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The demand for health, alcohol abuse, and labor market outcomes: a longitudinal study

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The demand for health, alcohol abuse, and labor market outcomes: A longitudinal study

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For the Graduate College

to my parents and my wife, Ya-Fen

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ABSTRACT

In the past fifteen years, substance abuse among teenagers and young adults has become a major public concern and policy issue. 'The war on drugs' is a ongoing nationwide campaign. Federal and state governments have been using law enforcement, excise taxes, and regulations, to discourage the underage consumption of drugs. A recent study from *Newsweek* (1996) revealed a trend of increasing illicit drug usage among eighth graders. Taking crack, heroin, marijuana, cocaine, cigarettes, and "been drunk" as examples, in 1991, the percentages of the eighth graders who had used each of these drugs in their lifetime was 1.3, 1.2, 10.2, 2.3, 44 and 26.7, respectively. In 1995, the percentages for each of these uses became 2.7, 2.3, 19.9, 4.2, 46.4 and 25.3. As more teenagers begin to experiment with drugs, in particular illicit drugs, the government seems to be losing the battle of preventing underage drug use.

Becker and Murphy (1988) presented a rational addiction theory to rationalize the behavior of addiction. This dissertation extends rational addiction theory to examine the hypothesis of rational addiction and the long-term impact of addiction on labor productivity and labor supply. The theoretical model explicitly considers investment in health, drug consumption, and labor supply as joint decision variables, and treats wage as the outcome of these decisions. A simultaneous framework is empirically estimated to test the forward-looking hypothesis and the government policies are evaluated by simulation. The data set is the National Longitudinal Survey of Youth Cohort (1979-1994).

The results show that there is a trade off between the demand for health and the occasions of binge drinking. Youths reduce their occasions of binge drinking when they increase the demand for health, and vice versa. The finding supports the forward-looking

hypothesis and that heavy drinking is addictive. Furthermore, we found a statistically weak effect of the alcohol price on the demand for binge drinking, and the long run alcohol price elasticity of the probability of heavy drinking, binge drinking, and no binge drinking are relatively small, -0.24, 0.03, and 0.21, respectively. The short run price elasticity are -0.09, 0.01, and 0.08. The results suggest that the demand for heavy drinking is not price responsive in the short run or long run.

Continued binge drinking results in lower wage and health profiles, whereas it does not have significant impact on hours worked. Policy simulations show that increasing alcohol price by 100% decreases the occasions of binge drinking by only 5%, but raising the minimum legal drinking age one year reduces the occasions of binge drinking among underage youths by about 5%. The effect of increasing the alcohol price and the minimum drinking age on health status, hours worked, and log wage are positive, however, their magnitudes are small. Our results suggest that policy makers should focuses on affecting the age at which young people start drinking and taxing alcohol is a relatively inefficient policy for achieving this.

CHAPTER 1. INTRODUCTION

In the past fifteen years, substance abuse among teenagers and young adults has become a major public concern and policy issue. "The war on drugs" is as important as welfare reform, and it is an ongoing nationwide battle. Federal and state governments have been using law enforcement, excise tax, regulations (for example, the Drug Free Workplace Act of 1988), public campaign, and minimum legal age for drinking and smoking to discourage early initiation of substance use and the consumption of alcohol, cigarettes, and illicit drugs among teenagers and young adults.

Although it is believed that *persistent* substance abuse adversely affects the users' economic and social status, a large increasing number of youths in the U. S. engage in substance abuse. According to the 1991 survey from the U.S. Department of Health and Human Services (DHHS), the percentage of reporting use of any illicit drug in the past year is 33 percent among high school seniors, 33 percent among college students, and 31 percent among all young adults between the ages of 19 to 28. Although it is illegal for high school students and most college students to purchase alcohol, experience with alcohol and active use of it are widespread. Ninety percent of the high school seniors have tried alcoholic drinks. The occurrence of binge drinking occasions, measured by the percent reporting five or more drinks in a row at least once in the prior two-week period, is 32 percent among high school seniors and 41 percent among college students.

