last two decades economists have also showed growing interest in the study of drug use and its consequences. They have brought unique and useful perspectives to the understanding of drug users' behaviour, the onset of drug use, and abuse prevention, all of which have made important contributions to the drug policy debate. Economic frameworks and methodological tools have, by far and large, complemented other research approaches. One attribute of economists' take on drug studies has been to rationalise drug use using approaches they have adopted in the study of other goods' consumption. This has led them to explore the impact of economic factors such as price and income on drug consumption.[2] With the increasing availability of drug data, sophisticated econometric techniques and modelling approaches also offer potential to further enhance the investigation of drug use and abuse.

Against this background, a thorough investigation of drug consumption in Australia could not be more emphasised. This book conducts a comprehensive analysis of licit and illicit drug consumption at an individual level. In particular, it examines the effects of price and other socioeconomic and demographic factors on individuals' drug consumption. More importantly, the book makes use of advanced econometric techniques to explore relationships across drugs. In particular, drug use is examined using a multi-drug framework in order to account for individuals' unobserved characteristics. This allows estimations of conditional and joint probabilities of drug use which cast light on the characteristics and economic behaviour of subpopulations of drug users.

In particular, the book attempts to answer several questions raised in current drug policy debates. Developing cost effective drug programs and policies require a sound knowledge of drug users and their characteristics. Who are the drug users in Australia? Can demographic factors help towards predicting drug usage? What subpopulation groups should be targeted for drug-related campaigns and educational programs?

Despite their legal status, alcohol and tobacco use is regulated in order to discourage high levels of consumption that can be detrimental to an individual's health. Are existing alcohol and tobacco policies effectively discouraging their use? While these policies are developed to discourage the use of each drug individually, there are reasons to believe that they also affect the consumption of other closely related drugs. For instance, a tobacco policy is very likely to also affect marijuana use given that cigarettes and marijuana are often rolled together for smoking. If drugs are related in consumption, what is the nature of the economic relationships between them? Do policies aimed at reducing the use of one drug have any unintended effects on the consumption of other drugs?

As mentioned above, the criminal status of marijuana is heavily contended. Has the decriminalisation of marijuana increased its usage? Should the drug be

[2]The most fundamental law of economics links the price of a product to the demand for that product. Accordingly, increases in the monetary price of, say, alcohol (i.e., through tax increases) would be expected to lower alcohol consumption and its adverse consequences. Consumers also respond to income changes. When the income of the consumer rises with the price of say, tobacco, held constant, demand for tobacco increases. Income and prices thus play an important role in a consumer's decision to consume a drug.

legalised? Is marijuana consumption price responsive? Should taxes be considered as an alternative policy instrument to criminal sanctions given that they provide better social benefits?

Drugs are potentially correlated in their usage. It is very likely that a person who consumes marijuana will also smoke cigarettes; or a person who uses a hard drug such as cocaine will most likely also smoke marijuana. Are there any intrinsic relationships across drugs that cannot be accounted for by observable factors but which are induced by individuals' unobserved characteristics such as addictive personalities and risk-taking attitudes? Can the impact of such unobservables be quantified, or accounted for?

In 2004–2005, drug abuse related loss of productive capacity in the Australian paid workforce was estimated at around AUD11.0 billion. This represented loss in productive capacity due to deaths and illnesses causing premature retirement, absenteeism from sickness or injury, and reduced productivity (Collins and Lapsley 2008). On the other hand, drinking is known to have some health and social benefits. It is increasingly argued that moderate amounts of wine consumption lowers the incidence of heart disease and strokes (Fagrell et al. 1999; Reynolds et al. 2003). It is also believed that alcohol reduces stress and tension levels and plays a networking role (Peters and Stringham 2006; Vasse et al. 1998). Better health or increased social capital in turn results in increased productivity which generates greater promotional opportunities and higher wages. Is there enough empirical evidence to support such claims? Do moderate drinkers earn higher wages than abstainers or heavy drinkers? The relationship between patterns of alcohol consumption and earnings is an important area for policy development and requires further insights and empirical evidence.

This book attempts to answer all of the above questions.

1.2 Objectives of the Book

The questions set out above have important implications for policy development. While there is a modest international body of literature addressing most of these issues, very little research has been undertaken in Australia on economic issues related to drug consumption. The broad objective of the book is to provide a thorough empirical investigation of Australian individuals' recreational drug consumption in order to contribute to the drug-related policy debate.

The primary objectives of the book are as follows.

1. To examine empirically Australians' consumption of a range of licit and illicit recreational drugs collectively using large scale survey data from the National Drug Strategy Household Survey (NDSHS). This comprehensive national survey conducted on a random sample of Australians allows for a micro investigation of drug consumption at an individual level. The magnitude and coverage of the survey lends confidence and reliability to the findings from the book.

2. To extend and improve existing economic tools used in the literature. A battery of advanced econometric techniques are used here to extract crucial information contained in the data. These include techniques that allow for more flexible specifications in individual behaviour, and that jointly model the consumption behaviour for related drugs, by allowing unobservable characteristics such as individual tastes and addictive personalities to be accounted for across different drugs.

   Specifically, the book addresses these issues in the following ways.

- *Empirical Evidence*. It lends further empirical evidence to the budding economic literature on drugs in Australia. While findings from other countries have been useful for policy development in Australia, there has been a lack of such research at the local level. This book makes a significant contribution in terms of providing empirical evidence on the social and economic factors driving drug consumption, price effects and the effectiveness of policies, based on data that is nationally representative of the Australian population. The findings, in turn, provide inputs to policy-related discussions and lend support to policy formulations.
- *Illicit Drugs*. A very small body of research has explored the consumption of illicit drugs due to scarcity of data. In addition, most of these studies have focused on marijuana consumption. With the increasing popularity of other illicit drugs, in particular, among the youth population, and an increased availability of drugs in recent years, there is now a growing need to channel research into these areas. This book fills the dearth in the literature by conducting a thorough investigation into a number of illicit drugs.
- *Binge Drinking*. Although there has been some international media focus of the adverse consequences of binge drinking, studies related to this harmful pattern of drinking are sparse in Australia as well as overseas. On the other hand, there has been a growing media coverage on the benefits associated with moderate drinking. This book explores drinking patterns of Australians to shed light on the characteristics of drinkers and their economic behavior.
- *Drinking and Earnings*. Drinking patterns have important implications on the productive capacity of an economy. Premature retirement, absenteeism from sickness or injury and reduced on-the-job productivity resulting from excessive drinking have been associated with a significant loss in productive capacity. This research provides insights on the relationship between drinking patterns and earnings. It contrasts with previous studies in terms of the disaggregation of heavy drinkers into frequent and non-frequent binge drinkers and measures the earnings differentials across the various drinking groups. It also attempts to identify the factors that contribute to such earnings differentials.
- *Beer, Wine and Spirits*. Anecdotal evidence suggest that consumers of beer, wine and spirits relate to quite different socioeconomic and demographic groups and respond quite heterogeneously to economic factors such as price. There is an abundant literature on the consumption of alcohol, treated as a homogenous product. Aggregating beer, wine and spirit into a single commodity fails to

reveal the differential demographic or policy effects. This book investigates participation in beer, wine and spirit consumption separately.
- *Economic Relationships*. The book investigates the nature of the economic relationships across licit and illicit drugs. Own and cross price participation elasticities are estimated for both marginal and conditional probabilities of drug use. These findings are important from a policy perspective because they indicate the likely consequences of policies designed towards one drug on the consumption of other closely related drugs.
- *Price Elasticities*. Economic literature on illicit drugs is mostly nonexistent because of the lack of availability of price data. Those few studies which have investigated marijuana consumption in the last two decades have often used proxies such as criminal status, in the absence of its monetary price. This book estimates own and cross price elasticities for a selection of illicit drugs using price data from the Illicit Drug Reporting System, a project funded by the Australian Government. These drug prices are collected chiefly by interviewing injecting drug users and key informants who have regular contacts with illicit drug users.

1.3 Outline of the Book

The book is structured as follows. In the following chapter (Chap. 2), the economic literature on recreational drug consumption is reviewed. The chapter starts with a discussion of a few alternative theories underpinning drug consumption. These include economists' formulation of the traditional consumer demand theory and the more recent rational addiction and gateway theories. It then reviews empirical studies on the consumption of licit and illicit drugs, and provides evidence gathered in the literature, on cross-drug relationships. The chapter ends with a discussion of the econometric techniques used in the literature and some data issues, highlighting their implications on research.

Chapter 3 gives an overview of recreational drug consumption in Australia. In particular, it provides insights on a number of licit and illicit drugs commonly consumed by Australians, highlighting their prevalence and patterns of use. It also outlines the National Drug Strategy Household Survey which is one of the main sources of comprehensive drug data in Australia which forms the basis of the research in this book. In addition, it gives a brief overview of the laws related to illicit drugs in Australia and Australians' attitudes towards drug laws and drug use.

Chapter 4 uses standard modelling approaches employed in the literature to investigate the factors relating to the consumption of a selection of licit and illicit drugs *individually*. It estimates the effects of price and other socioeconomic and demographic factors that influence individuals' decisions to consume each of these drugs. Price elasticities are estimated and the economic relationships across the drugs are established via cross price responses. The chapter first examines the consumption of the two legal drugs, alcohol and tobacco. It models the levels of alcohol and cigarette consumption in order to examine Australians' drinking and smoking patterns and identify their important drivers. In addition, alcohol is disaggregated in terms of the three major alcoholic types (beer, wine and spirits) in order to examine individuals' participation in each type of alcoholic drink separately. The second part of the chapter studies illicit drug consumption. Here, participation in marijuana, cocaine, heroin and amphetamines is individually modelled. Existing studies on illicit drugs have often used proxies for prices. Here, monetary prices of illicit drugs are used and own and cross price elasticities of participation are estimated. The research also investigates the policy effect of marijuana decriminalisation on marijuana participation.

Chapter 5 examines multi-drug consumption and cross-drug relationships using a more sophisticated system of equations. Here, the five-dimensional consumption status of marijuana, cocaine, heroin, amphetamines and tobacco is modelled in a multivariate framework. Due to unobserved characteristics such as individual tastes, addictive personalities and risk-taking attitudes, individuals' decisions to participate across a range of drugs can be potentially related through the error terms. As a consequence, vital cross-drug information is lost by using a univariate approach as in Chap. 4. The system approach used in Chap. 5 accounts for the correlation across such unobservables. The key advantage of the multivariate approach is that it models joint and conditional probabilities of drug use as functions of observable covariates. The multivariate results are thoroughly examined and compared to univariate estimates in order to highlight the extra insights provided by the multivariate technique. Two forthcoming papers have resulted from this chapter.

Chapter 6 uses the Ordered Generalised Extreme value (OGEV) model, which is an extended model of the Multinomial Logit (MNL), but allows correlation across ordered choices, and applies it to investigate levels of alcohol consumption. To address model selection issues and highlight the superiority of the OGEV model, the OP and the MNL models are estimated using the same dataset and compared with the OGEV results. Part of the contents of this chapter has been published.

Chapter 7 examines the relationship between drinking patterns and earnings. In particular, this analysis attempts to test the hypothesis whether there is any positive return to drinking relative to abstaining and whether this positive return also prevails for excessive drinking. Controlling for demographic factors and job characteristics and addressing issues of selectivity bias, separate earnings equations are estimated for various drinking groups. Earnings differentials are then calculated and a thorough decomposition is carried out to identify the factors that predominantly contribute to these differences.

Chapter 8 summarises the main findings of the book. In the light of these findings, it discusses some policy implications. It ends by outlining the limitations of the research and delineating some areas for future research.

Chapter 2
Literature Review

2.1 Introduction

Complementing research on recreational drugs in other disciplines, such as epidemiology, sociology, psychology and medicine, economists have investigated an array of issues related to drug consumption and its adverse effects. Their contribution to the drug debate has provided valuable insights and assistance to health professionals and policymakers towards the development of effective policies to contain drug use and minimise the associated harms.

The economic approach considers drug consumption within the context of individual consumer decision-making. This has led economists to examine policy tools that impact on the demand and supply of psychoactive drugs. Economic theories have been developed and examined empirically. The development of more sophisticated econometric tools and methods and improved quality of data in recent years have significantly enhanced drug analysis to provide a better understanding of drug consumption behaviour.

While there exists an exhaustive literature on licit drugs, research on illicit drug use has been rather sparse due to unavailability of data. Nevertheless, the last two decades have seen a growing number of economic studies on illicit drugs, most of which examined US data. Drug decriminalisation, or legalisation, has stirred significant discussion across many disciplines. Economists have been at the forefront of this debate and have provided important insights on the economic impact of criminal law enforcement regarding drug use.

This chapter carries out a selective review of the economic literature on drug use. It focuses on studies that have investigated the demand for drugs predominantly in the post-1980 period. Section 2.2 outlines the economic theory related to drug consumption. Section 2.3 surveys the literature on drug consumption, reviewing studies on licit and illicit drugs separately. Empirical evidence on cross drug relationships is examined in Sect. 2.4. Section 2.5 discusses the econometric methods used in the empiric and Sect. 2.6 raises a few data issues. Finally, Sect. 2.7

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summarises the chapter highlighting some limitations in the literature and presenting scope for further research.

2.2 Economists' Formulation of Drug Consumption

Economic studies have made important contributions to the drug debate. The economic approach considers the demand for drugs as a result of the traditional consumer utility maximisation problem (see Pacula 1998b; Sickels and Taubman 1991). Individuals are assumed to derive utility from the consumption of a bundle of goods and services which can include substance use. They make decisions about choosing, purchasing and consuming the best combination of goods and services that maximise their utility subject to a budget constraint. The constrained utility maximisation yields demand equations for each of the commodities consumed. A substantial body of empirical research provides evidence that consumers' decisions to consume drugs are consistent with the economic law of demand: an increase in the price of a drug is expected to deter its consumption, and thus, its adverse consequences. Drug demand has been estimated using different types of data and measures of consumption, such as time-series data on national aggregate consumption and individual-level data from micro surveys.

The addictive nature of drugs has received extended attention in the drug literature. Until the mid-eighties, most studies focused on the habit formation, or reinforcement, aspect of addiction. This led researchers to explore the dynamic behavior of addictive goods' consumption using imperfectly rational addiction models (Strotz 1955) or myopic models of addiction (see Houthakker and Taylor 1970, Chapter 5). The imperfectly rational addiction model recognises the impact of past and current choices on future consumption decisions when an individual makes current choices, but argues that the individual changes his plan in the future. On the other hand, in the myopic model, current consumption decisions are backward-looking. They are influenced by only past consumption such that myopic drug users ignore any forward-looking intertemporal aspect of consumption when they determine the optimum quantity of drug consumption in the current period. Most of the earlier economic studies that modelled drug consumption assumed drug users to be myopic or imperfectly rational. This led them to believe that habit, or addiction, is not quickly abandoned such that drug users would not necessarily respond to expected price increases. There is a considerable amount of empirical evidence in support of habit formation in the literature (see Grossman et al. 1998a).

Becker and Murphy (1988) brought a new perspective to the analysis of addictive behaviour. They argue that addicts can also be forward-looking and rational such that the consumption of addictive goods can be analyzed in a standard rationally optimizing framework. In their model of rational addiction consumers take account of both past consumption, and future effects, of current consumption when making current choices. They believe that while utility rises from current consumption, long-run utility is lower because they are building up a stock of the addictive good that has a negative marginal utility. Thus, their model assumes that individuals consistently maximize utility over their life cycle, taking into account past and future consequences of their choices. For instance, the decision to take drugs is based on present and future costs and benefits of consumption. The costs are related to the negative effects of drug use on health which are often realised in the longer run. The perceived benefits are usually immediately realised and might include relaxation, enhancement of concentration, stress alleviation, etc. To the extent that such costs and benefits are reflected in current and future prices, the latter can be used as instruments for past and future consumption. In contrast to the conventional wisdom that addictive goods are not price sensitive, they suggested that demand for an addictive good falls following a price increase, with a greater response to a permanent price increase in the long term than in the short term. A sizeable empirical literature has since evolved on rational addiction, examining and generally supporting the key empirical contention of the Becker and Murphy model on intertemporal complementarity (Becker et al. 1994; Chaloupka 1991; Grossman and Chaloupka 1998; Keeler et al. 1993). However, scarcity of intertemporal consumption data restricts the use of the rational addiction model as a standard approach to modelling the consumption of drugs.

Another strand of the drug theory which has considered the intertemporal consumption of drugs is the gateway, or stepping-stone, theory pioneered by Kandel (1975). The gateway hypothesis suggests that there is a systematic progression or sequencing in drug use with soft drugs such as alcohol and cigarettes providing a gateway, or stepping stone, to marijuana and finally to the use of hard drugs such as cocaine and heroin. It postulates that the early onset of legal drugs causes individuals, in particular adolescents, to experiment with harder drugs later. A small literature has evolved on the gateway theory broadly underpinned by two key lines of arguments. On the one hand, the gateway effect is considered to be causal and generative where the use of soft drugs induces the consumption of hard drugs (Baumrind 1983). On the other hand, it is argued that the gateway effect is only predictive where the use of a soft drug helps predict the use of a hard drug without implying causality (O'Donnell and Clayton 1982). Until recently the gateway effect had been discussed mostly by non-economists, including epidemiologists, sociologists and psychiatrists. In recent years, economists have shown increasing interest in testing the gateway hypothesis. Notwithstanding the paucity of intertemporal data, a growing, but modest, body of theoretical and empirical economic literature has amassed on the gateway hypothesis (see Beenstock and Rahav 2002; Bretteville-Jensen et al. 2008; Degenhardt et al. 2010; DeSimone 1998; Pacula 1997; Pudney 2003; van Ours 2003).

2.3 Drug Consumption

Drug consumption has been examined using a variety of data and econometric methods. Most of the earlier studies used state or national time series data on *aggregate* consumption. The prime objective of those studies was to examine price effects. The availability of *individual-level* data has, however, brought an improved understanding of consumer behaviour. The analysis of differential policy responses by demographic characteristics such as age, gender and ethnicity, along with the demographic differential effects themselves, has been very useful for the development of drug policies and other educational programs.

The main focus of economic demand studies has been on the price elasticity of demand. Economists argue that in addition to the monetary price of drugs, drug prohibition, or restrictions on availability, are also potential deterrents of drug use. By making purchases more difficult or illegal, restrictions on availability increase the full cost of drugs. A negative demand response to such restriction policies is thus predicted as another example of the law of demand.

In contrast to licit drugs, demand studies have focused very little on illicit drug use given that consumption data and price measures of illicit substances are generally difficult to obtain. In the absence of data on money prices, economists have often used the legal status of drugs, and/or fines and prison sentences for drug possession, as proxies for their full price. Decriminalisation which entails lowering, or eliminating, criminal sanctions against the use of illicit drugs is predicted to decrease the price of drugs. The literature has shown mixed evidence of the impact of such policies on drug consumption.

2.3.1 Licit Drug Consumption

In most countries and jurisdictions, the use of alcohol and tobacco is legal although some have restrictions on where drinking and smoking are allowed. Notwithstanding their legal status, various policies have been developed to contain their misuse. Economic studies have made important contributions to developing tobacco and alcohol abuse prevention policies. The literature has examined a host of licit drug policies including: taxes; restrictions on drinking and smoking in public places or on-campus; minimum legal drinking and smoking age; regulations limiting place and time to sell alcohol and cigarettes; enforcement of drunk driving laws; and label warning of the dangers of drinking and smoking. Given the long-standing legal status of tobacco and alcohol in most countries, there exists a more extensive and comprehensive set of data on the two drugs as compared to illicit drugs. In addition, self-reported surveys attract higher response rates for questions relating to licit drugs compared to illicit drugs as there is no fear of any adverse consequences. Also, drug-related information such as price, excise duties and fines imposed for drunk-driving are typically easily and cheaply obtained from public sources. Against this background, licit drug consumption has been extensively examined over the past couple of decades.

Alcohol

A large body of economic literature has developed over the last few decades on alcohol consumption. Again, most of the earlier research examined *aggregate* demand for alcoholic beverages. Of more interest to policymakers has been the prevalence of drinking, bingeing, and chronic heavy drinking, given that the adverse consequences of alcohol are mostly associated with excessive drinking. There has also been a particular interest in drinking patterns across certain demographic groups such as adolescents, young women in their child-bearing age and the unemployed. With the availability of individual-level data, several of these issues of interest have been examined empirically (for example, Hammer 1992; Sen 2003).

Economic demand studies have generally found evidence of a decline in alcohol consumption in response to demand restriction policies. Chaloupka (1993) carried out a survey of studies which assessed the sensitivity of alcohol use to price changes. He found considerable evidence that an increase in the price of alcoholic beverages could effectively reduce drinking. Pacula and Chaloupka (2001) reviewed studies which examined the impact of price and public policies on alcohol abuse. They concluded that addictive behaviour is sensitive to changes in the full price of drugs, where the full price of a drug reflects not only its monetary cost, but also health, legal and time costs involved in obtaining and using the drugs. More recently, Cook and Moore (2002) reviewed some studies which examined the impact of prices on alcohol use and abuse and alcohol-related problems. They also concluded that excise taxes on alcoholic beverages are effective at controlling alcohol consumption and therefore can be effectively used to promote public health. In addition, they found that other policies such as minimum purchase age, advertising restrictions, and fines and liability laws can also help curb alcohol use and its adverse consequences. Chaloupka et al. (2002) drew similar conclusions from a survey of studies that examined the impact of alcohol prices on drinking and heavy drinking by teenagers and young adults.

The impact of price and other alcohol policies on drinking usually varies by type of alcoholic drinks (Asplund et al. 2007; Clements and Johnson 1983; Nelson 1997; Selvanathan and Selvanathan 2004) and consumption levels (Cook and Moore 1993b; DiNardo and Lemieux 2001; Grossman et al. 1994, 1987; Kenkel and Manning 1996; Williams 2005). The next sections discuss these issues in more detail.

Demand for Beer, Wine and Spirits

Alcohol is consumed in heterogenous product forms. Anecdotal evidence suggests that the three broad alcoholic types—beer, wine and spirits—are consumed by quite different socioeconomic and demographic groups. These user groups, with some distinctive characteristics, exhibit different consumer behaviour. For instance, their price responses are quite different across the three alcoholic types. Generally beer consumption tends to be the least responsive to its price, whereas spirits, more commonly used by young people, are the most price sensitive. The scarcity of data by specific alcoholic types has restricted economic analyses of beer, wine and spirits separately at individual level. Nonetheless, a few epidemiologists and health professionals have examined the association between demographic and personality traits and individuals' preference for particular alcohol types (see Klatsky et al. 1990; McGregor et al. 2003).

Most economic studies that have examined the demand for beer, wine and spirits individually have used aggregated time series data and a system-wide approach with again, a focus on price elasticities. From an extensive review of the economic literature on the relationship between price and the demand for the three beverages, Leung and Phelps (1993) concluded that the demand for beer was significantly price inelastic while those for wine and spirits were elastic. Similar evidence was found from an earlier survey by Ornstein and Hanssens (1985), but no reliable estimates were obtained for wine price elasticity. In contrast, a few studies have found all three types of alcoholic beverages to be price inelastic (Clements and Selvanathan 1987; Heien and Pompelli 1989; Nelson 1997) of which some have been examined using Australian data (for example, Clements and Johnson 1983; Clements and Selvanathan 1991; Selvanathan 1991).[1] Fogarty (2006); Gallet (2007) and Wagenaar et al. (2009) shed light on this disparate and conflicting literature by showing that most of the variations in the own price elasticity of demand estimates for alcohol could be related to demand specifications, data issues, estimation methods, the level of alcohol consumption, and the ethanol share in the beverages. The results on cross price responses have been equally conflicting in the literature. As a result, there is mixed evidence on the economic relationships across the three types of alcoholic drinks.

Heavy Drinking, Bingeing and Youth Drinking

Heavy drinking and bingeing are of particular interest to policymakers given the adverse outcomes they have on society. Several studies have examined the effect of alcohol policies such as taxes, drink driving laws and alcohol restrictions on heavy drinking and bingeing. In general, these studies have focused on youth drinking. Teenagers and young adults, prone to potentially risky behaviour (Gruber 2001; Markowitz et al. 2005), are of considerable concern to policymakers. Young people are more likely to indulge into heavy or binge drinking which results in a high incidence of motor vehicle fatalities and crime and violence across this segment of the population. Also of concern is the habit forming aspect of drinking—adolescent drinking appears to set the pattern for alcohol use in later life (see Cook and Moore 2001; French and Maclean 2006; Grossman et al. 1998b; Williams 2005). Finally, youth drinking can have some detrimental, and often irreversible, consequences in

[1] However, using more recent Australian data, Selvanathan and Selvanathan (2004) has found the demand for spirits to be price elastic.

terms of health, human capital and social status (Cook and Moore 1993a; Dee and Evans 2003; Kenkel et al. 1994; Williams et al. 2003).

The effectiveness of a price policy on adolescents' and young adults' drinking behaviour has been the subject of extensive debate among researchers and policymakers. The price sensitivity of youth drinking, problem drinking and drinking consequences have been examined by a number of economists using a variety of data sets over different time periods. While most studies have agreed that price increases result in a lower frequency of youth drinking and binge drinking (Chaloupka and Wechsler 1996; Coate and Grossman 1988; Laixuthai and Chaloupka 1993; Saffer and Dave 2006; Williams 2005; Williams et al. 2004), the magnitude of the effects has varied across studies. Coate and Grossman (1988) obtained a negative effect of price on youths' frequency of alcohol consumption: the impact being larger for frequent to fairly frequent drinkers as compared to infrequent drinkers. Chaloupka and Wechsler (1996) found that an increase in beer prices led to moderate reductions in both binge drinking and drinking among female youths, but had no effect on males. In contrast, Chaloupka and Wechsler (1996) and Williams and Mahmoudi (2004) found little impact of beer price on youth drinking or binge drinking. Chaloupka et al. (2002) argued that most of the disparities in youths' price response in the literature could be associated with the price measure. They claimed that college students' drinking often takes place at local bars that offer sharply discounted prices to attract college students, or in parties and other social and recreational occasions where alcohol is available at no charge. However, studies investigating youth drinking have generally used state level alcohol prices as a measure of monetary price and neglected the low-cost or no-cost drinking that occurs on frequent occasions.

Prohibition from selling to underaged adolescents has also been recognised as a coercive tool to contain alcohol consumption. Several studies have investigated the effect of the Minimum Legal Drinking Age (MLDA) on alcohol participation, the amount of alcohol consumption and alcohol-related consequences (for example, Coate and Grossman 1988; Dee 1999a; DiNardo and Lemieux 2001; Laixuthai and Chaloupka 1993; Pacula 1998b; Thies and Register 1993). Most of these studies concluded that an increase in MLDA reduces the prevalence of youth drinking, frequency of drinking and heavy drinking.

The use of alcohol restriction policies on campus has also been recognised as an effective means to contain drinking and excessive drinking among youths. Campus bans, restrictions on "happy hours" and on open cans, appear to be significant deterrents to young drinkers (see Chaloupka and Wechsler 1996; Williams 2005; Williams et al. 2005; Williams and Mahmoudi 2004). For instance, Chaloupka and Wechsler (1996) found that restrictions imposed on on-campus bars and the number of outlets selling alcoholic beverages within an institution's proximity, could be more effective in reducing binge drinking than beer taxes. In addition, they showed that more aggressive drink driving policies, such as increasing the probability of arrest and raising the penalties upon conviction for young drunk drivers, could reduce both drinking in general and binge drinking among males.

A study by Manning et al. (1995) appears to be the only one that has examined price responsiveness of alcohol demand for light, moderate and heavy drinkers on the *general population* as opposed to adolescents and young adults. It found that light and heavy drinkers were much less responsive to alcohol price than moderate drinkers. The study also examined how price influenced the pattern of consumption by considering the number of days of heavy drinking for a sample of heavy drinkers. Recognising the small sample size of heavy drinkers, they found such a drinking pattern to be less price responsive than overall drinking.

Tobacco

Over the past few decades, a fairly large economic literature has evolved on the demand for tobacco. The studies have been based on a variety of data and modelling techniques. While economic analyses have predominantly focused on the relationship between price and consumption of tobacco, several studies have examined the effects of other policy tools that can potentially curb tobacco consumption such as fines for smoking in public places, prohibition from selling to underaged and bans on self-service displays of cigarettes in shops (see, for example, Bardsley and Olekans 1999; Czart et al. 2001; Goel and Nelson 2005, 2006, 2012). Other studies have investigated the effects of advertising and promotional activities that encourage smoking (see Hu et al. 1995; Saffer 1998) while a small literature has examined the impact of anti-smoking advertisements or campaigns (Bardsley and Olekans 1999). With the advent of sophisticated econometric models and longitudinal survey data, there has also been a growing interest in recent years in investigating the factors that affect the initiation and cessation of smoking (see, for example, DeCicca et al. 2002; Jones 1994; Kidd and Hopkins 2004). Cigarette smoking has also been examined in the context of gateway theory to test for any gateway effect it may potentially have on the use of other harmful drugs (Beenstock and Rahav 2002; Degenhardt et al. 2010).

Most of the earlier studies have used time-series data aggregated at national or state level. However, in recent decades, economists have increasingly used individual-level data to examine issues that generally cannot be addressed using aggregate data. As in the case of alcohol, policymakers are more interested in the prevalence of smoking and the pattern of smoking, particularly across certain socioeconomic and demographic groups such as youths and the unemployed. The use of unit-level data has allowed them to estimate differential policy responses across those population groups of interest and examine demographic differentials effects useful for the development of public policies (Goel and Nelson 2005; Hersch 2000).

Cameron (1998) and Chaloupka and Warner (2000) and more recently Gallet and List (2003) reviewed the economic literature on cigarette consumption. They found that cigarette consumption was generally price inelastic although the estimates of the price elasticities varied across studies. They argued that most of the disparity in the estimates of price elasticities resulted from sensitivity to model specifications, data issues and estimation methods.

In recent years, with the development of the rational addiction model and the availability of longitudinal data, a small number of studies have made attempts to model cigarette demand considering the addiction aspect of its consumption (for example, Becker et al. 1994; Chaloupka 1991; Chen and Lin 2012; Gruber 2000; Keeler et al. 1993; Sung et al. 1994; Suranovic et al. 1999). Findings across most of these studies have been consistent with the hypothesis that smoking is addictive and that farsighted smokers reduce their current consumption because of expected increase in future prices.

Youth Smoking

Youths' smoking has been a matter of considerable concern to public health officials and policymakers given the pandemic use of cigarettes in this segment of the population, and its adverse implications in terms of habit formation and long-term health consequences. The earliest of the studies that used individual-level data showed important differential effects in terms of age (Lewit and Coate 1982; Lewit et al. 1981). In particular, these studies found an inverse relationship between age and price responsiveness, at least in the short run. The weak price sensitivity among adults was associated with the addictive nature of smoking. Presumably, long-term adult smokers who get addicted to smoking are less likely to adjust to price changes than youths. They also found that price did not only reduce youth smoking directly but also indirectly through its impact on peer smoking. Chaloupka and Wechsler (1997) contributed to this discussion by arguing that a stronger response by youths is a result of a larger fraction of their disposable income being spent on smoking and a higher future discount rate given their present-oriented attitude. In another study, Emery et al. (2001) investigated whether adolescents' price responsiveness varied by smoking experience. They found that experimenters were not as sensitive to price changes as established smokers were.

Several recent studies on teenage and young adults' smoking using individual-level data have reinforced the evidence of youths' price sensitivity (see Chaloupka and Wechsler 1997; Czart et al. 2001; Goel and Nelson 2005; Harris and Chan 1999; Tauras and Chaloupka 1999). A small body of literature has also examined the effectiveness of tobacco control policies in deterring youth smoking (Chaloupka and Grossman 1996; Chaloupka and Wechsler 1996; Evans and Huang 1997; Tauras and Chaloupka 1999; Wasserman et al. 1991). Workplace smoking bans, restrictions on smoking in public places and limits on smoking in schools have been found to reduce smoking prevalence and intensity while other restriction policies such as minimum legal purchase age and restrictions on vending machines appeared to have little impact on youth smoking. There is also some evidence of differential policy response across demographic groups. Chaloupka and Pacula (1999) and Farrelly et al. (2001a) found price responses to vary by demographic characteristics such as age, ethnicity and socioeconomic background. Chaloupka and Pacula (1999) estimated significant differences by race in youths' responsiveness to tobacco control policies while Goel and Nelson (2005) found male smokers to be more responsive to indoor smoking restrictions than females.

2.3.2 *Illicit Drug Consumption*

Illicit drugs impose heavy social and economic burdens on society in terms of negative externalities including the cost of health care and lost productivity. However, due to data unavailability, very little was known until recently on illicit drug use and the impact of drug policies on their consumption. In recent decades, data on illicit drug use have been collected through various surveys although fear of consequences is argued to result in potential underreporting (Del Boca and Noll 2000; Kim and Hill 2003). In addition, unlike licit drugs, price information on illicit drugs are not typically collected and recorded in a systematic way. Nonetheless, a small body of literature has evolved in the last few decades examining the consumption of marijuana. More recently, the demand for some other illicit drugs such as cocaine, heroin and opium has also been examined.

Marijuana is the most commonly used drug after tobacco and alcohol, particularly among youths. Its illicit status has been a subject of continuing debate over past decades. Decriminalisation/legalisation of marijuana entails lowering/eliminating criminal sanctions against the use and possession of small amounts of the drug. A few countries or jurisdictions within some countries such as the US, UK, Portugal, Belgium and Australia have decriminalised or legalised the criminal status of marijuana arguing that prohibition laws do not discourage its use but rather impose substantial financial costs on society at large. They further argue that criminalising the soft drug, widely popular among young people, groups it with other more harmful hard drugs. As a result marijuana users face a greater risk of exposure to sellers of harder drugs and to consumption of harder drugs. On the other hand, opponents contend that marijuana decriminalisation or legalisation decreases the drug's non-pecuniary value and therefore increases its consumption. This discussion has motivated researchers to investigate the effectiveness of removing or softening prohibition laws on marijuana consumption. In earlier studies, the criminal status of marijuana was often used as a proxy for its monetary price in the absence of price information.

The first economic study that examined marijuana consumption was conducted by Nisbet and Vakil (1972) but was based on a small sample collected from one single US institution. Since the 1990s, several studies have modelled the demand for marijuana using nationally representative survey data, but mostly in the US. Cross-state variation in marijuana decriminalisation along with the monetary price of marijuana have been used to capture the full price effect of the drug. Findings on the impact of marijuana decriminalisation have generally been mixed. With the exception of Chaloupka et al. (1999a) who found an increase in consumption following decriminalisation using a sample of youths, studies which have focused on adolescents and young adults have generally found no significant impact of decriminalisation on marijuana consumption (see DiNardo and Lemieux 2001; Pacula 1998b; Thies and Register 1993; Williams 2004; Williams and Mahmoudi 2004). On the other hand, studies which have examined the impact of decriminalisation on the general population have found evidence of an increase in marijuana consumption (for example, Cameron and Williams 2001; Damrongplasit et al. 2010; Saffer and Chaloupka 1998, 1999; Zhao and Harris 2004). Saffer and Chaloupka (1998) pointed out some important differential effects of decriminalisation with respect to ethnicity. A few other studies have also investigated the impact of marijuana decriminalisation on adverse consequences of drug use, such as traffic fatalities and medical emergencies (see Chaloupka and Laixuthai 1997; Model 1993).

More recently, a small number of studies have addressed the demand for cocaine (Chaloupka et al. 1999b; DeSimone and Farrelly 2003; DiNardo 1993; Grossman and Chaloupka 1998; Saffer and Chaloupka 1998, 1999), all of which have focused on adolescents and young adults. With the exception of DiNardo (1993), all others found cocaine demand to be price sensitive. DeSimone and Farrelly (2003) observed a price response only among adults but not juveniles. There exist even fewer studies on heroin (see Dave 2006; Saffer and Chaloupka 1998, 1999; van Ours 1995) or opium (van Ours 1995) consumption.

A small body of literature has examined the effect on illegal drug use, of drug policies such as fines and jail sentences for possession, arrests rates and police enforcement (see DeSimone and Farrelly 2003; Farrelly et al. 2001b, 1999; Williams 2004). Chaloupka et al. (1999b) found that while sanctions for sale, manufacture or distribution of cocaine and marijuana had little impact on young cocaine and marijuana users, increased sanctions for their possession discouraged the use of both drugs. However, the magnitude of the estimates implied that very large increases in monetary fines were required to achieve meaningful reductions in use. Farrelly et al. (2001b) and DeSimone and Farrelly (2003) found evidence that higher fines for marijuana possession and increased probability of arrest decreased the probability of marijuana consumption among youths. A few studies have also examined the demographic differential effects related to illegal drug use, highlighting the impact of factors such as age, gender, education and ethnicity (Cameron and Williams 2001; Pudney 2004; Saffer and Chaloupka 1998; Williams and Mahmoudi 2004). Saffer and Chaloupka (1998) pointed out that the demographic pattern for marijuana use was rather similar to that of alcohol but different from those of cocaine and heroin.

2.4 Cross-Drug Relationships

The use of a drug cannot be considered in isolation from other drugs given that their consumption is potentially related. It is often argued that drug policies intended to discourage the use of one drug can also impact on the use of other related drugs.

For example, increases in the minimum legal drinking age or higher alcohol excise taxes, intended to deter alcohol consumption can signal societal disapproval for all drugs, not only alcohol. Similarly, advertisements to promote the use of one drug can also increase the use of their economic complements but discourage the use of their economic substitutes. This has led researchers to investigate the nature of economic relationships among the various drugs. Such findings have been potentially useful to policymakers to anticipate policy effects of one drug on the use of other closely related drugs and thus better coordinate drug policies. For instance, if cigarettes and alcohol are economic complements, public policy needs to check consumption of only one drug to reduce consumption of both.

Economic relationships between commodities are central to microeconomic consumer theory. They are determined using the sign of the cross price derivatives derived from Hicksian demand functions. Where individual-level drug data have been examined using discrete choice models, the economic relationships between drugs have been determined directly using the signs of the cross price coefficients or marginal effects. The literature has shown conflicting findings on economic relationships across drugs. Dee (1999a) examined the relationship between youth alcohol and cigarette consumption and found the two legal drugs to be economic complements. Similar results were obtained by Cameron and Williams (2001) and Zhao and Harris (2004) for the broader population while Goel and Morey (1995) found the two drugs to be substitutes in consumption. On the other hand, Picone et al. (2004) observed that cigarettes and alcohol are economic complements for those individuals who consider drinking or smoking as a source of pleasure or a stress reliever, but the two drugs act as economic substitutes for social drinkers and smokers. Decker and Schwartz (2000) found mixed evidence on the relationship between alcohol and cigarettes where both drugs were found to be substitutes in levels of consumption but an increase in alcohol price led to lower smoking participation.

Policymakers have been particularly concerned about the unintended effect that legal drug policies can have on the use of illicit drugs which are much harder to regulate. There has also been concern that decriminalising a soft drug such as marijuana may result in an increased use of harder drugs such as cocaine and heroin. Several studies have examined the economic relationship of marijuana with *alcohol* (Cameron and Williams 2001; Chaloupka and Laixuthai 1997; DiNardo and Lemieux 2001; Farrelly et al. 1999; Model 1993; Pacula 1998a,b; Saffer and Chaloupka 1998, 1999; Thies and Register 1993; Williams and Mahmoudi 2004; Williams et al. 2004; Zhao and Harris 2004); *cigarettes* (Cameron and Williams 2001; Farrelly et al. 2001b, 1999; Zhao and Harris 2004); *cocaine* (DeSimone and Farrelly 2003; Saffer and Chaloupka 1998, 1999; Thies and Register 1993); and *heroin* (Saffer and Chaloupka 1998, 1999). While there seems to be ample evidence that marijuana is an economic complement for tobacco, cocaine and heroin, studies that have examined the relationship between marijuana and alcohol have yielded mixed results. Most of the earlier studies that have used the legal status of marijuana as a proxy for its price have found marijuana to be a substitute for alcohol. However, the more recent ones which have also accounted for the monetary price of marijuana and which are based on more recent data, have found evidence of complementarity between the two drugs.

The conflicting findings in the literature on cross drug relationships arise for several reasons. Pacula (1998a) attributed them predominantly to the potential endogeneity of control variables such as income, education and marital status; the lack of monetary prices in the estimation of demand equations; and the estimation of drug consumption in isolation. DiNardo and Lemieux (2001) also made an attempt to explain the conflicting results across studies. They attributed these differences broadly to the inclusion of potentially endogenous regressors, model specifications and sampling errors. Saffer and Chaloupka (1999) suggested that the conflicting findings across studies on the effect of marijuana decriminalisation could be attributed to the age of the cohorts being considered.

2.5 Econometric Approaches

The literature shows that studies which have examined drug consumption at an individual-level have mostly used discrete choice models. The use of such models has been driven by the categorical nature of the consumption data obtained from surveys. The decision to participate in drug consumption has generally been estimated using Probit or Logit models (see Cameron and Williams 2001; Chaloupka and Laixuthai 1997; Chaloupka et al. 1999b; Chaloupka and Wechsler 1996; DeSimone and Farrelly 2003; Farrelly et al. 1999; Saffer and Chaloupka 1998; Sen and Wirjanto 2010). Where researchers have estimated categorical levels of drug consumption, Multinomial Logit or Ordered Probit models have predominantly been used (Chaloupka and Wechsler 1996; Coate and Grossman 1988; Laixuthai and Chaloupka 1993; Williams et al. 2005). A few studies have modelled drug demand using two-part models where, in the first stage the decision to participate in drug use is estimated using a Probit/Logit model and in the second stage, the conditional amount of drug consumed is estimated using some form of linear regression model for continuous measures of drug use (Chaloupka et al. 1999a; Farrelly et al. 2001b; Manning et al. 1995; Pacula 1998b) and Ordered Probit models for categorical measures (Williams 2004). A few others have estimated tobit-type models to account for data censoring (Pacula 1998a; Thies and Register 1993; Williams 2005) or instrumental variable methods to address endogeneity issues (Dee 1999b; Picone et al. 2004).

Most economic studies on drugs have used a univariate approach, estimating drug consumption equations individually. However, this approach ignores the potential cross-commodity correlations across various drugs for the same individual that are potentially induced through unobservable characteristics such as personal tastes, addiction and risk-taking attitudes. Those few studies that have used multivariate techniques to estimate drug consumption (DiNardo and Lemieux 2001; Williams et al. 2004; Zhao and Harris 2004) have mostly focused on marginal probabilities of drug use, failing to fully explore the multivariate aspects of the model. The most attractive feature of these multivariate models is that they can be used to model joint and conditional probabilities. For instance, the multivariate models provide information such as how being a smoker increases the probability of consuming marijuana or how being a hard drug user relates to a very high probability of marijuana use. The estimation of policy effects and other socioeconomic and demographic differential effects on such joint and conditional probabilities can provide important policy information, in particular on multiple or polydrug[2] use.

2.6 Data Issues

Until the 1980s most studies that examined the relationship between price and drug consumption were based on time-series aggregated data. Individual level surveys appeared to be very scarce at the national level and were mostly conducted on a small scale in localised areas. The late 1980s and early 1990s saw the first studies that examined drug use using nationally representative individual-level survey data. These came predominantly from the US, most of which focused on a particular segment of the population, mainly youths and young adults. Cross-sectional and longitudinal surveys, such as the National Health and Nutritional Examination Survey (NHANES), the Monitoring the Future (MTF) survey and the National Longitudinal Survey of Youth (NLSY), were the few early sources of individual-level data providing information on drug use in the US.[3]

It is generally argued by researchers that studies which use individual-level data yield more precise estimates of price elasticities given that they consist of individual amounts of drug consumed by subjects. Studies based on individual-level data and time series aggregate data have often produced inconsistent results. Leung and Phelps (1993) observed that studies based on unit-level data estimate a much higher price response than those which use annual time-series data, mainly because they can capture differential price responses of individuals from various demographic groups.

Studies that use state or national data can only provide average (per capita) or total drug consumption. However, very often policymakers are interested in examining the prevalence of consumption and heavy drug consumption. Such issues cannot be addressed using aggregated state or national level data. In addition, unit-level data allow policymakers to examine price responses and policy effects which may potentially vary across a sub-population by demographic characteristics such as

[2]Wilkinson et al. (1987) define polydrug users as "users of a variety of psychoactive substances, either concurrently or sequentially". These can include licit and/or illicit drugs.

[3]The NHANES has been conducted since the early sixties on all segments of the US population. The MTF was first introduced in 1975 and collects data on American secondary school students, college students, and young adults while the NLSY is a longitudinal survey which first begun in 1979 and collects information on American teenagers and young adults.

age, gender and ethnicity. For instance, it is useful to find out whether the beneficial effects of a tax increase or some other drug policy, will be shared equally by all or whether specific policies are required to curtail drug abuse in certain sub-population groups. Blanket policies that fail to take into account such differences are very likely to prove ineffective and economically inefficient. The estimation of socioeconomic and demographic differential effects also provides vital information for designing anti-drug campaigns and educational programs. In particular, such information can help develop more efficacious counseling services and information services by targeting those population groups where drug use is more prevalent.

However, using individual-level data does have some limitations. They are typically obtained from cross-sectional surveys which measure individuals' drug consumption at the time of the survey. As such, price elasticity does not reflect individuals' response to a change in price but rather the effect on consumption resulting from a variation in alcohol prices across various states or geographical areas where individuals within the same state or geographical area face the same price. However, since individual-specific price information are rarely available, state level data are commonly used in such studies. Theoretically, the use of panel data addresses this problem but given that the time dimension of panel data is usually small, the variation in prices is likely to be insufficient to accurately measure price elasticities.