A recent study by *Newsweek* in 1996 revealed a significant increase in illicit drug usage among eighth graders in recent years, whereas cigarette and alcohol usage is relatively stable. For crack, heroin, marijuana, cocaine, cigarettes, and "been drunk," the percentages of the eighth graders who have used each of these drugs in their lifetime are 1.3, 1.2, 10.2, 2.3, 44 and 26.7, respectively, in 1991. In 1995, the percentages for each of these uses became 2.7, 2.3, 19.9, 4.2, 46.4, and 25.3. The percentage increase in illicit drug usage is almost double for most of the cases, while crack use grew more than 100 percent. As more teenagers begin to experiment with drugs, in particular illicit drugs, the government seems to be losing the battle. Because early initiation of substance abuse is more likely to result in addiction, which will impose considerable costs on both the addict and the society, more effort from the government and society is needed to reduce adolescent substance abuse.

The public concern on substance abuse (or addiction) mainly arises from the social cost generated by substance abuse. The most commonly cited example is the fatal motor vehicle accidents caused by drunk driving. Although alcohol use by drivers involved in fatal accidents has decreased over the years, nearly half of the drivers and more than 40% of the passengers killed in motor accidents have been drinking (Zobeck et al., 1994). State and federal governments have passed more stringent drunk-driving laws and raised the minimum legal drinking age aimed at reducing alcohol-involved driving. In early 1998, President Clinton's administration proposes to withhold 5 percent of Federal highway funds from states failing to lower their blood alcohol content limit for drunk driving to 0.08 percent by three years. However, the proposal failed in Congress.

Contemporary studies on the social cost of substance abuse also indicate other types of externalities caused by substance abuse. Locke (1998) covered a research report conducted by Dr. Leonard Miller at the University of California, Berkeley in the *Iowa State Daily*. The report showed that smoking-related illnesses cost taxpayers $12.9 billion a year in

Medicaid expenditures. Kronson (1991) demonstrated that, excluding loss of productivity, the prevalence of drug abuse in the workplace costs the U.S. $38 billion for substance abuse and related mental health treatment in 1988. This equals 7 percent of the total health expenditures. In 1990, drug abuse cost the U.S. economy more than $100 billion and loss of productivity accounted for more than one-third of the total cost. Research Triangle Institute (1991) predicted that the cost of reduced productivity alone is over $99 billion annually. Although the estimates of the economic loss from different studies vary widely, the consensus is that substance abuse impairs the U.S. economy substantially.

The recent growth of economic literature focusing on substance abuse is the result of the enormous economic losses from substance abuse at both individual and aggregate levels. Research related to substance abuse can be generally classified into two groups. The first group focuses on the effectiveness of the government policies, such as excise tax, minimum legal age for drinking and smoking, and law enforcement, on highway drunk driving, and the consumption of legal and illegal drugs. The second group investigates the impact of substance abuse on socioeconomic status. In particular, most of the research in this group is conducted by labor and public health economists. Therefore, the main attention is directed toward the influence of harmful addiction on health, educational attainment, labor productivity, labor supply, and job stability.

This dissertation associates with the second group, and its focus centers on the joint decisions of individuals for investment in health, the demand for leisure, and the consumption of alcohol. In addition, the number of healthy days and labor productivity are the main outcomes of these joint decisions.

The Concept of Drug Addiction

The development of drug addiction (or dependence) is a complex process. A complete understanding requires research from different professions, such as biology, sociology, psychology, pharmacology, pathology, and medicine. Before proceeding to the economic discussion of drug addiction, it is essential to understand the concept of addiction and the ongoing debate centering on its development. Because binge drinking is the focus of this study, the following discussion will be directed towards alcoholism.

The *Diagnostic and Statistical Manual of Mental Disorders*, (DSM-IV, 1994) and the International Classification of Diseases (ICD-10, 1992) are the two most important diagnostic manuals for drug addiction (or drug dependence). Substance abuse is defined as regular, sporadic or, intensive use of higher doses of drugs, which leads to social, legal, interpersonal problems, and/or health damages. Substance dependence is characterized as a drug-seeking behavior, which involves the compulsive use of high doses of one or more drugs, resulting in the significant impairment of health and social functioning. Substance dependence in individuals usually is accompanied by tolerance and withdrawal. Tolerance refers to the need for an individual to increase the amount of substance consumed to achieve intoxication or a desired effect. Withdrawal not only accounts for the cessation of the substance, but also implies the condition of the individual who experiences the cessation. Depending upon the substance, an individual's withdrawal syndrome usually includes anxiety, tremor, depression, sweating, and nausea.