The reliability of self-reported surveys has often been questioned in the literature. Self-reported surveys have some inherent measurement errors and often tend to understate actual consumption (see Dave 2004; Harrison and Hughes 1997; Hoyt and Chaloupka 1994; Skog 1992; Wechsler and Kuo 2000). In addition, national surveys do not usually consider consumption by the homeless and prison inmates who generally have a high incidence of drug use and may potentially behave differently from the population at large. In fact, these individuals are much more likely to be hardcore users than those selected at random from the non-institutionalised population.

2.7 Summary

Economic research can make valuable contributions to drug policies and intervention programs by disseminating their research findings to policymakers, health professionals and consumers. This chapter has reviewed some of the theoretical and empirical economic literature on drugs focusing on studies that have modelled their consumption. The empirical literature on licit and illicit drug consumption is reviewed separately, examining the effects of drug policies and demographic factors. Cross-drug relationships are then discussed in the light of empirical evidence gathered from the literature. Finally, the chapter gives a brief discussion of issues related to data and modelling approaches, highlighting the importance of using individual-level data and multivariate techniques to examine drug consumption.

The above review has often showed conflicting and disparate findings across studies. Thus, further investigation of drug issues is required using more comprehensive drug data and enhanced modelling techniques that would provide additional empirical evidence or reinforce existing findings. In addition, most of these findings are based on US data and may be inappropriate to formulate policies for the Australian population given disparity in tastes and demographic factors.

The literature review also shows that there is an abundance of studies on licit drugs. In contrast, research on illicit drugs is sparser mainly due to data unavailability. Notwithstanding the growing popularity of other illicit substances such as cocaine, heroin, and amphetamines, the majority of illicit drug studies have focused on marijuana. This book investigates a selection of licit and illicit drugs using a comprehensive drug data set and advanced econometric techniques. The case of Australia is an interesting one for several reasons. Firstly, the availability of a rich dataset and price information enables to explore economic relationships across the various legal and illegal drugs, findings which are a first in the literature. Moreover, the study provides a good understanding of the various socioeconomic and demographic factors that are associated with a range of drugs including heroin and amphetamines, which have not quite been explored in the literature. Secondly, Australia is among the few countries in the world which has decriminalised the use of marijuana, albeit a recent experience. The findings in this book thus contribute to the small body of evidence on the effect of decriminalisation on drug use. Thirdly, Australia has a good record of success in tobacco control with a gradual decline in the smoking rate over the years. A battery of anti-smoking policies have been implemented across the years including a gradual increase in cigarette taxation. This study investigates the effectiveness of price policies with regard to smoking. Finally, per capita consumption of alcohol in Australia is among the highest by world standards. Australia also has a drinking culture that is similar to that of the U.S. with a high number of people, in particular teenagers, engaging into excessive drinking. This study investigates the relationship between drinking patterns and earnings, looking specifically at binge drinking behaviors.

Chapter 3
An Overview of Recreational Drug Consumption in Australia

In 2002, about 205,000 Australian secondary school students aged 12–17 were smokers. If they all continue to smoke, about half will die from smoking-related diseases.
(How to treat, Australian Doctor Newspaper, 10 March 2006)

Australia's binge-drinking culture is a 'ticking time bomb' threatening to overload the public health system within decades, health experts have warned.
(The Age, 5 May 2007)

More than 40,000 children live in a house where an adult uses cannabis daily, and more than 14,000 live in a household with an adult using ice, or crystal methamphetamine.
(Australian National Council on Drugs, 21 May 2007)

3.1 Introduction

Recreational drugs are an important part of the Australian lifestyle. The 2004 national survey on drugs (NDSHS 2005a) shows that the majority of Australians consume alcohol on a regular basis, one fifth of the population uses tobacco regularly and two out of five people have used some illicit drug at some point in their lives (Fig. 3.1). The alcohol and tobacco industries are significant contributors to the Australian economy in terms of employment and tax revenue. In 2004–2005, some AUD11.8 billion was received by the Australian Government in alcohol and tobacco taxes (AIHW 2007).

However, the misuse of drugs has a major impact on crime, violence, family life and work, resulting in enormous economic and social costs to the Australian community. Also of concern are the health consequences of drug use. Drugs are associated with a staggering level of morbidity and mortality (Begg et al. 2007). In 2003, more than 20,000 Australians died as a direct or indirect result of harmful drug use which represented almost 16 % of all deaths.

P.R. Srivastava, *Recreational Drug Consumption*, Developments in Health Economics and Public Policy 11, DOI 10.1007/978-3-319-02405-9_3,

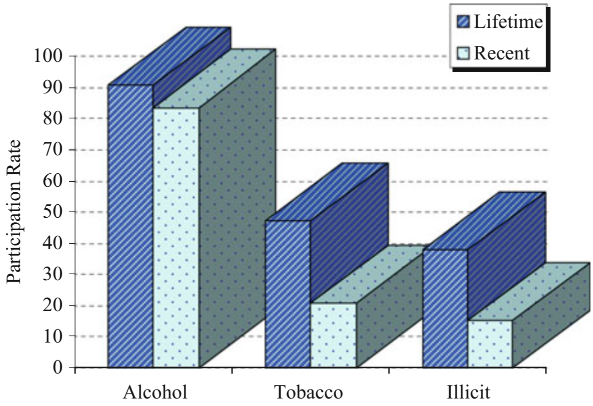

Fig. 3.1 Recreational drug consumption: prevalence of lifetime and recent[a] drug use. Notes: [a]Used in the last 12 months. Source: NDSHS (2005b)

Drug use has attracted a high level of political interest in Australia. Over the past few decades, Australian legislators and policymakers have implemented a range of policies and laws aiming to minimise the harmful effects of drug use in society. The Government has closely monitored the demand for drugs through the National Drug Strategy and other non Government bodies, while organisations such as the Australian Institute of Criminology and the Australian Customs Service have watched over the supply of drugs and drug-trafficking.

The misuse of drugs is an area of particular concern in indigenous communities. Drug misuse is strongly linked to morbidity and mortality among Aboriginals and Torres Strait Islanders. It is also associated with a high level of crime, incarceration and violent behaviour in these communities. The 2004–2005 National Aboriginal and Torres Strait Islander Health Survey (NATSIHS) indicated that over half (50–57%) of Aboriginal and Torres Strait Islander people aged between 18 and 54 years were current daily smokers, and in the year prior to the survey, nearly 70 % consumed alcohol and approximately one quarter used illicit substances (ABS 2006b).

This chapter gives an overview of recreational drug consumption in Australia. The structure of the chapter is as follows. Section 3.2 reports some estimates of the social cost of drug abuse in the Australian community. Section 3.3 gives a brief description of the National Drug Strategy Household Survey, one of the main sources of drug statistics in Australia and which forms the basis of the research in this book. Section 3.4 provides an insight on the use of the two legal drugs in Australia, highlighting their associated harms and benefits and outlining the patterns of drinking and smoking in Australian society. A similar outlook on illicit drug consumption is provided in Sect. 3.5. Section 3.6 outlines the laws related to illicit drugs in Australia followed by a brief overview of Australians' attitudes towards drug laws and drug use; Sect. 3.7 summarises.

3.2 The Costs of Recreational Drug Use

Harms associated with the use of psychoactive substances do not only affect the user but also impose significant costs on society through impacts on the health, criminal justice and social welfare systems. Therefore any costs associated with drug use comprise two components: *private costs* that are borne by the drug users themselves such as a decline in their personal income or the cost of detoxification/rehabilitation; and *social costs* that result from negative externalities such as crime, legal expenses and productivity losses.[1] Collins and Lapsley (2002) estimated the social costs of drug abuse in Australia. Their estimates showed that drug-related illness, death and crime, cost the Australian nation approximately AUD35 billion in 1998–1999 in terms of tangible and intangible costs.[2] This suggests that every man, woman, and child in Australia paid on average nearly AUD1,800 in that year to cover the expenses of unnecessary health care, extra law enforcement, road accidents, crime, and lost productivity resulting from drug abuse. The social cost of tobacco far outweighed those of other drugs. Approximately AUD21 billion, or 61 % of total costs, was attributable to smoking. Alcohol was estimated to cost the community about AUD7.6 billion while illicit drug misuse contributed to nearly 18 % (AUD6 billion) of the total cost (Table 3.1).

A few epidemiological studies have made attempts to quantify the causal links between drug abuse and its health consequences (see English et al. 1995; Mathers et al. 1999; Ridolfo and Stevenson 2001). Ridolfo and Stevenson (2001) found that nearly 42 % of all stroke deaths and 18 % of pneumonia deaths of Australian males in the 35–39 age group were causally associated with smoking. The Australian Burden of Disease Study by Mathers et al. (1999) found that illicit drugs are a direct cause of death. They are also risk factors for conditions such as HIV/AIDS, hepatitis, low birth-weight, inflammatory heart disease, poisoning and suicide, and self-inflicted injuries in Australia and account for nearly 2 % of all disability-adjusted life years.[3]

Large amount of public funds are spent by the Australian government to address the negative health and social consequences of alcohol consumption. In 2004–2005 the Australian Commonwealth and State and Territory Governments spent around AUD1.4 billion on public health activities out of which nearly 14 % was

[1] Loss in productivity in this context refers to a reduction in the size of the available workforce, absenteeism and reduced on-the-job productivity as a result of drug-attributable morbidity and mortality.

[2] Tangible costs result from loss in productive capacity, medical expenses, road accidents and crime costs associated with policing, courts, prisons, customs etc. Intangible costs are associated with loss of life, and pain and suffering. Note that the monetary value attributed to non-pecuniary costs can be argued to be subjective.

[3] One disability-adjusted life year 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 (WHO 2007).

Table 3.1 The social costs of drug use, 1998–1999

	Alcohol	Tobacco	Illicit drugs	All drugs
	AUDm			
Tangible	5,541.3	7,586.7	5,107.0	18,340.8
Intangible	2,019.0	13,476.3	968.8	16,099.0
Total	7,560.3	21,063.0	6,075.8	34,439.8
%	22.0	61.2	17.6	100.0

Source: Collins and Lapsley (2002)

spent on the prevention of hazardous and other drug use, including alcohol and tobacco (AIHW 2007).

Moore (2005) estimated government expenditure related to illicit drugs. This represented spending in several sectors such as health, policing, customs and education. Based on his estimates, in 2002–2003, the Australian government's expenditure on illicit drugs amounted to AUD3.2 billion. Direct spending on drug interventions such as prevention, interdiction, treatment and harm reduction was AUD1.3 billion and represented 41 % of total spending, while AUD1.9 billion were spent indirectly by the government on the health, crime and other consequences of illicit drug use.

3.3 Data: The National Drug Strategy Household Survey

Until the 1980s, there was no official source for any data on illicit drug use. Some data on licit drug use were collected by the Australian Bureau of Statistics through national household expenditure surveys. The first comprehensive national survey on licit and illicit drugs was conducted in 1985 by the National Drug Strategy, known then as the National Campaign Against Drug Abuse (NCADA). Since then, a number of surveys have been conducted every 3–4 years.[4] The National Drug Strategy Household Survey known as the National Campaign Against Drug Abuse Household Survey prior to 1995, is a nationally representative survey of the non-institutionalised civilian population aged 14 and above in Australia.[5] It collects information on individuals' opinions and perceptions on issues related to licit and illicit drugs, their drug consumption histories, and related behaviour. The quality, size, spread and scope of the surveys have improved over the years making use of better techniques and more enhanced statistical methods. The 2001 and 2004 surveys encompass almost 27,000 and 30,000 individuals respectively, and contain

[4]The three most recent surveys have been conducted by the Australian Institute of Health and Welfare (AIHW).

[5]For the first time the 2004 survey included persons aged 12 and older.

more comprehensive questions on drug consumption. The response rates in the surveys up until 2004 have ranged from 33 % to 57 %.[6]

The surveys have been designed in such a way to minimise sampling bias and measurement errors. Households are selected by a multi-stage, stratified area random sample design in order to provide a random sample of households within each geographical stratum. Minimum sample sizes sufficient to return reliable strata estimates are allocated to States and Territories, and the remainder distributed in proportion to population size. Respondents within each stratum are assigned weights designed to overcome imbalances arising in the design and execution of the sampling.[7] Once contact is established with a selected household, the respondent who is selected is the person with the next birthday. If the selected person is not available for interview three callbacks are made. No substitution within household is permitted except where the selected respondent is known to be unavailable for the entire fieldwork procedure, in which case the person in the household with the next birthday is selected (NDSHS 2005c).

The earlier surveys were conducted using face-to-face interviews about individuals' general attitudes to drugs, while more sensitive questions about personal drug usage and exposure to crime were answered by means of self-completed "drop-and-collect" method. In the 2001 and 2004 surveys, in addition to these methods, a computer assisted telephone interviewing method (CATI) has also been used. A number of strategies have been adopted to ensure confidentiality that would minimise cases of non-contact and non-response. For instance, respondents are asked to seal their questionnaires in envelopes prior to handing them back and interviewers working on the survey are required to sign confidentiality agreements.

However, as is the case with most surveys, this survey also has some limitations in terms of coverage. The sample excludes homeless persons and institutional settings such as hospital, nursing homes, drug rehabilitation centers and prisons, some of which may potentially contribute to an underrepresentation and underestimation of drug consumption. In addition, because illicit drug use is illegal, fear of prosecution may also result in an underestimation of actual drug prevalence despite the various measures taken to ensure confidentiality.

Table 3.2 gives a summary of participation rates for recent drug use over the period 1993 through 2004, as taken from the 2004 survey (NDSHS 2005b). Between 1993 and 2004, the proportions of persons aged 14 years and over recently using alcohol (i.e. in the last twelve months) increased and the proportions using illicit drugs generally declined. Questions on tobacco and alcohol usage relate to number of cigarettes or number of standard drinks consumed, while those on illicit drug

[6]The respective response rates for the eight surveys are 33%, 43%, 47%, 52%, 57%, 56% and 50% and 46%. The decline in the later years is attributed mainly to the sensitive nature of questions on drug use, the length of the questionnaire and a general decline in response rates in such market research surveys.

[7]Imbalances arise due to various factors such as the underrepresentation of some regions, size of households, age, gender and the interview methods.

Table 3.2 Summary of participation rates for recent[a] drug use (percent)

	1993	1995	1998	2001	2004
Tobacco[b]	n.a.	n.a.	24.9	23.2	20.7
Alcohol	73.0	78.3	80.7	82.4	83.6
Illicits:	14.0	17.0	22.0	16.9	15.3
Marijuana/Cannabis	12.7	13.1	17.9	12.9	11.3
Heroin	0.2	0.4	0.8	0.2	0.2
Cocaine	0.5	1.0	1.4	1.3	1.0
Amphetamines[c]	2.0	2.1	3.7	3.4	3.2

Notes: [a]Used in the last 12 months. [b]Comparison of recent use of tobacco is possible only for 1998, 2001 and 2004 due to a change in definition. [c]For non-medical purposes

Source: NDSHS (2005b)

usage are in the form of multiple choices, referring to respondents' frequencies of drug consumption. Interviewees are also questioned about their perceptions and acceptability of drug use, and access to drugs. In addition, the survey collects information on respondents' experiences of drug-related incidents, impact of drug use on health and crime and their views regarding drug laws. The survey also collects social, economic and demographic information for each respondent. Several of these individual characteristics are used as explanatory variables throughout the book. A detailed description of these variables is given in Appendix A.

3.4 Licit Drugs

3.4.1 Alcohol

Alcohol consumption is an integral part of Australian lifestyle. According to the World Drink Trends (WDT 2002), Australia was 19th in the world in terms of per capita alcohol consumption, with 7.8 L of pure alcohol consumed per person per year. This ranked Australia behind major European countries but ahead of the US, Canada and New Zealand. When broken down to specific alcohol types, an average Australian consumed 95 L of beer (9th in the world), 19.7 L of wine (18th in the world) and 1.3 L of pure alcohol from spirits (34th in the world) in the year.

The misuse of alcohol causes significant harm to individuals and to the Australian community. Alcohol is second only to tobacco as a preventable cause of death and hospitalisation in Australia. Alcohol harm was responsible for 3.2 % of the total burden of disease and injury in Australia in 2003 (Begg et al. 2007). Its hazardous and harmful use led to the deaths of more than 3000 Australians in 2003, which represented almost 3 % of all deaths. These deaths were primarily related to road accidents, stroke, alcoholic liver cirrhosis and suicide. Alcohol is also responsible for a significant level of crime, violence and sexual assaults (AIHW 2007).

However, alcohol is also recognised to have some social and health benefits. In recent years, there has been evidence linking wine consumption to some positive health outcomes among middle-aged and older people (Camargo Jr et al. 1997; Coate 1993; Malinski et al. 2004; Razay et al. 1992). In particular, regular and moderate use of red wine has been associated with a reduced risk of heart disease. Alcohol was found to prevent 0.9 % of the total burden in 2003 (Begg et al. 2007). The study also reported that in females over the age of 65, the benefits of alcohol consumption outweighed its harmful effects. Additionally, moderate drinking has been associated with beneficial socialising and networking effects, as well as better labour market outcomes (see Barrett 2002; Lee 2003).

Alcohol is the most commonly used drug in Australia. In 2004, 6.8 million Australians (41% of the population) drank at least weekly and 1.5 million (9%) consumed alcohol on a daily basis (NDSHS 2005b). Daily drinking was more common in the 50 and over age group and among daily drinkers males were found to be twice as likely to drink than females. The NDSHS records information both on frequency and amount of alcohol consumption. The adverse consequences of alcohol consumption are generally linked to heavy or binge drinking. Table 3.3 reports the pattern of drinking across the 1998, 2001 and 2004 surveys to demonstrate, in particular, Australians' bingeing behaviour. Although binge drinking is a term widely recognised as the act of drinking heavily on an occasion, there appears to be a lack of consensus on its definition worldwide.[8] In the absence of a standard measure of binge drinking, risk levels for short-term harms associated with drinking as defined by the National Health and Medical Research Council (NHMRC) are used to separate individuals into different drinking categories (NHMRC 2001).[9] Bingers are thus defined as those indulging in medium to high risk drinking, that is to say men drinking at least seven and women drinking at least five drinks on a single occasion. This is also consistent with the definition of binge or heavy drinking, in the literature (for example, Barrett 2002; Chaloupka and Wechsler 1996; Dee 1999a; Kenkel et al. 1994; Laixuthai and Chaloupka 1993; Manning et al. 1995; Williams et al. 2005).

Based on their drinking patterns, individuals are grouped into four categories: abstainers; non bingers; occasional bingers; and frequent bingers. Abstainers are

[8]Much of the difference in the definition of bingeing has been driven by variations in the units of measurement of alcoholic beverages and in other instances, the number of drinks. A problematic feature of these definitions is that neither the duration of an occasion nor the drink sizes and strengths are defined. A similar dispute prevails over the definition of moderate drinking.

[9]In Australia, the NHMRC recommends guidelines for the maximum number of standard drinks to be consumed in order to minimise risks in the short and long terms and maximise any potential health benefits. They indicate three risk levels—low, medium and high—based on both the amount (i.e. number of standard drinks consumed on any one day) and frequency of alcohol consumption. These definitions also vary with respect to the risks of harm in the short and long terms. Table B.1 in Appendix B depicts the drinking guidelines as set by the NHMRC. According to the 2004 NDSHS, about 10 % of Australians consume alcohol in a way considered risky or a high risk to health in the long term and about one third put themselves at risk of alcohol-related harm in the short term (NDSHS 2005b).

Table 3.3 Pattern of recent[a] alcohol consumption (percent)

	1998		2001		2004		Pooled
	Male	Female	Male	Female	Male	Female	All
Abstainers	16.9	22.2	14.9	20.4	12.9	18.6	17.1
Non Binger	44.1	45.2	46.9	47.5	45.2	48.1	47.1
Occasional Binger	29.7	26.0	29.6	26.3	31.8	27.2	28.5
Frequent Binger	9.4	6.7	8.6	5.7	10.1	6.2	7.4
Drinking participation[b]	83.1	77.8	85.1	79.6	87.1	81.4	82.9
Binge participation	39.1	32.6	38.2	32.0	41.9	33.3	35.9

Notes: [a]Used in the last 12 months. [b]The use of a different set of more detailed questions has caused a small discrepancy in drinking participation from that reported in Table 3.2

Source: NDSHS (2004)

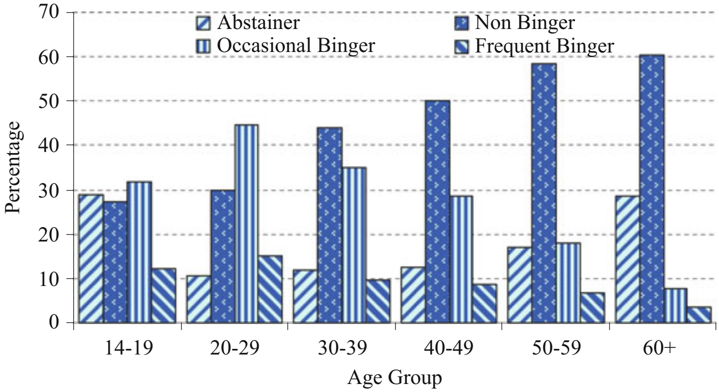

Fig. 3.2 Pattern[a] of alcohol use by age. Notes: [a]Proportions of abstainers, non bingers, occasional bingers and frequent bingers within each age group. Source: NDSHS (2004)

defined as those who have not consumed any alcohol in the past year; non bingers refer to those who drink but do not binge (consumption in a day of less than seven drinks by males and less than five drinks by females); occasional bingers are those who binge less than 3 days a week; and frequent bingers are those who binge at least 3 days a week.

Table 3.3 shows the pattern of alcohol use among males and females aged 14 and above. The statistics have remained rather stable in the period 1998 through 2004. In 2004, 31.8 % of males and 27.2 % of females binged occasionally while 10.1 % of males and 6.2 % of females binged at least 3 days a week. Figure 3.2 depicts drinking patterns within various age groups based on the pooled sample of the last three surveys. The highest proportion of occasional and frequent bingeing occurs in the 14–29 age group. Thereafter, bingeing seems to decrease progressively over older cohorts.

The early onset of drinking is known to be linked to a higher risk of later alcohol abuse and dependence. A study on the drinking behaviour of Australian secondary

Table 3.4 Observed proportions[a] of drinkers by types of alcohol (percent)

	1991	1993	1995	1998	2001	All
Beer	34.9	31.9	41.9	46.2	43.9	42.8
Wine	27.7	29.3	40.0	49.9	51.5	47.2
Spirits[b]	17.6	14.4	29.6	42.9	42.6	38.1
Premixed spirits	–	–	–	*12.4*	*14.0*	*13.6*
Bottled spirits	–	–	–	*37.1*	*35.3*	*35.8*
Premixed bottles	–	–	–	*10.3*	*13.5*	*12.6*
Other alcoholic drinks	3.4	2.4	4.3	11.4	5.5	6.3

Notes: [a]Figures relate to percentages out of the whole sample for the respective beverages consumed in the last 12 months. Note that the proportions do not add up to a 100 for a given year because drinkers may consume multiple alcohol types. [b]A disaggregation of spirits by the three types is not available prior to 1998

Source: NDSHS (2004)

students aged between 12 and 17 years shows that in 2005 around 86 % of students had tried alcohol by the age of 14 and by the age of 17, 70 % had consumed alcohol in the month prior to the survey (White and Hayman 2006a). Of current drinkers, almost 30 % had binged in the previous week, peaking at 44 % among 17-year olds.

Beer, Wine and Spirits

The NDSHS also collects information by type of alcoholic drinks. Grouping alcoholic drinks into three broad groups—beer, wine and spirits, Table 3.4 depicts the proportions of individuals who consumed the three alcoholic types over the years 1991 through 2001.[10] The proportion of individuals who consumed wine increased gradually from 27.7 % in 1991 to 51.5 % in 2001, representing a rise of around 24 % over the decade. The proportion of beer consumers fluctuated between 32 % and 46 % across the years. In 2001, 43.9 % of Australians were found to be drinking beer. A slight drop was observed in the proportion of spirit consumers between 1991 to 1993. It then picked up considerably in the subsequent years to reach 43 % in 2001. This substantial rise in spirit consumption can be attributed to the increased popularity of pre-mixed alcoholic or ready-to-drink (RTD) beverages in the last decade. These drinks have been tailored to teenage tastes with the alcohol masked by sweet flavourings and have eventually gained significant popularity among the younger generation. Another inducement for these RTDs, also known as flavoured alcoholic beverages (FAB), has been tax differentials that seem to greatly favour

[10]One possible source of measurement error in grouping alcoholic beverages by types is that respondents in the 1998 and 2001 surveys were offered a more disaggregated set of options with regard to the beverages they consumed in contrast to earlier surveys that contained fewer choices. It is to be noted that some alcoholic drinks such as pre-mixed beverages have become popular only in recent years.

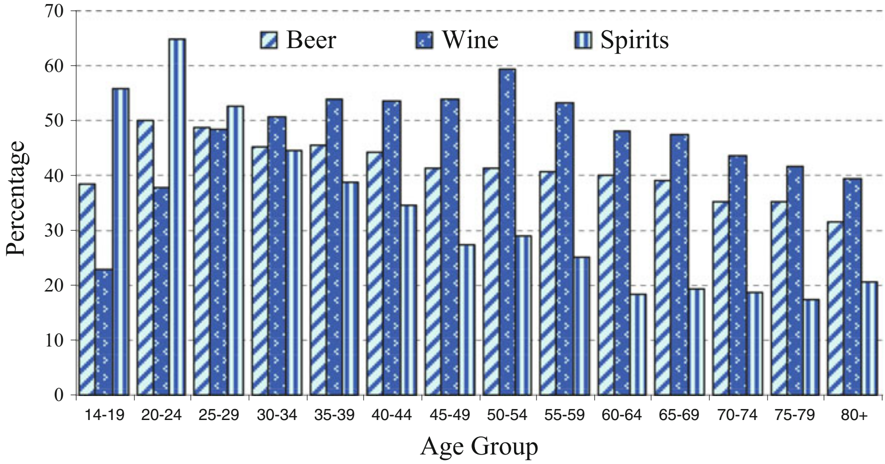

Fig. 3.3 Participation[a] in beer, wine and spirits consumption by age. Notes: [a]Proportions of beer, wine and spirits drinkers within each age group. Note that the proportions do not add up to a 100 for a given age group because drinkers may consume multiple alcohol types. Source: NDSHS (2004)

them to the traditional spirit products making them more accessible to the young (ATO 2006; Twentyman 2003). Thus, lower prices coupled with the marketing of these products have largely contributed towards an increased participation rate of spirits over the years. A more disaggregated picture of spirit consumption, which is available since the 1998 survey, shows that the proportion of individuals who consumed pre-mixed spirits (e.g. UDL) went up from 12.4 % in 1998 to 14 % in 2001 while the share of individuals who consumed bottled spirits (e.g. scotch, brandy, vodka) declined from 37.1 % to 35.3 % during the same period. Those consuming pre-mixed bottles (e.g. sub-zero, Bacardi Breezer) also recorded a rise from 10.3 % in 1998 to 13.5 % in 2001.

Figure 3.3 illustrates the percentages of individuals within each age group who consume beer, wine and spirits based on data pooled over the 1991–2001 surveys. Clearly, beer and spirits are more popular than wine among teenagers and young adults. In fact, spirit consumption is distinctly more appealing to teenagers and young adults.

3.4.2 Tobacco

Tobacco smoking is the single largest preventable cause of premature death and disease in Australia and worldwide (see, for example, Doll et al. 1994; LaCroix et al. 1991; Peto et al. 1996). Projections made by the WHO (1999) suggest that by 2030, tobacco use will become the leading cause of death and the greatest international public health problem. Tobacco smoking is a major risk factor for a wide range of diseases, including many types of cancer, heart disease and stroke, chest and lung illnesses and stomach ulcers (CCA 2007). As well as affecting the smoker himself, tobacco smoke can potentially affect the health of non-smokers. In fact, environmental tobacco smoke can cause similar diseases and health conditions as tobacco consumption does to a smoker (see Glantz and Parmley 1995; NHMRC 1997).

Tobacco is the second most widely used drug in Australia. Although the prevalence of smoking has shown a slow decline since the mid-eighties, tobacco use remains the leading risk factor for health in Australia (AIHW 2007). In 2004, 2.9 million Australians (17.4% of the population) smoked on a daily basis (NDSHS 2005b). Smoking rates peaked at age 20–29 years, with a slightly higher proportion of males (24.0%) than females (22.9%) being daily smokers. In 2003, more than 15,000 individuals died as a result of tobacco use and smoking was responsible for 7.8 % of the total burden of disease and injury (Begg et al. 2007).

A wide range of demand and supply reduction policies, campaigns, and educational programs have been implemented in Australia to discourage tobacco use. Over the years, the tobacco laws have been strengthened to include more comprehensive smoking bans in public areas and workplaces in order to reduce the public's exposure to environmental tobacco smoke, support smokers who try to quit, and discourage young people from taking up the habit. Note that States and Territories Governments have their own separate tobacco legislation and policies. The last couple of years have been marked by the legislation of even tougher smoking bans in some states and territories. These include bans on smoking in public areas such as clubs, pubs and restaurants, on beaches and in public parks (ASH 2007).

As with drinking, the harmful consequences of smoking are associated with both the frequency and intensity of smoking. Table 3.5 shows the pattern of cigarette consumption for males and females across the three surveys between 1998 and 2004 (NDSHS 2004).[11] Respondents are grouped into four categories based on their smoking behaviour: nonsmokers; occasional smokers; moderate smokers; and heavy smokers. Nonsmokers are those who have not smoked in the year prior to the survey; occasional smokers refer to those who smoke less than daily; moderate smokers are those who smoke daily with less than 20 cigarettes (1 pack) per day and; heavy smokers are those who smoke more than 20 cigarettes daily.[12] These definitions of smokers are broadly consistent with the literature (see Chaloupka and Wechsler 1997; Farrell et al. 2003; Goodman and Capitman 2000; Johnson et al. 2000).

Table 3.5 shows that the proportion of smokers decreased among both males and females between 1998 and 2004. This was reflected in corresponding declines in all three categories of smokers. In 2004, 8.4 % of males and 6.0 % of females were

[11] Cigarette use accounts for approximately 98 % of tobacco consumed in Australia (NDARC 2006b).

[12] The key question used from the survey is "how often (and how many), if at all, do you now smoke cigarettes?".

Table 3.5 Pattern of recent[a] cigarette consumption (percent)

	1998		2001		2004		Pooled
	Male	Female	Male	Female	Male	Female	All
Nonsmoker	70.6	73.3	76.6	79.1	79.2	81.3	78.2
Occasional smoker	5.4	5.0	4.3	3.1	4.1	3.0	3.8
Moderate smoker	15.3	14.9	12.6	13.3	8.3	9.7	11.6
Heavy smoker	8.7	6.8	6.5	4.4	8.4	6.0	6.5
Smoking participation[b]	29.4	26.7	23.4	20.9	20.8	18.7	21.8

Notes: [a]Used in the last 12 months. [b]The use of a different set of more detailed questions causes a small discrepancy in smoking participation from that reported in Table 3.2

Source: NDSHS (2004)

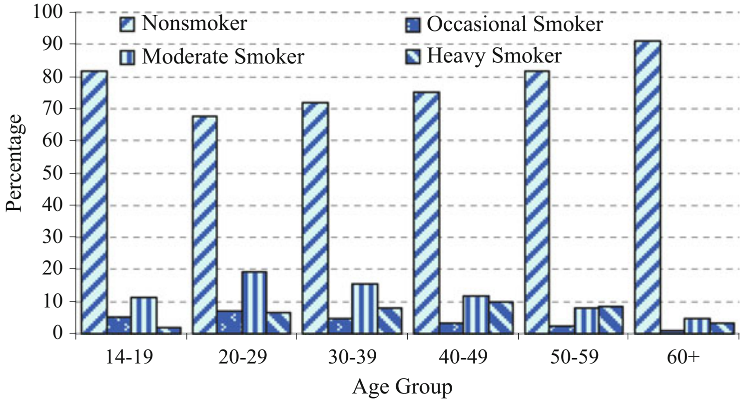

Fig. 3.4 Pattern[a] of smoking by age. Notes: [a]Proportions of non smokers, occasional smokers, moderate smokers and heavy smokers within each age group. Source: NDSHS (2005b)

heavy smokers, smoking at least 20 cigarettes daily. On the other hand, a similar proportion of males (8.3%) but a higher proportion of females (9.7%) were moderate smokers, smoking daily with less than 20 cigarettes. A small proportion of about 4.0 %, among both males and females, were occasional smokers while about 80 % were non-smokers (including ex-smokers).

Figure 3.4 depicts smoking patterns within various age groups based on the pooled sample. The highest prevalence of moderate smoking is observed for the 20–29 age group while the age-group 30–59 seems to have the highest incidence of heavy smoking. While this is consistent with anecdotal evidence that the early onset of cigarette smoking leads to heavy smoking at adulthood, it is, however, unclear whether the decline in moderate smoking reflects a shift towards heavy smoking or an increase in the number of quitters.

Smoking rates are even more alarming among adolescents and young adults, most of whom initiate smoking during their secondary school years (Winstanley et al. 1995). A study on the smoking behaviour of Australian secondary students aged between 12 and 17 years, found that, in 2005, nearly 16 % of 12-year olds had experienced smoking and this increased to 55 % among 17-year olds (White and Hayman 2006c). The proportion of current smokers who smoked on a daily basis was around 32 % with the number of cigarettes consumed per week increasing substantially with age, from 38 cigarettes among 13-year olds to 57 cigarettes among students aged 15 years and older.

3.5 Illicit Drugs

The 2004 NDSHS shows that over a third of the population aged 14 and older, or approximately 6 million Australians, used an illicit drug at some stage in their lives, and about 15 % reported using any illicit drug in the twelve months preceding the survey (NDSHS 2005a). Table 3.6 gives a summary of participation rates for illicit drug use, as taken from the 2004 NDSHS (2005a).

While marijuana remains the most widely used drug in Australia, in the last decade there has been a shift in the drug market away from heroin and cocaine towards cheaper synthetic drugs such as amphetamines (DCPC 2004; Stafford et al. 2005). Table 3.7 depicts the consumption frequencies for marijuana, cocaine, heroin and amphetamines across the three surveys between 1998 and 2004 (NDSHS 2004). These represent the patterns of consumption of those who have consumed the respective drugs at least once in the year before the survey. While the proportions of drug users may appear small, when translated to the Australian population of around 16 million aged 14 and over, they represent nearly 2 million marijuana users, approximately 530,000 amphetamines users, 170,000 cocaine users and around 56,000 heroin users in 2004.

A 2005 national survey specific to Australian youth in the age group 12–17 showed that 15 % of secondary students in the 12–15 age group had tried at least one of cannabis, hallucinogens, amphetamines, ecstasy, opiates or cocaine and this reached 33 % among 16–17 year olds (White and Hayman 2006b). Across all ages, cannabis was the most commonly used illicit drug, with approximately 30 % of the 16–17 year olds reporting the use of this substance in their lifetime and around 25 % having used it in the year preceding the survey. Around 5 % reported using amphetamines and nearly 2 % had used cocaine and opiates respectively, in the year prior to the survey.

3.5.1 Marijuana

Among all illicit drugs used in Australia, marijuana is by far the most popular drug. According to the 2004 NDSHS, over a third of Australians aged 14 and older (34%, 5.5 million) had used marijuana at some stage in their lives (NDSHS 2005a). As shown in Table 3.7, in 2004 nearly 11 % reported use of marijuana in the last 12 months and more than 4 % had used it in the previous week. Commonly known as

Table 3.6 Pattern of use of illicit drugs, by age, by gender, 2004 (percent)

	Age group				Gender		
	14–19	20–29	30–39	40+	Males	Females	All
Lifetime	29.3	58.1	58	26.7	41.8	34.4	38.1
In the last 12 months	21.3	31.5	20.2	7.4	18.2	12.5	15.3
In the last month	11.3	19.2	13.2	4.5	11.4	7.3	9.3
In the last week	0.2	12.4	9.5	3.1	7.8	4.5	6.2

Source: NDSHS (2005b)

Table 3.7 Pattern of marijuana, amphetamines, cocaine, and heroin recent[a] use (percent)

	1998	2001	2004	All
Marijuana				
Abstainer	80.90	87.23	89.07	87.05
Every few months or less	8.96	6.09	5.19	6.15
Once a month	2.64	1.62	1.31	1.65
Once a week or more	7.51	5.05	4.43	5.16
Amphetamines				
Abstainer	96.23	96.72	97.03	96.78
Every few months or less	2.99	2.35	2.15	2.36
Once a month	0.48	0.53	0.44	0.48
Once a week or more	0.30	0.41	0.38	0.38
Cocaine				
Abstainer	98.00	98.89	99.08	98.84
Every few months or less	1.89	0.95	0.79	1.03
Once a month	0.08	0.10	0.08	0.09
Once a week or more	0.03	0.05	0.05	0.05
Heroin				
Abstainer	98.71	99.81	99.85	99.66
Every few months or less	1.11	0.08	0.06	0.23
Once a month	0.08	0.03	0.02	0.03
Once a week or more	0.10	0.09	0.07	0.08

Notes: [a]Used in the last 12 months. Some inconsistency may arise with published reports because participation rates may have been compiled using a different set of questions

Source: NDSHS (2005b)

dope, pot, mull, grass, weed, hashish and gunja, marijuana is produced in most areas of Australia with a trend in recent years towards the use of hydroponics. Marijuana is generally smoked either as hand-rolled cigarettes or through a water pipe. The drug's typical effect is to make the user feel relaxed and less inhibited. Chronic use of marijuana can cause respiratory illnesses such as lung cancer and chronic bronchitis (AIC 2006; NDARC 2006a). Some heavy users lose energy and motivation and experience a deterioration in memory, concentration and learning abilities. Vulnerable individuals also risk suffering from marijuana psychosis which is similar to schizophrenia.

3.5.2 *Amphetamines*

Amphetamines are the second most commonly used illicit drugs after marijuana. Nearly one out of ten Australians aged 14 years and over had tried them at one stage in their lives (NDSHS 2005a). Amphetamines are available in various forms such as "ice" and "base" but powder methamphetamine known as "speed" is the most frequently consumed form. If used often or over an extended period of time, amphetamines can lead to a range of physical and psychological consequences such as dependency, psychosis, violent behaviour, depression, not to mention HIV and hepatitis infections through sharing of needles (NDC 2005). As with the consumption of any other hard drug, overdoses can result in collapse, seizure, heart failure or death. Amphetamines are also available on prescription for medical conditions such as narcolepsy, hyperactivity and obesity. However, the possession, use, manufacture and distribution of the drug for non-medical purposes is illegal throughout Australia (AIC 2006). Amphetamine use and supply have increased in Australia from 1998–1999, and this increase has co-occurred with an increase in related problems such as stimulant-induced psychosis and other stimulant-related disorders (McKetin and McLaren 2004). The 2004 national drug survey shows that 3.2 % of Australians aged 14 and over or approximately half a million individuals reported recent use of amphetamines for non-medical purposes (NDSHS 2005a).

3.5.3 *Cocaine*

The incidence of cocaine use is comparatively lower than that of marijuana and amphetamines but this hard drug has more severe ill-consequences on individuals' mental and physical health. The 2004 NDSHS found that about 4 % of Australians aged 14 and above had used cocaine at some stage in their lives and one in a hundred individuals had used cocaine in the past year (NDSHS 2005a). Australians aged 14–19 years were the most likely to have used cocaine once a month or more often. Cocaine is a stimulant, increasing the speed of the central nervous system activity. It comes in a variety of forms but in Australia it is most commonly available as a white powder (cocaine hydrochloride). It produces euphoria, enhances sensation and heightens confidence in mental and physical powers. If taken in large doses or used repeatedly over hours, cocaine can lead to extreme agitation, panic, paranoia, hallucinations, dizziness, trembling, nausea and heart attack (AIC 2006). Cocaine is typically consumed by both high and low socioeconomic status groups. The former are mainly casual and recreational users while those from lower socioeconomic groups consist of habitual long-term users (ABCI 2000).

3.5.4 Heroin

According to the 2004 NDSHS, about 1.4 % of Australians aged 14 years and over have tried heroin at some stage in their lives and nearly 0.2 % had used the hard drug in the past year (NDSHS 2005a). Heroin is a depressant, slowing the activity of the central nervous system. It is most commonly injected intravenously but it can be smoked or snorted. Long-term use of heroin can lead to a loss of appetite, sexual dysfunction, pneumonia, constipation, collapsed lungs, and veins and infections. Deaths from illicit drug use in Australia are mainly associated with overdoses of opiates, of which heroin is the refined product form. Mathers et al. (1999) found that in the eleven years from 1986 to 1996, out of the 4,658 deaths from illicit drug dependence, abuse or poisoning, there were only 23 that were not related to opiates. In late 2000 and early 2001, Australia experienced a heroin "drought" resulting in part from a shortage in world supply, mainly from an opium production decline in Afghanistan and the cracking down of a number of trafficking groups supplying the Australian market (UNODC 2003). 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 and the use of other drugs (Weatherburn 2001). The Australian Bureau of Criminal Intelligence (ABCI 2002) claimed that the reduction in heroin use might also have resulted from an increased efficiency in law enforcement that might have disrupted heroin importation networks and thus reduced heroin availability in the country. However, there have been reports that heroin originated, or trafficked, via North Korea took up the Australian market in 2003 (UNODC 2003).

3.6 Illicit Drug Laws in Australia

3.6.1 Chronicles of Illicit Drug Law Changes

Until the sixties, recreational use of illicit drugs was strongly regulated by way of penalties in Australia. The possession of drugs such as heroin,[13] cocaine, morphine, medicinal opium and marijuana was legal only if obtained on a medical prescription. Since then, with an increasing trend in the use of these drugs for recreational purpose, most Australian states gradually strengthened their laws with a criminal justice orientation, raising penalties, creating additional offences and establishing new investigative bodies. The 1980s was marked with some raft of reforms of drug laws in Australia. In particular, prohibition laws related to marijuana possession and use were eased. South Australia (SA) was the first jurisdiction to implement an expiation system for minor marijuana offences, namely the Cannabis Expiation Notice (CEN) system in 1987. Under this scheme, simple marijuana offences such

[13] An absolute prohibition was imposed on the medicinal use of heroin in the early 1950s.

Table 3.8 Penalties for minor cannabis offences

Jurisdiction	Amount of marijuana	Penalty
Prohibition with civil penalty schemes (infringement notices)		
South Australia (1987)	Less than 100 g and no more than one plant (recently reduced from three)	60 days to pay-adults only. Fines between AUD50 and AUD150, where failure to pay usually results in a conviction
Australian Capital Territory (1992)	Not more than 25 g or five plants	60 days to pay-adults and juveniles. AUD100 fine, where failure to pay does not usually lead to a conviction
Northern Territory (1996)	Less than 50 g and no more than two plants	28 days to pay-adults only. AUD100 fine, where failure to pay results in a debt to the state but not conviction
Western Australia (2004)	Less than 30 g and no more than two plants	28 days to pay-adults only. AUD100-200 fine or attendance at a specified education session
Prohibition with cautioning and diversion to treatment		
Tasmania (1998)	Less than 50 g, plants excluded	Caution for first three offences
Victoria (1998)	Less than 50 g, plants excluded	Up to two formal cautions for those aged over 17 years
New Southwales (2000)	Less than 15 g	Statewide trial extended. Up to two formal cautions
Queensland (2001)	Less than 50 g	Mandatory assessment and brief intervention session

Source: DrugInfo ClearingHouse, Australian Drug Foundation (ADF 2007)

as possessing or cultivating small amounts of marijuana for personal use were subject to minor penalties, although the sanctions for commercial dealings were still rather significant. Similar expiation systems have since been introduced in the Australian Capital Territory (ACT) in 1992 and the Northern Territory (NT) in 1996. In the rest of the states, a scheme involving cautioning notices to minor and early marijuana offenders, rather than initiating criminal proceedings, was implemented. These were introduced in Victoria (VIC), Tasmania (TAS) and Western Australia (WA) in 1998, in New South Wales (NSW) in 2000 and in Queensland (QLD) in 2001. In 2004, WA has also decriminalised the use of marijuana (ADF 2007). In those four states that have decriminalised the use of marijuana, convictions for cultivation, trafficking or possession of commercial quantities of marijuana still attract significant jail sentences and large fines and the penalties vary from state to state. Table 3.8 details the penalties for minor marijuana offences imposed in the various states.

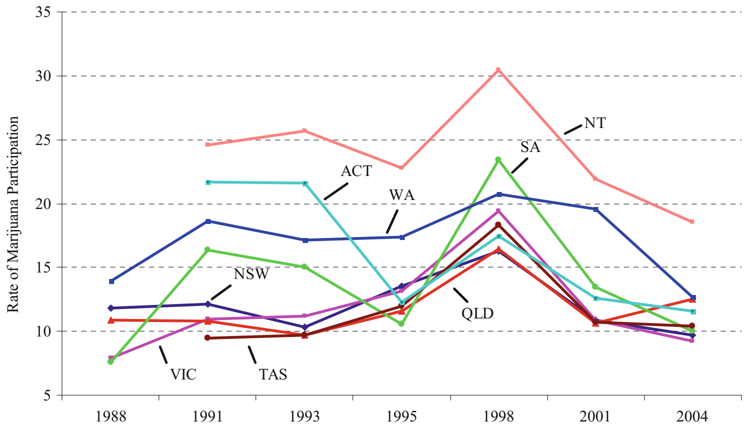

Fig. 3.5 Trends in the prevalence of marijuana consumption by states and territories[a]. Notes: [a] Rates of participation in the last 12 months. Source: NDSHS (2004)

Figure 3.5 shows the prevalence of marijuana use in individual states and territories across the past seven surveys covering the period 1988 through 2004 based on data from the NDSHS (NDSHS 2005a). It is interesting to compare prevalence rates in states which have decriminalised marijuana use to those states where marijuana use is still a criminal offence. While this trend can be associated with various other factors, nonetheless it appears that in SA the immediate effect of decriminalisation laws introduced in 1987 was an increase in the rate of participation in marijuana. However, in subsequent years the proportion of users settled down to levels comparable to other states where such laws did not prevail and the use of marijuana was strictly prohibited. Similarly, the rate of participation in the ACT which liberalised marijuana laws in 1992, declined in subsequent years to levels comparable to states that imposed heavy sanctions. The NT has a historically high prevalence of marijuana users. This high rate of marijuana use is primarily associated with the ethnic structure of its population. The NT comprises the largest indigenous communities in Australia, for which drug use is an entrenched part of lifestyle and culture (see Aagaard et al. 2004; Clough et al. 2002, 2004). While there appears to be an increase in the proportion of marijuana users in the NT in 1998, it is not clear whether this rise resulted from a softening in marijuana laws in 1996 or whether it was the effect of other factors given that a general increase in participation was observed across all other states in that particular year. In 2001 and 2004, in line with the general decline, a significant drop was observed in the proportion of the NT users although it was still way above the prevalence rates in states where the use of marijuana was prohibited. QLD which has generally had the lowest prevalence of marijuana is the only state which experienced an increase in 2004.

Table 3.9 Acceptance for regular drug use and support for drug legalisation (percent)

	Approval for regular drug use	Support[a] for drug legalisation	Support[a] for increased penalties
Tobacco	39.3	–	–
Alcohol	77.0	–	–
Marijuana	23.2	27.0	58.2
Heroin	0.9	5.0	86.0
Amphetamines[b]	3.1	4.7	83.7
Cocaine	2	4.7	84.6

[a] Support or strongly support (based on those respondents who were informed enough to indicate their level of support). [b]For non-medical purposes

Source: NDSHS (2005b)

3.6.2 *Attitudes to Drug Use and Drug Laws*

According to the 2004 NDSHS, the regular use of alcohol was approved by Australians more than was any other drug (NDSHS 2005b). About 77 % of the population aged 14 and over approved its use. Regular use of tobacco by adults was considered acceptable by around 39 % of Australians. On the other hand, the regular use of illicit drugs was not considered to be acceptable among the vast majority of Australians. Among illicit drugs, as expected, marijuana was found to be the most widely accepted drug with 23 % of Australians supporting its regular use.

Support for the legalisation of illicit drugs follows a similar pattern to that of regular drug use approval. The legalisation of marijuana was supported by 27 % of Australians. In contrast, support for the legalisation of heroin, cocaine and amphetamines was much lower hovering around 5 %. Those who supported the legalisation of drugs were generally in the 20–39 age group. Table 3.9 depicts the summary of regular drug use approval, and support for drug legalisation and increased penalties among Australians aged 14 or older. Across all drugs, males were more likely to accept regular drug use than females.

3.7 Summary

This chapter has given a brief overview of recreational drug consumption in Australia, the laws related to illicit drugs and Australians' attitudes towards such drug laws and drug use. In particular, it has highlighted the enormous economic and social burden that drug use imposes on the Australian community. It has also described the National Drug Strategy Household Survey which forms the basis of analysis in the book. In addition, the chapter has provided insights on a selection of licit and illicit drugs commonly consumed by Australians, outlining the prevalence and patterns of drug use and highlighting a few characteristics of drug users. It is worthwhile to note that such observed sample proportions can only indicate how drug participations vary across different demographic groups but cannot isolate partial effects of individual attributes which are often correlated. For instance, an unemployed individual is very likely to use drugs. However, he/she is more also likely to be young, unmarried and uneducated making him/her more likely to use drugs. In such case, the high observed probability of using drugs among the unemployed may not necessarily represent the impact of unemployment on drug use. Econometric analysis can isolate the partial effects of a particular factor when other variables are controlled for at the same levels.

Chapter 4
Modelling Consumption of Individual Drugs

4.1 Introduction

Developing good drug policies requires a sound understanding of drug users and their behaviour. One major contribution of economics to the drug policy debate is to provide empirical evidence on the consumption of drugs in terms of what are the determinants of drug use and how individuals respond to existing policies. Using a variety of individual-level data, studies have examined individuals' response to prices and a range of other demand reduction drug policies. Studies that have used micro data have also provided insights on the demographic and socioeconomic characteristics of drug users. While there is a fairly large body of empirical literature on licit drugs using US data, such studies are scarce for Australia. With regard to illicit drugs, evidence is sparser even overseas due to data unavailability. A small body of literature has developed on marijuana in recent decades but very little work has been undertaken on other illicit drugs.

This chapter examines the factors relating to individuals' participation and levels of consumption for a selection of licit and illicit drugs used in Australia. In particular, it investigates the socioeconomic and demographic factors that determine drug use and the impact of drug policies, such as price and marijuana decriminalisation, on drug consumption. Distinguishing between light and heavy users for the licit drugs, it provides insights on how individuals' characteristics and policy responses vary according to patterns of use. The analysis on illicit drug, on the other hand, focuses on participation. Price elasticities of participation are estimated and the nature of the economic relationships across drugs are determined.

The chapter is structured as follows. Section 4.2 gives an overview of the econometric models used for the analysis. Section 4.3 models legal drug consumption. The levels of alcohol consumption are first examined identifying drinkers according to their frequency and intensity of use. Next, alcohol is disaggregated in terms of beer, wine and spirits and individuals' participation in each alcoholic type is examined. Finally, the levels of cigarette consumption are examined. Section 4.4 examines illicit drug use, modelling individuals' participation in marijuana, cocaine, heroin

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and amphetamines individually. The chapter ends with a summary of the findings in Sect. 4.5.

4.2 Economic and Econometric Framework

The economic approach considers the demand for drugs as the result of the traditional consumer utility maximisation problem (see Cameron and Williams 2001; Pacula 1998b; Sickels and Taubman 1991). Individuals are assumed to derive utility from the consumption of a set of goods which include a range of recreational drugs. They maximise utility subject to their budget constraint. The constrained utility maximisation problem leads to demand functions for each of the goods including drugs. Conceptually, economists utilise a broad definition of drug price, often referred to as its full price, which entails not only its monetary value but also its nonpecuniary value in terms of legal, social or health costs. Both the pecuniary and nonpecuniary costs lower the marginal utility of consuming drugs.

The reduced form demand equation for drug j can be specified as

$$Y_j^* = \mathbf{x}'_j \boldsymbol{\beta}_j + \boldsymbol{\varepsilon}_j \qquad (j = 1, \dots J) \tag{4.1}$$

where Y_j^* $[Y_j^* \subseteq (-\infty, \infty)]$ is proportional to the constrained-utility-maximising quantity of drug j. $\boldsymbol{\beta}_j$ is a vector of unknown parameters, $\mathbf{x}_j$ is a vector of explanatory variables such as price, income and other demographic variables, that allows for individual heterogeneity in taste, and ε_j represents the unobserved component. In order to model an individual's decision to consume drug j, Eq. (4.1) is mapped to an observable binary discrete variable which indicates whether or not the individual consumes the drug. Without loss of generality (Maddala 1983), this can be written as

$$Y_j = \begin{cases} 1 \text{ if } Y_j^* > 0 \\ 0 \text{ if } Y_j^* \le 0. \end{cases} \qquad (j = 1, \dots J), \tag{4.2}$$

Assuming that ε_j follows a standard normal distribution with mean zero and variance one and dropping the subscript, Eq. (4.3) defines the binary Probit model,

$$\begin{aligned} P(Y = 1 \mid \mathbf{x}) &= \Phi(\mathbf{x}'\boldsymbol{\beta}), \\ P(Y = 0 \mid \mathbf{x}) &= 1 - \Phi(\mathbf{x}'\boldsymbol{\beta}), \end{aligned} \tag{4.3}$$

where $\Phi(\mathbf{x}'\boldsymbol{\beta}) = \int_{-\infty}^{\mathbf{x}'\boldsymbol{\beta}} (2\pi)^{-1/2} \exp(\frac{-z^2}{2}) dz$, i.e. the standard normal cumulative distribution function. Note that the variance is assumed to be one for identification purposes.

Another popular economic formulation for analysing such binary discrete choice behavior is the random utility model (See Greene 2003, pg 670). The essential idea of the random utility models is that a consumer faces a choice between two alternatives, each of which has an associated utility index describing the attractiveness of the alternative to the consumer. Utilities are unobservable, but consumers reveal their preferences by choosing the alternative with the highest utility index. For example, an individual might be faced with the choice of consuming or not consuming a particular drug. The two outcomes can be defined as state-specific utilities U_Y^*

$$\begin{aligned} U_{Y=1}^* &= \mathbf{x}'\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1 \\ U_{Y=0}^* &= \mathbf{x}'\boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}_0. \end{aligned} \tag{4.4}$$

Individual will consume drug if $U_{Y=1}^* > U_{Y=0}^*$, such that

$$\begin{aligned} Y &= 1(U_{Y=1}^* > U_{Y=0}^*) \\ &= 1(\mathbf{x}'\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1 > \mathbf{x}'\boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}_0) \\ &= 1[\boldsymbol{\varepsilon}_1 - \boldsymbol{\varepsilon}_0 > -\mathbf{x}'(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_0)] \end{aligned} \tag{4.5}$$

The binary choice model can be reparametrised as

$$Y = 1(Y^* > 0)$$

where $Y^* = \mathbf{x}'(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_0) + (\boldsymbol{\varepsilon}_1 - \boldsymbol{\varepsilon}_0) = \mathbf{x}'\boldsymbol{\beta} + \boldsymbol{\varepsilon}$.

Given an $i.i.d.$ sample of N individuals, the vector of parameters $\boldsymbol{\beta}$ can be estimated by maximising the following log-likelihood function,

$$Log(L) = \sum_{i=1}^{N} \sum_{k=0}^{1} Y_{ik} \log[P(Y_i = k)] \tag{4.6}$$

where $Y_{ik} = \begin{cases} 1 \text{ if individual } i \text{ chooses alternative } k, \ (k = 0 \text{ or } 1) \\ 0 \text{ if otherwise.} \end{cases}$

However, sometimes an individual faces multiple choices ($k = 0, 1, \ldots K$) which are inherently ordered (McKelvey and Zavoina 1975). Here, the latent propensity to consume a drug given by Y^* is translated into the observed variable Y by the mapping

$$Y = \begin{cases} 0 \ \text{ if } Y^* \leq 0 \\ 1 \ \text{ if } 0 < Y^* \leq \mu_1 \\ 2 \ \text{ if } \mu_1 < Y^* \leq \mu_2 \\ \vdots \\ K \text{ if } Y^* > \mu_{K-1} \end{cases} \tag{4.7}$$

where the μ_i's are unknown threshold parameters. Again, assuming that ε follows a standard normal distribution with mean zero and variance one, Eq. (4.8) here defines the Ordered Probit model,

$$\begin{aligned}
P(Y &= 0 \mid \mathbf{x}) = \Phi(-\mathbf{x}'\boldsymbol{\beta}),\\
P(Y &= 1 \mid \mathbf{x}) = \Phi(\mu_1 - \mathbf{x}'\boldsymbol{\beta}) - \Phi(-\mathbf{x}'\boldsymbol{\beta}),\\
P(Y &= 2 \mid \mathbf{x}) = \Phi(\mu_2 - \mathbf{x}'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}'\boldsymbol{\beta}),\\
&\vdots\\
P(Y &= K \mid \mathbf{x}) = 1 - \Phi(\mu_{K-1} - \mathbf{x}'\boldsymbol{\beta}),
\end{aligned} \tag{4.8}$$

where $0 < \mu_1 < \mu_2 < \ldots \mu_{K-1}$. Given an $i.i.d.$ sample of N individuals, the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$ can be estimated by maximising the following log-likelihood function,

$$Log(L) = \sum_{i=1}^{N}\sum_{k=0}^{K} Y_{ik} \log[P(Y_i = k)] \tag{4.9}$$

where $Y_{ik} = \begin{cases} 1 \text{ if individual } i \text{ chooses alternative } k, \ (k = 0, 1, \ldots K) \\ 0 \text{ if otherwise.} \end{cases}$

Note that the coefficients of the Probit and Ordered Probit models are not the marginal effects on the probabilities. The marginal effect of a change in regressor x_j on the probabilities is obtained as follows for the Probit model,

$$\begin{aligned}
\frac{\partial P(Y = 1 \mid \mathbf{x})}{\partial x_j} &= \phi(\mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta}_j,\\
\frac{\partial P(Y = 0 \mid \mathbf{x})}{\partial x_j} &= -\phi(\mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta}_j,
\end{aligned} \tag{4.10}$$

and represents the absolute change in the probability for the respective drug use status in response to a unit change in an individual explanatory variable. For each continuous explanatory variable, the marginal effect relates to one unit increase in the explanatory variable while for a dummy variable, it represents the change in the probability when the variable changes from 0 to 1. These can be either evaluated at the sample mean of the data for a typical or stylised individual, or alternatively marginal effects can be estimated for every individual and averaged over the whole sample.

For the Ordered Probit, given that the model consists of multiple choices but is built on a single latent regression, it is even more unclear how the coefficients should be interpreted (Greene 2003). The marginal effect of a change in regressor x_j is obtained as follows

$$
\begin{aligned}
\frac{\partial P(Y=0 \mid \mathbf{x})}{\partial x_j} &= -\phi(\mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta}_j, \\
\frac{\partial P(Y=1 \mid \mathbf{x})}{\partial x_j} &= [\phi(-\mathbf{x}'\boldsymbol{\beta}) - \phi(\mu_1 - \mathbf{x}'\boldsymbol{\beta})]\boldsymbol{\beta}_j, \\
&\vdots \\
\frac{\partial P(Y=K \mid \mathbf{x})}{\partial x_j} &= \phi(\mu_{K-1} - \mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta}_j.
\end{aligned}
\tag{4.11}
$$

Note that the marginal effects across the $K+1$ choices sum to zero, which follows from the requirement that the probabilities add up to one. As is standard in the literature, standard errors are estimated using the delta method (see Greene 2003, pg 670).

4.3 Legal Drug Consumption

4.3.1 Alcohol

As discussed in Chap. 2, a modest body of literature has examined alcohol consumption using individual-level data. Most of these studies have focused on youth drinking to examine impacts of policies such as taxes, minimum legal drinking age and drinking restrictions on campus. While empirical evidence is predominantly based on US data, in recent years, a couple of studies have modelled alcohol participation and levels of consumption using Australian data (Cameron and Williams 2001; Zhao and Harris 2004).

This section examines Australians' drinking patterns. In particular, it provides insights on how the different important drivers affect different levels of alcohol consumption. The contribution of this section is three-fold. Firstly, it adds to the sparse literature in Australia by providing firsthand empirical evidence using a rich data set. Secondly, most international studies have focused on adolescent and young adult drinking. Here, the analysis considers alcohol consumption by all segments of the population. Thirdly and most importantly, it uses unique information on both frequency and intensity of use to identify "bingers". Heavy drinkers, or bingers, are often of more interest to policymakers since the worst consequences of alcohol consumption are mostly related to problem drinking. This study focuses on Australians' bingeing behaviour.

The study uses the 1998, 2001 and 2004 sweeps of the NDSHS (NDSHS 2005a). In particular, individuals are categorised into abstainers, non bingers, occasional bingers and frequent bingers, using the Australian Alcohol Guidelines set by the National Health and Medical Research Council (NHMRC 2001)—see Chap. 3.

About 40 % of males and 30 % of females binge drink in Australia, and more than 7 % binge frequently (at least 3 days a week).

Alcohol, tobacco and marijuana prices by state of residence and year, are used to examine price responses. Data on alcohol and tobacco prices are obtained in the form of indices from the Australian Bureau of Statistics (ABS 2006b). Price series for marijuana are obtained from the Illicit Drug Reporting System (NDARC 2004). They represent price per ounce of the drug and 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, it is constructed using information from the Australian Bureau of Criminal Intelligence (ABCI 2002), later replaced by the Australian Crime Commission (ACC 2006).[1] All price and income series are deflated using the all-items CPI for individuals' respective states of residence (ABS 2006a). A detailed description of all variables used in the book is given in Appendix A.

Section 4.2 shows that alcohol consumption can be formulated as a function of drug prices, income, and a range of personal characteristics to account for taste heterogeneity. Any change in attitude towards alcohol use across surveys is controlled for using year indicators. Given an ordering in the four levels of alcohol consumption, an Ordered Probit model is estimated. Results are reported in Table 4.1. The estimated coefficients, threshold parameters and their associated standard errors are presented in the first two columns. Also reported for each drinking group, are the marginal effects and their corresponding standard errors. As mentioned above, the marginal effects of the Ordered Probit model have more a meaningful interpretation than the coefficients in terms of the effects of covariates on the probability for the respective drinking status.

Own Price Effects

Price effects are examined first. The negative significant coefficient of alcohol's own price in Table 4.1 suggests that drinking is price responsive where a price increase decreases the utility of alcohol consumption. When translated into marginal effects, this indicates lower probabilities of occasional and frequent bingeing and higher probabilities of moderate drinking and abstaining. Note that the marginal effect for a continuous explanatory variable relates to the actual change in the *probability of consumption* for a particular drinking status in response to a unit change in the explanatory variable, while for a dummy variable it represents the change in the *probability of consumption* when the dummy variable changes from 0 to 1.

Evaluated at sample proportions of the four drinking categories, the marginal effects represent probability elasticities of −0.70 and −1.37 for occasional

[1]The ABCI/ACC is an alternative source for drug prices. It collects information on drugs through covert police units and police informants. The advantage of using price data from the IDRS is that they are provided with unified measures and fewer missing observations.

Table 4.1 Ordered probit estimates for alcohol consumption

			Abstainer		*Non binger*		*Occasional binger*		*Frequent binger*	
	Coefficient		Marginal Effect							
Constant	6.805	(1.868)**	–		–		–		–	
P^{alc}	−0.917	(0.211)**	0.171	(0.039)**	0.182	(0.042)**	−0.214	(0.049)**	−0.140	(0.032)**
P^{tob}	−0.885	(0.179)**	0.166	(0.034)**	0.176	(0.036)**	−0.206	(0.042)**	−0.135	(0.027)**
P^{mar}	−0.212	(0.042)**	0.040	(0.008)**	0.042	(0.008)**	−0.050	(0.010)**	−0.032	(0.006)**
$Income^{p}$	0.153	(0.008)**	−0.029	(0.002)**	−0.030	(0.002)**	0.036	(0.002)**	0.023	(0.001)**
Age	2.769	(0.256)**	−0.518	(0.048)**	−0.550	(0.051)**	0.645	(0.060)**	0.422	(0.039)**
Agesq	−0.501	(0.036)**	0.094	(0.007)**	0.099	(0.007)**	−0.117	(0.008)**	−0.076	(0.005)**
Male	0.182	(0.012)**	−0.034	(0.002)**	−0.036	(0.002)**	0.042	(0.003)**	0.028	(0.002)**
Married	−0.129	(0.013)**	0.024	(0.002)**	0.026	(0.003)**	−0.030	(0.003)**	−0.020	(0.002)**
Depchld	−0.134	(0.018)**	0.027	(0.004)**	0.024	(0.003)**	−0.032	(0.004)**	−0.019	(0.002)**
Singpar	0.018	(0.021)	−0.003	(0.004)	−0.004	(0.004)	0.004	(0.005)	0.003	(0.003)
Capital	−0.101	(0.012)**	0.018	(0.002)**	0.021	(0.003)**	−0.023	(0.003)**	−0.016	(0.002)**
ATSI	0.160	(0.048)**	−0.027	(0.007)**	−0.036	(0.012)**	0.036	(0.010)**	0.027	(0.009)**
Degree	−0.070	(0.017)**	0.013	(0.003)**	0.013	(0.003)**	−0.016	(0.004)**	−0.010	(0.003)**
Yr12qual	0.110	(0.018)**	−0.020	(0.003)**	−0.023	(0.004)**	0.025	(0.004)**	0.018	(0.003)**
Diploma	0.059	(0.015)**	−0.011	(0.003)**	−0.012	(0.003)**	0.014	(0.003)**	0.009	(0.002)**
Bluejob	0.094	(0.021)**	−0.017	(0.004)**	−0.020	(0.005)**	0.022	(0.005)**	0.015	(0.004)**
Whitejob	0.047	(0.018)**	−0.009	(0.003)**	−0.009	(0.004)**	0.011	(0.004)**	0.007	(0.003)**
Unemp	0.117	(0.029)**	−0.021	(0.005)**	−0.025	(0.007)**	0.027	(0.006)**	0.019	(0.005)**
Study	0.083	(0.031)**	−0.015	(0.005)**	−0.017	(0.007)**	0.019	(0.007)**	0.013	(0.005)**
μ_1	1.491	(0.007)**								
μ_2	2.617	(0.009)**								

Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Table 4.2 Probability elasticities for alcohol consumption

	Abstainer		Non binger		Occasional binger		Frequent binger	
P^{alc}	1.325	(0.305)**	0.393	(0.090)**	−0.700	(0.161)**	−1.372	(0.316)**
P^{tob}	1.280	(0.259)**	0.380	(0.077)**	−0.676	(0.137)**	−1.326	(0.269)**
P^{mar}	0.307	(0.061)**	0.091	(0.018)**	−0.162	(0.032)**	−0.318	(0.063)**
$Income^{p}$	−0.221	(0.012)**	−0.066	(0.004)**	0.117	(0.006)**	0.229	(0.012)**
Own price probability elasticities by age group:								
14–19 yrs	3.404	(1.301)**	1.689	(0.645)**	−0.704	(0.272)**	−3.127	(1.197)**
20–24 yrs	1.497	(1.269)	0.770	(0.653)	−0.145	(0.124)	−1.172	(0.993)
25–29 yrs	2.746	(1.137)**	1.186	(0.490)**	−0.648	(0.269)**	−2.467	(1.022)**
30+ yrs	1.131	(0.355)**	0.225	(0.071)**	−0.707	(0.222)**	−1.253	(0.393)**

Probability elasticity is calculated by dividing marginal effect by the mean of the dependent variable, for the respective category. Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

and frequent bingers and, 0.39 and 1.33 for moderate drinkers and abstainers respectively. Note that a probability elasticity represents a percentage change rather than an absolute change in drinking probability in response to a 1 % change in price and is calculated by dividing the marginal effect by the mean of the dependent variable, for the respective category. For example, a price probability elasticity of −1.37 for the frequent bingers indicates that a 1 % rise in the price of alcohol will result in a 1.37 % reduction in the probability of frequent bingeing. Here, heavy drinkers are found to be the most price sensitive among all four drinking groups.[2]

In contrast to these results, Manning et al. (1995) and Kenkel and Manning (1996) found heavy drinkers to be much less price responsive than moderate drinkers. However, their study was based on a continuous measure of alcohol consumption. On the other hand, several studies found heavy and very heavy drinkers to be highly sensitive to alcohol prices although their findings were based on young cohorts (Coate and Grossman 1988; Dee 1999a; Grossman et al. 1987; Laixuthai and Chaloupka 1993). Most of these studies estimated probability elasticities of price close to or greater than one for heavy drinkers. For comparison purposes, probability elasticities of own price are next estimated by age groups.[3] They are reported in the lower panel of Table 4.2. The results indicate that teenagers are relatively more price elastic than any other age groups. Surprisingly, no evidence of any price response was found in the 20–24 age group. Once again, frequent bingers are found to be the most sensitive to prices with elasticities ranging from −1.2 to −3.1.

[2]Note that participation elasticities estimated here do not compare directly to the conventional quantity elasticities with continuous measures of alcohol consumption.

[3]Here, the sample is partitioned into four age groups and the model is estimated separately on each cohort. Since the key objective is to assess variations in the effect of price at different ages, the full set of parameter estimates is not reported.

Cross Price Effects

Given their addictive characteristics, it is very likely that drugs are related in consumption. When goods are related in consumption, policy aimed at one good will undoubtedly affect the other. For instance, policymakers can better coordinate policies in light of the information about how cigarettes and alcohol are related in consumption. If cigarettes and alcohol are economic complements, an alcohol tax increase is likely to discourage the use of both drugs. On the other hand, if they are economic substitutes, then policy to reduce the use of one drug is likely to increase consumption of the other. Thus, it is important to have a good understanding of the economic relationships across various drugs.

Studies which have examined cross-drug relationships have often found alcohol to be an economic complement for *tobacco* (see Cameron and Williams 2001; Dee 1999a; Zhao and Harris 2004) and *marijuana* (see Farrelly et al. 1999; Pacula 1998a,b; Saffer and Chaloupka 1999; Williams and Mahmoudi 2004; Williams et al. 2004; Zhao and Harris 2004). The cross price effects in Table 4.1 lend support to such empirical evidence found in the literature that alcohol is an economic complement for tobacco and marijuana. Drinking is found to respond negatively to both tobacco and marijuana price. In Table 4.2, the cross-price probability elasticities are computed for the four drinking groups. These elasticities correspond to the *percentage* changes in the values of probabilities in response to a 1 % change in the relevant prices. As expected, drinkers are found to be more price responsive to tobacco than marijuana price. For instance, a 1 % increase in tobacco price results in 0.68 % and 1.33 % declines in the probability values of occasional and frequent bingeing, respectively, while a similar increase in marijuana price decreases the probability values of occasional and frequent bingeing by 0.16 % and 0.32 %, respectively.

Income Effects

Consistent with findings from the empirical literature, alcohol is found to be a normal good. The positive and significant income coefficient in Table 4.1 indicates that an increase in personal income increases the utility of alcohol consumption. This translates into positive marginal effects for moderate and frequent drinkers and negative effects for occasional drinkers and abstainers. The corresponding income probability elasticities in Table 4.2 indicate that a 10 % increase in income results in 1.2 % and 2.3 % increase in the probability values of occasional and frequent bingeing and 0.6 % and 2.2 % declines in the probability values of moderate drinking and abstention, respectively.

Socioeconomic and Demographic Effects

Age effects are examined first. To capture any nonlinear relationship between age and drinking behaviour, age is entered in the model as a quadratic. Table 4.1 shows

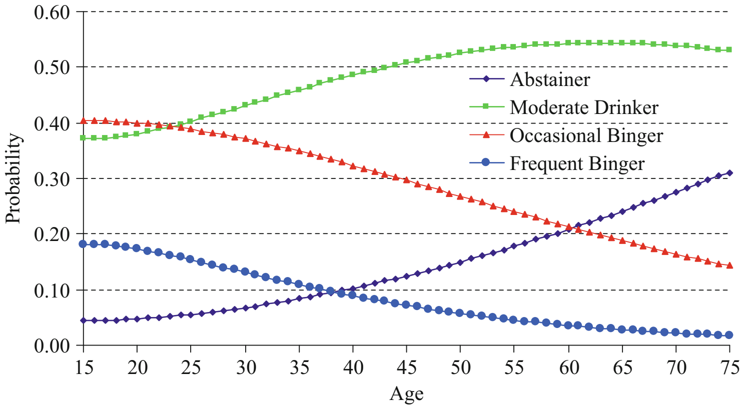

Fig. 4.1 Predicted probabilities for alcohol consumption: effect of age

that both age variables are statistically significant. The effect of age is best illustrated through Fig. 4.1 which depicts predicted probabilities by drinking status for different ages (evaluated at sample means of all other explanatory variables). Occasional or frequent bingeing appear to have the highest incidence amongst teenagers and young adults. Almost 40 % of teenagers indulge into occasional bingeing and nearly 20 % are predicted to be frequent bingers. The probability of occasional and frequent bingeing clearly decreases for older individuals. On the other hand, older individuals have higher chances of drinking moderately or abstaining although there appears to be a slight decreasing trend in the moderate drinking probability for individuals in the 60+ age group.

Turning to the impact of gender, consistent with observed probabilities, males are more likely to binge than females. In particular, a male has 4.2 pp and 2.8 pp higher chances of being an occasional binger or a frequent binger than his female counterpart. Being married reduces the chances of being an occasional or a frequent binger. The presence of dependent children in the household also decreases the chances of bingeing. However, being a single parent or coming from a single-parent family has a positive, although insignificant, effect on drinking. Those who live in capital cities are less likely to indulge into bingeing and, Aboriginal and Torres Strait Islanders have higher chances of bingeing.

To examine the effect of education on drinking behaviour, individuals are categorised into four groups: degree holders; hold year-12 qualifications; hold a trade/non-trade certificate or an associate diploma; and not finished high school (used as the reference category). Relative to the reference category, degree holders have lesser chances to binge but those who have completed secondary education or hold a diploma are more likely to binge. Cameron and Williams (2001) and Zhao and Harris (2004) who estimated participation equations for alcohol using earlier sweeps of the NDSHS found degree holders to be more likely to drink than the less educated educational groups. These contrasting findings tend to suggest that while the rate of alcohol *participation* is higher among degree holders, when examined by *levels of consumption*, degree holders are found less likely to be bingers and more likely to be non bingers.

Employment status as well as job characteristics have often been identified as important drivers of problem drinking (see Ames and Janes 1987; Crawford et al. 1987; Janes and Ames 1989; Webb et al. 1990). To explore the relationship between drinking and their employment status, individuals are categorised into five groups: white-collar workers; blue-collar workers; students; unemployed and looking for work; and homemakers (which comprises those who are engaged in home duties, pensioners, retirees or are unable to work—used as the reference group). After controlling for income, education, age and other factors, some important differential effects are observed across the five groups. Epidemiologic studies have often found heavy drinking to be highly prevalent among blue collar workers (see Bacharach et al. 2004; Yang et al. 2007). Not surprisingly, blue collar workers and unemployed individuals are found to have the highest chances to binge occasionally or frequently compared to other employment groups.

4.3.2 Beer, Wine and Spirits

The alcoholic beverage market is diversified and heterogenous. Most of the variation in alcoholic beverages arises from the level of alcohol content fermentation. Alcoholic beverages are broadly classified into three groups—beer, wine and spirits—with the lowest average alcohol content in beer and highest in spirits and wine ranging somewhere between the two. Anecdotal evidence suggests that consumers of beer, wine and spirits relate to rather different socioeconomic and demographic groups. For instance, spirits are known to be mostly popular amongst female teenagers and young adults. Wine is primarily associated with middle to old aged individuals whereas beer is more popular amongst men (Groenbaek et al. 2000; Klatsky et al. 1990). To some extent, the choice of beverages is also related to individuals' occupations. Hence, it appears that the three types of alcoholic beverages are likely to be quite heterogenous in consumption patterns.

While there are abundant empirical economic studies on drinking and its price response, most papers have considered alcohol as a homogeneous beverage and have combined beer, wine and spirits into a single product. On the other hand, those few studies which examined drinking by specific alcohol types found that beer, wine and spirit consumption respond differently to own price (for example, Clements 1983; Clements et al. 1997; Edwards et al. 1994; Leung and Phelps 1993). However, these studies are all based on data aggregated at state or national level.

Also, from a health point of view, recent medical and epidemiological studies have increasingly reported the benefits of drinking moderate amount of red wine (Camargo Jr et al. 1997; Coate 1993; Malinski et al. 2004; Razay et al. 1992). This further emphasises the importance of investigating alcohol consumption by types of alcoholic drinks.

Some epidemiologists and health professionals have studied the association between demographic and personality traits and individuals' preference for particular alcohol types (Klatsky et al. 1990; McGregor et al. 2003). They have pointed out that investigation into the alcohol-health relationship needs to control for the effects of such personal characteristics. The same could be argued for the need of controlling for individual heterogeneity in economic studies that investigate the effects of economic instruments on consumption. While Cameron and Williams (2001) and Zhao and Harris (2004) studied alcohol consumption using micro level Australian data, not a single study has examined the consumption of beer, wine and spirits individually. This study makes an important contribution to the literature where, to the best of the author's knowledge, an individual-level economic analysis of beer, wine and spirits is almost nonexistent.

This section investigates the factors that influence participation in beer, wine and spirits using the 1991, 1993, 1995, 1998 and 2001 sweeps of the NDSHS. The NDSHS provides information on a range of alcoholic beverages consumed by Australians. These are grouped into the three broad categories of alcoholic beverages—beer, wine and spirits—in this analysis.[4] Unfortunately, the survey does not contain information on the amount consumed for each alcohol type. Thus, this study focuses on participation only. Data on the respective price of beer, wine and spirits are obtained from the Australian Bureau of Statistics (ABS 2006b). They correspond to the Consumer Price Index (CPI) for each of these sub-categories. The three price series are then deflated using the all-items CPI for individuals' respective states of residence. Participation equations for beer, wine and spirits are estimated separately using Probit models. Tables 4.3 presents the estimated coefficients and marginal effects along with their corresponding standard errors. Again, any change in attitude towards the use of alcoholic beverages across surveys is controlled for using year dummies. Unfortunately, the effect of income cannot be examined in this analysis because such data was not available prior to the 1995 survey.

Price Effects

The price results strongly support the hypothesis that, like most goods, beer, wine and spirit consumption all respond negatively to their respective own price (Table 4.3). However, the price effects do vary across the three types of beverage. Note that, here, the marginal effect for a continuous explanatory variable relates to the actual change in the *probability of participation* for a particular alcoholic beverage in response to a unit change in the explanatory variable, while for a dummy

[4] An inconsistency in the construction of these series is that respondents in the 1998 and 2001 surveys were offered a more disaggregated set of options with regard to the beverages they consumed in contrast to earlier surveys. To some extent, this is understandable given that some alcoholic drinks such as pre-mixed beverages have become popular only in recent years.

Table 4.3 Probit estimates for beer, wine and spirits consumption

	Beer				*Wine*				*Spirits*			
	Coefficient		Marginal effect		Coefficient		Marginal effect		Coefficient		Marginal effect	
Constant	−9.121	(1.343)**	−3.567	(0.525)**	−5.562	(1.316)**	−2.213	(0.523)**	−1.423	(1.322)	−0.537	(0.499)
P^{beer}	−1.037	(0.270)**	−0.406	(0.106)**	0.282	(0.265)	0.112	(0.105)	0.023	(0.265)	0.009	(0.100)
P^{wine}	0.458	(0.268)*	0.179	(0.105)*	−2.197	(0.263)**	−0.874	(0.104)**	0.635	(0.265)**	0.240	(0.100)**
$P^{spirits}$	0.700	(0.229)**	0.274	(0.090)**	1.540	(0.225)**	0.613	(0.090)**	−0.722	(0.227)**	−0.273	(0.086)**
Age	4.474	(0.294)**	1.749	(0.115)**	2.788	(0.292)**	1.109	(0.116)**	1.499	(0.291)**	0.566	(0.110)**
Agesq	−0.647	(0.041)**	−0.253	(0.016)**	−0.323	(0.040)**	−0.128	(0.016)**	−0.331	(0.041)**	−0.125	(0.015)**
Male	1.193	(0.014)**	0.445	(0.005)**	−0.474	(0.014)**	−0.186	(0.005)**	−0.156	(0.014)**	−0.059	(0.005)**
Married	−0.090	(0.020)**	−0.035	(0.008)**	0.168	(0.020)**	0.067	(0.008)**	−0.215	(0.020)**	−0.082	(0.008)**
Divorced	−0.111	(0.028)**	−0.043	(0.011)**	0.074	(0.027)**	0.030	(0.011)**	−0.127	(0.027)**	−0.047	(0.010)**
Widow	−0.065	(0.039)*	−0.025	(0.015)*	−0.037	(0.036)	−0.015	(0.014)	−0.166	(0.039)**	−0.061	(0.014)**
Depchld	−0.036	(0.007)**	−0.014	(0.003)**	−0.014	(0.005)**	−0.006	(0.002)**	−0.048	(0.007)**	−0.018	(0.003)**
ATSI	0.009	(0.051)	0.003	(0.020)	−0.332	(0.052)**	−0.129	(0.020)**	−0.056	(0.050)	−0.021	(0.018)
Capital	−0.114	(0.015)**	−0.045	(0.006)**	0.208	(0.015)**	0.082	(0.006)**	0.001	(0.015)	0.000	(0.006)
Work	0.073	(0.018)**	0.028	(0.007)**	0.216	(0.017)**	0.086	(0.007)**	0.050	(0.018)**	0.019	(0.007)**
Study	−0.028	(0.030)	−0.011	(0.012)	0.242	(0.030)**	0.096	(0.012)**	−0.232	(0.030)**	−0.085	(0.010)**
Unemp	0.039	(0.037)	0.015	(0.014)	−0.002	(0.037)	−0.001	(0.015)	0.025	(0.036)	0.009	(0.014)
Degree	0.026	(0.023)	0.010	(0.009)	0.905	(0.023)**	0.342	(0.008)**	0.033	(0.023)	0.012	(0.009)
Diploma	0.097	(0.021)**	0.038	(0.008)**	0.403	(0.021)**	0.160	(0.008)**	0.224	(0.021)**	0.086	(0.008)**
Yr12qual	0.077	(0.023)**	0.030	(0.009)**	0.455	(0.023)**	0.179	(0.009)**	0.286	(0.023)**	0.111	(0.009)**
Yr10qual	0.004	(0.022)	0.002	(0.009)	0.214	(0.022)**	0.085	(0.009)**	0.196	(0.022)**	0.075	(0.009)**

Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Table 4.4 Participation elasticities for beer, wine and spirits consumption

	Beer		Wine		Spirits	
P^{beer}	−0.948	(0.247)**	0.238	(0.223)	0.022	(0.263)
P^{wine}	0.418	(0.245)*	−1.852	(0.221)**	0.630	(0.263)**
$P^{spirits}$	0.640	(0.210)**	1.298	(0.190)**	−0.717	(0.226)**

Probability elasticity is calculated by dividing marginal effect by the mean of the dependent variable. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

variable it represents the change in the *probability of participation* when the dummy variable changes from 0 to 1.

When converted into elasticities of participation, these marginal effects translate into own price elasticities of −0.95, −1.85 and −0.72 for beer, wine and spirits respectively, indicating that participation in wine consumption is highly responsive to its own price (Table 4.4). Note that these estimates cannot be directly compared to price elasticities of demand measured in terms of quantities of consumption, in most of the literature.[5]

Interesting cross price effects are also estimated across the three alcoholic beverages (Table 4.4). From both the wine and spirits equations there is evidence that these two alcoholic beverages are economic substitutes. However, from the wine equation the cross price elasticity is estimated at 1.30, while in the spirits equation a lower cross elasticity of 0.63 is estimated. The cross price elasticities between beer–spirits and beer–wine are significant only in the beer equation and are estimated at 0.64 and 0.42 respectively. These results indicate that all three alcoholic types are economic substitutes in participation.

Socioeconomic and Demographic Effects

The inclusion of both a linear and a quadratic age term in the analysis allows for a flexible age profile for participation. Both terms are significant in all three equations (Table 4.3). The effect of age on the consumption of the three alcoholic beverages is illustrated in Fig. 4.2 using predicted participation probabilities for different ages, evaluated at the sample means of all other explanatory variables. As expected, the probability of wine consumption increases with age although at a decreasing rate. Other characteristics being equal, the probability of wine participation for an "average" person aged 40 years or more, is twice the probability that an "average" 20-year old would consume wine. The participation probability of beer shows an interesting inverted U-shaped age profile. Individuals in the 30–35 age group have

[5]The literature generally shows that spirit is the most elastic and beer, the least elastic in terms of quantities of alcohol consumed. Participation elasticities can only be compared to the conventional quantity elasticities under the assumption that the average consumption quantity per drinker remains constant.

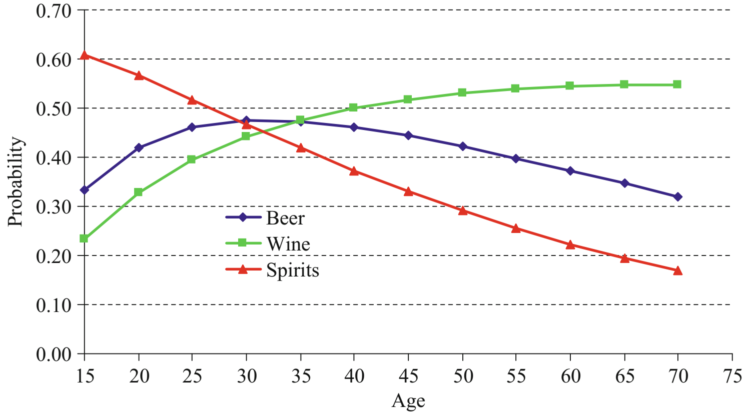

Fig. 4.2 Predicted probabilities for beer, wine and spirits consumption: effect of age

the highest chances to consumer beer, while the probability declines sharply for younger people and declines slowly for individuals older than 35 years. Opposite to wine, the age effect on spirits use is almost linear with the highest probability of participation amongst teenagers. With an increased popularity of RTDs (Ready To Drink beverages that are already pre-mixed) amongst young people, it is not surprising to see such a high prevalence of spirits use in this age group.

In terms of gender, while males are more likely to consume beer, females have a greater probability of consuming wine and spirits, other factors being controlled for. The marginal effects indicate that males are 45 pp more likely to consume beer than females but 19 pp and 6 pp less likely to participate in wine and spirit consumption respectively. Single individuals are more likely to consume beer and spirits and less likely to consume wine that those who are married, divorced or widowed. The higher the number of dependent children in the house, the lower is the probability of participation in any of the three alcoholic beverages. Aboriginals/Torres Strait Islanders (ATSI) are 13 pp less likely to consume wine than the rest of the population. However, there seems to be no such difference in the prevalence of beer and spirit consumption. People living in capital cities are more likely to consume wine but less likely to drink beer relative to those living in other regions. However, no such difference is observed for spirit consumers.

In terms of an individual's main occupation, those who work or study are more likely to drink wine and people who mainly study are least likely to drink spirits. Unlike in the earlier analysis of the levels of alcohol consumption where unemployment was associated with increased probability of bingeing, here, it does not appear to be a significant factor for participation of any of the three alcoholic beverages. Wine is found to be highly associated with education levels. The marginal effects in Table 4.3 indicate that the better educated are more likely to consume wine. However, there does not appear to be any distinct association between beer consumption and educational attainment. Finally, the marginal effects indicate an inverted U-shaped relationship between spirit consumption and education levels although the effect of tertiary education is statistically insignificant.

4.3.3 *Tobacco*

A substantial body of literature has investigated tobacco consumption at an individual level over recent decades. As in the case of alcohol, most studies have focused on youth smoking given the pandemic use of tobacco in this segment of the population and its adverse effects in terms of habit formation and long-term health consequences. Economic literature on smoking is, however, scarce in Australia. Most of the earlier studies on Australian data were examined using time series with a focus on advertising effects (Bardsley and Olekans 1999; Clements et al. 1985; Johnson 1986). Some recent work used individual-level data to examine smoking participation and levels of use (Cameron and Williams 2001; Harris and Zhao 2007; Zhao and Harris 2004).

To contribute to this scant literature, Australians' smoking patterns are examined in this section using data on smoking from the 1998, 2001 and 2004 sweeps of the NDSHS (2005a). Individuals are grouped into four categories based on their frequency and intensity of smoking: nonsmoker, occasional smoker, moderate smoker, and heavy smoker. The description and computation of these smoking groups are detailed in Chap. 3. Alcohol, tobacco and marijuana prices series by states of residence and years, are similar to those used in the analysis of alcohol consumption in Sect. 4.3.

Cigarette consumption is specified as a function of drug prices, income, and a range of socioeconomic and demographic characteristics to account for taste heterogeneity. Given an ordering in the four smoking status, an Ordered Probit model is again estimated. The estimated coefficients, threshold parameters and their associated standard errors are presented in the first two columns of Table 4.5. Also reported in the table are the marginal effects and their corresponding standard errors.