The American Psychiatric Association defines alcohol abuse as continued drinking despite the personal social, occupational, psychological, or physical problems it causes. And, alcohol dependence is defined as alcohol abuse with the symptoms of tolerance and withdrawal.

The controversy over the concept of drug addiction does not lie in the definitions of the signs of addiction, but on the process that accounts for them. Two major theories, physical and social causes, have been proposed to explain the causes of alcoholism. Physical causes, also known as disease theory, are taken by Alcoholics Anonymous and are also broadly accepted by the American public. This conventional concept of alcoholism views alcoholism as a progressive disease. The phases of alcoholism usually begin from excessive drinking, then move to alcohol dependence, and finally reach the final stage–chronic alcoholism.

It is believed that a biological mechanism causes alcohol dependence and addiction. Sufficient use of alcohol causes an organism to behave in some stereotypical way. Tolerance and withdrawal are properties of particular drugs. The entire process is universal and is independent of individual, group, environmental, and cultural variations. Some empirical evidence also shows that alcoholism may be inherited genetically. The genetic susceptibility seems to predispose some individuals to become alcoholics. For instance, sons of alcoholics may have a higher incidence of alcoholism than others at the same age. However, whether alcoholism is inherited genetically or by familial cultural transformation is still unclear. The key element of the disease theory is the addict's lack of control or inability to drink moderately or to stop; hence, the image is of an alcoholic being powerless, unable to make decisions, and in need of professional treatment. Because alcoholism is considered to be a disease, the only effective treatment recommended is complete abstinence.

On the other hand, many scientists studying addiction in experimental or natural settings have noted that the simple disease model of addiction is not observed in reality and that the behaviors of the drug addicts are far more variable than the simple theory predicts. For example, many Vietnam War veterans who had been addicted to narcotics in Asia gave up their habits without any treatment when they returned to the United States; Native Americans, Irish, and Slavic populations have a high incidence of drinking problems, whereas Italians, Chinese, and Jews have low incidence. The disease theory apparently can't explain widely divergent evidence about drug addiction. Fingarett (1988) criticized the classical disease concept of lack–of–control, by providing experimental evidence that heavy drinkers *can* control their drinking under some environments. He pointed out that it is the social settings, not the chemical effect of alcohol, that influence drinkers' ability to control their drinking. Peele (1985) also argues that addiction is no different from other human behavior. Addiction represents an individual's adjustment to changing psychological and life circumstances. Many non-biological factors have been shown to significantly influence the likelihood of addiction, particularly, cultural, social, and developmental factors.

Cultural attitudes toward drinking are a principal component in alcoholism. Italians, Greeks, Chinese, and Jews have low incidence of drinking problems because alcohol is gradually introduced to children in the family setting, where drinking is controlled by group attitudes about both the proper amount of drinking and the person's behavior when drinking. Strong disapproval is expressed when a family member violates these standards. On the contrary, some cultures hold the belief that drunkenness excuses aggressive and antisocial behavior, or view alcohol consumption as a passage to adulthood and associated with power and masculinity. These cultural differences translate into different visions of alcohol, which strongly affect the appearance of alcoholism.

The social and peer groups, which an individual belongs to also influence the likelihood that he/she will have a drinking problem. Peer pressure has been shown to have strong power not only on the style of drinking and the pattern of drinking, but also on the initiation of drinking among young adults and adolescents, e.g., college fraternity initiations and partying. In addition, the social setting and environment also affect people's drinking behavior. For example, the problem of binge drinking among college students is mainly attributed to the campus drinking culture. Binge drinking is more common when drinking is accepted among students and alcohol is easily available.

The patterns of alcohol consumption and the attitude toward drinking change when people progress through their life cycle. Many young adults leave their binge drinking lifestyle when they accept an adult role in life. The process is referred to as "maturing out." Under the theory of social causes, drinking behavior is controllable by changing the social settings and adopting a healthier drinking culture. The treatment of alcoholism does not aim at achieving complete abstinence; rather, it is directed to attaining controlled drinking.