Own Price Effects

The price results in Table 4.5 strongly support the hypothesis that, like any economic good, cigarette consumption is price responsive. Such price sensitivity has been obtained by several previous studies (for example, Chaloupka 1991; Chaloupka and Grossman 1996; Gruber 2000; Harris and Chan 1999; Hersch 2000; Lewit et al. 1981, 1997; Ross and Chaloupka 2003). The marginal effects indicate that a tobacco price rise will result in higher probability of non smokers and lower probabilities for all other three groups of smokers. Evaluated at sample proportions of the four smoking levels, these translate into probability elasticities of −0.19, −0.25 and −0.33 for the occasional, moderate and heavy smokers and 0.08 for non smokers (Table 4.6). (for example, Chaloupka and Grossman 1996; Chaloupka and

Table 4.5 Ordered probit estimates for cigarette consumption

	Coefficient		*Non smoker* Marginal effect		*Occasional smoker*		*Moderate smoker*		*Heavy smoker*	
Constant	−13.069	1.627**	–		–		–		–	
P^{tob}	−0.210	0.099**	0.061	0.029**	−0.008	0.004**	−0.030	0.014**	−0.023	0.011**
P^{alc}	−0.667	0.234**	0.193	0.068**	−0.025	0.009**	−0.095	0.033**	−0.073	0.026**
P^{mar}	0.106	0.065	−0.031	0.019	0.004	0.002	0.015	0.010	0.012	0.008
$Income^h$	−0.144	0.012**	0.042	0.003**	−0.005	0.000**	−0.020	0.002**	−0.016	0.001**
Age	10.587	0.345**	−3.061	0.099**	0.395	0.013**	1.504	0.049**	1.163	0.039**
Agesq	−1.539	0.048**	0.445	0.014**	−0.057	0.002**	−0.219	0.007**	−0.169	0.005**
Male	0.140	0.015**	−0.041	0.004**	0.005	0.001**	0.020	0.002**	0.016	0.002**
Married	−0.287	0.017**	0.085	0.005**	−0.010	0.001**	−0.041	0.002**	−0.034	0.002**
Depchld	−0.107	0.022**	0.030	0.006**	−0.004	0.001**	−0.015	0.003**	−0.011	0.002**
Singpar	0.091	0.026**	−0.027	0.008**	0.003	0.001**	0.013	0.004**	0.011	0.003**
Capital	−0.032	0.015**	0.009	0.004**	−0.001	0.001**	−0.004	0.002**	−0.003	0.002**
ATSI	0.259	0.056**	−0.082	0.019**	0.009	0.002**	0.038	0.008**	0.035	0.009**
Degree	−0.516	0.022**	0.134	0.005**	−0.019	0.001**	−0.068	0.003**	−0.047	0.002**
Yr12qual	−0.189	0.022**	0.052	0.006**	−0.007	0.001**	−0.026	0.003**	−0.019	0.002**
Diploma	−0.142	0.019**	0.040	0.005**	−0.005	0.001**	−0.020	0.003**	−0.015	0.002**
Bluejob	0.131	0.025**	−0.039	0.008**	0.005	0.001**	0.019	0.004**	0.015	0.003**
Whitejob	−0.047	0.021**	0.014	0.006**	−0.002	0.001**	−0.007	0.003**	−0.005	0.002**
Unemp	−0.083	0.037**	0.023	0.010**	−0.003	0.001**	−0.012	0.005**	−0.009	0.004**
Study	−0.046	0.039	0.013	0.011	−0.002	0.001	−0.006	0.005	−0.005	0.004
μ_1	0.157	0.004**								
μ_2	0.804	0.009**								

Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Table 4.6 Probability elasticities for cigarette consumption

	Non smoker		Occasional smoker		Moderate smoker		Heavy smoker	
P^{tob}	0.079	(0.037)**	−0.189	(0.089)**	−0.248	(0.117)**	−0.328	(0.155)**
P^{alc}	0.251	(0.088)**	−0.601	(0.210)**	−0.788	(0.276)**	−1.045	(0.366)**
P^{mar}	−0.040	(0.025)	0.096	(0.058)	0.125	(0.083)	0.166	(0.114)
$Income^{h}$	0.054	(0.004)**	−0.130	(0.010)**	−0.170	(0.014)**	−0.225	(0.018)**
Own price probability elasticities by age group:								
14–19 yrs	0.815	(0.198)**	−1.646	(0.403)**	−2.520	(0.613)**	−3.304	(0.830)**
20–24 yrs	0.312	(0.167)*	−0.346	(0.199)*	−0.628	(0.414)*	−0.964	(1.227)*
25–29 yrs	0.233	(0.141)*	−0.296	(0.160)*	−0.488	(0.331)*	−0.726	(1.251)*
30+ yrs	0.015	(0.041)	−0.042	(0.051)	−0.052	(0.094)	−0.067	(0.531)

Participation elasticity is calculated by dividing marginal effect by the mean of the dependent variable, for the respective category. Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Wechsler 1997; Gruber 2000; Harris and Chan 1999; Hersch 2000; Lewit et al. 1981, 1997; Ross and Chaloupka 2003). It is very likely that a new smoker is price elastic but as his addictive stock increases, a price increase is more likely to lead to only a marginal reduction in his tobacco consumption. To compare with those previous studies, own price elasticities for four different age cohorts are estimated and reported in the lower panel of Table 4.6.[6] These results reinforce previous findings that price responsiveness of smoking varies inversely with age. Among all four smoking status, probability elasticities of price are far higher for teenagers than other age groups. These probability elasticities indicate that a 1 % increase in tobacco price would result into 3.3 %, 2.5 % and 1.6 % reductions in the probability values of heavy, moderate and occasional smoking, respectively and a 0.82 % increase in the probability value of non smokers, amongst teenagers aged 14–19 years. The probability elasticities are found to decline gradually over older cohorts and they become statistically insignificant for adults aged thirty and older. These results are comparable to those of Harris and Chan (1999) who used a similar approach to assess variations in the effect of price at different ages. Their estimates of smoking participation elasticities also showed a gradual decline, decreasing from −0.83 for the 15–17 age group to elasticities in the range of −0.10 to −0.37 for the 21–23 age group, becoming insignificant for adults older than 23.

Cross Price Effects

Individuals' smoking behaviour is also found to respond significantly to alcohol price. Surprisingly, the effect is larger than the own price response of smoking.

[6] As in the previous analysis of alcohol consumption, the sample is partitioned into four groups and the model is estimated separately on each age cohort.

However, the results agree with previous findings by Cameron and Williams (2001) and Zhao and Harris (2004) using Australian data. The cross price elasticity in Table 4.6 shows that a 1 % increase in alcohol price decreases the respective probability values of heavy, moderate and occasional smoking by 1.0 %, 0.79 % and 0.60 % but increases that of non smokers by 0.25 %. Alcohol and tobacco are thus found to be economic complements. This result agrees with the earlier evidence obtained in Sect. 4.3 and also with those of Zhao and Harris (2004). Finally, the cross price elasticity of marijuana is found to be positive and statistically insignificant.[7]

Income Effects

Several studies have examined the effect of *household* income on smoking, in particular, amongst youths. This variable is very often observed to be inversely related to cigarette consumption (for example, Harris and Chan 1999; Hersch 2000; Townsend et al. 1994; Wasserman et al. 1991; Zhao and Harris 2004) indicating that smoking is associated with poor and poorly educated social groups. Also, Hersch (2000) argued that the higher their income, the more people become health conscious and invest in their health. With smoking being a potential threat for health, the willingness to incur health risks declines with income (Hersch 2000). The income effect in Table 4.5 indeed indicates that cigarette consumption is likely to be higher among low socioeconomic groups. The income probability elasticities indicate that a 10 % higher household real income results in reductions of 2.3 %, 1.7 % and 1.3 % in the probability values of heavy, moderate and occasional smoking but increases the probability value of non smokers by 0.54 % (Table 4.6).[8]

Studies that have used *personal* income have shown mixed results. Tobacco have been found to be a normal good, in particular amongst young people (see Chaloupka and Grossman 1996; Chaloupka et al. 1999a) while a few studies have found that an increase in personal income reduces cigarette consumption (Huang et al. 2004; Keeler et al. 1993). To assess the impact of personal income on smoking status, the model is again estimated by substituting household income with personal income although the results are not reported here. The effect of this variable is positive but insignificant over the full sample. However, when estimated over a young cohort aged under 25, in line with previous studies, a positive significant effect of personal income on youth smoking is obtained. In particular, the estimated income probability elasticities range from 0.11 for occasional smokers to 0.25 for the heavy

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[7] Note that using Australian data, Zhao and Harris (2004) found some evidence of complementarity between marijuana and tobacco while cross-price effects with respect to tobacco and marijuana, estimated by Cameron and Williams (2001) were inconclusive.

[8] The implied income elasticity of participation by the four estimates for individual drinking groups (0.054, −0.130, −0.170 and −0.225) would seem to compare closely to the value of 0.169 estimated by Zhao and Harris (2004) in their earlier study. Also, on separate samples for male and female, Hersch (2000) estimated elasticities of participation with respect to family income of −0.17 for women and −0.19 for men for a sample of 18–65 years old.

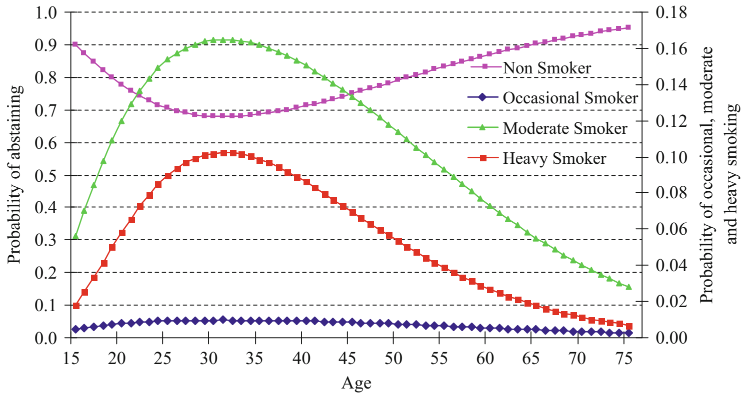

Fig. 4.3 Predicted probabilities for cigarette consumption: effect of age

smokers and −0.07 for nonsmokers. This tends to suggest that tobacco has the characteristics of a normal good for young individuals such that their consumption increases as income rises.

Socioeconomic and Demographic Effects

To allow for a flexible age profile for smoking consumption, the model includes a quadratic term for age. Both age variables are statistically significant and their combined effect is shown in Fig. 4.3 which depicts predicted probabilities by smoking status for different ages, evaluated at the sample means of all other explanatory variables. The probability of moderate and heavy smoking clearly increases with age, peaks for individuals in their mid-thirties and declines gradually for older individuals. For instance, an "average" 35-year old is over 50 % more likely to be a heavy smoker relative to a 60-year old who has only about 20 % chances of smoking heavily. On the other hand, occasional smokers appear to have a much flatter age profile than the other groups of smokers. The probability of being a non-smoker is the lowest for individuals in their thirties.

Males are more likely to smoke heavily than females. Being married decreases the chances of smoking and so does the presence of dependent children in the household. However, the chances of smoking is higher among single parents with dependent children. It is quite likely that parents would abstain from smoking in order to protect their children from passive smoking harms but single parents would indulge into stress-relieving activities such as smoking because of a stressful life. Those living in capital cities have marginally lower probabilities of smoking and Aborigines are more likely to be smokers than the rest of the population. With regard to individuals' main occupations, blue collar workers have the highest chances of smoking and smoking heavily.

Educational attainment which is often considered as a proxy for social class, is found to be highly associated with smoking. In addition, Keeler et al. (1993) argued that better educated individuals are more accessible and acceptable to the information of severe health problems from smoking. The marginal effects of the levels of education achieved show that those who hold a university degree, diploma and high school qualifications are found to have lower chances of smoking occasionally, moderately or heavily than those who with lower qualifications. For instance, a university graduate has 13.4 pp higher chances of being a nonsmoker and between 4 and 7 pp less chances of being a moderate or heavy smoker than someone with less than year-12 qualifications. Similar results were obtained in previous studies (Cameron and Williams 2001; Zhao and Harris 2004).

4.4 Illegal Drug Consumption

While there exists a vast economic literature on the consumption of licit recreational drugs, research on illicit drugs is limited due to unavailability, or poor quality, of data. As discussed in Chap. 2, the majority of studies related to illicit drugs have focused on marijuana consumption. In contrast, a very small body of literature has examined the use of other illicit drugs such as cocaine, heroin and amphetamines, although their consequences are even more serious than the harms caused by marijuana. In Australia, despite the concern over illicit drug use, only a very small amount of economic research has been carried out on such harmful drugs. Recently, a few studies have examined marijuana consumption using Australian data (see Cameron and Williams 2001; Williams 2004; Zhao and Harris 2004) but none so far has investigated the use of any other illicit drug.

This section models the consumption of marijuana, amphetamines, cocaine and heroin in Australia. It thus makes an important contribution to the drug literature which is sparse on drugs such as cocaine and heroin, and almost nonexistent for amphetamines. In addition, it uses unique information on illicit drug prices to examine price sensitivity of illicit drug use, which is very rare in the literature. In the light of cross price responses, the nature of economic relationships is established across the four illicit drugs and with alcohol and tobacco.

Data are pooled together from the 1998, 2001 and 2004 sweeps of the NDSHS. The dependent variables in this study are dichotomous measures for participation in the use of marijuana, amphetamines, cocaine and heroin. Price series for marijuana, cocaine and heroin for individual years and states/territories are obtained mainly from the Illicit Drug Reporting System (NDARC 2004). They correspond to price per ounce of marijuana and per gram of amphetamines, cocaine and heroin. Again, all price and income series are deflated using the all-items Consumer Price Indexes by individuals' states of residence. Probit model estimates for marijuana, cocaine, heroin and amphetamines consumption are reported in Tables 4.7 and 4.8.

Table 4.7 Probit estimates for marijuana and amphetamine consumption

	Marijuana				*Amphetamines*			
	Coefficient		Marginal effect		Coefficient		Marginal effect	
Constant	−15.374	(1.682)**	–		−25.082	(2.333)**	–	–
P^{mar}	−0.138	(0.083)*	−0.0215	(0.013)*	−0.083	(0.105)	−0.0022	(0.003)
P^{coc}	0.112	(0.050)**	0.0176	(0.008)**	0.147	(0.071)**	0.0039	(0.002)**
P^{her}	0.137	(0.043)**	0.0215	(0.007)**	0.189	(0.063)**	0.0050	(0.002)**
P^{amp}	−0.024	(0.022)	−0.0038	(0.003)	−0.084	(0.033)**	−0.0022	(0.001)**
P^{tob}	−0.187	(0.162)	−0.0292	(0.025)	0.839	(0.221)**	0.0223	(0.006)**
Income^{h}	−0.078	(0.014)**	−0.0123	(0.002)**	−0.016	(0.021)	−0.0004	(0.001)
Decrim	0.006	(0.032)	0.0010	(0.005)				
Age	10.363	(0.475)**	1.6222	(0.067)**	11.931	(0.849)**	0.3170	(0.018)**
Agesq	−1.656	(0.068)**	−0.2592	(0.009)**	−1.921	(0.125)**	−0.0510	(0.003)**
Male	0.314	(0.019)**	0.0502	(0.003)**	0.213	(0.030)**	0.0058	(0.001)**
Married	−0.420	(0.021)**	−0.0709	(0.004)**	−0.488	(0.033)**	−0.0155	(0.002)**
Depchld	−0.151	(0.027)**	−0.0219	(0.004)**	−0.212	(0.044)**	−0.0047	(0.001)**
Singpar	0.071	(0.031)**	0.0115	(0.005)**	−0.043	(0.047)	−0.0011	(0.001)
Capital	0.029	(0.020)	0.0045	(0.003)	0.181	(0.032)**	0.0045	(0.001)**
ATSI	0.156	(0.066)**	0.0271	(0.013)**	0.141	(0.096)	0.0044	(0.003)
Degree	−0.041	(0.029)	−0.0063	(0.004)	−0.215	(0.046)**	−0.0051	(0.001)**
Diploma	0.034	(0.025)	0.0054	(0.004)	0.015	(0.039)	0.0004	(0.001)
Yr12qual	−0.014	(0.028)	−0.0021	(0.004)	−0.104	(0.043)**	−0.0026	(0.001)**
Bluejob	0.074	(0.033)**	0.0119	(0.006)**	0.004	(0.054)	0.0001	(0.001)
Whitejob	0.003	(0.029)	0.0004	(0.004)	−0.103	(0.048)**	−0.0027	(0.001)**
Unemp	0.122	(0.042)**	0.0205	(0.008)**	−0.094	(0.064)	−0.0023	(0.001)
Study	0.060	(0.045)	0.0097	(0.008)	−0.143	(0.068)**	−0.0033	(0.001)**

Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Price Effects

The results in Table 4.7 indicate that marijuana and amphetamines respond negatively to their own prices. However, there is no evidence of own price response for cocaine and heroin use (Table 4.8). Evaluated at sample means, the marginal price effects are converted into elasticities in Table 4.9. The own price elasticity for marijuana indicates that a 1 % increase in its price results in 0.15 % fewer marijuana users. This result is consistent with the estimates of −0.18 and −0.21 of price elasticities of participation obtained by Williams (2004) and Zhao and Harris (2004) using Australian data.

The cross price effects indicate that marijuana use responds positively to cocaine and heroin prices suggesting that it is an economic substitute for both of these hard drugs. On the other hand, a rise in amphetamine or tobacco price has a negative impact on the probability of using marijuana, indicating a complementarity relationship of marijuana with the two drugs although the effects are statistically insignificant at conventional levels of significance. Except for marijuana price, amphetamines use has a positive significant response to all

Table 4.8 Probit estimates for cocaine and heroin consumption

	Cocaine				*Heroin*			
	Coefficient		Marginal effect		Coefficient		Marginal effect	
Constant	−26.413	(3.463)**	–		−7.363	(5.311)	–	–
P^{mar}	0.334	(0.155)**	0.0032	(0.002)**	0.656	(0.278)**	0.0020	(0.001)**
P^{coc}	0.050	(0.101)	0.0005	(0.001)	−0.289	(0.199)	−0.0009	(0.001)
P^{her}	−0.217	(0.090)**	−0.0021	(0.001)**	−0.075	(0.167)	−0.0002	(0.001)
P^{amp}	−0.044	(0.046)	−0.0004	(0.000)	−0.069	(0.081)	−0.0002	(0.000)
P^{tob}	0.087	(0.300)	0.0008	(0.003)	−1.735	(0.483)**	−0.0052	(0.002)**
$Income^h$	0.129	(0.033)**	0.0012	(0.000)**	−0.078	(0.047)*	−0.0002	(0.000)*
Age	13.426	(1.324)**	0.1299	(0.012)**	8.656	(1.747)**	0.0259	(0.005)**
Agesq	−2.059	(0.193)**	−0.0199	(0.002)**	−1.328	(0.253)**	−0.0040	(0.001)**
Male	0.138	(0.041)**	0.0014	(0.000)**	0.225	(0.074)**	0.0007	(0.000)**
Married	−0.453	(0.046)**	−0.0054	(0.001)**	−0.305	(0.080)**	−0.0011	(0.000)**
Depchld	−0.214	(0.066)**	−0.0017	(0.000)**	−0.007	(0.104)	−0.0001	(0.000)
Singpar	−0.212	(0.081)**	−0.0016	(0.001)**	0.069	(0.106)	0.0002	(0.000)
Capital	0.373	(0.054)**	0.0031	(0.001)**	0.150	(0.080)*	0.0004	(0.000)*
ATSI	0.114	(0.151)	0.0013	(0.002)	0.205	(0.186)	0.0008	(0.001)
Degree	0.045	(0.068)	0.0004	(0.001)	−0.292	(0.116)**	−0.0007	(0.000)**
Diploma	0.079	(0.064)	0.0008	(0.001)	−0.125	(0.092)	−0.0004	(0.000)
Yr12qual	−0.006	(0.068)	−0.0001	(0.001)	−0.152	(0.095)	−0.0004	(0.000)*
Bluejob	0.078	(0.087)	0.0008	(0.001)	−0.094	(0.110)	−0.0003	(0.000)
Whitejob	0.067	(0.076)	0.0007	(0.001)	−0.363	(0.104)**	−0.0011	(0.000)**
Unemp	0.107	(0.100)	0.0012	(0.001)	−0.139	(0.135)	−0.0003	(0.000)
Study	0.008	(0.110)	0.0001	(0.001)	−0.055	(0.144)	−0.0002	(0.000)

Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Table 4.9 Participation elasticities for marijuana, amphetamine, cocaine and heroin consumption

	Marijuana		Amphetamines		Cocaine		Heroin	
P^{mar}	−0.1526	(0.092)*	−0.0613	(0.078)	0.2498	(0.118)**	0.6006	(0.264)**
P^{coc}	0.1247	(0.055)**	0.1087	(0.053)**	0.0372	(0.076)	−0.2648	(0.185)
P^{her}	0.1525	(0.048)**	0.1394	(0.047)**	−0.1623	(0.069)**	−0.0684	(0.154)
P^{amp}	−0.0271	(0.024)	−0.0619	(0.024)**	−0.0332	(0.035)	−0.0632	(0.074)
P^{tob}	−0.2071	(0.180)	0.6195	(0.167)**	0.0653	(0.225)	−1.5884	(0.512)**
$Income^h$	−0.0870	(0.016)**	−0.0116	(0.016)	0.0963	(0.026)**	−0.0719	(0.045)*

Participation elasticity is calculated by dividing marginal effect by the mean of the dependent variable. Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

other drug prices suggesting that cocaine, heroin and tobacco are economic substitutes for amphetamines. Both cocaine and heroin consumption are insensitive to amphetamine price but respond positively to marijuana price, reinforcing the substitutability relationship found in the marijuana equation (Table 4.8). There is also evidence that heroin and cocaine are economic complements from the cocaine equation but the effect of cocaine price on heroin consumption is statistically insignificant.

The Effect of Decriminalisation

The effect of the criminal status of marijuana is examined using an indicator variable that identifies the decriminalised states from the rest. In this particular sample that covers the period 1998–2004, three states and territories (South Australia, Northern Territory and Australian Capital Territory) have decriminalised minor marijuana offences over the years. For the decriminalisation indicator, "decrim" to effectively capture the effect of the policy, individuals need to be randomly allocated to the various states without any selection bias via the observable and unobservable factors. While this is a reasonable assumption in the sample for the major states, the Northern Territory has a very different demographic composition compared to the rest (see, for example, Taylor 2003). To partly account for the potential selection bias arising from such a demographic difference, an indicator variable for the Northern Territory is entered in the model. Note, however, that a proper account of the selectivity bias or the endogeneity of decriminalisation, requires a system of equation approach (see Damrongplasit et al. 2010).

The coefficient of the decriminalisation variable in Table 4.7 is found to be positive but statistically insignificant. In other words, decriminalisation is found to have no significant effect on the probability of using marijuana. However, this result is sensitive to the inclusion of the indicator variable for Northern Territory. In the absence of the indicator, the effect of the decriminalisation variable is positive and significant. Such results were obtained by Cameron and Williams (2001) and Zhao and Harris (2004) in their studies, which did not control for any state-specific effects. On the other hand, controlling for state-specific effects using state indicators, Williams (2004) found an insignificant impact of decriminalisation on marijuana use. However, controlling for state-specific effects for all the states is problematic in this study as state indicators are very likely to be collinear with the price variables which have insufficient variation across time. Another main concern related to the policy effect is that the sample covers only the period after the policy change while ideally the investigation of a policy impact requires data that covers adequately long periods before and after the policy change.

Income Effects

Turning to the effects of socioeconomic and demographic factors, the impact of *household* income on illicit drug use is first discussed. To the extent that household, or family, income represents a proxy for social class, drug use is associated with poorly educated social groups and low-income families (see, for example, Barr et al. 1993). With the exception of cocaine, participation in all other drugs are inversely related to household income, as in the case of cigarette consumption. In other words, as with tobacco, illicit drugs are more commonly used by the low socioeconomic groups. The income effect of amphetamines is, however, statistically insignificant. In particular, the income elasticities in Table 4.9 indicate that a 10 % increase in household income results in 0.87 % and 0.72 % declines in marijuana[9] and heroin participation probability values, respectively.

The positive association between cocaine use and income tends to suggest that cocaine is commonly used by higher socioeconomic groups. Hando et al. (1997) found that a high proportion of cocaine users in Sydney and Melbourne belonged to the middle to upper socioeconomic status groups and were employed in a range of professions, white collar jobs and creative occupations. These individuals were found to have above average income and education, and lived in affluent areas. Similar patterns of use have been observed by police intelligence (see ACC 2006); they have found that Australian cocaine users include a high number of "culturally influenced" users and young people of high socioeconomic status who use cocaine at parties and social occasions. Although not reported here, the model is also estimated by replacing *household* income with *personal* income. For all four drugs, personal income is positively related to their consumption although the effects are significant for only cocaine and amphetamines consumption. These results suggest that while the illicit drugs are mostly consumed by lower socioeconomic groups, they do have the characteristics of a normal good where a rise in personal income increases their consumption.

Socioeconomic and Demographic Effects

So, what are the effects of individuals' personal factors on illegal drug consumption? Once again, a quadratic term for age is included in the analysis to allow for a more flexible age profile for drug participation. In all four equations, both age coefficients are statistically significant. The combined effect of the age variables is depicted for all four drugs in Fig. 4.4. In particular, participation probabilities for different ages are predicted at the sample means of all other explanatory variables. Marijuana and amphetamines are found to be more prevalent amongst young adults in their early twenties while cocaine and heroin are more commonly used by individuals in their late twenties. In general, the 20–30 age group is mostly likely to indulge into illicit drugs.

Males are more likely to use illicit drugs than females (Tables 4.7 and 4.8). Single individuals have higher chances to participate in any of the drugs. The presence of dependent children in the household decreases the chances of consuming drugs in general but those from single-parent families with dependent children have higher chances of using marijuana although there is some evidence that it lowers the chances of using cocaine. Note that empirical research on the relationship between drug use and family structure has often shown that young adults from disrupted families are more likely to indulge into drugs (see, for example, Flewelling and Bauman 1990; Jenkins and Zunguze 1998). Those living in capital cities have,

[9] This is consistent with the −0.072 estimate of income elasticity of participation estimated by Zhao and Harris (2004) using Australian data.

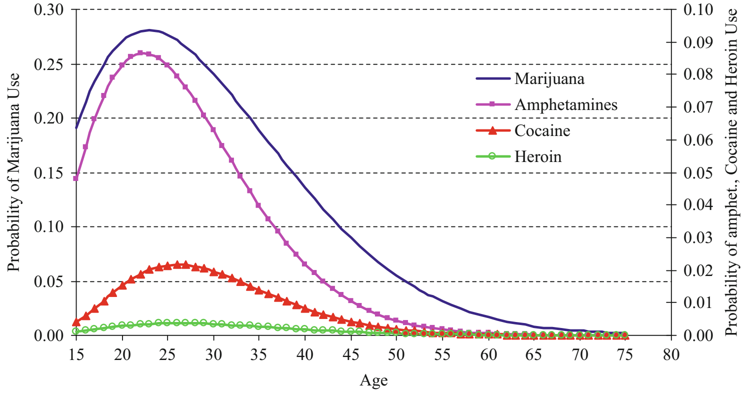

Fig. 4.4 Predicted probabilities for illicit drug consumption: effect of age

in general, higher chances of using illicit drugs except for marijuana where drug use in capital cities is not significantly different from consumption in other regions. As expected, Aboriginal and Torres Strait Islanders (ATSI) have higher chances of using marijuana than the rest of the population but surprisingly, no significant differences are found for the other illicit drugs.

With regard to employment status, some differences were found across the various groups. Relative to the reference group of home makers, those with blue collar jobs and who are unemployed are more likely to use marijuana. For amphetamines, chances of using the drug are lower among white collar workers and those who study. While cocaine use is not particularly affected by employment status, white collar workers are less likely to consume heroin than the reference group. While there does not appear to be any significant difference across the various education groups for marijuana and cocaine, some differential effects are observed for amphetamines and heroin users. Relative to those who have not finished high school, degree holders are less likely to use amphetamines and heroin. To the extent that educational attainment reflects social class, these results indicate that the better educated are less likely to engage into drug use.

4.5 Summary

This chapter has carried out a thorough investigation of Australians' consumption of a selection of licit and illicit drugs. In particular, it has examined the effects of price, income and a range of socioeconomic and demographic characteristics on drug participation and levels of consumption. It has also investigated the effect of marijuana decriminalisation which is a highly debated policy issue in Australia.

The consumption of alcohol and cigarettes are first modelled to examine individuals' drinking and smoking patterns. Constructing four levels of drinking and smoking status that would account for individuals' frequency and intensity of alcohol and cigarettes consumption, the study provides insights on how user characteristics and policy responses are associated with patterns of drug use. The analysis of alcohol consumption, in particular, focuses on Australians' bingeing behaviour.

A high incidence of binge drinking is noted among Australians. Approximately 40 % of males and 30 % of females are bingers, out of which about 20 % binge at least 3 days a week. The heaviest drinkers and smokers are found to be the most price sensitive groups. Teenage drinking and smoking are relatively more price sensitive that any other age groups. The demographic and socioeconomic variables reveal some important differential effects. As expected, bingeing is found to be more common among teenagers and young adults. On the other hand, both moderate and heavy smoking have an inverted U-shaped relationship with age. Heavy drinking and smoking are more common among males, singles, Aborigines and those in blue collar jobs. Heavy smoking is typically prevalent in low socioeconomic groups. When disaggregated by type of alcoholic drinks, participation in wine consumption is found to be more price sensitive than participation in beer or spirits consumption. In addition, the three alcohol types are found to be quite heterogenous relating to different demographic and socioeconomic characteristics. For instance, wine is more commonly consumed by highly educated individuals, females and older age groups. Beer is consumed mostly by males in the 25–35 age group while spirits are clearly the dominant beverage of choice for young females.

The second part of the chapter models illicit drug consumption. In particular, it identifies the important drivers of marijuana, amphetamines, cocaine and heroin participation. Using unique price data, the study examines the price sensitivity of illicit drug use and provides estimates of elasticities of participation. Marijuana and amphetamine consumption are found to be sensitive to their own prices. The study also provides insights on the socioeconomic and demographic characteristics of illicit drug users. Drugs are typically used by males, singles, Aborigines and those living in capital cities. Marijuana use is associated with blue collar workers, and amphetamines and heroin participation relate to those with low levels of education and are less likely to be used by white collar workers. Cocaine is mostly associated with high socioeconomic groups while the other drugs are more commonly used by low income groups.

Marijuana decriminalisation is found to have no effect on its participation. However, this result is sensitive to model specifications. In particular, for the decriminalisation indicator to effectively capture the effect of the policy, individuals need to be randomly allocated to the various states without any selection bias via observed or unobserved factors. While this is a reasonable assumption in the sample for the major states, the Northern Territory has a very different demographic composition compared to the rest. The potential selection bias arising from such demographic difference is accounted for using an indicator for the Northern Territory. The result indicates a positive but insignificant effect of the decriminalisation policy on marijuana participation. However, in the absence of the indicator, decriminalisation is found to increase marijuana participation.

The chapter has also established the nature of economic relationships across the various drugs on the basis of cross price responses. Such cross-drug relationships have rarely been studied jointly in empirical studies and are almost nonexisting for illicit drugs. The results can be summarised as follows. Alcohol is found to be an economic complement to tobacco and marijuana. Both marijuana and amphetamines are economic substitutes for cocaine and heroin. Amphetamines are also found to be economic substitutes for tobacco. However, heroin and cocaine are found to be economic complements and both the hard drugs are also complements to tobacco.

Chapter 5
Modelling Multiple Drug Use Using a Multivariate Approach

5.1 Introduction

Recreational drugs are habit-forming substances and are therefore often consumed in a consumption bundle. For instance, the probability of using marijuana in the general Australian population is 13 %. However, in a subpopulation of tobacco smokers, nearly 32 % consume marijuana, and among those who consume hard drugs such as cocaine, heroin and amphetamines, nearly 96 % use marijuana. This kind of multiple drug or polydrug use, is a common occurrence amongst drug users (see Boys et al. 1997; Hando et al. 1997; Mugford 1994).[1] While Chap. 4 established economic relationships across drugs on the basis of cross price effects, the focus of this chapter is on estimating relationships across the consumption of different drugs via the dependent drug consumption variables. This provides information such as how being a smoker increases the probability of consuming marijuana, or how being a hard drug user relates to a very high probability of marijuana use.

While each drug is considered in isolation in Chap. 4, here the relationships across drugs are addressed in a multi-drug framework where consumption decisions are considered to be taken jointly by the same individual. The univariate Probit (UVP) approach used earlier ignores the potential cross-commodity correlations across multiple drugs for the same individual that are not reflected in his/her *observable* characteristics. Due to *unobservable* characteristics such as individual taste, addictive trait and risk-taking attitude, an individual's decision to consume multiple drugs can be potentially related through the error terms of the participation equations, that is, via the unobservables. As a consequence, vital cross-drug information is lost when the conventional univariate approach is adopted.

[1] Wilkinson et al. (1987) define polydrug users as 'users of a variety of psychoactive substances, either concurrently or sequentially'. These can include licit and/or illicit drugs. Polydrug use has been associated with higher risks of overdose, mortality, suicide and HIV risk behaviours (see Baker et al. 1994; Borges et al. 2000; Coffin et al. 2003; Darke et al. 2000).

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This chapter uses a system approach to account for correlation across the participation decisions of various drugs. In particular, a multivariate Probit (MVP) model for drug participation is estimated.[2] The key advantage of the multivariate approach is that conditional and joint probabilities of drug consumption can be modelled as functions of observable covariates, whereas, the univariate approach models only marginal probabilities. Consequently, the multivariate model helps determine the policy response as well as the socioeconomic and demographic characteristics of those subpopulations of drug users who use multiple drugs. For instance, it is quite likely that a marijuana user who also consumes hard drugs such as cocaine and heroin, will be less sensitive to marijuana price because of his addiction to several drugs compared to someone who consumes only marijuana. A good understanding of such subpopulations of drug users can have important implications for the development of targeted policies to address drug misuse and also for designing effective drug prevention programs.

The chapter is structured as follows. Section 5.1 describes the multivariate Probit model for drug participation. Section 5.2 examines the relationship across drugs by estimating a five-dimensional participation status of marijuana, amphetamines, cocaine, heroin and tobacco using a multivariate Probit model. In Sect. 5.3, the consumption of beer, wine and spirits is modelled using the multivariate approach to examine the heterogeneity of user attributes across the three alcoholic types. Section 5.4 provides a summary of the findings.

5.2 The Multivariate Probit Model for Joint Drug Participation

Assume that there is an underlying latent propensity variable $Y_j^* (-\infty < Y_j^* < \infty)$ which is proportional to the unobserved level of demand for each of the drugs j $(j = 1, \ldots .m)$. The latent demand is determined by

$$Y_j^* = \mathbf{x}_j' \boldsymbol{\beta}_j + \epsilon_j \qquad (j = 1, \ldots m) \tag{5.1}$$

where $\mathbf{x}_j$ represents a vector of observed personal characteristics and other economic variables that relate to the consumption of drug j by an individual (the subscript i representing individuals is dropped for simplicity); $\boldsymbol{\beta}_j$ is a vector of unknown parameters; and ϵ_j is the error term. Without loss of generality (Maddala 1983), Eq. (5.1) is mapped to an observable binary discrete variable Y_j indicating whether or not an individual consumes a particular drug via the following

[2]While this approach can be extended to MVOP to estimate ordered discrete levels of consumption, the significant computational burden it entails is beyond the scope of this thesis.

$$Y_j = \begin{cases} 1 \text{ if } Y_j^* > 0 \\ 0 \text{ if } Y_j^* \leq 0 \end{cases}, \ (j = 1, \ldots m), \tag{5.2}$$

If the ϵ_j's $(j = 1, \ldots m)$ are assumed to be independently and identically distributed with a standard normal distribution, Eqs. (5.1) and (5.2) define m 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 participation probability for another drug.

A more general specification is to assume that the error terms in the m latent equations in (5.1) jointly follow a multivariate normal distribution, that is, $(\epsilon_1, \epsilon_2, \ldots..\epsilon_m)' \sim MVN(0, \Sigma_m)$. The variance–covariance matrix Σ_m is given by

$$\Sigma_m = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \ldots & \rho_{1m} \\ \rho_{21} & 1 & \rho_{23} & \ldots & \rho_{2m} \\ \rho_{31} & \rho_{32} & 1 & \ldots & \rho_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{m1} & \rho_{m2} & \rho_{m3} & \ldots & 1 \end{pmatrix}$$

where ρ_{ij} is the correlation coefficient between ϵ_j and ϵ_k $(j, k = 1, 2, \ldots..m;$ $j \neq k)$. Under this assumption, Eqs. (5.1) and (5.2) result in a multivariate Probit (MVP) model that jointly represents the participation decisions for the m drugs. The MVP specification with potentially non-zero off-diagonal elements in Σ_m, allows for correlations across the disturbances of the m latent equations which embody unobserved characteristics of the same individuals. While the MVP model has the UVP as a special case $(\rho_{ij} = 0 \ \forall \ ij, \ i \neq j)$, the knowledge on an individual's participation in one drug can now help predict his/her probability of using another. Note that the assumption of unit variance ensures that the parameters can be identified separately from the variance of $\boldsymbol{\epsilon}$ (Greene 2003).

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

$$P(Y_j = 1|\mathbf{x}_j) = \Phi(\mathbf{x}_j' \boldsymbol{\beta}_j) \qquad (j = 1, \ldots m) \tag{5.3}$$

where $\Phi(.)$ is the univariate normal cumulative distribution function.

The bivariate joint probabilities are given by

$$\begin{aligned} P(Y_j = 1, Y_k = 1|\mathbf{x}_j, \mathbf{x}_k) &= \Phi_2(\mathbf{x}_j' \boldsymbol{\beta}_j, \mathbf{x}_k' \boldsymbol{\beta}_k; \rho_{jk}) \\ P(Y_j = 1, Y_k = 0|\mathbf{x}_j, \mathbf{x}_k) &= \Phi_2(\mathbf{x}_j' \boldsymbol{\beta}_j, -\mathbf{x}_k' \boldsymbol{\beta}_k; -\rho_{jk}) \\ P(Y_j = 0, Y_k = 0|\mathbf{x}_j, \mathbf{x}_k) &= \Phi_2(-\mathbf{x}_j' \boldsymbol{\beta}_j, -\mathbf{x}_k' \boldsymbol{\beta}_k; \rho_{jk}) \\ (j, k = 1, 2 \ldots..m; j \neq k) \end{aligned} \tag{5.4}$$

where $\Phi_2(z_j, z_k; \rho_{jk})$ denotes the bivariate normal cumulative distribution function with ρ_{jk} as the correlation coefficient between the two random elements z_j and z_k.

The multivariate joint probabilities are given by

$$\begin{aligned}
&P(Y_1 = s_1, Y_2 = s_2, \ldots, Y_m = s_m; \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m) \\
&= \Phi_m((2s_1 - 1)\mathbf{x}_1'\boldsymbol{\beta}_1, (2s_2 - 1)\mathbf{x}_2'\boldsymbol{\beta}_2 \ldots, (2s_m - 1)\mathbf{x}_m'\boldsymbol{\beta}_m; \tilde{\Sigma}_m) \\
&(s_1, s_2, \ldots, s_m = 0 \text{ or } 1)
\end{aligned} \tag{5.5}$$

and

$$\tilde{\Sigma}_m = \begin{pmatrix} 1 & (2s_1-1)(2s_2-1)\rho_{12} & \ldots & (2s_1-1)(2s_m-1)\rho_{1m} \\ (2s_2-1)(2s_1-1)\rho_{12} & 1 & \ldots & (2s_2-1)(2s_m-1)\rho_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ (2s_m-1)(2s_1-1)\rho_{1m} & (2s_m-1)(2s_2-1)\rho_{2m} & \ldots & 1 \end{pmatrix}, \tag{5.6}$$

where $\Phi_m(z_1, z_2 \ldots z_m; \tilde{\Sigma}_m)$ denotes the cumulative distribution function of a standard multivariate normal distribution with variance–covariance matrix $\tilde{\Sigma}_m$.

Various conditional probabilities can also be obtained. Below are a few such conditional probabilities for a five-dimensional model.

$$\begin{aligned}
&P(Y_1 = 1 | Y_2 = 1, Y_3 = 1, Y_4 = 1, Y_5 = 1; \mathbf{x}_1, \mathbf{x}_2, \ldots .\mathbf{x}_5) \\
&= \frac{\Phi_5(\mathbf{x}_1'\boldsymbol{\beta}_1, \mathbf{x}_2'\boldsymbol{\beta}_2, \mathbf{x}_3'\boldsymbol{\beta}_3, \mathbf{x}_4'\boldsymbol{\beta}_4, \mathbf{x}_5'\boldsymbol{\beta}_5; \hat{\Sigma}_5)}{\Phi_4(\mathbf{x}_2'\boldsymbol{\beta}_2, \mathbf{x}_3'\boldsymbol{\beta}_3, \mathbf{x}_4'\boldsymbol{\beta}_4, \mathbf{x}_5'\boldsymbol{\beta}_5; \hat{\Sigma}_4)}
\end{aligned} \tag{5.7}$$

$$\text{where } \hat{\Sigma}_5 = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \rho_{15} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} & \rho_{25} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} & \rho_{35} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 & \rho_{45} \\ \rho_{15} & \rho_{25} & \rho_{35} & \rho_{45} & 1 \end{pmatrix} \text{ and } \hat{\Sigma}_4 = \begin{pmatrix} 1 & \rho_{23} & \rho_{24} & \rho_{25} \\ \rho_{23} & 1 & \rho_{34} & \rho_{35} \\ \rho_{24} & \rho_{34} & 1 & \rho_{45} \\ \rho_{25} & \rho_{35} & \rho_{45} & 1 \end{pmatrix}.$$

$$\begin{aligned}
&P(Y_1 = 1 | Y_2 = 0, Y_3 = 0, Y_4 = 0, Y_5 = 0; \mathbf{x}_1, \mathbf{x}_2, \ldots .\mathbf{x}_5) \\
&= \frac{\Phi_5(\mathbf{x}_1'\boldsymbol{\beta}_1, \mathbf{x}_2'\boldsymbol{\beta}_2, \mathbf{x}_3'\boldsymbol{\beta}_3, \mathbf{x}_4'\boldsymbol{\beta}_4, \mathbf{x}_5'\boldsymbol{\beta}_5; \acute{\Sigma}_5)}{\Phi_4(\mathbf{x}_2'\boldsymbol{\beta}_2, \mathbf{x}_3'\boldsymbol{\beta}_3, \mathbf{x}_4'\boldsymbol{\beta}_4, \mathbf{x}_5'\boldsymbol{\beta}_5; \acute{\Sigma}_4)}
\end{aligned} \tag{5.8}$$

$$\text{where } \acute{\Sigma}_5 = \begin{pmatrix} 1 & -\rho_{12} & -\rho_{13} & -\rho_{14} & -\rho_{15} \\ -\rho_{12} & 1 & \rho_{23} & \rho_{24} & \rho_{25} \\ -\rho_{13} & \rho_{23} & 1 & \rho_{34} & \rho_{35} \\ -\rho_{14} & \rho_{24} & \rho_{34} & 1 & \rho_{45} \\ -\rho_{15} & \rho_{25} & \rho_{35} & \rho_{45} & 1 \end{pmatrix} \text{ and } \acute{\Sigma}_4 = \begin{pmatrix} 1 & \rho_{23} & \rho_{24} & \rho_{25} \\ \rho_{23} & 1 & \rho_{34} & \rho_{35} \\ \rho_{24} & \rho_{34} & 1 & \rho_{45} \\ \rho_{25} & \rho_{35} & \rho_{45} & 1 \end{pmatrix}.$$

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:

$$Log(L) = \sum_{i=1}^{N} \sum_{s_1=0}^{1} \sum_{s_2=0}^{1} \ldots . \sum_{s_m=0}^{1} h_i(s_1, s_2, \ldots s_m) \; \log(P(Y_{1i} = s_1, Y_{2i} = s_2, \ldots$$
$$\ldots Y_{mi} = s_m; \mathbf{x}_{1i}, \mathbf{x}_{2i}, \ldots .\mathbf{x}_{mi})) \tag{5.9}$$

where

$$h_i(s_1, s_2, \ldots s_m) = \begin{cases} 1 \text{ if individual } i \text{ chooses } (Y_{1i} = s_1, Y_{2i} = s_2, \ldots . Y_{mi} = s_m) \\ 0 \text{ otherwise.} \qquad\qquad (s_1, s_2, \ldots s_m = 0 \text{ or } 1) \end{cases} \tag{5.10}$$

Because the probabilities that enter the likelihood are functions of high dimensional multivariate normal distributions, they are simulated using the GHK algorithm (see Greene 2003). In addition, since the joint and conditional probabilities are highly non-linear functions of $\mathbf{x}$, analytical solutions of marginal effects are difficult to obtain. Thus, the marginal effects are calculated using numerical gradients (see Appendix C). As is standard in the literature, the standard errors of the marginal effects are then estimated using the delta method (using the estimated Hessian) which provides an approximation to the asymptotic distributions of the marginal effects (see, for example, Greene 2003).

5.3 Marijuana, Cocaine, Heroin, Amphetamines and Tobacco (MCHAT) Consumption: A Multivariate Approach

In Chap. 4, participation in illicit drugs was examined individually using a univariate approach. This section explores relationships across the dependent drug participation variables using a multivariate Probit model. In particular a system of five equations that jointly models participation in marijuana, cocaine, heroin, amphetamines and tobacco is estimated. Unlike the univariate Probit model, the multivariate approach accounts for any cross-commodity correlations for the same individual via factors such as personal taste, peer effects, and risk-taking attitude (see Adlaf and Smart 1983; Amoateng and Bahr 1986; Steinberg et al. 1994; Wallace Jr and Bachman 1991) that are potential attributes influencing the individual's participation in a variety of drugs but which are unobserved.

5.3.1 MCHAT: Observed Joint, Conditional and Marginal Probabilities

Before estimating the multivariate model, sample joint and conditional participation in the five drugs are calculated, based on observed data. This gives a preliminary indication of the extent to which the consumption of the five drugs are interrelated. Table 5.1 illustrates the joint and marginal probabilities of consuming the five drugs based on the same data set as in Chap. 4. The marginal probability for marijuana shows that nearly 13 % of individuals consume this soft drug. However, a decomposition of the marginal probability shows that only 5 % of individuals consume marijuana on its own while the rest consumes it jointly with other drugs. Similar patterns of consumption are observed for most of the other drugs. For instance, while about 3 % of individuals consume amphetamines, only 0.2 % is observed to use the drug on its own.

Based on the figures in Table 5.1, selected conditional probabilities of participation are estimated in Table 5.2. These figures further confirm that the five drugs are closely related in consumption. For instance, while 13 % of individuals consume marijuana in the general population, in a subpopulation of cocaine users, nearly 84 % use marijuana and among those who jointly consume cocaine, heroin and amphetamines, nearly 96 % use marijuana. Similarly, while 23 % of individuals are smokers in the general population, in a subpopulation of cocaine, heroin and amphetamines users, 50 % of the drug users are smokers and in a subpopulation of marijuana, cocaine and amphetamines users, more than 90 % are smokers. Such large proportions of drug users consuming multiple drugs indicate that the drugs are closely related in consumption.

5.3.2 Multivariate Probit Estimates of MCHAT Consumption

The relationship across the five drugs is next modelled using a more formal model. The estimated coefficients and their corresponding standard errors are presented in Appendix C, Table C.1 for marijuana, Table C.2 for cocaine and heroin and Table C.3 for amphetamines and tobacco. Also reported in each table are the resultant marginal effects of explanatory factors on the probability of participation, and their corresponding standard errors. Note that the marginal effects correspond to those of marginal probabilities and they are evaluated at sample means.

Firstly, the correlation coefficients reported in the last three columns of Table C.1 are examined. 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 five drugs for the same individuals. All ten correlation coefficients are statistically highly significant at the 5 % level. This suggests that the null hypothesis of five UVP models, or the hypothesis of independence across the error terms of the five latent equations, can be rejected and

Table 5.1 MCHAT-joint and marginal probabilities

		Marginal probability				
	Joint probability	Marijuana	Cocaine	Heroin	Amphet.	Tobacco
Marijuana only	4.692	4.692				
Cocaine only	0.057		0.057			
Heroin only	0.005			0.005		
Amphetamines only	0.248				0.248	
Tobacco only	14.978					14.978
Marijuana and Cocaine only	0.114	0.114	0.114			
Marijuana and Heroin only	0.003	0.003		0.003		
Marijuana and Amphetamines only	0.595	0.595			0.595	
Marijuana and Tobacco only	5.238	5.238				5.238
Cocaine and Heroin only	–		–	–		
Cocaine and Amphetamines only	0.049		0.049		0.049	
Cocaine and Tobacco only	0.033		0.033			0.033
Heroin and Amphetamines only	–			–	–	
Heroin and Tobacco only	0.016			0.016		0.016
Amphetamines and Tobacco only	0.213				0.213	0.213
Marijuana, Cocaine and Heroin only	0.003	0.003	0.003	0.003		
Marijuana, Cocaine and Amphetamines only	0.152	0.152	0.152		0.152	
Marijuana, Cocaine and Tobacco only	0.148	0.148	0.148			0.148
Marijuana, Heroin and Amphetamines only	0.014	0.014		0.014	0.014	

(continued)

Table 5.1 (continued)

	Joint probability	Marginal probability				
		Marijuana	Cocaine	Heroin	Amphet.	Tobacco
Marijuana, Heroin and Tobacco only	0.036	0.036		0.036		0.036
Marijuana, Amphetamines and Tobacco only	1.331	1.331			1.331	1.331
Cocaine, Heroin and Amphetamines only	–		–	–	–	
Cocaine, Amphetamines and Tobacco only	0.039		0.039		0.039	0.039
Cocaine, Heroin and Tobacco only	0.002		0.002	0.002		0.002
Heroin, Amphetamines and Tobacco only	0.014			0.014	0.014	0.014
Marijuana, Cocaine, Heroin and Amphetamines only	0.095	0.095	0.095	0.095	0.095	
Marijuana, Cocaine, Heroin and Tobacco only	0.006	0.006	0.006	0.006		0.006
Marijuana, Cocaine, Amphetamines and Tobacco only	0.365	0.365	0.365		0.365	0.365
Marijuana, Heroin, Amphetamines and Tobacco only	0.055	0.055		0.055	0.055	0.055
Cocaine, Heroin, Amphetamines and Tobacco only	0.008		0.008	0.008	0.008	0.008
Marijuana, Cocaine, Heroin, Amphetamines and Tobacco	0.085	0.085	0.085	0.085	0.085	0.085
None	71.406					
Total	100.00	12.933	1.156	0.343	3.263	22.568

– denotes negligible. Measured as percentages of total respondents. Missing observations are excluded in calculations. Consequently, some of these proportions are inconsistent with those reported in Table 3.7

Table 5.2 MCHAT-selected conditional participation probabilities

	Marijuana	Cocaine	Heroin	Amphet.	Tobacco
$P(.)$	12.9	1.2	0.3	3.3	22.6
$P(.\|Y_M = 1)$	100.0	7.5	2.3	20.8	56.2
$P(.\|Y_C = 1)$	83.7	100.0	17.2	68.6	59.4
$P(.\|Y_H = 1)$	87.1	58.1	100.0	79.3	65.0
$P(.\|Y_A = 1)$	82.5	24.3	8.3	100.0	64.7
$P(.\|Y_T = 1)$	32.2	3.1	1.0	9.4	100.0
$P(.\|Y_C = 1, Y_H = 1, Y_A = 1)$	95.8	100.0	100.0	100.0	49.6
$P(.\|Y_C = 1, Y_H = 1, Y_T = 1)$	90.6	100.0	100.0	92.2	100.0
$P(.\|Y_H = 1, Y_A = 1, Y_T = 1)$	86.4	57.3	100.0	100.0	100.0
$P(.\|Y_M = 1, Y_C = 1, Y_H = 1)$	100.0	100.0	100.0	95.0	48.3
$P(.\|Y_M = 1, Y_C = 1, Y_A = 1)$	100.0	100.0	25.9	100.0	90.5
$P(.\|Y_M = 1, Y_C = 1, Y_T = 1)$	100.0	100.0	15.1	74.4	100.0
$P(.\|Y_M = 1, Y_H = 1, Y_A = 1)$	100.0	72.2	100.0	100.0	76.7
$P(.\|Y_M = 1, Y_H = 1, Y_T = 1)$	100.0	50.0	100.0	76.7	100.0
$P(.\|Y_C = 1, Y_H = 1, Y_A = 1, Y_T = 1)$	91.5	100.0	100.0	100.0	100.0
$P(.\|Y_M = 1, Y_H = 1, Y_A = 1, Y_T = 1)$	100.0	60.7	100.0	100.0	100.0
$P(.\|Y_M = 1, Y_C = 1, Y_A = 1, Y_T = 1)$	100.0	100.0	18.9	100.0	100.0
$P(.\|Y_M = 1, Y_C = 1, Y_H = 1, Y_T = 1)$	100.0	100.0	100.0	93.1	100.0
$P(.\|Y_M = 1, Y_C = 1, Y_H = 1, Y_A = 1)$	100.0	100.0	100.0	100.0	47.4

Measured as percentages of total respondents. Missing observations are excluded in calculations

the MVP model is a better model for the observed data. The largest correlation is estimated for cocaine–heroin (0.757) and cocaine–amphetamines (0.753) and the lowest, yet substantial, correlation is estimated between heroin and tobacco (0.320). The strong correlation between cocaine, heroin and amphetamines indicates that these hard drugs are more likely to be related with each other than with softer drugs such as marijuana or tobacco. These results highlight the importance of estimating drug consumption, in particular illicit drugs, within a multivariate framework.

In Chap. 4, the marginal effects of marginal probabilities for each of the five drugs was thoroughly discussed. Given that both UVP and MVP give consistent estimates for marginal probabilities, to avoid repetition, results related to marginal probabilities are not discussed here.[3] So, the key advantage of the multivariate model is that it also allows to estimate joint and conditional probabilities using information on cross-commodity correlation via the unobservable characteristics. Such information is not available in a univariate approach which assumes zero correlations across the error terms. The larger the correlation coefficient, the more divergent are the conditional and unconditional probabilities likely to be. In this analysis, with a high degree of correlation estimated across the five participation

[3]As is well known for the Seemingly Unrelated Regression (SUR) model for the continuous dependent variable case, there is no gain in using the system equations approach when all equations have the same explanatory variables. Similarly, with the MVP model there is little to gain over the UVP model in terms of the univariate marginal probabilities.

equations, it is expected that information on participation in one drug will significantly alter the predicted probability of participation in another.

5.3.3 MCHAT: Predicted Joint, Conditional and Marginal Probabilities

Table 5.3 presents some predicted joint, conditional and marginal probabilities for an individual, evaluated at mean values of all explanatory variables, using both the multivariate Probit (MVP) and univariate Probit (UVP) models. As mentioned in the model section, the conditional and joint probabilities are highly non-linear in both parameters and **x** variables which prevents tractable analytical solution of marginal effects and standard errors. Numerical gradients and hessians and the delta method are therefore used to estimate marginal effects and standard errors.

As shown in Table 5.3, the probability of marijuana consumption is 8.7 % for a typical individual in the general population. However, if it is known that he/she participates in the consumption of cocaine, heroin, amphetamines and tobacco, the probability for the same person is predicted as 98.3 % using a MVP model. On the other hand, for such an individual, a UVP model would predict the same probability as the marginal probability as if the extra information were not available. Similarly, a typical individual's participation in cocaine consumption is predicted as 0.3 %. However, if he/she is known to consume heroin and amphetamines, his/her predicted probability increases to 90 % using the MVP model. The last set of results correspond to joint probabilities. For instance, the joint probability of participation in marijuana and non-participation in the other drugs is predicted as 2.2 % by the MVP model as against 6.7 % predicted by the UVP.

5.3.4 MCHAT: Marginal Effects on Joint and Conditional Probabilities

A knowledge of the likely effects of individual explanatory factors on different conditional and joint probabilities have important implications for policy development. A thorough understanding of the characteristics and consumption patterns of multiple drug users can also be useful for designing educational programs that help target subpopulation groups of drug users, hence making such programs more cost effective and beneficial. Note again that such results cannot be estimated using the univariate approach where cross-drug correlations via unobservable factors are not available. Some results depicting price, and socioeconomic and demographic differential effects on joint and conditional probabilities of consumption are discussed next.

Table 5.3 MCHAT—Predicted probabilities

	Marijuana			*Cocaine*	
	MVP	UVP		MVP	UVP
$P(Y_M = 1\|\overline{\mathbf{x}})$	0.0869	0.0857	$P(Y_C = 1\|\overline{\mathbf{x}})$	0.0033	0.0032
	(0.0019)	(0.0019)		(0.0005)	(0.0004)
$P(Y_M = 1\|Y_C = 1, Y_H = 1, Y_A = 1, Y_T = 1, \overline{\mathbf{x}})$	0.9834		$P(Y_C = 1\|Y_M = 1, Y_A = 1, Y_T = 1, \overline{\mathbf{x}})$	0.3357	
	(0.0286)			(0.0515)	
$P(Y_M = 1\|Y_C = 1, Y_H = 1, Y_A = 1, \overline{\mathbf{x}})$	0.9886		$P(Y_C = 1\|Y_M = 1, Y_H = 1, Y_A = 1, \overline{\mathbf{x}})$	0.8993	
	(0.0109)			(0.0498)	
$P(Y_M = 1\|Y_C = 1, Y_H = 1, \overline{\mathbf{x}})$	0.8436		$P(Y_C = 1\|Y_H = 1, Y_A = 1, \overline{\mathbf{x}})$	0.8995	
	(0.0429)			(0.0502)	
$P(Y_M = 1\|Y_A = 1, \overline{\mathbf{x}})$	0.8198		$P(Y_C = 1\|Y_H = 1, \overline{\mathbf{x}})$	0.4183	
	(0.0464)			(0.0573)	
	Heroin			*Amphetamines*	
	MVP	UVP		MVP	UVP
$P(Y_H = 1\|\overline{\mathbf{x}})$	0.0008	0.0009	$P(Y_A = 1\|\overline{\mathbf{x}})$	0.0109	0.0100
	(0.0003)	(0.0002)		(0.0007)	(0.0008)
$P(Y_H = 1\|Y_M = 1, Y_C = 1, Y_A = 1, \overline{\mathbf{x}})$	0.0707		$P(Y_A = 1\|Y_M = 1, Y_C = 1, Y_H = 1, Y_T = 1, \overline{\mathbf{x}})$	0.3142	
	(0.0210)			(0.0355)	
$P(Y_H = 1\|Y_M = 1, Y_C = 1, \overline{\mathbf{x}})$	0.1129		$P(Y_A = 1\|Y_M = 1, Y_C = 1, Y_H = 1, \overline{\mathbf{x}})$	0.3130	
	(0.0292)			(0.0332)	
$P(Y_H = 1\|Y_C = 1, Y_A = 1, \overline{\mathbf{x}})$	0.0665		$P(Y_A = 1\|Y_C = 1, Y_H = 1, \overline{\mathbf{x}})$	0.2671	
	(0.0203)			(0.0300)	
$P(Y_H = 1\|Y_C = 1, \overline{\mathbf{x}})$	0.1027		$P(Y_A = 1\|Y_M = 1, \overline{\mathbf{x}})$	0.1030	
	(0.0278)			(0.0082)	

(continued)

Table 5.3 (continued)

	Tobacco			*Joint*	
	MVP	UVP		MVP	UVP
$P(Y_T = 1 \mid \overline{\mathbf{x}})$	0.2166	0.2168	$P(Y_M = 1, Y_C = 1, Y_H = 1, Y_S = 1, Y_T = 1, \overline{\mathbf{x}})$	0.0001	0.0000
	(0.0022)	(0.0023)		(0.0000)	(0.0000)
$P(Y_T = 1 \mid Y_M = 1, Y_C = 1, Y_H = 1, Y_S = 1, \overline{\mathbf{x}})$	0.8363		$P(Y_M = 1, Y_C = 0, Y_H = 0, Y_S = 0, Y_T = 0, \overline{\mathbf{x}})$	0.0217	0.0670
	(0.0373)			(0.0012)	(0.0014)
$P(Y_T = 1 \mid Y_M = 1, Y_C = 1, Y_S = 1, \overline{\mathbf{x}})$	0.8496		$P(Y_M = 0, Y_C = 1, Y_H = 0, Y_S = 0, Y_T = 0, \overline{\mathbf{x}})$	0.0003	0.0023
	(0.0126)			(0.0001)	(0.0003)
$P(Y_T = 1 \mid Y_C = 1, Y_H = 1, Y_S = 1, \overline{\mathbf{x}})$	0.8407		$P(Y_M = 0, Y_C = 0, Y_H = 0, Y_S = 1, Y_T = 0, \overline{\mathbf{x}})$	0.0014	0.0078
	(0.0309)			(0.0003)	(0.0005)
$P(Y_T = 1 \mid Y_M = 1, \overline{\mathbf{x}})$	0.7171		$P(Y_M = 0, Y_C = 0, Y_H = 0, Y_S = 0, Y_T = 1, \overline{\mathbf{x}})$	0.1534	0.1948
	(0.0119)			(0.0022)	(0.0021)

Standard errors are given in parentheses and are estimated using the delta method

Price and Income Effects

Economic research has shown that price and income changes can have potentially differing impacts on polydrug users relative to those who consume a single drug (see Petry 2000, 2001). For instance, a "hardcore" drug user is very likely to engage in multiple drug use. He/she is likely to be more addicted and less responsive to drug prices than someone who consumes a single drug. Thus, from policy perspective, it is useful to examine how price sensitive individuals are in subpopulation groups of drug users. Do these subpopulations of drug users have a lower, or higher, price elasticity than those in the general population? Are the cross price elasticities in the subpopulation groups different from those in the general population? What implications do these results have on the nature of the economic relationships across drugs?

The price marginal effects and corresponding probability elasticities on selected conditional and joint participation probabilities are reported in Table 5.4 for marijuana, cocaine and tobacco; and Table 5.5, for heroin and amphetamines; and compared to those on unconditional participation probabilities from a UVP approach. Table 5.4 shows that while marijuana price has a significant negative impact on its consumption for a typical individual in the general population, in a subpopulation of heroin and cocaine users, the price effect is statistically insignificant. This suggests that a hardcore drug user with a strong addiction for drugs is less likely to be price sensitive than a casual user. From the effect on the general population, there is evidence that tobacco is an economic complement and heroin an economic substitute, for marijuana. From a subpopulation of cocaine and heroin users, heroin and cocaine are both found to be economic substitutes for marijuana, but there is no evidence of complementarity with tobacco.

It is interesting to see how cocaine consumption of a typical individual in the general population is insensitive to its own price but, among heroin users, is price responsive (Table 5.4). In particular, a 10 % increase in cocaine price results in 2.98 % fewer cocaine users among those who are heroin users.

Tobacco consumption is found to be sensitive to its own price in the general population (Table 5.4). However, among those who are marijuana users, tobacco consumption is not likely to be affected by its own price. Tobacco is found to be an economic substitute for marijuana in a subpopulation of marijuana users although in the general population, tobacco consumption is insensitive to marijuana price.

Table 5.5 shows that amphetamine users are quite price sensitive in the general population. They respond significantly to its own price as well as the price of all other drugs. On the other hand, among those who consume marijuana, cocaine, heroin and tobacco, amphetamines users are sensitive to only marijuana and heroin prices. The elasticities in the general population are also quite different from those in the subpopulation. The unconditional amphetamines participation elasticity with respect to marijuana price is estimated at -0.451, while conditional on the consumption of the other four drugs, the elasticity declines to -0.154.

Also reported in Table 5.5 are price effects on a joint probability. All those who consume marijuana, cocaine, heroin, amphetamines and tobacco jointly, are highly

Table 5.4 Marijuana, cocaine and tobacco—price effects on unconditional and conditional probabilities

	Marijuana				*Cocaine*				*Tobacco*			
	$P(Y_M = 1\|\bar{\mathbf{x}})$		$P(Y_M = 1\|Y_C = 1, Y_H = 1, \bar{\mathbf{x}})$		$P(Y_C = 1\|\bar{\mathbf{x}})$		$P(Y_C = 1\|Y_H = 1, \bar{\mathbf{x}})$		$P(Y_T = 1\|\bar{\mathbf{x}})$		$P(Y_T = 1\|Y_M = 1, \bar{\mathbf{x}})$	
Marginal Effects:												
P^{mar}	−0.048	(0.013)**	−0.041	(0.037)	−0.003	(0.002)*	−0.139	(0.146)	0.014	(0.017)	0.100	(0.029)**
P^{coc}	0.012	(0.008)	0.052	(0.024)**	−0.0002	(0.001)	−0.173	(0.100)*	0.019	(0.011)*	0.008	(0.018)
P^{her}	0.016	(0.007)**	0.089	(0.027)**	−0.004	(0.001)**	−0.184	(0.085)**	−0.015	(0.010)	−0.048	(0.016)**
P^{amp}	−0.001	(0.003)	−0.008	(0.010)	0.001	(0.001)	0.040	(0.043)	0.011	(0.005)**	0.018	(0.008)**
P^{tob}	−0.096	(0.026)**	0.117	(0.078)	−0.012	(0.004)**	0.416	(0.321)	−0.078	(0.035)**	0.040	(0.059)
Income^h	−0.014	(0.002)**	−0.034	(0.011)**	0.001	(0.000)**	0.097	(0.027)**	−0.044	(0.004)**	−0.044	(0.006)**
Participation Elasticities:												
P^{mar}	−0.375	(0.101)**	−0.043	(0.039)	−0.293	(0.157)*	−0.239	(0.252)	0.062	(0.074)	0.177	(0.052)**
P^{coc}	0.096	(0.060)	0.055	(0.025)**	−0.020	(0.093)	−0.298	(0.173)*	0.085	(0.049)*	0.015	(0.033)
P^{her}	0.121	(0.053)**	0.093	(0.028)**	−0.348	(0.100)**	−0.316	(0.146)**	−0.067	(0.044)	−0.086	(0.029)**
P^{amp}	−0.007	(0.027)	−0.008	(0.011)	0.048	(0.046)	0.069	(0.074)	0.049	(0.023)**	0.032	(0.015)**
P^{tob}	−0.742	(0.199)**	0.123	(0.082)	−1.005	(0.347)**	0.716	(0.553)	−0.345	(0.155)**	0.071	(0.105)
Income^h	−0.105	(0.018)**	−0.035	(0.012)**	0.087	(0.031)**	0.166	(0.047)**	−0.197	(0.016)**	−0.079	(0.010)**

Participation elasticity is calculated by dividing marginal effect by the mean of the dependent variable. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table 5.5 Heroin and amphetamines—price effects on unconditional and conditional probabilities

	Heroin				*Amphetamines*				*Joint*	
	$P(Y_H = 1 \mid \overline{\mathbf{x}})$		$P(Y_H = 1 \mid Y_M = 1, Y_C = 1, Y_A = 1, \overline{\mathbf{x}})$		$P(Y_A = 1 \mid \overline{\mathbf{x}})$		$P(Y_A = 1 \mid Y_M = 1, Y_C = 1, Y_H = 1, Y_T = 1, \overline{\mathbf{x}})$		$P(Y_M = 1, Y_C = 1, Y_H = 1, Y_A = 1, Y_T = 1, \overline{\mathbf{x}})$	
Marginal Effects:										
P^{mar}	−0.0004	(0.0009)	0.006	(0.060)	−0.015	(0.003)**	−0.143	(0.059)**	−0.0001	(0.000)
P^{coc}	−0.0013	(0.0010)*	−0.083	(0.043)*	0.004	(0.002)*	−0.004	(0.107)	−0.0001	(0.000)
P^{her}	−0.0003	(0.0005)	0.028	(0.035)	0.005	(0.002)**	0.113	(0.037)**	0.0000	(0.000)
P^{amp}	−0.0001	(0.0003)	−0.011	(0.017)	−0.002	(0.001)**	−0.023	(0.018)	0.0000	(0.000)
P^{tob}	−0.0075	(0.0030)**	−0.352	(0.148)**	0.023	(0.007)**	0.119	(0.165)	−0.0006	(0.000)**
Income^h	−0.0003	(0.0000)*	−0.0303	(0.012)**	−0.001	(0.001)	−0.036	(0.014)**	0.0000	(0.000)*
Participation Elasticities:										
P^{mar}	−0.113	(0.2672)	0.025	(0.231)	−0.451	(0.098)**	−0.154	(0.064)**	−0.033	(0.047)
P^{coc}	−0.374	(0.1999)*	−0.320	(0.167)*	0.120	(0.063)*	−0.004	(0.115)	−0.097	(0.064)
P^{her}	−0.096	(0.1535)	0.110	(0.136)	0.153	(0.055)**	0.121	(0.039)**	−0.108	(0.088)
P^{amp}	−0.016	(0.0741)	−0.043	(0.067)	−0.061	(0.029)**	−0.025	(0.019)	−0.004	(0.022)
P^{tob}	−2.177	(0.7929)**	−1.363	(0.572)**	0.705	(0.203)**	0.128	(0.178)	−0.672	(0.220)**
Income^h	−0.078	(0.0469)*	−0.117	(0.046)**	−0.028	(0.019)	−0.039	(0.015)**	−0.027	(0.014)*

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

sensitive to tobacco price. In particular, a 1 % increase in tobacco price results in 6.72 % decrease in participation for this subpopulation group. However, this group of drug users are not sensitive to any other drug price.

Tables 5.4 and 5.5 also report marginal effects and corresponding elasticities of household income on the conditional and joint probabilities of drug consumption. Income elasticities related to conditional and unconditional probabilities are found to vary significantly in terms of magnitude and levels of significance. In particular, amphetamine participation is found to be insensitive to household income in the general population. However, in a subpopulation of marijuana, cocaine, heroin and tobacco users, amphetamines use is negatively related to income. The income elasticity of marijuana participation is lower (−0.035) for a subpopulation of cocaine and heroin users relative to an income elasticity of 0.105 for the general population. On the other hand, the income elasticity for cocaine participation is estimated at 0.087 for the general population, but it is higher at 0.166 for a subpopulation of heroin users.

Demographic Effects

Tables C.4–C.8 in Appendix C report for each of the drugs, the estimated marginal effects of explanatory variables on some selected conditional and joint probabilities. In each table, the marginal effects are compared to those on unconditional probabilities of consuming the respective drugs obtained from a UVP approach. Some important differences are observed between the conditional and unconditional estimates. These results thus demonstrate how the effect of exogenous factors such as education levels and main occupation on drug participation, differ across subpopulation groups. Some of the results are highlighted below.

Marijuana

Table C.4 shows that living in a capital city does not make any significant difference to marijuana participation in the general population. However, in a subpopulation of cocaine and heroin users, those living in capital cities have lower chances of using marijuana. Individuals' main occupation is found to have a significant impact on marijuana users in the general population. However, in a subpopulation of cocaine and heroin users, individuals' employment status is not related to marijuana consumption. While educational attainment does not seem to be associated with marijuana participation in the general population, it does have an impact on those who use only marijuana, without any of the other drugs.

Cocaine

Table C.5 points out some important demographic differences between unconditional and conditional use of cocaine. With regard to marital status, married individuals in the general population have marginally lower chances to participate in cocaine use than their single counterparts. On the other hand, in a subpopulation of heroin users, they are much less likely (12 pp) to use cocaine than singles. It is interesting to see how job characteristics are related to cocaine use. In particular, those in white collar jobs have only marginally higher chances to consume cocaine in the general population than the reference group of individuals who are home makers, pensioners and retirees. However, conditional on the use of marijuana, amphetamines and tobacco, those in white collar jobs have much higher chances (17 pp) of using cocaine. Among those who are heroin users, white collar workers are even more likely (24 pp) to indulge in cocaine use than the reference group. With regard to educational attainment, while degree holders have only marginally higher chances to use cocaine in the general population, among those who consume marijuana, amphetamines and tobacco, they are much more likely (28 pp) to consume cocaine than the reference group of those with less than year-12 qualifications.

Heroin

Table C.6 gives some insights on the conditional use of heroin. This is particularly useful for examining heroin consumption in a population where the incidence of use is relatively low. Given the harmful effects of this hard drug, a better understanding of the demographic differential effects of users will be particularly useful when designing educational programs to target the small population of heroin users. For instance, referring to the effect of main occupation, individuals in white collar jobs have only marginally lower chances to use heroin in the general population than the reference group of those who stay at home, but they are much less likely (12 pp) to do so in a subpopulation of cocaine users. Important differences are also observed between conditional and unconditional heroin consumption for the effect of educational attainment.

Amphetamines

Table C.7 shows that while in the general population, individuals' main occupation is not related to their participation in amphetamines, it does make a significant difference on the conditional probability of amphetamines participation. For instance, in a subpopulation of marijuana, cocaine and heroin users, white collar workers and those who are unemployed have a much lower probability (8 pp) of using amphetamines than the reference category of those who stay at home. Significant differences are observed between conditional and unconditional participation in amphetamines in terms of the effects of gender and marital status. The effect of educational attainment on amphetamines participation is much larger in the subpopulation of marijuana, cocaine and heroin users than in the general population. For instance, in a subpopulation of marijuana, cocaine, heroin users, degree holders are nearly 12 pp less likely to use amphetamines than those with less than year 12 qualifications but there is only a marginal difference in the probability of amphetamines consumption between these two educational groups in the general population.

Tobacco

Lastly, Table C.8 gives insights on how the use of illicit drugs impact on the demographic differential effects of tobacco participation. For instance, while living in capital cities does not seem to affect the probability of smoking in the general population, in a subpopulation of marijuana, cocaine and amphetamines users, individuals living in capital cities are less likely to consume tobacco. Significant differences are observed with regards to the differential effects of employment status and educational attainment, between conditional and unconditional tobacco participation. In the general population, those who study, or are unemployed, are less likely to smoke than the reference group of those who stay at home. But among those who consume marijuana, the two employment groups have even less likely to smoke. There are even larger disparities in conditional and unconditional smoking probabilities with respect to educational attainment. While degree holders are 15 pp less likely to consume tobacco in the general population, they have nearly 22 pp lower chances to smoke in a subpopulation of marijuana users.

5.4 Beer, Wine and Spirits (BWS) Consumption: A Multivariate Approach

In Chap. 4, participation in beer, wine and spirits was modelled individually using univariate Probit models. In particular, the results depicted a heterogeneity across these alcoholic consumers in terms of their socioeconomic and demographic characteristics. For instance, a typical individual who consumes beer was found to be single, male, who works, holds a diploma, and lives in a non-capital area while a typical wine drinker was found to be married, female, who either works or mainly studies, has tertiary education, and lives in a capital area. On the other hand, one who drinks spirits is typically a female, single, who works, and does not have higher than high school education. Age profile of drinkers was also found to vary across the three alcoholic types.

Economists commonly consider beer, wine and spirits to be closely related goods given the common alcohol ingredient that is assumed to satisfy the same need. It is

Table 5.6 BWS—joint and marginal probabilities

	Joint probability	Marginal probability		
		Beer	Wine	Spirits
Beer only	16.0	16.0		
Wine only	17.7		17.7	
Spirits only	11.4			11.4
Beer and Wine only	9.5	9.5	9.5	
Beer and Spirits only	6.6	6.6		6.6
Wine and Spirits only	9.3		9.3	9.3
Beer, Wine and Spirits	10.8	10.8	10.8	10.8
None	18.8			
Total	100.0	42.8	47.2	38.1

Measured as percentages of total respondents. Missing observations are excluded in calculations

important to test whether such intrinsic correlations exist across the three beverages. This is carried out by estimating a multivariate Probit model for beer, wine and spirit participation that takes into account the cross-commodity correlation induced by unobserved individual characteristics such as personal tastes and preferences. High correlations across the error terms of the participation equations would imply that individuals' decisions to consume the three alcoholic beverages are strongly related via such unobserved attributes. Low, or insignificant, correlations, on the other hand, would suggest that the relationship across beer, wine and spirits is weak and not as strong as generally assumed.

5.4.1 BWS: Observed Joint, Conditional and Marginal Probabilities

As in the previous section, sample joint, and conditional, participation in the three alcoholic types are calculated based on observed data. This gives an preliminary indication of the strength of the relationship across the alcoholic types. Table 5.6 illustrates the joint and marginal probabilities of consuming the three types of alcoholic beverages. As can be seen, close to 43 % of the sample consumes beer. A decomposition of this marginal probability reveals that out of the whole sample, around 7 % drink beer jointly with spirits, about 10 % drink it jointly with wine, and about 11 % consume it jointly with wine and spirits while 16 % drink beer on its own. Based on the sample data, that a large proportion drinks the three beverages on their own (16 % for beer, 18 % for wine and 11 % for spirits), it is expected that individuals have distinct preferences for each alcoholic type and that the consumption of the three drugs are only weakly related.

Sample conditional probabilities of participation are next calculated in Table 5.7 based on the figures in Table 5.6. Once again, a weak relationship is observed across

Table 5.7 BWS—conditional participation probabilities

	Beer	Wine	Spirits
$P(.)$	42.8	47.2	38.1
$P(.\|Y_B = 1)$	100.0	47.2	40.6
$P(.\|Y_W = 1)$	42.8	100.0	42.5
$P(.\|Y_S = 1)$	45.7	52.7	100.0
$P(.\|Y_W = 1, \|Y_S = 1)$	53.7	100.0	100.0
$P(.\|Y_B = 1, \|Y_S = 1)$	100.0	61.9	100.0
$P(.\|Y_B = 1, \|Y_W = 1)$	100.0	100.0	53.2

Measured as percentages of total respondents. Missing observations are excluded in calculations

the three alcoholic beverages. For instance, among those who consume beer, only around 47 % drink wine and about 41 % drink spirits.

5.4.2 *Multivariate Probit Estimates of BWS Consumption*

The hypothesised weak relationship between beer, wine and spirit consumption is next examined within a multivariate Probit framework. Table C.9 in Appendix C presents the estimated coefficients and their standard errors for the three alcoholic types. The resulting marginal effects of the explanatory factors on the probability of participation are presented along with their standard errors in Table C.10 (Appendix C). Note that the marginal effects reported in this table correspond to those of marginal probabilities and are evaluated at sample means.

As expected, the estimated correlation coefficients in Table C.9 are all found to be small in value although they are statistically significant. These correlation coefficients measure the relationship among the decisions of use of the three drinks for the same individual after the effects of observable factors in the explanatory variables have been accounted for. They embody correlations via unobservable personal characteristics such as tastes towards the three alcoholic beverages. The results suggest that while there is definitely a degree of correlation across the three drinks, the magnitude of the correlation is not very large after controlling for observable factors. These results are consistent with the earlier findings in Chap. 4 that the three types of alcoholic beverages are quite heterogenous, relating to very different consumer types. The lowest correlation of 0.058 is estimated in the case of beer and spirits, while correlation coefficients of 0.111 and 0.169 are estimated for beer–wine and wine–spirits.

Given an earlier discussion of the marginal probability results of beer, wine and spirits consumption in Chap. 4, a further discussion is superfluous here. The rest of this section focuses, instead, on the joint and conditional probabilities. Note again that such information is not available in a univariate approach assuming zero correlation across the error terms. For example, in the case of a large correlation coefficient, information on participation in one drink could significantly alter the predicted probability of participation in another drink, and hence the conditional and unconditional probabilities could be significantly different. Although the estimated ρ's here are "small", they still provide extra information for a better prediction of multivariate probabilities.

5.4.3 BWS: Predicted Joint, Conditional and Marginal Probabilities

Table 5.8 presents some predicted joint, conditional and marginal probabilities for an individual, evaluated at mean values of all explanatory variables, using both the MVP and UVP models. For example, the probability of wine consumption for a typical individual in the general population is predicted as 46.4 %. However, if it is known that he/she consumes both beer and spirits, the predicted probability increases to 57.2 % based on results from the MVP model. Note that a UVP model would predict the same probability as if the extra information were not available. Also, the joint probability of a typical individual consuming all three beverages is predicted as 9.1 % allowing for cross drink correlations, while it would be 7.0 % using a UVP.

5.4.4 BWS: Marginal Effects on Joint and Conditional Probabilities

Tables 5.9 and 5.10 depict the effects of individual explanatory factors on a selection of joint and conditional probabilities.

Price Effects

Price elasticities of conditional and joint participation probabilities relating to beer, wine and spirit consumption are presented in Table 5.9 and compared to those of the unconditional probabilities. For example, from the upper panel of the Table 5.9 it is found that while the own price elasticity of participation for beer for the general population is −0.948, the own price elasticity for beer for the subpopulation of wine and spirits drinkers is lower at −0.789. This implies that in a subpopulation of drinkers of both wine and spirits, beer drinkers are less sensitive to any change in beer price than beer drinkers in general. Similarly, the cross price elasticities indicate that in a subpopulation of both wine and spirits drinkers, the effect of any spirits price change on beer drinkers is likely to be smaller (0.463) than the effect on beer drinkers in general (0.637). Price effects can also be computed on any bivariate and

Table 5.8 BWS—predicted probabilities

	Beer			*Wine*	
	MVP	UVP		MVP	UVP
$P(Y_B = 1\|\bar{\mathbf{x}})$	0.4150	0.4148	$P(Y_W = 1\|\bar{\mathbf{x}})$	0.4642	0.4641
	(0.2527)	(0.2534)		(0.2600)	(0.2544)
$P(Y_B = 1\|Y_W = 0, Y_S = 0, \bar{\mathbf{x}})$	0.3972		$P(Y_W = 1\|Y_B = 0, Y_S = 0, \bar{\mathbf{x}})$	0.4125	
	(0.2391)			(0.2627)	
$P(Y_B = 1\|Y_W = 1, Y_S = 1, \bar{\mathbf{x}})$	0.4696		$P(Y_W = 1\|Y_B = 1, Y_S = 1, \bar{\mathbf{x}})$	0.5716	
	(0.2382)			(0.2674)	
$P(Y_B = 1\|Y_W = 1, \bar{\mathbf{x}})$	0.4523		$P(Y_W = 1\|Y_B = 1, \bar{\mathbf{x}})$	0.5059	
	(0.2491)			(0.2574)	
$P(Y_B = 1\|Y_S = 1, \bar{\mathbf{x}})$	0.4385		$P(Y_W = 1\|Y_S = 1, \bar{\mathbf{x}})$	0.5338	
	(0.2500)			(0.2515)	
	Spirits			*Joint*	
	MVP	UVP		MVP	UVP
$P(Y_S = 1\|\bar{\mathbf{x}})$	0.3638	0.3632	$P(Y_B = 1, Y_W = 1, Y_S = 1, \bar{\mathbf{x}})$	0.0912	0.0699
	(0.2488)	(0.2452)		(0.1393)	(0.1243)
$P(Y_S = 1\|Y_W = 0, Y_B = 0, \bar{\mathbf{x}})$	0.3061		$P(Y_B = 0, Y_W = 0, Y_S = 0, \bar{\mathbf{x}})$	0.2295	0.1997
	(0.2469)			(0.2055)	(0.2507)
$P(Y_S = 1\|Y_W = 1, Y_B = 1, \bar{\mathbf{x}})$	0.4344		$P(Y_B = 1, Y_W = 0, Y_S = 0, \bar{\mathbf{x}})$	0.1454	0.1729
	(0.2498)			(0.1752)	(0.1295)
$P(Y_S = 1\|Y_W = 1, \bar{\mathbf{x}})$	0.4184		$P(Y_B = 0, Y_W = 1, Y_S = 0, \bar{\mathbf{x}})$	0.1570	0.1416
	(0.2511)			(0.1917)	(0.1393)
$P(Y_S = 1\|Y_B = 1, \bar{\mathbf{x}})$	0.3844		$P(Y_B = 0, Y_W = 0, Y_S = 1, \bar{\mathbf{x}})$	0.1013	0.1139
	(0.2509)			(0.1734)	(0.1096)

Standard errors are given in parentheses

Table 5.9 BWS—price effects on unconditional, conditional and joint probabilities

	$P(Y_B = 1 \mid \bar{\mathbf{x}})$		$P(Y_B = 1 \mid Y_W = 1, Y_S = 1, \bar{\mathbf{x}})$		$P(Y_B = 1, Y_W = 1, Y_S = 1, \bar{\mathbf{x}})$	
Marginal Effects:						
P^{beer}	−0.406	(0.130)**	−0.424	(0.129)**	−0.060	(0.077)
P^{wine}	0.180	(0.093)*	0.234	(0.109)**	−0.050	(0.116)
$P^{spirits}$	0.273	(0.099)**	0.248	(0.094)**	0.091	(0.108)
Participation Elasticities:						
P^{beer}	−0.948	(0.303)**	−0.789	(0.240)**	−0.555	(0.718)
P^{wine}	0.421	(0.218)*	0.436	(0.202)**	−0.462	(1.076)
$P^{spirits}$	0.637	(0.231)**	0.463	(0.175)**	0.843	(1.004)

Participation elasticity is calculated by dividing marginal effect by the mean of the dependent variable. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table 5.10 Wine—marginal effects on joint and conditional probabilities

	$P(Y_W = 1 \mid \bar{\mathbf{x}})$		$P(Y_B = 1, Y_W = 1, Y_S = 1, \bar{\mathbf{x}})$		$P(Y_W = 1 \mid Y_B = 0, Y_S = 0, \bar{\mathbf{x}})$		$P(Y_W = 1 \mid Y_B = 1, Y_S = 1, \bar{\mathbf{x}})$	
Age	1.160	(0.278)**	0.662	(0.468)	0.862	(0.300)**	0.966	(0.272)**
Agesq	−0.135	(0.034)**	−0.100	(0.063)	−0.088	(0.035)**	−0.102	(0.039)**
Male	−0.189	(0.050)**	0.049	(0.073)	−0.192	(0.065)**	−0.215	(0.068)**
Married	0.066	(0.023)**	−0.015	(0.016)	0.075	(0.027)**	0.079	(0.028)**
Divorced	0.029	(0.017)*	−0.015	(0.012)	0.037	(0.019)*	0.038	(0.021)*
Widow	−0.015	(0.084)	−0.021	(0.048)	−0.002	(0.083)	−0.006	(0.089)
Numchld	−0.006	(0.009)	−0.007	(0.007)	−0.002	(0.009)	−0.003	(0.010)
Capital	0.083	(0.026)**	0.004	(0.014)	0.078	(0.028)**	0.086	(0.028)**
ATSI	−0.134	(0.034)**	−0.025	(0.022)	−0.119	(0.036)**	−0.132	(0.035)**
Degree	0.361	(0.087)**	0.062	(0.054)	0.328	(0.094)**	0.360	(0.089)**
Diploma	0.161	(0.039)**	0.052	(0.037)	0.131	(0.042)**	0.148	(0.039)**
Yr12qual	0.182	(0.045)**	0.059	(0.043)	0.148	(0.047)**	0.167	(0.044)**
Yr10qual	0.086	(0.021)**	0.030	(0.022)	0.067	(0.022)**	0.077	(0.020)**
Work	0.084	(0.024)**	0.023	(0.019)	0.072	(0.025)**	0.080	(0.023)**
Study	0.094	(0.023)**	−0.007	(0.016)	0.100	(0.027)**	0.105	(0.028)**
Unemp	−0.002	(0.007)	0.005	(0.005)	−0.004	(0.007)	−0.004	(0.007)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

trivariate joint probabilities relating to any two or three dimensional participation status. As shown in Table 5.9, the probability of consuming all three beverages is not responsive to changes in any of the three alcohol prices. This may be due to the opposing effects on the consumption of the three drinks with respect to changes in any one of the three prices.

Demographic Effects

Table 5.10 reports the estimated marginal effects of other explanatory variables on selected joint and conditional probabilities relating to wine consumption, again comparing them with marginal effects on the unconditional probability. While most of the demographic and socioeconomic differential effects are similar across the conditional and unconditional probabilities, a few differences are noted. For instance, with regard to marital status, while married people are 6.6 pp more likely to consume wine than singles in the general population, among the subpopulation of drinkers of both beer and spirits, married people are 7.9 pp more likely to drink wine. On the other hand, being married does not make any significant difference to the probability of an individual consuming all three drinks. Conditional on consuming neither beer nor spirits, degree holders are 32.8 pp more likely to drink wine than those with less than year-10 qualifications but have even higher chances (36.1 pp) to drink wine in the general population.

5.5 Summary

This chapter has examined relationships across drugs using a multi-drug framework where consumption decisions are considered to be jointly taken by the same individual. Due to unobservable traits, such as personal taste, addiction and risk-taking attitudes, it is likely that an individual's decision to consume multiple drugs would be related via such unobservables. Studies that model drug participation in a univariate Probit framework ignore the effects of such unobservables. Here, a multivariate Probit model is used which accounts for the intrinsic correlation across the unobservable characteristics by estimating participation decisions for various drugs jointly as a system. The key advantage of the multivariate approach is that conditional and joint probabilities of drug participation can be modelled as functions of observable covariates.

The first part of the chapter models participation in marijuana, cocaine, heroin, amphetamines and tobacco consumption using a multivariate framework. Large correlation coefficients are estimated across the five drugs. These correlation coefficients measure the relationship among the decisions of use of the five drugs for the same individual after the effects of observable factors have been accounted for. Effects of prices and other covariates are estimated on a selection of joint and conditional probabilities of drug use. The results clearly demonstrate how the effects of exogenous factors on participation differ across subpopulation groups from the general population. For instance, marijuana price has a significant effect on marijuana users in the general population but in a subpopulation of heroin and cocaine users, marijuana users are insensitive to their own price. This suggests that hardcore drug users with a strong addiction for drugs are less likely to be price sensitive. Such differences are also noted for the effects of demographic factors. For instance, individuals' main occupation is unrelated to amphetamines participation in the general population. However, in a subpopulation of marijuana, cocaine and heroin users, white collar workers and those who are unemployed have lower chances of using amphetamines.

The next part of the chapter examines the consumption of beer, wine and spirits using a multivariate Probit model. Economists commonly consider beer, wine and spirits to be closely related goods given the common alcohol ingredient that is assumed to satisfy the same need. The intrinsic correlation across the three beverages is examined again using the multivariate approach. A weak correlation is estimated across the participation equations suggesting that the three alcoholic types are only weakly related through individuals' unobserved characteristics. Beer, wine and spirits are thus found to relate to population groups with quite heterogenous characteristics. Effects of prices and other covariates are estimated on a selection of joint and conditional probabilities of drug use. In spite of the weak correlation across the three alcohol types, such results provided extra information for the prediction of multivariate probabilities.

Such results are very useful for designing public policies and educational programs that help target subpopulation groups of drug users. For instance, if we know what subgroups of the population (i.e age, ethnicity, educational and socio-economic background) consume a particular drug, campaign strategies will be designed and targeted to these specific audiences rather than the general population. Further, if we know how drugs are related to each other in terms of their usage, any policy or campaign aimed at one drug is likely to reduce consumption of the other drugs. Better targeted strategies and programs can, in turn, be more cost effective and beneficial to the society at large.

Chapter 6
Modelling Alcohol Consumption by Levels Using an Ordered Generalised Extreme Value (OGEV) Model

6.1 Introduction

Most of the harms caused by alcohol are related to excessive drinking. A good understanding of Australians' drinking patterns is very important from a policy perspective. In Chap. 4, an Ordered Probit (OP) model was used to examine individuals' levels of alcohol consumption. The OP model is characterised by a*single* latent variable representing the propensity of choosing higher levels which are mapped orderly to the observed levels of outcomes or choices made by individuals (see McKelvey and Zavoina 1975). This restricts correlates to have the same coefficients and levels of significance across all choices, making it an inflexible model. In addition, the OP model is inconsistent with a consumer preference framework of Random Utility Maximisation (RUM).

A more flexible model for multinomial choices is the frequently used Multinomial Logit (MNL) model. It estimates separate latent equations for the alternative choices, and therefore allows for more flexibility in estimating the effects of the same covariate on different outcomes. It is also consistent with the RUM (see, for example, Ben-Akiva and Lerman 1985) assumption of consumer behaviour. However, the MNL model cannot account properly for the fact that discrete choices may have a natural ordering. Moreover, the MNL model possesses 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 utilities for alternative choices, are independent.

This chapter uses a more flexible Ordered Generalised Extreme Value (OGEV) model, initially proposed by Small (1987) to examine Australians' drinking patterns. The OGEV model is a more flexible approach relative to the OP as it estimates separate latent equations for alternative choices. It therefore allows explanatory variables to have different coefficients and significance levels across the different choices. In addition, the OGEV model is consistent with the RUM framework and

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takes into account the ordered nature of the choices. While possessing the flexibility of the MNL model with separate latent equations for the multinomial choices, the OGEV model allows for correlations between the random utility components of choices, according to their close proximity in the ordering.

The chapter is structured as follows. The OGEV model is presented in Sect. 6.2. The model is estimated and the results are discussed in Sect. 6.3. Section 6.4 highlights the superiority of the OGEV model over the OP and MNL models. In particular, the OGEV results are compared to those of OP and MNL, estimated using the same data set and specification, and model selection issues are discussed. Section 6.5 summarises the findings.

6.2 The OGEV Model for Levels of Alcohol Consumption

McFadden (1978) proposed a class of random utility models known as the Generalised Extreme Value (GEV) models where the indirect utility function for consumer i choosing alternative j is given by

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad (i = 1, \ldots N \text{ and } j = 1, \ldots J). \tag{6.1}$$

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]

$$V_{ij} = \mathbf{x}_i' \boldsymbol{\beta}_j \quad \text{or} \tag{6.2}$$

$$U_{ij} = \mathbf{x}_i' \boldsymbol{\beta}_j + \varepsilon_{ij} \tag{6.3}$$

ε_{ij} is the random disturbance term accounting for unobserved individual tastes and preferences.

Let Y_i $(Y_i = 1, \ldots J)$ indicate 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 Eq. (6.3) are assumed to *independently* and identically follow a Type I Extreme Value distribution, Eq. (6.3) leads to the familiar MNL model (Maddala 1983), where the probability of individual i choosing alternative j is given by[2]

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[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, $\boldsymbol{\beta}_1 = \mathbf{0}$ (Maddala 1983). Note that the results are invariant to which category is normalised.

$$P_{ij}^{MNL} = P(Y_i = j) = \frac{\exp(\mathbf{x}_i' \boldsymbol{\beta}_j)}{\sum_{j=1}^{J} \exp(\mathbf{x}_i' \boldsymbol{\beta}_j)} \,. \tag{6.4}$$

Although the MNL model has been applied to modelling *ordered* discrete data, it does not account for any inherent ordering in the choices. Related to this point is another unattractive feature of Independence from Irrelevant Alternatives (IIA), implying that the odds ratio of any two choices is independent of all other choices.

Small (1987) proposed the Ordered Generalised Extreme Value (OGEV) model from the GEV class that is more suited for ordered discrete outcomes and which embodies the MNL model and the Nested Logit model as special cases. While maintaining the flexibility of allowing the explanatory variables to have different coefficients and significance levels for the utilities attached to different choices, 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 $(j, k = 1, \ldots, J; j \neq k)$. When $|j - k|$ is greater than a pre-selected integer M, the correlation is zero.

It is possible to allow the correlation window width M, across nearby outcomes to be arbitrarily large. However, this significantly increases the complexity of the model and therefore, the associated computing demands in the maximisation procedures for estimation (Small 1987). In this study, a standard OGEV model is considered with only the adjacent outcomes being 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 ρ (Small 1987).

The associated standard OGEV probabilities for $M = 1$ have the form[3]

$$\begin{aligned} P_{ij}^{OGEV} &\\ &= \exp\left(\rho^{-1} V_{ij}\right) \\ &\times \frac{\left[\left(\exp\left(\rho^{-1} V_{i,j-1}\right) + \exp\left(\rho^{-1} V_{ij}\right)\right)^{\rho-1} + \left(\exp\left(\rho^{-1} V_{ij}\right) + \exp\left(\rho^{-1} V_{i,j+1}\right)\right)^{\rho-1}\right]}{\sum_{r=1}^{J+1} \left(\exp\left(\rho^{-1} V_{i,r-1}\right) + \exp\left(\rho^{-1} V_{ir}\right)\right)^{\rho}} \end{aligned} \tag{6.5}$$

where $V_{ij} = \mathbf{x}_i' \boldsymbol{\beta}_j$ and with the convention that $\exp(\rho^{-1} V_{i0}) = \exp(\rho^{-1} V_{i,J+1}) = 0$ and $0 < \rho \leq 1$. As $\rho \to 1$, OGEV probabilities converge to MNL ones. Therefore, a simple parameter restriction based test $(H_0 : \rho = 1)$ is one of the OGEV *versus* MNL. In addition, this is also a test for ordering in the choices. Note that as $\rho \to 0$,

[3]There appears to be a typo in Small (1987) p. 414 where $M = 2$ should be $M = 1$ instead.

the associated cumulative distribution function is a degenerate one, but one that is still consistent with RUM (Small 1987).

The unknown parameters $\boldsymbol{\beta}$ and ρ are estimated using maximum likelihood techniques. As the probabilities in Eq. (6.5) are highly non-linear functions of $\mathbf{x}$, making analytical solution of marginal effects difficult, the marginal effects are calculated using numerical gradients. Standard errors are obtained using the delta method (Greene 2003).

6.3 Estimation Results

The analysis in this chapter is based on the 1995, 1998 and 2001 sweeps of the NDSHS. Here, the frequency of alcohol consumption is used as the dependent variable. Based on their drinking frequency, individuals are categorised into the following groups: abstainers, occasional drinkers, moderate drinkers and frequent drinkers. In particular, the observed dependent variable Y is defined as: $Y = 1$ for abstainers (no alcohol consumption in the previous year), $Y = 2$ for occasional drinkers (drinking 2 or 3 days a month), $Y = 3$ for moderate drinkers (drinking at least once a week but no more than 3 to 4 days a week), and $Y = 4$ for frequent drinkers (drinking at least 4 days a week). Levels of alcohol consumption are specified as functions of drug prices, income, and a range of personal socioeconomic and demographic characteristics to account for taste heterogeneity. Any change in attitude towards alcohol use across surveys is controlled for using year dummies.

Table 6.1 reports the estimated coefficients of the OGEV model, and their associated standard errors, for three of the random utility equations, the normalisation being on the parameter vector corresponding to abstainers. While the coefficients of the model β_j $(j = 2, 3, 4)$ indicate the impacts of explanatory variables on the utility level of choice j, it is important to note that the signs and significance of these coefficients do not necessarily imply the directions and significance of the marginal effects on the probability of choosing choice j. It is the ranking of the four utilities that determines the choice. For example, it could be the case that one independent variable has no significant impact on the utility of frequent drinking, but significantly increases the utilities of the other drinking categories. Consequently, the effect on the probability of frequent drinking could be negative and significant due to a change in ranking. Note that the OGEV results cannot be directly compared to those of the OP model in Chap. 4 given that the drinking categories are grouped differently, and the period of study and model specification, are different.

Table 6.2 reports the marginal effects and the associated standard errors of explanatory variables, on the probabilities of all four consumption levels. Note the marginal effects reported in Table 6.2 are average marginal effects over all individuals in the sample.

The parameter ρ is examined first. Recall that the OGEV model allows for correlations between the disturbances of outcomes that are ‘close’ to each other in the ordering. Here, the correlation between only the adjacent outcomes $(M = 1)$

Table 6.1 OGEV coefficient estimates for levels of alcohol consumption

	Occasional drinker		Moderate drinker		Frequent drinker	
Constant	12.600	(4.281)**	9.131	(4.766)**	−1.374	(5.284)
P^{alc}	−1.585	(0.550)**	−1.422	(0.618)**	−0.038	(0.671)
P^{mar}	−0.120	(0.082)	−0.185	(0.093)**	−0.103	(0.098)
P^{tob}	−0.779	(0.491)	−0.937	(0.555)*	−1.458	(0.629)**
$Income^h$	0.180	(0.022)**	0.438	(0.034)**	0.649	(0.042)**
Age	−0.519	(0.077)**	−0.274	(0.079)**	0.668	(0.077)**
Male	−0.098	(0.042)**	0.299	(0.033)**	0.689	(0.047)**
Married	−0.019	(0.047)	−0.149	(0.052)**	−0.248	(0.058)**
Divorced	0.146	(0.062)**	0.152	(0.068)**	0.145	(0.074)**
Widowed	−0.129	(0.073)*	−0.283	(0.089)**	−0.358	(0.096)**
Numchld	−0.001	(0.015)	−0.066	(0.017)**	−0.107	(0.020)**
Capital	−0.015	(0.031)	−0.045	(0.035)	−0.085	(0.039)**
Work	0.335	(0.042)**	0.541	(0.061)**	0.416	(0.050)**
Study	−0.294	(0.066)**	−0.323	(0.075)**	−0.739	(0.106)**
Unemp	0.204	(0.085)**	0.336	(0.098)**	0.424	(0.107)**
Degree	0.174	(0.042)**	0.462	(0.057)**	0.541	(0.058)**
Diploma	0.274	(0.041)**	0.471	(0.053)**	0.525	(0.053)**
Yr12qual	0.277	(0.045)**	0.474	(0.058)**	0.518	(0.060)**
ρ	0.516	(0.124)**				

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table 6.2 Marginal effects on OGEV probabilities

	Abstainer		Occasional drinker		Moderate drinker		Frequent drinker	
Constant	−1.340	(0.529)**	2.542	(0.847)**	0.959	(0.833)	−2.161	(0.739)**
P^{alc}	0.184	(0.073)**	−0.264	(0.113)**	−0.178	(0.119)	0.258	(0.090)**
P^{mar}	0.020	(0.007)**	−0.001	(0.014)	−0.025	(0.014)*	0.007	(0.020)
P^{tob}	0.142	(0.045)**	0.004	(0.090)	0.001	(0.068)	−0.148	(0.087)*
$Income^h$	−0.050	(0.002)**	−0.056	(0.005)**	0.030	(0.008)**	0.075	(0.006)**
Age	0.033	(0.006)**	−0.162	(0.017)**	−0.077	(0.013)**	0.206	(0.019)**
Male	−0.023	(0.003)**	−0.122	(0.008)**	0.027	(0.010)**	0.118	(0.006)**
Married	0.014	(0.005)**	0.034	(0.009)**	−0.014	(0.010)	−0.034	(0.008)**
Divorced	−0.022	(0.006)**	0.012	(0.015)	0.007	(0.021)	0.003	(0.010)
Widow	0.032	(0.008)**	0.028	(0.019)	−0.025	(0.007)**	−0.035	(0.015)**
Numchld	0.006	(0.002)**	0.017	(0.003)**	−0.007	(0.002)**	−0.015	(0.002)**
Capital	0.005	(0.004)	0.008	(0.008)	−0.002	(0.010)	−0.012	(0.006)**
Work	−0.060	(0.005)**	−0.008	(0.007)	0.063	(0.010)**	0.004	(0.010)
Study	0.058	(0.009)**	0.010	(0.020)	0.031	(0.012)**	−0.099	(0.014)**
Unemp	−0.042	(0.006)**	−0.018	(0.022)	0.022	(0.021)	0.038	(0.014)**
Degree	−0.047	(0.005)**	−0.054	(0.007)**	0.050	(0.010)**	0.050	(0.008)**
Diploma	−0.055	(0.004)**	−0.024	(0.009)**	0.040	(0.010)**	0.039	(0.008)**
Yr12qual	−0.055	(0.006)**	−0.023	(0.012)*	0.041	(0.011)**	0.037	(0.009)**

Standard errors are given in parentheses.*significant at 10 % level; **significant at 5 % level is considered. As noted, the correlation is *inversely* related to the parameter ρ. Table 6.1 shows that the parameter ρ is estimated to be 0.52 and is statistically different from zero at the 1% significance level. Remember that the OGEV model reduces to MNL when $\rho = 1$. A hypothesis test for H_0: $\rho = 1$ is also rejected at the 1 at the 1 % level. This indicates that the correlation across adjacent categories is significant and therefore the OGEV model is more appropriate than a MNL one. Although the correlation coefficient between categories cannot be written in explicit form, Small (1987) performed some numerical integrations for the standard OGEV that map the values of ρ to the actual correlation. An estimate of 0.52 for the parameter ρ in this application implies a correlation coefficient of about 0.35 between adjacent categories.

Socioeconomic and Demographic Effects

Next, the impacts of individual explanatory factors on a typical Australian's probability of consuming differing levels of alcohol are examined. Recall that an OGEV model, unlike the OP model, estimates separate latent equations for alternative choices, and therefore allows for more flexibility in the direction of the effects of the same covariate on different choices. For instance, it allows for the possibility that factors important for a frequent drinker may be different from those for an occasional drinker.

To start, the effects of socioeconomic and demographic factors are discussed. Table 6.2 shows that, on average, being an older individual increases the probability of abstaining and frequent drinking, but decreases the probability for the middle two categories. Note that the restrictive OP model would not allow such results. For instance, the OP model would restrict the marginal effect of "Age" to be positive for abstainers and negative for frequent drinkers. In addition, the marginal effects of the middle categories are also restricted by an imposed ordering. The effects of age on the four drinking groups are depicted in Fig. 6.1. Note that in Chap. 4, the effect of age on *binge drinking* indicated that young people are more likely to binge frequently while older individuals are more likely to be non bingers. In this analysis which considers *frequency of drinking*, the probability of being an abstainer or an occasional drinker decreases for older individuals, while the probability of moderate or frequent drinking increases. This is not against intuition. A high probability of frequent drinking among older individuals could well be an indication of the addictive nature of alcohol where individuals' drinking gradually increases over time (Becker and Murphy 1988).

Turning to the impact of gender, Table 6.2 shows that males are more likely to drink more frequently than females. In terms of marital status, once other factors are controlled for, married or widowed individuals have lower chances of frequent drinking than singles. A higher number of children is associated with a lower probability of drinking and so is living in a capital city.

In terms of individuals' main activity, the marginal effects in Table 6.2 indicate that, relative to the reference group of those who stay at home (otherAct), students

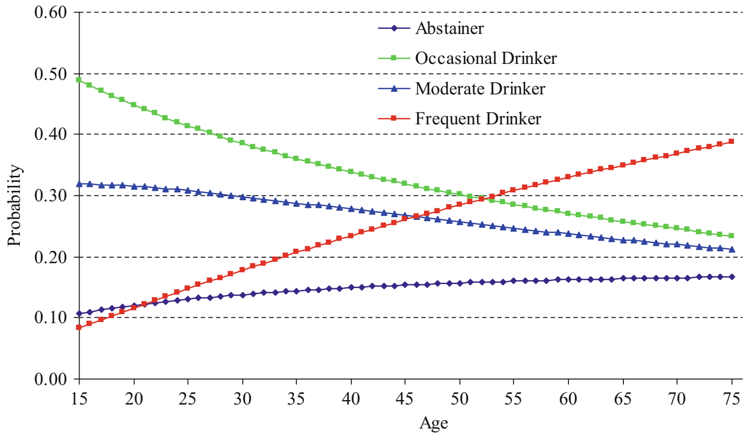

Fig. 6.1 Predicted probabilities: effect of age

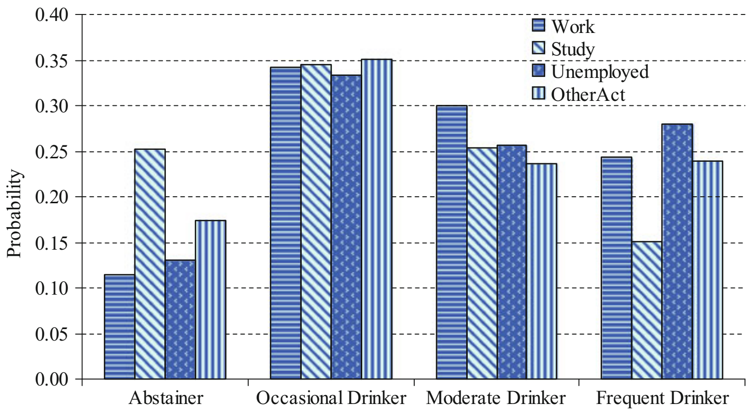

Fig. 6.2 Predicted probabilities: main activity

are more likely, but both employed and unemployed individuals, less likely to be abstainers. For ease of interpretation, Fig. 6.2 depicts the effects of employment status. The probability of being an abstainer is distinctly higher for students relative to all other groups. For the occasional drinking group, other explanatory factors being controlled for, probabilities do not seem to be much related to individuals' main activities such that an individual has about 35 % chances 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 frequent drinking category, other factors being equal, the highest participation relates to unemployed individuals.

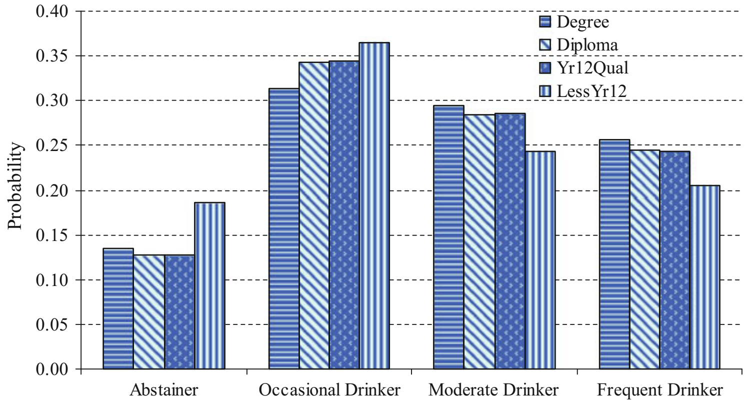

Fig. 6.3 Predicted probabilities: educational attainment

Table 6.3 Probability elasticities for alcohol consumption

	Abstainer		Occasional drinker		Moderate drinker		Frequent drinker	
P^{alc}	1.258	(0.496)**	−0.783	(0.336)**	−0.633	(0.424)	1.102	(0.385)**
P^{mar}	0.134	(0.049)**	−0.004	(0.042)	−0.091	(0.050)*	0.031	(0.087)
P^{tob}	0.971	(0.308)**	0.013	(0.266)	0.005	(0.241)	−0.632	(0.372)*
$Income^h$	−0.341	(0.011)**	−0.164	(0.016)**	0.107	(0.028)**	0.322	(0.025)**

Probability elasticity is calculated by dividing marginal effect by the mean of the dependent variable, for the respective category. Standard errors are reported in parentheses. *significant at 10 % level; **significant at 5 % level

Education seems to have a positive effect on the frequency of drinking (Table 6.2). Figure 6.3 shows the predicted probabilities with respect to educational attainment. It seems that the more educated a person is, the higher is his/her probability of drinking among moderate and frequent drinkers. Note that earlier findings on the bingeing-education relationship in Chap. 4 indicated that degree holders are less likely to be bingers and more likely to be non bingers.

Income Effects

From Table 6.1, consistent with the results of a positive income effect of alcohol demand from most of the empirical literature, an increase in household income is found to increase utilities of all three categories. This translates into negative marginal probability effects for abstainers and occasional drinkers but positive effects for the moderate and frequent drinking groups, all of which are statistically significant (Table 6.2). Evaluated at sample proportions of the four drinking levels, the income marginal effects are converted into probability elasticities in Table 6.3. In particular, a 10 % rise in household income would result into 3.4 % and 1.6 %

declines in the probability values of abstention and occasional drinking, and 1.1 % and 3.2 % increases in the probability values of moderate and frequent drinking, respectively.

Price Effects

Finally, the effects of own and cross prices are examined. Table 6.1 indicates that whilst an increase in alcohol price decreases the utilities of occasional and moderate drinkers, its effect on frequent drinkers' utility is statistically insignificant. The negative own price effect for occasional and moderate drinkers is consistent with consumer behaviour but the insignificant effect for the heavy drinkers is against intuition for a normal good. However, as a result of the changes in the utilities, the ranking of the respective utilities of the four drinking categories alters. This results into a positive significant effect on the probability of frequent drinkers as in Table 6.2, although the effect on their utility is insignificant. The price marginal effects are converted into respective elasticities in Table 6.3.

Table 6.3 also reports cross price elasticities. A marijuana price increase appears to discourage drinking by decreasing the probability of moderate drinking and increasing the chances of abstaining. Similarly, a tobacco price rise increases the probability of abstaining and decreases the chances of frequent drinking, with no significant effect on occasional or moderate drinking. It is worthwhile noting that the OP model estimated in Chap. 4 is characterised by a single underlying latent equation for all four drinking groups. As a result a negative price coefficient restricted the marginal effects to be positive for abstainers and negative for frequent drinkers. On the other hand, the OGEV model which estimates separate latent functions for each group, allows for more flexibility in the directions and magnitudes of the marginal effects. For instance, a marijuana price rise has a positive effect on both abstainers and frequent drinkers although the effect on frequent drinkers is statistically insignificant. However, the directions of the price effects are similar in both sets of results suggesting that both marijuana and tobacco are economic complements to alcohol. The subsequent section provides a better comparison of the Ordered Probit results to those of the OGEV by estimating the OP model on the same sample and with a common set of explanatory factors.

6.4 Comparison with OP and MNL Models

As mentioned earlier, alternative approaches to studying such ordered discrete choice data are Ordered Probit/Logit (OP/OL) and Multinomial Logit (MNL) models. To compare the OGEV with these alternative models, the same data set and model specification are used to estimate both OP and MNL models for levels of alcohol consumption. Table 6.4 presents a few of the estimated coefficients for the

Table 6.4 Comparison of coefficients: OGEV vs. MNL

	Occasional drinker				*Moderate drinker*				*Frequent drinker*			
	OGEV		MNL		OGEV		MNL		OGEV		MNL	
Constant	12.600	(4.281)**	12.350	(5.439)**	9.131	(4.766)*	7.213	(5.725)	−1.374	(5.284)	−6.153	(6.093)
P^{alc}	−1.585	(0.550)**	−1.611	(0.707)**	−1.422	(0.618)**	−1.405	(0.743)*	−0.038	(0.671)	0.492	(0.782)
P^{mar}	−0.120	(0.082)	−0.177	(0.110)	−0.185	(0.093)**	−0.294	(0.116)**	−0.103	(0.098)	−0.142	(0.119)
P^{tob}	−0.779	(0.491)	−0.517	(0.653)	−0.937	(0.555)*	−0.455	(0.688)	−1.458	(0.629)**	−1.226	(0.728)*
Income^{h}	0.180	(0.022)**	0.196	(0.029)**	0.438	(0.034)**	0.501	(0.032)**	0.649	(0.042)**	0.745	(0.035)**
Age	−0.519	(0.077)**	−0.727	(0.071)**	−0.274	(0.079)**	−0.480	(0.074)**	0.668	(0.077)**	0.753	(0.081)**
Male	−0.098	(0.042)**	−0.205	(0.041)**	0.299	(0.033)**	0.296	(0.042)**	0.689	(0.047)**	0.757	(0.044)**
Married	−0.019	(0.047)	0.000	(0.063)	−0.149	(0.052)**	−0.172	(0.065)**	−0.248	(0.058)**	−0.267	(0.069)**
Divorced	0.146	(0.062)**	0.195	(0.080)**	0.152	(0.068)**	0.181	(0.084)**	0.145	(0.074)**	0.187	(0.088)**
Widow	−0.129	(0.073)*	−0.171	(0.100)*	−0.283	(0.089)**	−0.350	(0.113)**	−0.358	(0.096)**	−0.393	(0.111)**
Numchld	−0.001	(0.015)	0.010	(0.020)	−0.066	(0.017)**	−0.073	(0.022)**	−0.107	(0.020)**	−0.116	(0.024)**
Capital	−0.015	(0.031)	−0.023	(0.042)	−0.045	(0.035)**	−0.053	(0.044)	−0.085	(0.039)**	−0.107	(0.046)**
Work	0.335	(0.042)**	0.413	(0.050)**	0.541	(0.061)**	0.709	(0.054)**	0.416	(0.050)**	0.464	(0.056)**
Study	−0.294	(0.066)**	−0.373	(0.084)**	−0.323	(0.075)**	−0.346	(0.092)**	−0.739	(0.106)**	−0.902	(0.115)**
Unemp	0.204	(0.085)**	0.259	(0.113)**	0.336	(0.098)**	0.424	(0.120)**	0.424	(0.107)**	0.487	(0.126)**
Degree	0.174	(0.042)**	0.182	(0.058)**	0.462	(0.057)**	0.572	(0.060)**	0.541	(0.058)**	0.587	(0.063)**
Diploma	0.274	(0.041)**	0.335	(0.050)**	0.471	(0.053)**	0.588	(0.054)**	0.525	(0.053)**	0.589	(0.055)**
Yr12qual	0.277	(0.045)**	0.343	(0.057)**	0.474	(0.058)**	0.594	(0.061)**	0.518	(0.060)**	0.583	(0.066)**
ρ	0.516	(0.124)**										

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

MNL model to compare with those from the OGEV model.[4] Table 6.5 reports the marginal effects and standard errors for selected explanatory factors, for all three models.

In choosing between the OP and the OGEV models, it is first noted that the usual method of hypothesis tests via parameter restrictions is no longer applicable as the OP is not nested in the OGEV.[5] In the lower panel of Table 6.5, the log-likelihood values for OGEV and OP, together with the LR statistic, are reported. The LR statistic indicates that the simpler model of OP will be rejected and the OGEV model is preferred. In addition, the models are compared using information criteria. The three widely used information based criteria are AIC, BIC and CAIC, given by

$$AIC = -2lnL + 2k,$$

$$BIC = -2lnL + (lnN)k, \text{ and}$$

$$CAIC = -2lnL + (1 + lnN)k.$$

where lnL is the log-likelihood value, N is the sample size and k is the number of parameters estimated in the model. All three criteria favour the OGEV model to the OP model.

Comparing the estimated marginal effects of the selected factors from OGEV and OP models in Table 6.5, some significant differences in magnitudes and, occasionally, in signs are noted. The inflexibility of the OP specification, with a single latent driving the propensity of drinking, imposes rigid relationships on the signs and sizes of the marginal effects of the four categories. For example, the OGEV model predicts the marginal effects of being a male, relative to female, to be $-2.3\,\%$ and $-12.2\,\%$ for abstainers and occasional drinkers, as compared to $-7.1\,\%$ and $-5.2\,\%$ estimated by the OP model. In terms of main activity, all three employment groups have higher magnitudes of marginal effects for the abstainer category using OGEV compared to the OP model. On the other hand, no significant marginal effects of main activities are found for the occasional drinking category from OGEV, while there are for the OP. As for the moderate and frequent drinking categories, the marginal effects from the OGEV model contrast with those from the OP both in magnitude and significance. With regard to education effects, for all four educated groups, the OGEV model predicts higher marginal effects for moderate drinkers and lower marginal effects for frequent drinkers than the OP does.

The inflexibility of the OP model relative to the OGEV model is best illustrated using Figs. 6.4 and 6.5 which depict marginal effects of the OP and the OGEV

[4]Estimated coefficients for the OP model are not presented as they are not directly comparable with the OGEV coefficients.

[5]In a different setting of comparing two non-nested models of OP and zero-inflated OP, some Monte Carlo studies in Harris and Zhao (2007) showed that a non-nested Vuong (1989) test does not perform well but a likelihood ratio (LR) test does.

Table 6.5 Selected marginal effects: comparison of OGEV, MNL and OP

	MNL		OGEV		OP	
Abstainer						
Income[h]	−0.050	(0.003)**	−0.050	(0.002)**	−0.056	(0.002)**
Age	0.033	(0.006)**	0.033	(0.006)**	−0.067	(0.004)**
Male	−0.022	(0.004)**	−0.023	(0.003)**	−0.071	(0.003)**
Work	−0.061	(0.005)**	−0.060	(0.005)**	−0.031	(0.003)**
Study	0.059	(0.007)**	0.058	(0.009)**	0.032	(0.005)**
Unemp	−0.043	(0.009)**	−0.042	(0.006)**	−0.035	(0.007)**
Degree	−0.047	(0.004)**	−0.047	(0.005)**	−0.051	(0.004)**
Diploma	−0.056	(0.005)**	−0.055	(0.004)**	−0.046	(0.004)**
Yr12qual	−0.056	(0.005)**	−0.055	(0.006)**	−0.044	(0.004)**
Occasional Drinker						
Income[h]	−0.055	(0.005)**	−0.056	(0.005)**	−0.041	(0.003)**
Age	−0.160	(0.011)**	−0.162	(0.017)**	−0.050	(0.005)**
Male	−0.122	(0.007)**	−0.122	(0.008)**	−0.052	(0.003)**
Work	−0.009	(0.008)	−0.008	(0.007)	−0.023	(0.003)**
Study	0.013	(0.015)	0.010	(0.020)	0.023	(0.005)**
Unemp	−0.017	(0.017)	−0.018	(0.022)	−0.026	(0.007)**
Degree	−0.054	(0.009)**	−0.054	(0.007)**	−0.038	(0.004)**
Diploma	−0.023	(0.008)**	−0.024	(0.009)**	−0.034	(0.004)**
Yr12qual	−0.021	(0.009)**	−0.023	(0.012)*	−0.033	(0.004)**
Moderate Drinker						
Income[h]	0.030	(0.006)**	0.030	(0.008)**	0.022	(0.002)**
Age	−0.076	(0.013)**	−0.077	(0.013)**	0.027	(0.002)**
Male	0.027	(0.008)**	0.027	(0.010)**	0.028	(0.003)**
Work	0.069	(0.010)**	0.063	(0.010)**	0.012	(0.002)**
Study	0.027	(0.016)*	0.031	(0.012)**	−0.013	(0.002)**
Unemp	0.026	(0.020)	0.022	(0.021)	0.014	(0.003)**
Degree	0.056	(0.010)**	0.050	(0.010)**	0.020	(0.002)**
Diploma	0.044	(0.009)**	0.040	(0.010)**	0.018	(0.002)**
Yr12qual	0.045	(0.010)**	0.041	(0.011)**	0.018	(0.002)**
Frequent Drinker						
Income[h]	0.075	(0.005)**	0.075	(0.006)**	0.075	(0.004)**
Age	0.203	(0.012)**	0.206	(0.019)**	0.090	(0.007)**
Male	0.117	(0.006)**	0.118	(0.006)**	0.095	(0.004)**
Work	0.001	(0.007)	0.004	(0.010)	0.042	(0.005)**
Study	−0.099	(0.015)**	−0.099	(0.014)**	−0.043	(0.008)**
Unemp	0.034	(0.015)**	0.038	(0.014)**	0.047	(0.010)**
Degree	0.046	(0.008)**	0.050	(0.008)**	0.068	(0.006)**
Diploma	0.035	(0.007)**	0.039	(0.008)**	0.062	(0.006)**
Yr12qual	0.033	(0.008)**	0.037	(0.009)**	0.060	(0.007)**
OGEV vs OP: lnL			−36270		−37258	$LR = 1976$
AIC			72601		74539	
BIC			73167		74743	
CAIC			73228		74765	
OGEV vs MNL: H_0: $\rho = 1$, $t = -3.90$						

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

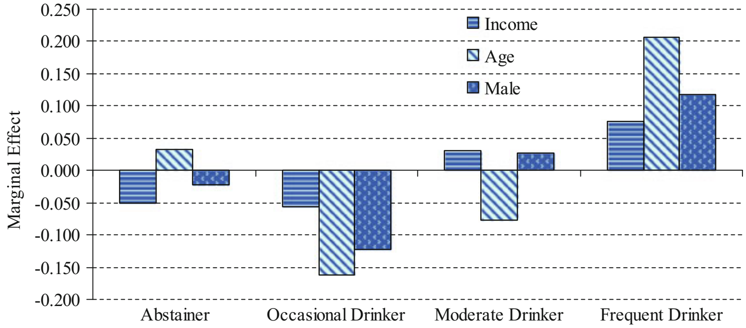

Fig. 6.4 OP-marginal effects of selected variables

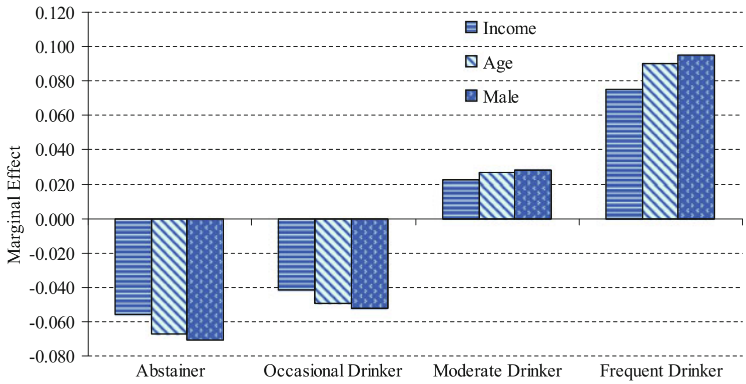

Fig. 6.5 OGEV-marginal effects of selected variables

models, respectively, for the three selected variables, income, age and gender. As mentioned earlier, the OP model restricts marginal effects at both ends to have opposite signs. For instance, with the OP, marginal effects of abstainers and frequent drinkers would always have opposite signs as illustrated in Fig. 6.4. In addition, the marginal effects have an imposed ordering, forcing them to have an increasing or decreasing trend for the same explanatory variable. In contrast, the OGEV model allows more flexibility in terms of signs and magnitudes of the marginal effects. As depicted by Fig. 6.5, the marginal effects of age are positive for both abstainers and frequent bingers and have a U-shaped pattern across the four ordered drinking categories. In other words, the marginal effects for OGEV do not necessarily have an increasing or decreasing trend as for the OP model given that the OGEV model is characterised by separate latent functions for each drinking group.

Turning to model selection between the two nested models, OGEV and MNL, it is simply undertaken by an asymptotic t-test of $H_0 : \rho = 1$. A t-statistic of -3.9 clearly indicates that the null of MNL is rejected at 1% significance level, and that OGEV is the preferred model. Comparison of the estimated coefficients of the OGEV and MNL models in Table 6.4 indeed shows quite significant differences. There are also some differences in the marginal effects in Table 6.5 from the two nested models, but the differences are not noticeable.[6]

6.5 Summary

An Ordered Generalised Extreme Value (OGEV) model, developed by Small (1987), was proposed in this chapter to model levels of alcohol consumption observed as discrete ordered choices. Conventional approaches for such ordered data are Ordered Probit (OP) and Ordered Logit (OL) models. However, with the specification of a single latent variable driving all choices, these models are inflexible and are inconsistent with an appropriate consumer behavioral assumption such as random utility maximisation (RUM). A flexible model for multiple discrete choice data that is consistent with a RUM assumption is the Multinomial Logit (MNL) model. However, the MNL model does not allow for correlations across choices for the same individuals arising from unobservable characteristics. The MNL also embodies the undesirable property of Independence from Irrelevant Alternatives (IIA). In contrast, the OGEV model that nests the MNL model as a special case, takes into account the ordered nature of the data by allowing for correlations across choices according to their locations in the choice set. Unlike the OP model, the OGEV is consistent with RUM and is a flexible model that is characterised by separate latent equations for the multinomial choices. It therefore allows explanatory variables to have different coefficients and significance levels across different choices.

The OGEV marginal effects indicate significant demographic differences across the four drinking groups. One interesting finding is that individuals' drinking patterns shift from occasional and moderate drinking to frequent drinking as they grow older. Household income is found to be positively related to drinking indicating that alcohol is a normal good. Other differential effects in terms of gender, occupation and educational attainment are also estimated across the four drinking

[6] While these differences are not discussed in detail, it is nevertheless important to note at this point that the marginal effects reported in Table 6.5 are those for the *marginal* (or unconditional) probabilities for the four categories. Note that the key difference between the OGEV and MNL models is that the former allows for correlation between the categories. While these results seem to indicate that there are some minor differences in the marginal effects on the *marginal* probabilities for the four categories, the differences in the marginal effects for some *conditional* probabilities are expected to be significant. For example, if it is known that an individual is not a frequent drinker, predicted probabilities for the other three categories using an OGEV model allowing for correlation across categories are expected to be significantly different from those using a MNL model. Unfortunately, the computing demand for calculating such conditional probabilities is beyond the scope of this thesis.

groups. In terms of price effects, some evidence of normal consumer behaviour is obtained for the abstention, occasional and moderate categories but the results for heavy drinkers are puzzling.

The OGEV model is compared to other models for multiple discrete choices such as the OP and the MNL. Some important differences are observed in magnitudes and, occasionally, signs between the estimated OGEV coefficients and the OP and MNL estimates. In particular, the inflexibility of the OP specification, with a single latent driving the propensity of drinking, is found to impose rigid restrictions on the signs and sizes of the marginal effects of the four drinking groups across a few covariates. The three models are compared on the basis of model selection criteria and they all favour the OGEV model. To conclude, the OGEV approach can be considered as a viable alternative to the more commonplace OP/OL or MNL models.

Chapter 7
Drinking Patterns and Earnings

7.1 Introduction

It is increasingly argued that heavy drinking has an adverse impact on labour market outcomes usually through impaired health, absenteeism and poor job performance (see Gmel and Rehm 2003; Mangione et al. 1999). Where workers receive wages that reflect their productivity, heavy drinking or bingeing is likely to have an adverse effect on their earnings. Collins and Lapsley (2002) estimated drug abuse related loss of productive capacity in the Australian paid workforce to be around AUD5.5 billion, of which alcohol contributed around 35 %. Their study identified three principal ways in which drug abuse has an important impact on productivity: deaths and illnesses causing premature retirement; absenteeism from sickness or injury; and reduced on-the-job productivity. In recent years, a small body of literature has examined the drinking-earnings relationship using Australian data (see Barrett 2002; Lee 2003; Lye and Hirschberg 2004). This chapter contributes to this literature by investigating the impact of *bingeing* on individuals' earnings.[1]

The relationship between alcohol use and abuse, and labour market outcomes has received growing attention in the international literature, more so in the last decade. It has been argued that while excessive drinking is associated with lower earnings through adverse health effects, absenteeism and low productivity, light, or moderate, alcohol consumption seems to generate positive wage effects (see Barrett 2002; French and Zarkin 1995; Hamilton and Hamilton 1997; Heien 1996; Lye and Hirschberg 2004; MacDonald and Shields 2001). These positive wage premiums are expected to arise from the beneficial health effects of drinking in moderation. Several studies have found that light and moderate drinking is associated with a lower incidence of stroke (see Baum-Baicker 1985; Denke 2000; Fagrell et al. 1999). One Dutch study had found that moderate drinkers under stress were less likely to be

[1]The content of this chapter has been presented at the 28th Australian Health Economics Conference in 2006 and is in process of being submitted to an academic journal.

P.R. Srivastava, *Recreational Drug Consumption*, Developments in Health Economics and Public Policy 11, DOI 10.1007/978-3-319-02405-9_7,

absent from work than were either abstainers or heavy drinkers under stress (Vasse et al. 1998). In addition, it is also argued that individuals derive benefits from the "networking" effect of alcohol consumption (see Peters and Stringham 2006). It is believed that drinking can increase social capital which in turn increases earnings.

Researchers have explored the impact of drinking on labour market outcomes using different approaches, modelling techniques, and various measures of alcohol use and abuse. The main empirical issue that has often been raised in the literature on alcohol consumption and labour market outcomes is endogeneity because some labor market outcomes and drinking may have a simultaneous relationship (i.e., structural endogeneity) and because there may exist unobserved heterogeneity (i.e., statistical endogeneity). The heterogeneity problem arises because unobserved attributes that affect earnings may be correlated with unmeasured personal characteristics that influence an individual's propensity to drink. For example, the unobserved characteristic could be a "willingness to socialise" (Lee 2003) or a lack of motivation (Dave 2004) that can potentially influence both drinking and labour earnings. MacDonald and Pudney (2000) identified a high rate of time preference as a potential unobservable characteristic causing individuals to select high-paying jobs without consideration for investment in human capital, but also, according to Becker and Murphy (1988), making them more likely to take drugs. Gill and Michaels (1992) suggested that the genetic predisposition to idleness could be a potential unobserved characteristic of drug users and that individuals with such characteristic would be relatively unproductive.

Most studies have dealt with the issue of endogeneity of substance abuse and earnings by using an instrumental variable approach (see Kenkel et al. 1994; MacDonald and Shields 2001, 2004; Mullahy and Sindelar 1996). Much as the IV technique is easily applied and estimated, the main challenge in empirical studies is finding valid instruments given that poor instruments can do more harm than good (see Bound et al. 1995; Heckman 1995).

Another approach to model the drinking-earnings relationship found in recent literature is the multinomial selectivity model. This is an extension of the standard sample selection model (Heckman 1979) generalised to polychotomous choices by Lee (1983). Trost and Lee (1984) used this model to study the returns to education.[2] They estimated separate earnings equations by education status, correcting for selection bias due to self-selection into different educational choices. Using a similar approach to examine drinking-earnings relationship, researchers have estimated separate earnings equations for each drinking group adjusting for selection bias due to individuals self selecting themselves into drinking categories (see Barrett

[2]Note that theirs is an endogenous regime switching model for which the one-step Full Information Maximum Likelihood estimator is the efficient choice. However, Lee (1983) suggested a two-step estimation method which is inefficient since estimating one equation at a time for each drinking status results in loss of information. In addition, the two-step estimation approach estimates the correlation coefficient ρ between drinking and earnings more than one time. However, since the main interest is in the earnings equations, this approach, albeit inefficient, still gives consistent estimates of the effects of drinking on earnings.

2002; Hamilton and Hamilton 1997; Lee 2003). This approach allows labour market returns to individual characteristics to vary by drinking status. Using a standard sample selection model, Berger and Leigh (1988) examined the wage differentials between drinkers and non-drinkers. They found that drinkers earned a substantial wage premium relative to abstainers. Hamilton and Hamilton (1997) extended this analysis to three drinking categories and found that abstainers and heavy drinkers earn less than moderate drinkers. Their study showed that selectivity bias had important implications on predicted wage differentials. Similar findings have been obtained by Barrett (2002) and Lee (2003). Table 7.1 summarises some of the literature related to alcohol and labour market outcomes, highlighting their findings and indicating the nature of the data.

The general consensus in the empirical literature is that drinkers earn more than abstainers. Those studies which have considered three drinking status have generally found an inverted U-shaped relationship between drinking and earnings indicating that moderate drinking leads to a significant earnings premium relative to abstention and heavy drinking. However, it is quite clear from the literature that the majority of studies looking into the relationship between drinking and labour market outcomes have focused on US data.

This chapter contributes to the scant literature on alcohol consumption and labour market outcomes in the local context and reinforces the existing body of international literature. In particular, following Trost and Lee (1984), it uses a multinomial selectivity model to examine the relationship between Australians' drinking patterns and their earnings. In contrast to earlier studies which focused on alcohol participation, or moderate and heavy drinking statuses, here the focus is on individuals' bingeing behaviour. The structure of the paper is as follows. Section 7.2 outlines the empirical model. Section 7.3 estimates the model, discusses the results and provides earnings predictions by drinking status. A thorough decomposition of the earnings differentials is carried out in Sect. 7.4 and their main drivers are identified. Section 7.5 summarises the findings.

7.2 A Multinomial Selectivity Model for Earnings

Let the earnings equation for individual i with drinking status j be given by,

$$E_{ij} = \mathbf{x}_i'\boldsymbol{\beta}_j + u_{ij} \qquad (i = 1, \dots N \text{ and } j = 1, \dots J). \tag{7.1}$$

where earnings E_{ij} are assumed to be a linear function of observable individual attributes $\mathbf{x}_i$ such as socioeconomic and demographic characteristics, job and occupation characteristics, and health status, and $u_{ij} \sim N(0, \sigma_j^2)$. Given separate earnings equations, the estimated coefficients β_j's across various drinking levels are then compared to determine whether labour market returns differ by drinker type. However, estimating separate earnings equations by drinking status can result in

Table 7.1 Selective survey of economic studies on drinking-earnings relationship

Author/Year	Data	Findings
Berger and Leigh (1988)	US data	Premium for drinkers over non-drinkers
Kenkel et al. (1994)	US NLSY data	Wage penalty for heavy male drinkers
French and Zarkin (1995)	Employees from 4 US worksites	Inverted U-shaped relationship with a peak premium at approx.1.5 to 2.5 drinks per day on average
Heien (1996)	US national survey on alcohol use	Inverted U-shaped relationship with highest premium for moderate drinkers
Mullahy and Sindelar (1996)	US national health survey data	Reduced employment
Hamilton and Hamilton (1997)	Canadian data	Inverted U-shaped relationship with highest premium for moderate drinkers
French et al. (1998)	US national data	Flat premium for drinkers over non-drinkers
Zarkin et al. (1998a)	US national survey on drug abuse	Flat premium for male drinkers over non-drinkers No such evidence for women
Zarkin et al. (1998b)	US national survey on drug abuse	Little effect on the number of hours worked by young men
MacDonald and Shields (2001)	UK health survey data	Inverted U-shaped relationship with highest premium for moderate drinkers
Barrett (2002)	Australian national health survey data	Inverted U-shaped relationship with highest premium for moderate drinkers
Terza (2002)	US national health survey data	Alcohol consumption decreases the likelihood of being employed
Lee (2003)	Australian Twin Registry data	Inverted U-shaped relationship with highest premium for moderate drinkers
Peters (2004)	US NLSY data	Controlling for unobserved heterogeneity shows no effect of drinking on wages
MacDonald and Shields (2004)	UK health survey data	Problem drinking substantially decreases probability of employment
Lye and Hirschberg (2004)	Australian national health survey data	Inverted U-shaped relationship with highest premiums for low/moderate drinkers

sample selectivity bias because the rational individual is likely to self-select himself into the alternative that yields the highest present value of net benefits to him.

Lee (1983) proposed a selection model to account for such bias. In particular, he generalised the two-step Probit selection Heckman model (Heckman 1979) into a polychotomous-choice setup where in the first stage the choices are modelled using a Multinomial Logit (MNL) model and the second stage is an OLS regression.

The indirect utility function for individual i with drinking status j is assumed to be given by

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad (i = 1, \ldots N \text{ and } j = 1, \ldots J). \tag{7.2}$$

V_{ij} is the observable part of the utility that is typically assumed to be a linear function of observable characteristics $\mathbf{x}_i$ plus additional variables that solely reflect the individual's preferences over levels of alcohol consumption, such that

$$U_{ij} = \mathbf{z}_i^{'} \boldsymbol{\gamma}_j + \varepsilon_{ij}. \tag{7.3}$$

ε_{ij} is the stochastic component accounting for unobserved individual tastes and preferences.

Let Y_i $(Y_i = 1, \ldots J)$ indicate the choice made by consumer i. The consumer is assumed to select the choice that gives him/her the maximum utility. That is, $Y_i = j$ if $U_{ij} > U_{ik}, (k = 1, 2, \ldots J;\ k \neq j)$. Assuming ε_{ij} error terms are distributed according to the Type I Extreme Value distribution, this results into the standard MNL choice model

$$P_{ij} = P(Y_i = j) = \frac{\exp(\mathbf{z}_i^{'} \boldsymbol{\gamma}_j)}{\sum_{j=1}^{J} \exp(\mathbf{z}_i^{'} \boldsymbol{\gamma}_j)}. \tag{7.4}$$

Now, conditional on alternative j being chosen, the specification of the earnings equation accounting for selection bias is

$$E_{ij}^{*} = \mathbf{x}_i^{\prime} \boldsymbol{\beta}_j + \theta_j \hat{\lambda}_j + w_{ij} \tag{7.5}$$

where

$$\hat{\lambda}_j = \frac{\phi \left\{ \Phi^{-1} \left[F(\mathbf{z}_i^{'} \boldsymbol{\gamma}_j) \right] \right\}}{F(\mathbf{z}_i^{'} \boldsymbol{\gamma}_j)}$$

and $F(.)$ denotes the MNL distribution function. The functions $\phi(.)$ and $\Phi(.)$ are the standard normal pdf and cdf respectively, and the error terms w_{ij} have mean zero. The selection term on the right-hand side of Eq. (7.5), $\hat{\lambda}_j$, is called the Inverse Mills Ratio (IMR) and is constructed using the first-stage MNL model results. It controls for the truncated mean of the observed residuals in the earnings equations arising from individuals selecting their preferred drinking status. The truncated mean is a generalisation of the standard Heckman correction term to the situation where individuals choose over multiple alternatives.

The parameter θ_j is estimated along with $\boldsymbol{\beta}_j$ where $\theta_j = \sigma_j \rho_j$, ρ_j being the correlation coefficient between u_{ij} and the error terms in the selection equation and σ_j is the standard deviation of the disturbance u_{ij}. The asymptotic covariance matrix of the two-stage estimation is adjusted using the (Murphy and Topel 1985) correction procedure. Once the selectivity bias is accounted for, Eq. (7.5) can be used to predict an individual's earnings given his/her drinking status as if he/she were randomly allocated to a given drinking status.

7.3 Model Estimates and Earnings Predictions

Data from the 2001 and 2004 sweeps of the NDSHS are pooled together in this analysis (NDSHS 2004). For the purpose of this study, the sample is restricted to individuals in their prime working age, 25–60 years, whose main activity is work and who are full-time employees.[3] The NDSHS does not contain data on hourly earnings or the number of hours worked. Individuals' personal annual income before tax for the year prior to the survey is therefore used as a measure of earnings. This measure of earnings may not strictly represent individuals' earnings given that it constitutes their income from all various sources. However, restricting the sample to prime working age full-time workers ensures that earnings will be the principal source of variation in individuals' income. Another shortcoming related to individuals' income reported in the NDSHS is that it involves categorical responses where respondents choose from many income categories the one that best represents their income level. As is common practice, midpoints of income brackets are used to convert the discrete income series into a continuous variable.

In contrast to previous literature that has examined the drinking-earnings relationship, individuals are grouped into abstainers, non bingers, occasional bingers and frequent bingers. Table D.1 in Appendix D presents summary statistics of the sample by drinking groups. From the raw data, it appears that occasional bingers have the highest earnings. In particular, individuals who binge occasionally earn about 26 % more than abstainers and about 9 % more than non bingers. On the other hand, frequent bingers earn about 10 % less than the occasional bingers and 2 % less than the non bingers.

[3] Note that the selectivity bias that arises because of individuals' self-selection into the labour force (see Heckman 1974), is not controlled for in this analysis. Accounting for this bias would add one more layer of complexity to the model which is beyond the scope of the thesis.

7.3.1 Discussion of Results

Model I with Exogenous Drinking Status

To start, the earnings equation is estimated using OLS by including dummy variables for three of the drinking levels and using abstainers as the base case. Controlling for individuals' demographic characteristics, the effects of the three dummies are found to be statistically significant. The estimated coefficients and standard errors are reported in the first two columns of results in Table 7.2 under Model I. From the results it appears that occasional bingers have the highest earnings. In particular, they earn 15.7 pp more than abstainers and 6.9 pp more than non bingers. On the other hand, frequent bingers face a penalty of 2.1 pp over occasional bingers. An analogous exercise was carried out by Hamilton and Hamilton (1997) who found a premium of 7.4 pp for moderate drinkers over non-drinkers and a premium of 6.6 pp (although statistically insignificant) for heavy drinkers over moderate drinkers.[4] Similar findings were obtained by Zarkin et al. (1998a). However, due to the endogeneity of drinking status and earnings it is very likely that these estimates of earnings differentials are biased.

Model II with Endogenous Drinking Status

Next, the multinomial selectivity model for earnings is estimated. In the first stage, individuals' drinking status choice is modelled using a MNL model. The model is specified as a function of a range of socioeconomic and demographic factors, alcohol price, health status and all the explanatory variables that determine earnings. Note that variables (such as alcohol price, single parent status, and whether individual started drinking before age 18) that are included in the drinking status choice equation and excluded from the earnings equation, give additional explanatory power to the model and help identify the earnings equation parameters.[5] Table D.2 in Appendix D reports the estimated coefficients for the drinking status choice model. Given that the focus of the study is on the earnings function, the results are not discussed here.

The second-stage of the multinomial selectivity model entails estimating the earnings equations separately for each drinking group. This requires an adjustment for the selectivity bias likely to arise given that individuals' unobservable characteristics influencing their drinking decision are correlated with those affecting their

[4] Hamilton and Hamilton (1997) defined moderate drinkers as those who recently consumed less than 8 drinks on a single day and heavy drinkers as those recently consuming at least 8 drinks on a single day.

[5] Note that the parameters in the earnings equation can also be identified through the nonlinearity of the inverse mills ratio, $\hat{\lambda}$, rather than through exclusion restrictions, unless $\mathbf{z}'\hat{\boldsymbol{\gamma}}$ in Eq. (7.5) does not have much variation in the sample (Wooldridge 2002).

Table 7.2 Earnings OLS estimates

	Model I		Model II							
			Abstainer		Non Binger		Occasional Binger		Frequent Binger	
Constant	9.424	(0.049)**	9.591	(0.179)**	9.215	(0.102)**	9.548	(0.086)**	9.962	(0.154)**
Age: 30–34	0.044	(0.014)**	0.021	(0.058)	0.032	(0.025)	0.063	(0.019)**	0.103	(0.042)**
35–39	0.096	(0.014)**	−0.051	(0.057)	0.121	(0.027)**	0.125	(0.020)**	0.150	(0.042)**
40–44	0.106	(0.014)**	0.028	(0.058)	0.169	(0.029)**	0.111	(0.022)**	0.163	(0.044)**
45–49	0.143	(0.014)**	0.091	(0.055)	0.222	(0.032)**	0.145	(0.025)**	0.167	(0.046)**
50–54	0.147	(0.015)**	0.029	(0.057)	0.251	(0.035)**	0.136	(0.029)**	0.213	(0.049)**
55–60	0.097	(0.016)**	−0.003	(0.059)	0.218	(0.039)**	0.103	(0.036)**	0.074	(0.056)
Male	0.309	(0.009)**	0.234	(0.033)**	0.325	(0.014)**	0.301	(0.014)**	0.220	(0.033)**
Married	−0.011	(0.008)	0.024	(0.031)	−0.022	(0.014)*	−0.005	(0.013)	0.102	(0.033)**
ATSI	−0.014	(0.036)	−0.020	(0.113)	−0.073	(0.064)	0.055	(0.058)	−0.098	(0.084)
Capital	0.100	(0.009)**	0.120	(0.034)**	0.104	(0.014)**	0.102	(0.013)**	0.130	(0.029)**
Degree	0.226	(0.013)**	0.118	(0.048)**	0.259	(0.021)**	0.238	(0.022)**	0.221	(0.053)**
SecEdu	0.055	(0.011)**	−0.023	(0.039)	0.066	(0.016)**	0.077	(0.018)**	0.049	(0.033)
Excelhlth	0.158	(0.043)**	0.171	(0.145)	0.263	(0.071)**	0.145	(0.077)*	0.082	(0.096)
Goodhlth	0.106	(0.043)**	0.155	(0.146)	0.191	(0.071)**	0.117	(0.077)	−0.014	(0.096)
VIC	−0.056	(0.011)**	−0.090	(0.041)**	−0.071	(0.016)**	−0.041	(0.017)**	0.017	(0.037)
QLD	−0.084	(0.012)**	−0.110	(0.042)**	−0.086	(0.018)**	−0.084	(0.019)**	−0.073	(0.037)**
SA	−0.107	(0.015)**	−0.227	(0.056)**	−0.100	(0.023)**	−0.102	(0.023)**	−0.104	(0.050)**
WA	−0.042	(0.013)**	−0.061	(0.054)	−0.070	(0.020)**	−0.013	(0.021)	−0.072	(0.043)*
TAS	−0.110	(0.021)**	−0.149	(0.105)	−0.051	(0.032)	−0.160	(0.031)**	−0.138	(0.060)**
ACT	0.016	(0.017)	−0.046	(0.064)	0.032	(0.025)	0.006	(0.028)	0.060	(0.073)
NT	0.066	(0.016)**	0.015	(0.061)	0.086	(0.026)**	0.053	(0.025)**	0.070	(0.046)

Industry										
Primary	0.223	(0.022)**	0.230	(0.101)**	0.208	(0.035)**	0.228	(0.032)**	0.227	(0.064)**
Manufac	0.180	(0.016)**	0.094	(0.058)	0.186	(0.024)**	0.187	(0.025)**	0.203	(0.045)**
Util & Cons	0.189	(0.017)**	0.055	(0.074)	0.194	(0.027)**	0.183	(0.027)**	0.282	(0.049)**
Transport	0.224	(0.020)**	0.156	(0.078)**	0.223	(0.031)**	0.232	(0.031)**	0.267	(0.059)**
Communic	0.309	(0.028)**	0.193	(0.087)**	0.331	(0.045)**	0.327	(0.045)**	0.297	(0.091)**
Finance	0.189	(0.014)**	0.116	(0.053)**	0.186	(0.022)**	0.210	(0.021)**	0.210	(0.044)**
Govt Admin	0.246	(0.017)**	0.276	(0.067)**	0.240	(0.027)**	0.252	(0.026)**	0.220	(0.057)**
Education	0.034	(0.017)**	−0.044	(0.064)	0.043	(0.025)*	0.027	(0.028)	0.128	(0.067)*
Health	0.002	(0.015)	−0.031	(0.055)	−0.005	(0.023)	0.025	(0.025)	0.015	(0.053)
Recreational	−0.080	(0.026)**	−0.222	(0.113)**	−0.100	(0.042)**	−0.030	(0.038)	−0.125	(0.093)
Personal	0.049	(0.021)**	−0.146	(0.077)*	0.080	(0.033)**	0.070	(0.033)**	0.016	(0.073)
Occupation										
Admin	0.466	(0.016)**	0.455	(0.070)**	0.441	(0.025)**	0.495	(0.024)**	0.381	(0.055)**
Prof	0.354	(0.013)**	0.338	(0.048)**	0.355	(0.020)**	0.366	(0.021)**	0.278	(0.051)**
AsscProf	0.294	(0.013)**	0.322	(0.051)**	0.282	(0.021)**	0.310	(0.021)**	0.224	(0.044)**
Traders	0.056	(0.016)**	0.046	(0.064)	0.020	(0.025)	0.116	(0.025)**	−0.071	(0.048)
Clerical	0.108	(0.023)**	0.180	(0.090)**	0.082	(0.035)**	0.137	(0.037)**	−0.026	(0.078)
Production	0.017	(0.019)	0.012	(0.068)	−0.022	(0.029)	0.091	(0.031)**	−0.081	(0.055)
Service	−0.156	(0.020)**	−0.140	(0.068)**	−0.217	(0.030)**	−0.052	(0.032)	−0.346	(0.067)**
Labourer	−0.235	(0.019)**	−0.216	(0.061)**	−0.249	(0.029)**	−0.174	(0.032)**	−0.408	(0.054)**
$\hat{\lambda}$			0.026	(0.043)	0.168	(0.054)**	−0.033	(0.034)	−0.171	(0.078)**
Selection Bias			0.049	(0.079)	0.144	(0.046)**	−0.034	(0.034)	−0.326	(0.149)**
D_{nb}	0.088	(0.014)**								
D_{ob}	0.157	(0.014)**								
D_{fb}	0.136	(0.018)**								
R^2	0.366		0.275		0.379		0.375		0.386	

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

D_{nb}, D_{ob} and D_{fb} represent dummies for non binger, occasional binger, and frequent binger respectively. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level. Selection bias is calculated as $\theta_j \bar{\lambda}_j$ where $\lambda_j = \frac{\phi(.)}{\Phi(.)}$

earnings. As a consequence, their earnings are not observed randomly and thus for a set of observed characteristics including drug use, they would earn higher or lower wages. For instance, here, a negative selectivity bias for the frequent bingeing status reveals that individuals with unobserved characteristics associated with a higher probability of frequent bingeing are associated with lower earnings as a frequent binger. In such case a random sorting would yield a higher average wage for frequent bingers as compared with the observed sorting.

Age Effects

Table 7.2 also presents the estimated results of the second-stage selectivity-corrected earnings regressions (Model II). The impact of age is examined first. The age effects indicate an inverted U-shaped relationship of earnings with age, in general, with a drop-off for individuals in the 55–60 age bracket. For non bingers, earnings are significantly higher in the age group 45–54 and decline slightly for older individuals. The age-earnings relationship is less distinct for occasional bingers. For frequent bingers, earnings are markedly higher in the age-group 50–54 and decline significantly for older individuals. In contrast, there does not appear to be any impact of age on abstainers' earnings.

Other Demographic Effects

Some other important differential effects due to individuals' characteristics are also observed across the four groups. In particular, among non bingers and occasional bingers, males earn about 30–33 % more than females whereas male frequent bingers earn about 22 % more than female frequent bingers. There appears to be a positive premium for married individuals as compared to their non-partnered counterparts among frequent bingers. There is no evidence of lower earnings for Aboriginals and Torres Strait Individuals (ATSI) across any drinking category. There are positive returns for those residing in capital cities among all four drinking groups, with a premium as high as 13 % for frequent bingers. As expected, education seems to generate a significantly higher premium across all four drinking groups suggesting that there is a payoff to being more educated relative to those with less than year-12 qualifications, but this pay-off is relatively smaller for abstainers.

State Effects

Differences in earnings across the various Australian States and Territories are controlled using state indicators. The results indicate that individuals in Victoria (VIC), Queensland (QLD) and South Australia (SA) have, in general, substantially lower earnings than workers in the base state, New South Wales (NSW). Among occasional and frequent bingers, Tasmanian (TAS) workers have the lowest earnings followed by South Australians.

Returns to Job Characteristics

The returns to job characteristics are estimated by including industry and occupation indicators in the model. There appears to be a significant difference in the earnings differentials with respect to industry. Among abstainers, those in the government administration and defence (Govt Admin) industry seem to receive the highest earnings; abstainers' earnings are comparatively higher in the primary industry as well. Among moderate and occasional bingers, those in communications services (Communic) receive markedly higher earnings while among frequent bingers, those in communication services, utilities and construction (Util & Cons), and transport and storage services (Transport) receive the highest earnings.

The pattern of earnings differentials is rather consistent with respect to individuals' occupation. Among all four categories of drinkers, those in administrative and professional occupations (Admin, Prof, AsscProf) receive substantially higher earnings while labourers receive the lowest earnings. In fact, earnings are found to be markedly lower for those who are in service, or labourer, occupations among frequent bingers. It is quite likely that in such physical-intensive occupations heavy drinking would significantly affect individuals' productivity.

Selection Correction

The selectivity bias which is captured through the Inverse Mills Ratio coefficient shows statistically significant biases for non bingers and frequent bingers. In particular, an upward bias of around 14 % is observed for non bingers and a downward bias of around 33 % is observed for frequent bingers, who self-select themselves as non bingers and frequent bingers, respectively. In other words, a worker who self-selects himself or herself into frequent bingeing has on average 33 % lower earnings than those of a frequent binger with similar characteristics but who is drawn at random from a population of income-earners.As mentioned above, this bias results from individuals self-selecting themselves into drinking groups because of certain observable and unobservable characteristics which are associated with both drinking and earnings. For example, if the unobserved characteristics is a "willingness to socialise" (Lee 2003), this attribute might result in a person having an above average probability of being a frequent binger but because he/she socialises rather than works hard, he/she has a below average earnings.

To assess the impact of selectivity bias, earnings equations are estimated separately by drinker type assuming that there is no selection bias. The detailed estimation results are however not reported here. The exclusion of the Inverse Mills Ratio from the earnings equations has, in general, little effect on the estimated coefficients and mostly affects the constant term. However, for the non binger and the frequent binger categories where selectivity bias is significant, the effect of excluding the IMR is slightly more significant across a few observed characteristics.

Table 7.3 Observed and predicted earnings

	Abstainer	Non binger	Occasional binger	Frequent binger
M1. Mean earnings based on observed data	10.180	10.328	10.410	10.306
M2. Single earnings equation with dummies	10.174	10.262	10.331	10.310
for drinking status				
M3. Separate earnings equations by drinking status excluding IMR				
Predicted earnings with "average" characteristics for all drinking groups	10.222	10.313	10.381	10.389
Predicted earnings with "average" characteristics for each drinking status	10.172	10.322	10.405	10.311
M4. Separate earnings equations by drinking status including IMR				
Predicted earnings with "average" characteristics for all drinking groups	10.232	10.312	10.382	10.385
Predicted earnings with "average" characteristics for each drinking status	10.184	10.329	10.403	10.288

Earnings are in natural logarithmic form

7.3.2 Observed and Predicted Earnings Under Various Model Specifications

Table 7.3 depicts a range of observed and predicted log of earnings using various approaches discussed above.[6] The first row represents earnings based on observed data for the respective drinking categories. The remaining rows depict predicted earnings. It is interesting to see the effects on predicted earnings when the latter are estimated using one set of "average" characteristics for each drinker type (second row of predictions under M3 and M4 respectively). The estimates are quite close to the observed average earnings. Also, lower earnings are predicted for frequent bingers as compared to non bingers and occasional bingers. On the other hand, an "average" set of characteristics for all drinking groups (first row of predictions under M3 and M4 respectively) smoothes the differential earnings across the four drinking groups. Here, the highest earnings are associated with frequent bingers. This tends to suggest that there are important earnings differential effects that can be attributed to individuals' characteristics. Finally, the set of predictions under M3 estimated by excluding the IMR can be compared to those under M4 where sample selectivity bias is accounted for. There does appear to be a discrepancy between the two set of predicted earnings, in particular for abstainers and frequent bingers.

[6]Natural logarithmic of real annual earnings before tax measured in Australian dollars.

In summary, these results indicate that occasional bingers have the highest earnings among all four drinking groups. The findings therefore substantiate the literature on the inverted U-shaped drinking-earnings relationship. Prior studies have mostly grouped individuals into abstainers, moderate drinkers and heavy drinkers. Those studies have found moderate drinkers to be the highest income earners. In this analysis, where individuals are categorised in terms of their bingeing behaviour, non bingers are found to earn more than abstainers but even higher earnings are associated with occasional bingers. Only the frequent bingers experience a drop-off in their earnings.

7.4 Earnings Differentials

To get an overall picture of the composite effect of individuals' characteristics on their earnings across the four drinking categories, a few earnings differentials across the four groups are next estimated. According to Oaxaca (1973), earnings differentials can be decomposed into two components—the difference due to individuals' characteristics and the difference due to productivity. Extending Oaxaca's work, Idson and Feaster (1990) included a third component which represents differences arising from selection bias. The earnings differential between individuals with drinking status j and k is thus estimated as

$$E(\ln E_j|\bar{\mathbf{x}}_j) - E(\ln E_k|\bar{\mathbf{x}}_k) = 0.5(\hat{\beta}_j + \hat{\beta}_k)(\bar{\mathbf{x}}_j - \bar{\mathbf{x}}_k) + (\hat{\beta}_j - \hat{\beta}_k)0.5(\hat{\mathbf{x}}_j + \hat{\mathbf{x}}_k) + (\hat{\theta}_j\overline{\lambda}_j - \hat{\theta}_k\overline{\lambda}_k) \quad (7.6)$$

where $\bar{\mathbf{x}}_j$ is the vector of sample means of observable characteristics for drinking group j, and $\overline{\lambda}_j$ is the mean IMR for drinking group j. Thus, the first term represents earnings gap attributed to differences in characteristics across drinking groups. The second term represents differences due to coefficients, or due to returns to the earnings-determining characteristics of workers. It suggests how the attributes, or characteristics, are rewarded and not as much the attributes themselves (in loose terms the "productivity" of the worker). For instance, it suggests how a non binger's earnings will change if he/she starts bingeing frequently. The third term represents the earnings differentials due to the unobserved characteristics of workers who self-select themselves into the respective drinking groups.

Standard errors for the earnings differentials and their respective components are estimated using simulation methods. In particular, 500 sets of parameters of the earnings equation for the respective drinking group are simulated from asymptotic normal distributions. Each time, earnings differentials and their components are calculated, thereby obtaining 500 sets of results. Sample standard errors are then calculated as estimates of the standard errors for the earnings differentials and their respective components.

7.4.1 *Earnings Differentials of Non Bingers and Frequent Bingers* vis-a-vis *Abstainers*

Table 7.4 reports a few earnings differentials and their decompositions. The first row of results depicts the average observed earnings differentials. Both non bingers and frequent bingers enjoy a positive premium over abstainers with differences as high as −0.1475 and −0.1254, respectively. Predicted earnings differentials and their decompositions are given in subsequent rows. The predicted earnings differential between non bingers and abstainers (column I) of −0.1447 is very close to the observed value. The predominant part of this differential is accounted by selectivity bias (−0.0949), although statistically insignificant, and differences in characteristics of the two drinking groups (−0.0594). The earnings differential attributable to differences in the regression coefficients is a negligible 0.0096 in favour of abstainers but statistically insignificant. This can further be decomposed into a part that is explained (differences due to returns to earnings-determining characteristics) and another part that is unexplained (differences in intercepts). Here, the explained component is quite substantial and negative (−0.3668) indicating that non bingers receive higher returns to their characteristics than abstainers. However, these returns are swamped by the equally large, but positive, unexplained difference of the intercepts (0.3763). This large intercept term results from the inability to account for other potential determinants of earnings such as employees' skills and experience.

The earnings differential between abstainers and frequent bingers (column II) is primarily driven by the difference in regression coefficients (−0.4998) while the selectivity bias is positive, significant and substantially large (0.3745) increasing the earnings gap in favour of abstainers. The difference of 0.0221 due to characteristics favours abstainers. These add up to an overall earnings differential of 0.1032 in favour of frequent bingers. The difference due to regression coefficients can further be split into an explained component of −0.1287 due to returns to characteristics while the major part of −0.3711 is due to the unexplained intercept differences. It appears that frequent bingers also receive higher returns to their characteristics than abstainers.

7.4.2 *Earnings Differentials of Non Bingers and Abstainers* vis-a-vis *Frequent Bingers*

The last two sets of results in Table 7.4 (Columns III and IV) depict the earnings differentials of frequent bingers *vis-a-vis* non bingers and occasional bingers, respectively. The predicted earnings differentials of −0.0415 and −0.1150 clearly indicate that non bingers and occasional bingers have higher earnings than frequent bingers. The earnings differential between frequent bingers and non bingers is primarily explained by the difference due to regression coefficients (0.5278) in

Table 7.4 Decomposition of earnings differentials

	$E_a - E_{nb}$ (I)		$E_a - E_{fb}$ (II)		$E_{fb} - E_{nb}$ (III)		$E_{fb} - E_{ob}$ (IV)	
Observed Earnings Differential	−0.1475		−0.1254		−0.0221		−0.1044	
Predicted Earnings Differential	−0.1447	(0.019)**	−0.1032	(0.023)**	−0.0415	(0.018)**	−0.1150	(0.017)**
Differences due to:								
1. Characteristics	−0.0594	(0.003)**	0.0221	(0.009)**	−0.0999	(0.008)**	−0.0899	(0.006)**
2. Coefficients (a+b)	0.0096	(0.086)	−0.4998	(0.162)**	0.5278	(0.148)**	0.2669	(0.151)*
(a) Returns to characteristics	−0.3668	(0.193)*	−0.1287	(0.199)	−0.2197	(0.148)	−0.1469	(0.141)
of which: Admin	*0.0011*	*(0.005)*	*0.0053*	*(0.006)*	*−0.0052*	*(0.005)*	*−0.0114*	*(0.006)**
Prof	*−0.0048*	*(0.015)*	*0.0129*	*(0.015)*	*−0.0177*	*(0.012)*	*−0.0190*	*(0.012)*
AsscProf	*0.0053*	*(0.007)*	*0.0138*	*(0.010)*	*−0.0083*	*(0.007)*	*−0.0134*	*(0.007)**
Traders	*0.0025*	*(0.007)*	*0.0159*	*(0.011)*	*−0.0128*	*(0.007)**	*−0.0277*	*(0.007)***
Clerical	*0.0029*	*(0.003)*	*0.0059*	*(0.003)**	*−0.0032*	*(0.002)*	*−0.0048*	*(0.002)***
Production	*0.0024*	*(0.005)*	*0.0083*	*(0.008)*	*−0.0050*	*(0.005)*	*−0.0137*	*(0.005)***
Service	*0.0045*	*(0.004)*	*0.0115*	*(0.005)***	*−0.0063*	*(0.004)**	*−0.0132*	*(0.003)***
Labourer	*0.0022*	*(0.005)*	*0.0166*	*(0.007)***	*−0.0113*	*(0.004)***	*−0.0156*	*(0.004)***
(b) Unexplained	0.3763	(0.212)*	−0.3711	(0.233)	0.7475	(0.187)**	0.4138	(0.177)**
3. Selection Bias	−0.0949	(0.094)	0.3745	(0.170)**	−0.4694	(0.152)**	−0.2920	(0.158)*

a: abstainers; *nb*: non binger; *ob*: occasional binger; *fb*: frequent binger. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level favour of frequent bingers and a selectivity bias of 0.4694 in favour of non bingers. The difference due to coefficients entails a component that explains the difference due to returns to characteristics (−0.2197) which is again dominated by a large unexplained intercept difference of 0.7475. A similar differential structure holds for the earnings differential between frequent bingers and occasional bingers. In both cases, the negative returns to characteristics indicate that non bingers and occasional bingers receive higher returns to their characteristics than frequent bingers.

From a further decomposition of the returns to individuals' observed characteristics in Table 7.4, it is interesting to note that although the overall earnings differentials favour non bingers and frequent drinkers to abstainers (i.e., negative $E_a - E_{nb}$ and $E_a - E_{fb}$), the differential effects due to returns to observed "occupational characteristics" are mostly positive, although generally statistically insignificant. This tends to indicate that in most occupations, abstainers would be "more productive" or at least the same (i.e., statistically insignificant differences) as non bingers and frequent bingers given their characteristics, although their overall earnings are lower. In fact, the differences due to returns to characteristics are mainly driven by the age factor (see Table D.3 in Appendix D that depicts the complete set of observable factors that contribute to earnings differentials). On the other hand, while the overall earnings differentials favour non bingers and occasional bingers to frequent bingers (i.e., negative $E_{fb} - E_{nb}$ and $E_{fb} - E_{ob}$), the differential effects due to the "occupational characteristics" are all negative. In other words, given their characteristics, for all occupations frequent bingers are "less productive" than non bingers and occasional bingers. Finally, the size and significance of the selectivity terms highlight the importance of accounting for sample selection bias. Ignoring selectivity bias can result in over or underestimation of the effect of drinking on earnings.

7.5 Summary

Empirical literature on alcohol consumption and labour market outcomes is scarce in Australia. This chapter has attempted to add to this literature by investigating the impact of Australians' drinking patterns, in particular bingeing, on their earnings. The analysis is conducted on full-time workers in their prime working age and their drinking levels are identified as abstainers, non bingers, occasional bingers and frequent bingers. Due to common unobservable factors that relate to both earnings and the propensity to drink, the relationship between drinking and earnings is endogenous. To account for endogeneity and allow flexibility, separate earnings equations are estimated by drinking status using a multinomial selectivity model that adjusts for selectivity bias due to workers' self-selection into the various drinking groups.

The results substantiate the empirical findings in the literature that moderate drinking is associated with significant earnings premium relative to abstention and heavy drinking. In particular, an inverted U-shaped relationship is found between drinking and earnings with an earnings premium over abstainers for non bingers and occasional bingers, and an earnings penalty for frequent bingers. In addition, some important differential effects are observed across all four drinking groups. In particular, abstainers are found to have a flat age-earnings profile while the inverted U-shaped relationship between age and earnings is quite pronounced for frequent bingers. Education appears to generate a higher premium across all four drinking groups but the payoff is found to be relatively lower for abstainers. Significant differential effects are observed across all four drinking groups by both industry of employment and occupation. Finally, significant selectivity bias is estimated for non bingers and frequent bingers, which highlights the importance of accounting for self-selection.

The second stage of the analysis entails a decomposition of the earnings differentials across the four groups. In particular, the earnings differentials are decomposed in terms of three contributing factors: selectivity; earnings-determining characteristics; and returns to the earnings-determining characteristics (or "productivity"). The results indicate that not only abstainers earn less than non bingers and frequent bingers, they also appear to be less "productive". However, a further decomposition of this "productivity component" indicates that across all occupations, abstainers are at least as, if not more, "productive" than non bingers or frequent bingers. These results are, however, masked by a large unexplained component most likely resulting from omission of important earnings determinants, such as workers' experience, that are unavailable for the analysis. Not surprisingly, across all occupations frequent bingers are found to be less "productive" than occasional bingers. The decomposition also reveals an important contribution of selectivity bias to earnings differentials.

This analysis has also made some contributions to the existing literature on the international front. Most prior studies have grouped individuals in terms of abstainers, moderate drinkers and heavy drinkers, and have found moderate drinkers to have the highest earnings. In this analysis, where individuals are categorised in terms of their bingeing behaviour, non bingers are found to earn more than abstainers but even higher earnings are associated with occasional bingers. Only the frequent bingers experience a drop-off in their earnings.

Chapter 8
Summary, Policy Implications and Further Research

This chapter summarises the principal findings of the book. It discusses the policy implications and outlines the limitations of the research and areas for further research. Section 8.1 highlights the contribution of the book and outlines the principal findings. In light of these findings, Sect. 8.2 discusses a few policy implications. Section 8.3 describes the limitations of the research and discusses some areas for further research.

8.1 Summary of Findings

Various policies have been developed by Australian policymakers over the last two decades in view of discouraging drug abuse. One of the major initiatives of the Australian Commonwealth Government is the National Drug Strategy which generally aims at reducing drug-related harms through demand reduction policies and programs. Note that demand reduction cannot be successful without limiting drug availability. Thus supply reduction, both on domestic and international fronts, is an essential component of a well-balanced strategic approach to drug control. Supply reduction strategies, however, require the collaborative participation of different agencies including law enforcement and the health sector, industry and regulatory authorities. A number of supply reduction strategies have been developed and implemented by some Commonwealth law enforcement agencies to reduce the supply of drugs including interception at borders and within Australia. For alcohol and tobacco, the supply reduction reforms range from liquor and tobacco licensing, licensed venues, to law enforcement of sales to minors. For illicit drugs, reduction of supply strategies include law enforcement against trafficking, cultivation and manufacture of drugs, collaboration with partner agencies at a global level, and improved technology for detection.

Research plays a vital part in forming decisions about such drug laws and policies. While a modest body of literature has amassed internationally on drug

P.R. Srivastava, *Recreational Drug Consumption*, Developments in Health Economics and Public Policy 11, DOI 10.1007/978-3-319-02405-9_8,

consumption in recent decades, empirical evidence on drug use is rather limited in Australia. This book has used individual level data from various sweeps of the National Drug Strategy Household Survey (NDSHS) to conduct a thorough investigation of Australians' consumption of various licit and illicit drugs. The econometric techniques used have allowed for more flexible specifications of models and results indicate that they give different estimates of important policy related measures relative to simpler and more standard methods used in the literature. In particular, the book has examined the demographic and socioeconomic characteristics of users of individual licit and illicit drugs, and the effects of own and related drug prices and the marijuana decriminalisation policy. It has also investigated cross drug relationships both via cross price relationships and other observable and unobservable factors. Finally, the relationship between Australians' drinking patterns and their earnings is also examined.

8.1.1 Binge Drinking

A high incidence of binge drinking is found in Australia. A main contribution of this research is to use unique information on both frequency and amount of alcohol consumption to identify bingers according to the National Health and Medical Research Council drinking guidelines. The observed sample data shows that nearly 30 % of males and 24 % of females binge occasionally (up to 3 days a week) while nearly 10 % of males and 6 % of females binge regularly at least 3 days a week. The high rate of binge drinking among Australian teenagers and young adults is not far behind what has been reported in the United States. According to the Global Status Report on Alcohol and Health 2011 (WHO 2011a), not only the volume of consumption but the pattern of drinking—especially binge drinking—is linked to injuries and cardiovascular diseases. According to the report, about 11.5 % of drinkers worldwide reportedly binge on a weekly basis, with male drinkers outnumbering women four-to-one. This book provides a deep insight on drinking patterns; the socio-economic characteristics of the different types of drinkers; the differential price responses across the various types of drinkers; and the association between drinking patterns and the labour market. The results have implications not only for Australia but for the rest of the world where there is a high prevalence of binge drinking.

8.1.2 Who Uses What Drugs and How Much? Do Prices Matter?

The book identifies the demographic and socioeconomic characteristics of drug users and examines price responses. The levels of consumption of the licit drugs, alcohol and tobacco are first modelled. Distinguishing between heavy and light users, a thorough analysis of the pattern of use of both drugs has been carried out. The analysis has then been extended to a selection of illicit drugs, namely marijuana, cocaine, heroin and amphetamines. Here, due to low incidences of drug use, participations in drug use rather than levels of consumption are estimated. The economic relationships across various drugs are also estimated on the basis of cross price responses. The main results are outlined below.

- **Own price effects.** Existing literature which focused on individuals of all age groups has found that heavy drinkers are insensitive to price. While these studies have mostly used quantity of alcohol consumed, in terms of probability of participation, this book has found that heavy bingers are more price-responsive relative to non bingers and occasional bingers. Similarly, with smoking, across all age groups heavy smokers are more price responsive than moderate or occasional smokers. Consistent with previous empirical findings in the international literature, teenage drinking and smoking are relatively more price elastic than any other age groups. When disaggregated by type of alcoholic beverages, participation in wine is found to more price responsive than beer and spirits. Price elasticities across all types of smokers are found to decline gradually with age and for individuals older than 30 years, there is no evidence of any price response. One important set of results in this book is the price effect of illicit drugs. Such analysis is almost nonexistent because of the scarcity of illicit drug prices. Using a unique price data source, this book has estimated price elasticities for illicit drugs. In particular, participation in marijuana and amphetamines is found to be price responsive. To the author's knowledge, this is the first study that has examined the demand for amphetamines in the general population and therefore the estimates of the price response is a unique and important contribution from an international perspective. Given that the use of marijuana and amphetamines is price responsive, the use of any strategy that limits the availability of these drugs will therefore shift prices upwards and reduce consumption. Hence, such findings provide a leverage to authorities to influence price and consumption of illegal drugs.
- **Cross price effects.** Based on the cross price effects on probability of participation, evidence on the economic relationships between the various drugs is as follows: alcohol is found to be an economic complement to tobacco and marijuana. Marijuana is an economic substitute for the hard drugs, cocaine and heroin. On the other hand, heroin is found to be a complement to cocaine. This tends to suggest that "hardcore" drug users most likely consume the two hard drugs together. Both heroin and cocaine are found to be complements to tobacco while cocaine, heroin and tobacco are economic substitutes for amphetamines. It is to be noted that such cross price responses have rarely been studied jointly in empirical studies and are almost nonexistent for illicit drugs both overseas and in Australia. Such results provide insights on how policy aimed at one drug is likely to affect consumption of others. For instance, given that cigarettes and alcohol are economic complements, a rise in cigarette taxes is likely to reduce

participation in both drugs. On the other hand, a cigarette price rise is likely to increase participation in amphetamines given that the two drugs are economic substitutes.

- **Age effects.** Controlling for other personal characteristics and prices, occasional and frequent bingeing are found to be more common among teenagers and young adults. The incidence of bingeing is found to decrease as individuals get older but increases with higher income. This calls for a more tailored set of anti-binge strategies that target the younger population. When disaggregated by type of alcoholic drinks, beer is found to have an inverted U-shaped relationship with age, peaking in the age-group 25–35 years. Participation in wine increases over older individuals while that of spirits decreases with age. Spirits are clearly the dominant beverage of choice among adolescents and young adults. As for tobacco, the probability of moderate and heavy smoking is found to have an inverted U-shaped relationship with age peaking for individuals in their mid-thirties. Marijuana and amphetamines are predicted to be more commonly used by individuals in their early twenties while cocaine and heroin use is more prevalent in the late twenties age group.
- **Other demographic effects**. Binge drinking is found to be more prevalent across males, singles, Aborigines, those who live in capital cities, those working in blue collar jobs, unemployed individuals and those with lower than tertiary education. Such findings indicate the characteristics of the target audiences to whom campaigns and policies should be specifically directed. When disaggregated by type of alcoholic beverages, beer, wine and spirits are found to relate to rather different socioeconomic and demographic groups. Beer is found to be more popular among males while wine is more commonly consumed by females and highly educated individuals. As for heavy smoking, it is more common in low socioeconomic groups, singles, males, single parents, Aborigines, those who have not completed secondary educations and those who are in blue collar jobs. Illicit drugs are more prevalent among males, singles, Aborigines and those who live in capital cities. Amphetamines and heroin participation is associated with those with low levels of education and both the drugs are less likely to be used by white collar workers. Marijuana use is associated with those working in blue collar jobs.
- **Decriminalisation Effects.** Marijuana decriminalisation is found to have no effect on its participation. However, this result is sensitive to model specifications. In particular, for the decriminalisation indicator to effectively capture the effect of the policy, individuals need to be randomly allocated to the various states without any selection bias via observed or unobserved factors. While this is a reasonable assumption in the sample for the major states, the Northern Territory has a very different demographic composition compared to the rest. The potential selection bias arising from such demographic difference is accounted for using an indicator for the Northern Territory. The results indicate a positive but insignificant effect of the decriminalisation policy on marijuana participation. However, failing to account for the selection bias, decriminalisation is found to increase marijuana participation. The results are also potentially sensitive to the

lack of within-state and across-time variation in the policy variable to detect a significant relationship. Given the limitations of this study, further research is required to establish the robustness of this finding. The data issues faced here are likely to be overcome when additional waves of the drug survey become available.

8.1.3 Exploring Cross-Drug Relationships Via Both Observable and Unobservable Individual Characteristics

A major contribution of the book is the use of multivariate techniques to model drugs in a multi-drug framework. Here, a system approach is used to jointly model an individual's participation in several drugs. Considering all consumption decisions to be jointly taken by the same individual, the relationship across different drugs is examined. In particular, the multivariate approach allows correlation across unobserved individual characteristics such as personal tastes, addictive traits and perceived risks, that potentially influence an individual's decision to consume multiple drugs. The key advantage of the multivariate approach is that conditional and joint probabilities of drug consumption can be modelled as functions of observable covariates while the univariate approach models only marginal probabilities. These conditional and joint probabilities are very useful to investigate polydrug usage. The main results are outlined below.

- **Beer, wine and spirits**. Using a univariate approach, beer, wine and spirits is found to relate to rather different socioeconomic and demographic groups. A multivariate Probit analysis provides further insights on the three alcoholic types commonly considered to be closely related economic goods by economists. Weak correlations across the error terms of their participation equations indicate that participations in beer, wine and spirits are also unrelated via unobservable characteristics. The heterogeneity of beer, wine and spirits consumption is thus an important factor to consider when developing alcohol-related policies. For instance, a campaign that aims at reducing the use of alcopops should target teenagers and young adults where the use of spirits is more prevalent, rather than the general population. Similarly, if the price elasticities across the three alcohol types are different, then a differential tax scheme is required to curb consumption.
- **Cross-drug relationships**. A system of five participation equations is jointly modelled for marijuana, cocaine, heroin, amphetamines and tobacco consumption. The main advantage of this technique although computationally demanding, is the estimation of conditional and joint probabilities and the effects of correlates on such probabilities. High correlations are estimated here across the error terms of the participation equations suggesting that the decisions to consume the various drugs are strongly correlated via unobserved individual characteristics. Using such information, some conditional and joint probabilities are estimated. For instance, conditional on the use of cocaine and heroin, the probability

of marijuana consumption is 84 % compared to an unconditional probability estimate of 9 %. In addition, the price responses also vary significantly across subpopulations of drug users relative to the general population. For instance, a marijuana price rise decreases the probability of marijuana consumption in the general population but has no effect on a subpopulation of cocaine and heroin users.

- **Differential price effects across subpopulations (on the basis of conditional and joint probabilities).** The economic relationships across drugs can also vary across polydrug users as against the general population. This book makes a significant contribution to the literature by examining the nature of the relationships across drugs in subpopulation of drug users. In the general population, there is evidence that tobacco is an economic complement and heroin an economic substitute for marijuana, but there is no evidence of any such relationships between marijuana and amphetamines or cocaine. However, in a subpopulation of cocaine and heroin users, there is no evidence of any complementarity between tobacco and marijuana while cocaine and heroin are found to be economic substitutes for marijuana.
- **Demographic effects.** The demographic differential effects are also quite significant across unconditional and conditional probabilities. One particular result is the effect of job characteristics on the probability of cocaine consumption. In the general population, those with white collar jobs are almost as likely to consume cocaine as those with blue collar jobs. However, among those who consume heroin, the probability of cocaine consumption increases significantly. Another result is the effect of educational attainment on cocaine participation. Degree holders have marginally higher chances to use cocaine than those with secondary school qualifications in the general population. However, in a subpopulation of heroin and amphetamines users, the probability of cocaine use is significantly higher for degree holders relative to those with secondary school qualifications.

8.1.4 Are Frequent Drinkers Different from Moderate or Occasional Drinkers? Can Advanced Econometric Techniques Enhance the Analysis of Drug Consumption?

This book has modelled the levels of alcohol consumption distinguishing between frequent, moderate and occasional drinking. An important contribution here is the use of the flexible Ordered Generalised Extreme Value (OGEV) model which imposes less restrictions on the determinants of the different drinking levels. The OGEV model allows separate latent equations for the multinomial choices, giving more flexibility in estimating the effects of the same covariate on different choices, thus modelling consumer behaviour more realistically. The OGEV estimates indicate significant demographic differences across the various drinking groups. Individuals' drinking patterns are found to shift from occasional and moderate drinking to frequent drinking as they age. Occasional and moderate drinking are both price responsive and the chances of frequent drinking increases for higher income groups. These findings indicate that there is a price response that can be used as a part of a broader public policy to influence drinking. Unfortunately, price response is lower among the group of greatest policy concern, ie the heavy drinkers. Thus, any alcohol taxes designed to discourage heavy or abusive drinking will impose welfare losses on drinkers who may not be imposing external costs by their drinking. The findings also indicate that higher taxes on alcohol may generate substantial revenues for state and federal governments in the least welfare distorting manner. That is, if heavy drinkers (who are also found to belong to high income groups) are price inelastic, higher taxes will not necessarily have a large effect on them. This book thus shows how the use of sophisticated and more flexible econometric techniques has the potential to enhance analysis.

8.1.5 Is There Any Association Between Individuals' Drinking Behaviour and Their Earnings?

Finally, the book examines the relationship between individuals' alcohol consumption patterns and their earnings. Controlling for demographic and job characteristics and addressing issues of selectivity bias, separate earnings equations are estimated for the four drinking groups. The findings reinforce the existing evidence in the literature that drinking has an inverted U-shaped relationship with earnings. Occasional bingers are found to have the highest earnings relative to frequent bingers, non bingers and abstainers. A decomposition of the earnings differentials reveals that non bingers and occasional bingers receive higher returns to their earnings-determining characteristics than frequent bingers. This book further extends the analysis to identify those individual factors that contribute to the wage differentials. It is found that across most occupations, frequent bingers are less "productive" than non bingers and occasional bingers.

8.2 Policy Implications

Drug-related policies and regulations are complex issues with many dimensions. Research plays an important part in assisting policymakers towards the development of such public policies. This book contributes to the drug policy debate by providing empirical evidence on several aspects of recreational drug consumption and for a range of drugs.

Tax Policy. The research concludes that price increases can potentially decrease alcohol and cigarette consumption among heavy users. Thus, taxes remain one of the broad-based prevention approaches from the standpoint of reducing abusive drinking and smoking in the Australian society. However, since taxes impose welfare costs on all drinkers and smokers equally, the choice between taxes and other policies will depend on a comparison of their welfare costs and benefits, which is beyond the scope of this book. In addition, high taxes are likely to encourage cross-border purchases and underground activities such as drug smuggling.

Youth. Adolescents and young adults accounts for a disproportionately high incidence of heavy drinking and smoking and adverse drug consequences such as accidents, crime and suicide, not to mention the social costs of such consequences. The research has found this age group to be more price responsive than adults. Given such evidence, taxes appear to be an effective means of reducing excessive use of alcohol and tobacco among adolescents and young adults. However, these findings also indicate that the beneficial effects of tax increases on alcohol or tobacco abuse may not be shared equally by all age groups and therefore policies in addition to tax increases must be pursued to curtail abuse in certain age groups. For instance, restrictive policies related to on-campus drinking and smoking, or minimum legal age of drinking and smoking, may be considered as additional means to curb drinking and smoking among young adults.

Beer, Wine and Spirits. Price responses are found to vary by types of alcoholic drinks. Although the price elasticities estimated in this book relate to *participation* in beer, wine and spirits and not to the *quantities* consumed, such information is still useful in the development of relevant tax policies.

Illicit Drug Prices. The research has found evidence that some illicit drugs are sensitive to their monetary price. In such case, supply reduction strategies which limit drug availability, such as drug law enforcement discouraging drug trafficking and production, will shift market prices of illegal drugs upwards and discourage their consumption.

Binge Drinking. Australia has an alarming rate of binge drinking. Public policies and programs should focus on strategies that target binge drinkers. The current drink-driving laws that impose more rigorous penalties for higher levels of PAC (Prescribed Concentration of Alcohol) are rightly designed for this purpose. The impact of these laws on binge drinking need to be closely monitored and in the event that the desired outcomes are not achieved, tougher penalties should be exercised.

Characteristics of Drug Users. This book provides deep insights on the demographic and socioeconomic profile of drug users in Australia. If campaigns, advertisements and educational programmes are tailored to account for the specific characteristics of drug users, they may turn out to be more cost effective.

Impact of Policies. When drugs are related in consumption, increased use of one is likely to have an effect on the consumption of others. For example, the 2001 heroin drought in Australia was characterised by a decrease in the prevalence and frequency of heroin use and a sharp drop in heroin-related deaths and arrests for heroin offences. At the same time an increase in the availability and use of other drugs such as cocaine, amphetamines and methadone was noted (Bush 2004; Dowling 2006; NDARC 2002). Similarly, drug policies aimed at discouraging the use of one drug are very likely to affect the use of other drugs which are its economic substitutes or complements. This research establishes the nature and strengths of the economic relationships across drugs. In the light of such findings, drug policies can be better coordinated to avoid any unintended consequences on substitute drugs or to benefit from the impact on complement drugs. For instance, if cigarettes and alcohol are economic complements, an alcohol tax increase is likely to discourage the consumption of both drugs.

8.3 Limitations and Potential Future Research

Some limitations are acknowledged and avenues for further research are highlighted:

Data Issues. The “exact” quantities of drug consumed would be of most value to policymakers. However, such data are not available at an individual level from the survey. Data unavailability has also restricted the analysis to pooled cross-sections rather than longitudinal observations. As a result, addiction theory and the gateway effects could not be explored. The availability of longitudinal data in the future will allow such issues to be investigated.

Illicit Drug Data. As with any drug survey data, the use of illicit drugs might be underreported. In terms of further research, new econometric techniques can be developed to account for such underreporting. In addition, underreporting itself should be minimised in surveys through improved strategies of data collection. An additional data limitation is the possible imprecision of the drug prices, in particular for the illegal drugs. These prices are mainly obtained from the Illicit Drug Reporting System (IDRS) as mentioned in Chap. 4. The IDRS collects such data predominantly from interviewing injecting drug users and key informants who have regular contact with illicit drug users but which may potentially exhibit coverage error.

Unobserved Social Factors. Other than socioeconomic and demographic factors there is a host of other factors that can potentially affect drug use. For instance, peer effect, a recent traumatising event and family environment such as parental drug consumption, poor relations with parents or insufficient parental monitoring, are all important factors that can potentially influence an individual’s drug consumption. Such factors are either not collected in the survey or altogether difficult to measure or calibrate.

Harms Caused by Drug Use. Of more relevance to policy development is an increased understanding of the relationship between drug use and drug-related problems. Subject to such data being available in the future, further work can be undertaken to investigate the impact of drug consumption or drug policies on health, crime and accidents, amongst others.

Polydrug Use and Drug Mixing. The NDSHS does not collect data on polydrug use where, in particular, individuals mix drug together during consumption. Several epidemiological studies have found that such kind of drug intake is associated with higher risks of overdose, mortality and criminal activities. Since the consequences of drug mixing are far more serious, it would be quite insightful to examine such drug consumption behaviour.

Appendix A
Definition of Variables

Levels of Alcohol Consumption

Abstainer	If not consumed any alcohol in the past year
$Y = 0$	
Non Binger	For males consuming less than 7 drinks and females consuming
$Y = 1$	less than five drinks on a single day
Occasional Binger	For males consuming at least 7 drinks and females consuming
$Y = 2$	at least 5 drinks on a single day no more than 3 days a week
Frequent Binger	For males consuming at least 7 drinks and females consuming
$Y = 3$	at least 5 drinks on a single day on more than 3 days a week

In Chap. 6, drinking statuses are defined according to only *frequency* of drinking as follows:

Abstainer	If not consumed any alcohol in the past year
$Y = 1$	
Occasional Drinker	If drinking 2 to 3 days a month or less on average
$Y = 2$	
Moderate Drinker	If drinking more than weekly but no more than
$Y = 3$	4 days a week on average
Frequent Drinker	If drinking more than 4 days a week on average
$Y = 4$	

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Levels of Cigarette Consumption

Non Smoker	If not smoked any cigarette in the past year
$Y = 0$	
Occasional Smoker	If smoking less than daily
$Y = 1$	
Moderate Smoker	If smoking daily with less than 20 cigarettes (1 pack) per day
$Y = 2$	
Heavy Smoker	If smoking more than 20 cigarettes daily
$Y = 3$	

Participation in Drugs
$\mathbf{Y}_M$: 1 if consumed marijuana in the past year, and 0 otherwise.
$\mathbf{Y}_A$: 1 if consumed amphetamines in the past year, and 0 otherwise.
$\mathbf{Y}_C$: 1 if consumed cocaine in the past year, and 0 otherwise.
$\mathbf{Y}_H$: 1if consumed heroin in the past year, and 0 otherwise.
$\mathbf{Y}_T$: 1 if consumed tobacco in the past year, and 0 otherwise.
$\mathbf{Y}_B$: 1 if consumed beer in the past year, and 0 otherwise.
$\mathbf{Y}_W$: 1 if consumed wine in the past year, and 0 otherwise.
$\mathbf{Y}_S$: 1 if consumed spirits in the past year, and 0 otherwise.

Price and Income
$\mathbf{P}^{alc}$: natural logarithm of real price index of alcohol.
$\mathbf{P}^{tob}$: natural logarithm of real price index of tobacco.
$\mathbf{P}^{mar}$: natural logarithm of real price of marijuana measured in dollars per ounce.
$\mathbf{P}^{amp}$: natural logarithm of real price of amphetamines measured in dollars per gram.
$\mathbf{P}^{coc}$: natural logarithm of real price of cocaine measured in dollars per gram.
$\mathbf{P}^{her}$: natural logarithm of real price of heroin measured in dollars per gram.
$\mathbf{P}^{beer}$: natural logarithm of real price index of beer.
$\mathbf{P}^{wine}$: natural logarithm of real price of wine.
$\mathbf{P}^{spirits}$: natural logarithm of real price of spirits.
Income^p: natural logarithm of real personal annual income before tax measured in Australian Dollars.
Income^h: natural logarithm of real household annual income before tax measured in Australian Dollars.
Marital Status
Married: 1 if married or *de facto,* and 0 otherwise.
Divorced: 1 if divorced, and 0 otherwise.
Widow: 1 if widowed, and 0 otherwise.
Non-partnered: 1 if single, and 0 otherwise.
Educational Attainment
Degree: 1 if the highest qualification is a tertiary degree, 0 otherwise.

Diploma: 1 if the highest qualification is a non-tertiary diploma or trade certificate, and 0 otherwise.
Yr12qual: 1 if the highest qualification is year 12, and 0 otherwise.
LessYr12: 1 if the highest qualification is less than year 12, and 0 otherwise.
Yr10qual: 1 if the highest qualification is year 10, and 0 otherwise.
LessYr10: 1 if the highest qualification is less than year 10, and 0 otherwise.
SecEdu: 1 if highest qualification is a non-tertiary diploma, trade or non-trade certificate or at least year 12, 0 otherwise.
Main Occupation
Work: 1 if employed part-time or full-time, and 0 otherwise.
Study: 1 if mainly study, 0 otherwise.
Unemp: 1 if unemployed, 0 otherwise.
Otheract: 1 if retired, on pension or performing home duties, 0 otherwise (used as the reference category).
Using the Australian Standard Classification of Occupations guidelines, employed individuals are classified into white and blue collar workers. Blue collar occupations includes tradespersons; intermediate production and transport workers; and labourers and related workers. White collar workers include managers; professionals, para-professionals; clerks; sales persons; and personal service workers.
Bluejob: 1 for a blue collar job, 0 otherwise.
Whitejob: 1 for a white collar job, 0 otherwise.
Health
Excelhlth: 1 if health is perceived as very good or excellent, 0 otherwise.
Goodhlth: 1 if health is perceived as fair to good, 0 otherwise.
Poorhlth: 1 if health is perceived as poor, 0 otherwise.
State
NSW: 1 if from New South Wales, 0 otherwise (used as the reference category).
VIC: 1 if from Victoria, 0 otherwise.
QLD: 1 if from Queensland, 0 otherwise.
SA: 1 if from South Australia, 0 otherwise.
WA: 1 if from Western Australia, 0 otherwise.
TAS: 1 if from Tasmania, 0 otherwise.
ACT: 1 if from Australian Capital Territory, 0 otherwise.
NT: 1 if from Northern Territory, 0 otherwise.
Industry
Primary: 1 if working in primary industry, 0 otherwise.
Manufac: 1 if working in manufacturing industry, 0 otherwise.
Utils & Cons: if working in utilities and construction industry, 0 otherwise.
Trade: 1 if working in trade industry, 0 otherwise (used as the reference category).
Transport: 1 if working in transport and storage industry, 0 otherwise.
Communic: 1 if working in communications services industry, 0 otherwise.
Finance: 1 if working in finance industry, 0 otherwise.
Govt Admin: 1 if working in govt. administration and defence industry, 0 otherwise.
Education: 1 if working in education industry, 0 otherwise.
Health: 1 if working in health and community services industry, 0 otherwise.

Recreat: 1 if working in cultural and recreational services industry, 0 otherwise.
Personal: 1 if working in personal and other services industry, 0 otherwise.
Occupation
Admin: 1 if occupation falls under "managers and administrators", 0 otherwise.
Prof: 1 if occupation falls under "professionals", 0 otherwise.
AsscProf: 1 if occupation falls under "associate professionals", 0 otherwise.
Traders: 1 if occupation falls under "tradesperson and related workers", 0 otherwise.
Clerical: 1 if occupation falls under "advanced clerical and service workers", 0 otherwise.
Sales: 1 if occupation falls under "intermediate clerical, sales and service workers", 0 otherwise (used as the reference category).
Production: 1 if occupation falls under "intermediate production and transport workers", 0 otherwise.
Service: 1 if occupation falls under "elementary clerical, sales and service workers", 0 otherwise.
Labourer: 1 if occupation falls under "labourers and related workers", 0 otherwise.
Other
Earnings: natural logarithm of real personal annual income before tax measured in Australian Dollars.
Age: natural logarithm of individual's actual age.
Agesq: square of Age variable.
Male: 1 for male, 0 otherwise.
Depchld: 1 if there are preschool children in the household, 0 otherwise.
Singpar: 1 if coming from a single parent household, 0 otherwise.
Numchld: number of dependent children aged 14 or below in the household.
Capital: 1 if resides in a capital city, 0 otherwise,
ATSI: 1 if respondent is of Aboriginal or Torres Strait Islander origin, 0 otherwise.
Yngdrnk: 1 if started drinking before age 18.
Decrim: 1 if resident of states where small possession is decriminalised and 0 otherwise.

Appendix B
Appendix to Chap. 3

Table B.1 Guidelines for alcohol consumption

	Low risk (standard drinks)	Risky	High risk
For risk of harm in the short-term:			
Males			
On any one day	Up to 6 on any one day, no more than 3 days per week	7–10 on any one day	11 or more on any one day
Females			
On any one day	Up to 4 on any one day, no more than 3 days per week	5–6 on any one day	7 or more on any one day
For risk of harm in the long-term:			
Males			
On an average day	Up to 4 per day	5–6 per day	7 or more per day
Overall weekly level	Up to 28 per week	29–42 per week	43 or more per week
Females			
On an average day	Up to 2 per day	3–4 per day	5 or more per day
Overall weekly level	Up to 14 per week	15–28 per week	29 or more per week

Note: It is assumed that the drinks are consumed at a moderate rate to minimise intoxication, e.g. for men, no more than 2 drinks in the first hour and 1 per hour thereafter, and for women, no more than 1 drink per hour. Applies to persons of average or larger size, i.e. above about 60 kg for men and 50 kg for women. Persons of smaller than average body size should drink within lower levels.
Source: National Health and Medical Research Council (NHMRC 2001)

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Appendix C
Appendix to Chap. 5

Marginal Effects and Standard Errors

Let $\hat{F} = f(\mathbf{x}, \hat{\boldsymbol{\beta}})$ represent the predicted probability which is a function of $\mathbf{x}$ and the estimated coefficients, $\hat{\boldsymbol{\beta}}$. Where analytical expressions of the marginal effects are hard to come by, they can be approximated via the numerical gradient command in Gauss,

$$\hat{\pi} = \frac{\partial \hat{F}}{\partial \mathbf{x}} = gradient(\hat{F}; \mathbf{x}).$$

Standard errors of predicted probabilities and marginal effects can be obtained using the delta method (Greene 2003). For the predicted probabilities,

$$Asy.\ Var[\hat{F}] = \left\{ \frac{\partial \hat{F}}{\partial \hat{\beta}} \right\}' V \left\{ \frac{\partial \hat{F}}{\partial \hat{\beta}} \right\}$$

where $V = Asy.Var(\hat{\beta})$.
For the marginal effects,

$$Asy.\ Var[\hat{\pi}] = \left\{ \frac{\partial^2 \hat{F}}{\partial \hat{\beta}\ \partial \mathbf{x}} \right\}' V \left\{ \frac{\partial^2 \hat{F}}{\partial \hat{\beta}\ \partial \mathbf{x}} \right\}$$

where $V = Asy.Var(\hat{\beta})$ and once again numerical techniques can be used to evaluate

$$\frac{\partial^2 \hat{F}}{\partial \hat{\beta}\ \partial \mathbf{x}} = hessian(\hat{F}; \mathbf{x}, \hat{\beta}).$$

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Table C.1 Multivariate probit results (marijuana)

	Marijuana						
	Coefficient		Marginal effect		Correlation coefficient		
Constant	−10.382	(1.681)**			ρ_{MC}	0.641	(0.019)**
P^{mar}	−0.306	(0.082)**	−0.048	(0.013)**	ρ_{MA}	0.679	(0.012)**
P^{coc}	0.079	(0.049)	0.012	(0.008)	ρ_{CH}	0.757	(0.034)**
P^{her}	0.099	(0.043)**	0.016	(0.007)**	ρ_{MH}	0.524	(0.047)**
P^{amp}	−0.006	(0.022)	−0.001	(0.003)	ρ_{CA}	0.753	(0.015)**
P^{tob}	−0.607	(0.163)**	−0.096	(0.026)**	ρ_{HA}	0.706	(0.031)**
Income^h	−0.086	(0.014)**	−0.014	(0.002)**	ρ_{MT}	0.484	(0.009)**
Decrim	0.008	(0.030)	0.001	(0.005)	ρ_{CT}	0.353	(0.021)**
Age	9.570	(0.476)**	1.514	(0.068)**	ρ_{HT}	0.320	(0.041)**
Agesq	−1.547	(0.068)**	−0.245	(0.010)**	ρ_{AT}	0.409	(0.015)**
Male	0.329	(0.019)**	0.052	(0.003)**			
Married	−0.418	(0.021)**	−0.066	(0.003)**			
Depchld	−0.145	(0.027)**	−0.023	(0.004)**			
Singpar	0.076	(0.031)**	0.012	(0.005)**			
Capital	0.014	(0.020)	0.002	(0.003)			
ATSI	0.185	(0.067)**	0.029	(0.011)**			
Degree	−0.024	(0.029)	−0.004	(0.004)			
Diploma	0.044	(0.026)*	0.007	(0.004)*			
Yr12qual	−0.013	(0.028)	−0.002	(0.004)			
Bluejob	0.111	(0.034)**	0.017	(0.005)**			
Whitejob	0.031	(0.029)	0.005	(0.005)			
Unemp	0.122	(0.042)**	0.019	(0.007)**			
Study	0.075	(0.045)*	0.012	(0.007)*			

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.2 Multivariate probit results (cocaine and heroin)

	Cocaine				*Heroin*			
	Coefficient		Marginal effect		Coefficient		Marginal effect	
Constant	−6.813	(4.131)*			1.762	(6.975)		
P^{mar}	−0.342	(0.172)**	−0.003	(0.002)*	−0.140	(0.324)	−0.0004	(0.0009)
P^{coc}	−0.023	(0.109)	0.000	(0.001)	−0.464	(0.234)**	−0.0013	(0.001)*
P^{her}	−0.406	(0.098)**	−0.004	(0.001)**	−0.119	(0.187)	−0.0003	(0.0005)
P^{amp}	0.056	(0.053)	0.001	(0.001)	−0.020	(0.092)	−0.0001	(0.0003)
P^{tob}	−1.173	(0.363)**	−0.012	(0.004)**	−2.704	(0.684)**	−0.0075	(0.003)**
$Income^h$	0.101	(0.033)**	0.001	(0.000)**	−0.097	(0.055)*	−0.0003	(0.000)*
Age	8.902	(1.606)**	0.088	(0.011)**	9.633	(2.363)**	0.0266	(0.006)**
Agesq	−1.420	(0.235)**	−0.014	(0.002)**	−1.477	(0.351)**	−0.0041	(0.001)**
Male	0.105	(0.041)**	0.001	(0.000)**	0.211	(0.081)**	0.0006	(0.000)**
Married	−0.476	(0.046)**	−0.005	(0.001)**	−0.387	(0.088)**	−0.0011	(0.000)**
Depchld	−0.067	(0.062)	−0.001	(0.001)	0.114	(0.115)	0.0003	(0.0003)
Singpar	−0.198	(0.079)**	−0.002	(0.001)**	0.085	(0.121)	0.0002	(0.0003)
Capital	0.307	(0.054)**	0.003	(0.001)**	0.109	(0.093)	0.0003	(0.0003)
ATSI	0.080	(0.224)	0.001	(0.002)	−0.052	(0.242)	−0.0001	(0.0007)
Degree	0.169	(0.070)**	0.002	(0.001)**	−0.191	(0.129)	−0.0005	(0.0004)
Diploma	0.194	(0.067)**	0.002	(0.001)**	−0.058	(0.101)	−0.0002	(0.0003)
Yr12qual	0.050	(0.070)	0.000	(0.001)	−0.082	(0.111)	−0.0002	(0.0003)
Bluejob	0.174	(0.086)**	0.002	(0.001)**	−0.068	(0.127)	−0.0002	(0.0004)
Whitejob	0.165	(0.077)**	0.002	(0.001)**	−0.365	(0.129)**	−0.0010	(0.000)**
Unemp	0.153	(0.098)	0.002	(0.001)	−0.097	(0.140)	−0.0003	(0.0004)
Study	0.033	(0.102)	0.000	(0.001)	−0.092	(0.151)	−0.0003	(0.0004)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.3 Multivariate probit results (amphetamines and tobacco)

	Amphetamines				*Tobacco*			
	Coefficient		Marginal effect		Coefficient		Marginal effect	
Constant	−12.253	(2.352)**			−14.458	(1.169)**		
P^{mar}	−0.512	(0.106)**	−0.015	(0.003)**	0.047	(0.057)	0.014	(0.017)
P^{coc}	0.140	(0.072)*	0.004	(0.002)*	0.065	(0.037)*	0.019	(0.011)*
P^{her}	0.195	(0.063)**	0.005	(0.002)**	−0.052	(0.034)	−0.015	(0.010)
P^{amp}	−0.082	(0.033)**	−0.002	(0.001)**	0.037	(0.017)**	0.011	(0.005)**
P^{tob}	−0.819	(0.229)**	0.023	(0.007)**	−0.265	(0.120)**	−0.078	(0.035)**
$Income^{h}$	−0.031	(0.022)	−0.001	(0.001)	−0.151	(0.012)**	−0.044	(0.004)**
Age	9.416	(0.789)**	0.271	(0.020)**	9.987	(0.359)**	2.931	(0.104)**
Agesq	−1.556	(0.114)**	−0.045	(0.003)**	−1.471	(0.050)**	−0.432	(0.015)**
Male	0.211	(0.030)**	0.006	(0.001)**	0.135	(0.016)**	0.040	(0.005)**
Married	−0.498	(0.032)**	−0.014	(0.001)**	−0.297	(0.017)**	−0.087	(0.005)**
Depchld	−0.153	(0.043)**	−0.004	(0.001)**	−0.097	(0.023)**	−0.028	(0.007)**
Singpar	−0.047	(0.047)	−0.001	(0.001)	0.106	(0.028)**	0.031	(0.008)**
Capital	0.122	(0.032)**	0.004	(0.001)**	−0.014	(0.016)	−0.004	(0.005)
ATSI	0.211	(0.096)**	0.006	(0.003)**	0.266	(0.059)**	0.078	(0.017)**
Degree	−0.129	(0.046)**	−0.004	(0.001)**	−0.507	(0.023)**	−0.149	(0.007)**
Diploma	0.071	(0.038)*	0.002	(0.001)*	−0.123	(0.020)**	−0.036	(0.006)**
Yr12qual	−0.054	(0.043)	−0.002	(0.001)	−0.173	(0.023)**	−0.051	(0.007)**
Bluejob	0.087	(0.054)	0.003	(0.002)	0.122	(0.026)**	0.036	(0.008)**
Whitejob	−0.029	(0.048)	−0.001	(0.001)	−0.026	(0.022)	−0.008	(0.007)
Unemp	−0.052	(0.061)	−0.002	(0.002)	−0.079	(0.038)**	−0.023	(0.011)**
Study	−0.090	(0.066)	−0.003	(0.002)	−0.080	(0.041)*	−0.023	(0.012)**

* significant at 10 % level; ** significant at 5 % level

Table C.4 Marginal effects on selected probabilities-marijuana

	$P(Y_M = 1\|\bar{\mathbf{x}})$		$P(Y_M = 1, Y_A = 0, Y_T = 0, Y_C = 0, Y_H = 0, \bar{\mathbf{x}})$		$P(Y_M = 1\|Y_C = 1, Y_H = 1, \bar{\mathbf{x}})$	
Age	1.5138	(0.068)**	0.2089	(0.031)**	1.2135	(0.420)**
Agesq	−0.2446	(0.010)**	−0.0384	(0.005)**	−0.2029	(0.065)**
Male	0.0520	(0.003)**	0.0150	(0.001)**	0.0742	(0.018)**
Married	−0.0661	(0.003)**	−0.0133	(0.001)**	−0.0435	(0.015)**
Depchld	−0.0229	(0.004)**	−0.0051	(0.002)**	−0.0414	(0.013)**
Singpar	0.0120	(0.005)**	0.0016	(0.002)	0.0438	(0.021)**
Capital	0.0023	(0.003)	0.0004	(0.001)	−0.0414	(0.013)**
ATSI	0.0292	(0.011)**	0.0015	(0.004)	0.0483	(0.077)
Degree	−0.0038	(0.004)	0.0164	(0.002)**	−0.0187	(0.017)
Diploma	0.0070	(0.004)*	0.0065	(0.002)**	−0.0084	(0.014)
Yr12qual	−0.0021	(0.004)	0.0053	(0.002)**	−0.0060	(0.014)
Bluejob	0.0175	(0.005)**	0.0023	(0.002)	0.0147	(0.016)
Whitejob	0.0049	(0.005)	0.0030	(0.002)*	0.0083	(0.018)
Unemp	0.0193	(0.007)**	0.0107	(0.003)**	0.0224	(0.026)
Study	0.0119	(0.007)*	0.0081	(0.003)**	0.0235	(0.032)
Decrim	0.0013	(0.005)	0.0005	(0.002)	0.0026	(0.011)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.5 Marginal effects on selected probabilities-cocaine

	$P(Y_C = 1\|\bar{\mathbf{x}})$		$P(Y_C = 1\|Y_H = 1, Y_A = 1, \bar{\mathbf{x}})$		$P(Y_C = 1\|Y_H = 1, \bar{\mathbf{x}})$		$P(Y_C = 1\|Y_M = 1, Y_A = 1, Y_T = 1, \bar{\mathbf{x}})$	
Age	0.0882	(0.011)**	−0.2542	(0.697)	1.2105	(1.289)	0.4555	(1.495)
Agesq	−0.0141	(0.002)**	0.0376	(0.103)	−0.2169	(0.190)	−0.0406	(0.224)
Male	0.0010	(0.000)**	−0.0376	(0.021)*	−0.0244	(0.037)	−0.0617	(0.040)
Married	−0.0047	(0.001)**	−0.0123	(0.025)	−0.1161	(0.042)**	−0.0409	(0.042)
Depchld	−0.0007	(0.001)	−0.0215	(0.030)	−0.0840	(0.067)	0.0569	(0.057)
Singpar	−0.0020	(0.001)**	−0.0785	(0.040)*	−0.1472	(0.102)	−0.1429	(0.071)**
Capital	0.0030	(0.001)**	0.0668	(0.031)**	0.1312	(0.044)**	0.1800	(0.052)**
ATSI	0.0008	(0.002)	0.0049	(0.091)	0.0664	(0.371)	−0.0987	(0.228)
Degree	0.0017	(0.001)**	0.1167	(0.046)**	0.1731	(0.065)**	0.2800	(0.073)**
Diploma	0.0019	(0.001)**	0.0679	(0.035)*	0.1338	(0.051)**	0.1278	(0.060)**
Yr12qual	0.0005	(0.001)	0.0420	(0.030)	0.0613	(0.054)	0.0960	(0.063)
Bluejob	0.0017	(0.001)**	0.0604	(0.045)	0.1266	(0.081)	0.0839	(0.077)
Whitejob	0.0016	(0.001)**	0.1333	(0.055)**	0.2403	(0.063)**	0.1695	(0.071)**
Unemp	0.0015	(0.001)	0.0807	(0.049)	0.1261	(0.137)	0.1851	(0.087)**
Study	0.0003	(0.001)	0.0436	(0.042)	0.0555	(0.136)	0.1057	(0.087)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.6 Marginal effects on selected probabilities-heroin

	$P(Y_H = 1\mid\bar{\mathbf{x}})$		$P(Y_H = 1\mid Y_M = 1, \bar{\mathbf{x}})$		$P(Y_H = 1\mid Y_C = 1, Y_A = 1, \bar{\mathbf{x}})$		$P(Y_H = 1\mid Y_C = 1, \bar{\mathbf{x}})$	
Age	0.0266	(0.006)**	0.1183	(0.036)**	0.8072	(0.348)**	0.9239	(0.545)*
Agesq	−0.0041	(0.001)**	−0.0175	(0.005)**	−0.1194	(0.051)**	−0.1323	(0.081)*
Male	0.0006	(0.000)**	0.0016	(0.002)	0.0284	(0.015)*	0.0354	(0.022)
Married	−0.0011	(0.000)**	−0.0045	(0.002)**	−0.0206	(0.015)	−0.0170	(0.022)
Depchld	0.0003	(0.0003)	0.0034	(0.004)	0.0250	(0.020)	0.0403	(0.031)
Singpar	0.0002	(0.0003)	0.0011	(0.004)	0.0378	(0.023)	0.0555	(0.039)
Capital	0.0003	(0.0003)	0.0021	(0.002)	−0.0152	(0.017)	−0.0246	(0.025)
ATSI	−0.0001	(0.0007)	−0.0025	(0.030)	−0.0146	(0.049)	−0.0269	(0.129)
Degree	−0.0005	(0.0004)	−0.0037	(0.003)	−0.0563	(0.026)**	−0.0773	(0.036)**
Diploma	−0.0002	(0.0003)	−0.0015	(0.002)	−0.0320	(0.020)	−0.0478	(0.029)
Yr12qual	−0.0002	(0.0003)	−0.0015	(0.003)	−0.0214	(0.020)	−0.0293	(0.033)
Bluejob	−0.0002	(0.0004)	−0.0022	(0.003)	−0.0310	(0.025)	−0.0469	(0.035)
Whitejob	−0.0010	(0.000)**	−0.0076	(0.004)**	−0.0843	(0.033)**	−0.1207	(0.044)**
Unemp	−0.0003	(0.0004)	−0.0029	(0.009)	−0.0363	(0.027)	−0.0507	(0.041)
Study	−0.0003	(0.0004)	−0.0024	(0.014)	−0.0218	(0.028)	−0.0288	(0.060)

* significant at 10 % level; ** significant at 5 % level

Table C.7 Marginal effects on selected probabilities-amphetamines

	$P(Y_A = 1\|\bar{\mathbf{x}})$		$P(Y_A = 1\|Y_M = 1, \bar{\mathbf{x}})$		$P(Y_A = 1\|Y_M = 1, Y_C = 1, Y_H = 1, Y_T = 1, \bar{\mathbf{x}})$		$P(Y_A = 1\|Y_M = 1, Y_C = 1, Y_H = 1, \bar{\mathbf{x}})$	
Age	0.2708	(0.020)**	0.9050	(0.171)**	1.9374	(0.693)**	2.0122	(0.528)**
Agesq	−0.0448	(0.003)**	−0.1545	(0.024)**	−0.3314	(0.584)	−0.3414	(0.077)**
Male	0.0061	(0.001)**	0.0045	(0.007)	0.0573	(0.017)**	0.0579	(0.017)**
Married	−0.0143	(0.001)**	−0.0602	(0.008)**	−0.1047	(0.018)**	−0.1054	(0.018)**
Depchld	−0.0044	(0.001)**	−0.0163	(0.010)*	−0.0357	(0.027)	−0.0353	(0.024)
Singpar	−0.0014	(0.001)	−0.0218	(0.011)**	0.0229	(0.040)	0.0265	(0.030)
Capital	0.0035	(0.001)**	0.0270	(0.008)**	−0.0110	(0.020)	−0.0136	(0.021)
ATSI	0.0061	(0.003)**	0.0244	(0.024)	0.0579	(0.096)	0.0602	(0.082)
Degree	−0.0037	(0.001)**	−0.0272	(0.011)**	−0.1053	(0.030)**	−0.1166	(0.030)**
Diploma	0.0020	(0.001)*	0.0107	(0.009)	−0.0193	(0.025)	−0.0238	(0.025)
Yr12qual	−0.0016	(0.001)	−0.0110	(0.010)	−0.0395	(0.026)	−0.0434	(0.026)*
Bluejob	0.0025	(0.002)	0.0054	(0.012)	−0.0165	(0.031)	−0.0178	(0.032)
Whitejob	−0.0008	(0.001)	−0.0111	(0.011)	−0.0788	(0.031)**	−0.0842	(0.033)**
Unemp	−0.0015	(0.002)	−0.0294	(0.014)**	−0.0781	(0.042)*	−0.0833	(0.035)**
Study	−0.0026	(0.002)	−0.0318	(0.016)**	−0.0622	(0.050)	−0.0657	(0.039)*

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.8 Marginal effects on selected probabilities-tobacco

	$P(Y_T = 1 \mid \bar{\mathbf{x}})$		$P(Y_M = 0, Y_C = 0, Y_H = 0, Y_T = 1, Y_A = 0, \bar{\mathbf{x}})$		$P(Y_T = 1 \mid Y_M = 1, \bar{\mathbf{x}})$		$P(Y_T = 1 \mid Y_M = 1, Y_C = 1, Y_A = 1, \bar{\mathbf{x}})$	
Age	2.931	(0.104)**	1.657	(0.092)**	1.912	(0.197)**	1.407	(0.203)**
Agesq	−0.432	(0.015)**	−0.231	(0.013)**	−0.247	(0.028)**	−0.189	(0.029)**
Male	0.040	(0.005)**	0.005	(0.004)	−0.025	(0.008)**	0.006	(0.006)
Married	−0.087	(0.005)**	−0.037	(0.004)**	−0.023	(0.008)**	−0.015	(0.007)**
Depchld	−0.028	(0.007)**	−0.011	(0.006)**	−0.005	(0.011)	−0.011	(0.010)
Singpar	0.031	(0.008)**	0.021	(0.007)**	0.027	(0.013)**	0.041	(0.015)**
Capital	−0.004	(0.005)	−0.006	(0.004)	−0.010	(0.008)	−0.030	(0.006)**
ATSI	0.078	(0.017)**	0.051	(0.014)**	0.069	(0.036)*	0.055	(0.081)
Degree	−0.149	(0.007)**	−0.127	(0.006)**	−0.216	(0.011)**	−0.155	(0.013)**
Diploma	−0.036	(0.006)**	−0.036	(0.005)**	−0.065	(0.009)**	−0.054	(0.008)**
Yr12qual	−0.051	(0.007)**	−0.043	(0.006)**	−0.072	(0.011)**	−0.052	(0.011)**
Bluejob	0.036	(0.008)**	0.021	(0.007)**	0.025	(0.013)**	0.012	(0.012)
Whitejob	−0.008	(0.007)	−0.009	(0.006)*	−0.019	(0.011)*	−0.023	(0.009)**
Unemp	−0.023	(0.011)**	−0.031	(0.010)**	−0.066	(0.019)**	−0.043	(0.027)
Study	−0.023	(0.012)**	−0.027	(0.010)**	−0.054	(0.022)**	−0.030	(0.029)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table C.9 BWS—multivariate probit coefficient estimates

	Beer		Wine		Spirits	
Constant	−9.185	(1.339)**	−5.774	(1.313)**	−1.500	(1.318)
P^{beer}	−1.040	(0.269)**	0.283	(0.268)	0.036	(0.265)
P^{wine}	0.462	(0.267)*	−2.201	(0.262)**	0.649	(0.266)**
$P^{spirits}$	0.699	(0.229)**	1.541	(0.228)**	−0.735	(0.227)**
Age	4.509	(0.289)**	2.920	(0.285)**	1.516	(0.282)**
Agesq	−0.652	(0.040)**	−0.340	(0.039)**	−0.333	(0.039)**
Male	1.194	(0.014)**	−0.475	(0.014)**	−0.159	(0.014)**
Married	−0.091	(0.020)**	0.166	(0.020)**	−0.217	(0.020)**
Divorced	−0.111	(0.028)**	0.072	(0.027)**	−0.127	(0.027)**
Widow	−0.064	(0.039)	−0.038	(0.037)	−0.167	(0.039)**
Numchld	−0.034	(0.007)**	−0.015	(0.002)**	−0.046	(0.007)**
Capital	−0.114	(0.015)**	0.208	(0.014)**	0.001	(0.015)
ATSI	0.009	(0.049)	−0.336	(0.051)**	−0.055	(0.051)
Degree	0.025	(0.023)	0.909	(0.023)**	0.030	(0.023)
Diploma	0.096	(0.021)**	0.405	(0.021)**	0.222	(0.021)**
Yr12qual	0.076	(0.023)**	0.459	(0.023)**	0.285	(0.023)**
Yr10qual	0.005	(0.022)	0.216	(0.022)**	0.195	(0.022)**
Work	0.073	(0.018)**	0.212	(0.017)**	0.051	(0.018)**
Study	−0.028	(0.029)	0.236	(0.030)**	−0.232	(0.029)**
Unemp	0.040	(0.036)	−0.005	(0.037)	0.026	(0.036)
ρ_{BW}	0.111	(0.009)**				
ρ_{WS}	0.169	(0.009)**				
ρ_{BS}	0.058	(0.009)**				

Standard errors are given in parentheses

* significant at 10 % level; ** significant at 5 % level

Table C.10 BWS—marginal effects on unconditional probabilities

	Beer		Wine		Spirits	
Constant	−3.581	(0.945)**	−2.294	(0.681)**	−0.563	(0.426)
P^{beer}	−0.406	(0.130)**	0.113	(0.091)	0.014	(0.082)
P^{wine}	0.180	(0.093)*	−0.875	(0.235)**	0.244	(0.109)**
$P^{spirits}$	0.273	(0.099)**	0.612	(0.171)**	−0.276	(0.104)**
Age	1.758	(0.424)**	1.160	(0.288)**	0.569	(0.156)**
Agesq	−0.254	(0.060)**	−0.135	(0.035)**	−0.125	(0.034)**
Male	0.465	(0.116)**	−0.189	(0.051)**	−0.060	(0.026)**
Married	−0.036	(0.017)**	0.066	(0.024)**	−0.081	(0.026)**
Divorced	−0.043	(0.017)**	0.029	(0.018)	−0.048	(0.019)**
Widow	−0.025	(0.082)	−0.015	(0.084)	−0.063	(0.089)
Numchld	−0.013	(0.009)	−0.006	(0.009)	−0.017	(0.009)*
Capital	−0.044	(0.019)**	0.083	(0.026)**	0.000	(0.017)
ATSI	0.003	(0.013)	−0.134	(0.035)**	−0.021	(0.014)
Degree	0.010	(0.006)	0.361	(0.090)**	0.011	(0.006)*
Diploma	0.038	(0.013)**	0.161	(0.041)**	0.084	(0.025)**
Yr12qual	0.030	(0.014)**	0.182	(0.046)**	0.107	(0.032)**
Yr10qual	0.002	(0.005)	0.086	(0.022)**	0.073	(0.021)**
Work	0.029	(0.014)*	0.084	(0.025)**	0.019	(0.014)
Study	−0.011	(0.005)**	0.094	(0.024)**	−0.087	(0.024)**
Unemp	0.016	(0.007)**	−0.002	(0.006)	0.010	(0.007)

Standard errors are given in parentheses

* significant at 10 % level; ** significant at 5 % level

Appendix D
Appendix to Chap. 7

Table D.1 Summary statistics by drinking status

	Abstainer	Non binger	Occasional binger	Frequent binger
Mean:				
Earnings[a]	10.180	10.328	10.410	10.306
Age	42.859	43.693	38.500	39.673
%:				
Capital	70.843	69.278	66.422	59.508
Male	46.194	51.350	56.757	63.131
Married	70.035	73.050	68.749	56.781
Depchld	14.573	13.606	17.244	10.478
Singpar	4.884	5.772	7.154	6.746
ATSI	1.827	0.956	1.151	2.471
Yngdrnk	31.014	59.931	83.449	84.955
Degree	32.187	34.005	34.550	20.456
SecEdu	44.105	46.819	49.441	55.468
LessYr12[b]	23.399	19.039	15.884	23.969
Excelhlth	59.8592	60.1177	57.0139	42.2553
Goodhlth	39.0845	39.2048	42.3889	56.1892
Poorhlth[b]	1.0563	0.6775	0.5972	1.5554
Industry:				
Primary	2.751	3.453	4.851	4.654
Manufac	12.092	10.277	10.319	12.526
Util & Cons	2.815	3.908	4.331	5.441
Trade[b]	16.507	14.179	15.110	19.507
Transport	4.607	4.991	5.182	6.845

(continued)

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Table D.1 (continued)

	Abstainer	Non binger	Occasional binger	Frequent binger
Communic	3.135	1.715	1.913	1.985
Finance	15.867	16.474	18.982	16.632
Govt Admin	7.230	7.628	8.587	6.708
Education	10.173	12.382	8.361	5.749
Health	15.995	15.196	11.223	8.624
Recreat	1.663	2.200	2.802	2.122
Personal	4.223	3.560	3.977	3.696
Occupation:				
Admin	5.932	9.176	11.598	8.380
Prof	25.983	28.724	26.317	16.274
AsscProf	12.830	13.650	15.647	15.028
Traders	9.478	10.205	11.781	17.521
Clerical	2.901	3.086	3.075	2.909
Sales[b]	20.245	17.813	16.865	15.235
Production	7.157	6.580	5.540	10.803
Service	6.512	5.084	4.429	4.571
Labourer	8.511	5.395	4.399	9.141

[a]used as the reference category in the estimation. [b]Natural logarithmic of real annual earnings before tax measured in Australian dollars

Table D.2 First-stage drinking status choice model estimates

	Moderate drinkers		Occasional bingers		Frequent bingers	
Constant	−1.823	(8.068)	−6.219	(8.445)	8.578	(10.676)
Age	2.616	(3.705)	8.002	(3.888)**	−1.969	(4.923)
Agesq	−0.236	(0.503)	−1.263	(0.529)**	0.166	(0.671)
Male	0.051	(0.058)	0.242	(0.061)**	0.541	(0.079)**
Married	0.133	(0.065)**	0.027	(0.069)	−0.547	(0.085)**
Depchld	−0.094	(0.087)	−0.291	(0.090)**	−0.603	(0.124)**
Singpar	0.281	(0.132)**	0.507	(0.136)**	0.143	(0.169)
ATSI	−0.577	(0.231)**	−0.551	(0.242)**	0.119	(0.274)
Yngdrnk	1.259	(0.060)**	2.259	(0.064)**	2.454	(0.094)**
Capital	−0.035	(0.062)	−0.195	(0.065)**	−0.404	(0.081)**
Degree	0.298	(0.078)**	0.349	(0.083)**	−0.544	(0.110)**
SecEdu	0.266	(0.073)**	0.324	(0.078)**	0.023	(0.096)
P^{alc}	−0.832	(0.929)	−1.330	(0.978)	−1.020	(1.251)

Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

Table D.3 Decomposition of earnings differentials due to returns to characteristics

	$E_a - E_{nb}$		$E_a - E_{fb}$		$E_{fb} - E_{nb}$		$E_{fb} - E_{ob}$	
Ret. to Charac.	−0.3668	(0.193)*	−0.1287	(0.199)	−0.2197	(0.148)	−0.1469	(0.141)
of which:								
Age:30–34	−0.0013	(0.009)	−0.0117	(0.010)	0.0097	(0.006)	0.0069	(0.008)
35–39	−0.0245	(0.009)**	−0.0316	(0.011)**	0.0044	(0.007)	0.0044	(0.008)
40–44	−0.0220	(0.010)**	−0.0201	(0.011)	−0.0010	(0.008)	0.0083	(0.007)
45–49	−0.0221	(0.011)**	−0.0120	(0.012)	−0.0085	(0.008)	0.0029	(0.007)
50–54	−0.0365	(0.011)**	−0.0249	(0.010)**	−0.0054	(0.008)	0.0077	(0.006)
55–60	−0.0319	(0.010)**	−0.0082	(0.009)	−0.0161	(0.007)**	−0.0019	(0.004)
Male	−0.0437	(0.017)**	0.0075	(0.025)	−0.0595	(0.021)**	−0.0478	(0.021)**
Married	0.0334	(0.023)	−0.0490	(0.029)*	0.0808	(0.023)**	0.0670	(0.022)**
ATSI	0.0007	(0.002)	0.0016	(0.003)	−0.0004	(0.002)	−0.0026	(0.002)
Capital	0.0111	(0.025)	−0.0069	(0.027)	0.0172	(0.021)	0.0183	(0.020)
Degree	−0.0480	(0.017)**	−0.0279	(0.020)	−0.0105	(0.016)	−0.0049	(0.016)
SecEdu	−0.0405	(0.020)**	−0.0359	(0.026)	−0.0089	(0.018)	−0.0146	(0.020)
Excelhlth	−0.0550	(0.098)	0.0461	(0.091)	−0.0930	(0.063)	−0.0317	(0.062)
Goodhlth	−0.0138	(0.064)	0.0800	(0.084)	−0.0972	(0.058)*	−0.0642	(0.060)
VIC	−0.0039	(0.009)	−0.0203	(0.010)*	0.0178	(0.008)**	0.0115	(0.008)
QLD	−0.0041	(0.007)	−0.0068	(0.010)	0.0022	(0.007)	0.0020	(0.007)
SA	−0.0098	(0.005)**	−0.0095	(0.006)	−0.0003	(0.004)	−0.0002	(0.005)
WA	0.0008	(0.006)	0.0010	(0.007)	−0.0002	(0.005)	−0.0068	(0.005)
TAS	−0.0026	(0.003)	−0.0004	(0.004)	−0.0036	(0.003)	0.0010	(0.003)
ACT	−0.0051	(0.004)	−0.0052	(0.005)	0.0014	(0.004)	0.0025	(0.004)
NT	−0.0044	(0.004)	−0.0045	(0.006)	−0.0012	(0.004)	0.0014	(0.004)

(continued)

Table D.3 (continued)

	$E_a - E_{nb}$		$E_a - E_{fb}$		$E_{fb} - E_{nb}$		$E_{fb} - E_{ob}$	
Industry								
Primary	0.0007	(0.003)	0.0001	(0.004)	0.0008	(0.003)	0.0000	(0.004)
Manufac	−0.0101	(0.007)	−0.0133	(0.009)	0.0019	(0.006)	0.0018	(0.006)
Utils & Cons	−0.0094	(0.005)*	−0.0190	(0.007)**	0.0082	(0.005)	0.0097	(0.006)*
Transport	−0.0031	(0.004)	−0.0062	(0.005)	0.0025	(0.004)	0.0020	(0.004)
Communic	−0.0034	(0.002)	−0.0026	(0.003)	−0.0006	(0.002)	−0.0006	(0.002)
Finance	−0.0113	(0.009)	−0.0152	(0.011)	0.0039	(0.008)	−0.0001	(0.009)
Govt Admin	0.0026	(0.005)	0.0039	(0.006)	−0.0014	(0.004)	−0.0024	(0.005)
Education	−0.0100	(0.008)	−0.0140	(0.008)*	0.0078	(0.006)	0.0073	(0.005)
Health	−0.0041	(0.010)	−0.0057	(0.009)	0.0023	(0.007)	−0.0011	(0.006)
Recreat	−0.0024	(0.002)	−0.0018	(0.003)	−0.0005	(0.002)	−0.0022	(0.002)
Personal	−0.0089	(0.003)**	−0.0065	(0.004)	−0.0023	(0.003)	−0.0021	(0.003)
Occupation								
Admin	0.0011	(0.005)	0.0053	(0.006)	−0.0052	(0.005)	−0.0114	(0.006)*
Prof	−0.0048	(0.015)	0.0129	(0.015)	−0.0177	(0.012)	−0.0190	(0.012)
AsscProf	0.0053	(0.007)	0.0138	(0.010)	−0.0083	(0.007)	−0.0134	(0.007)*
Traders	0.0025	(0.007)	0.0159	(0.011)	−0.0128	(0.007)*	−0.0277	(0.007)**
Clerical	0.0029	(0.003)	0.0059	(0.003)*	−0.0032	(0.002)	−0.0048	(0.002)**
Production	0.0024	(0.005)	0.0083	(0.008)	−0.0050	(0.005)	−0.0137	(0.005)**
Service	0.0045	(0.004)	0.0115	(0.005)**	−0.0063	(0.004)*	−0.0132	(0.003)**
Labourer	0.0022	(0.005)	0.0166	(0.007)**	−0.0113	(0.004)**	−0.0156	(0.004)**

a: abstainers; nb: non binger; ob: occasional binger; fb: frequent binger. Standard errors are given in parentheses. *significant at 10 % level; **significant at 5 % level

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