Background Review in Economic Analysis of Substance Abuse

The demand for health

Wage inequality in the population has motivated extensive research on the determinants of wage and labor productivity. Mincer (1974) attributed the productivity difference mainly to two human capital variables, education and work experience. Ever since, schooling and experience have received the greatest attention for their effects on wage rates and labor productivity. Topel (1997) indicates that the rising wage premium to a college degree contributes to the increase in higher education enrollment in the past two decades.

Another potentially important form of human capital is health. Many studies (Berkowitz et al., 1983; Lee, 1982a; Luft, 1975) have shown that, like education and work experience, health is also a key determinant of labor productivity and the wage. In fact, health has a broader impact on a person's life than education and work experience. Good health improves the quality of life and serves as the foundation for many human activities and achievements. Poor health not only impairs the labor productivity due to physical and mental limitations, but also reduces healthy days available for market and non-market activities. Because maintaining good health has monetary, physical, and mental rewards like education and work experience, a rational person has an incentive to invest in his health,

In 1972, Grossman (1972 a,b) developed his well-known demand for health model. Health is viewed as a stock of human capital in the model. It depreciates over time and its level can be increased or maintained by investing in health. An individual can invest in health using medical care, own time, or other market inputs, such as nutritious foods. While aging is the main cause of health depreciation, many daily activities can be considered directly or indirectly related to the investment in health. For example, routine exercise and healthy diets can enhance health, whereas excess alcohol and illicit drug consumption accelerate the depreciation of the health capital and can be perceived as a type of disinvestment.

Health consists of two components in Grossman's model, consumption and investment. As a consumption good, an individual derives utility directly from good health. As an investment, health is demanded because it reduces an individual's number of sick days so he/she can work longer, earn more income, and expand the consumption set, or can have more time for leisure. Although the wage is assumed to be independent of the health capital in Grossman's model, which implies that good health does not improve labor productivity, his model has become the foundation for many analyses of the demand for health and medical care markets.

Rational addiction model versus myopic model

The discussion of the concept of drug addiction in the earlier section can be easily linked to the demand for health framework and the traditional rational agent model in the economics. There are two hypotheses about the addictive behavior in the economic literature. Economists have sometimes viewed harmful addictions as irrational behavior. Drug addicts are myopic, and they ignore the adverse consequences of substance abuse on their future utility and socioeconomic status when determining current consumption of the addictive good. This hypothesis is similar to the disease theory in the sense that current consumption is mainly driven by the severity of the dependence syndromes, as determined by the level of past consumption. The future impact of substance abuse is not a part of the consideration of current consumption even the addicts realize that the continuation of substance abuse will harm them in the future.

On the other hand, several economists adopt an alternative view toward the addictive behavior. Becker and Murphy (1988) chose to model the consumption of addictive drugs as rational behavior. They claimed that rational consumers are not myopic; instead, they take the adverse consequences of addiction into account and make a consistent plan to maximize utility over time. That is, the recognition of the harmful consequences from substance abuse by the addicts is as important as the dependence syndromes in the consumer's consumption decision. The recognition of the future impact of substance abuse in the consumption decision mainly depends on the perception of the risks of substance abuse. People holding the perception of low risk will behave in the myopic way. However, their decision is still rational because their subjective beliefs lead them to set future costs equal to zero.

Becker and Murphy (1988) give young smokers as evidence of forward-looking behavior. Teenagers are usually impatient and share a sense of immortality. Therefore, their current smoking behavior should not be affected by health consequences that occur with a long lag, e.g., 10 or more years after initiating smoking. We observe that the cigarette smoking rate is highest among individuals in their late teens, but that smoking rates of males aged 21 to 24 declined by more than one-third from 1964-1975. The decline is related to the first Surgeon General's report published in 1964, which altered the public's perception of smoking risks. The conclusion drawn by Becker and Murphy is consistent with Fingarette's (1988) argument that social settings, health information, and lifetime events, such as the loss of a loved one or being unemployed, influence the drinker's ability to control drinking.

The major distinction in the empirical rational addiction model, as opposed to the myopic model, is that future consumption is explicitly incorporated into the framework. A rational addiction model applies multi-period, e.g., lifetime, optimization while myopic model involves only one-period decision-making. The rational addiction model has been tested empirically and the results (Becker, Grossman, and Murphy, 1994; Chaloupka, 1991; Grossman, Chaloupka, and Brown, 1995a; Grossman, Chaloupka, and Sirtalan, 1995b) support the hypothesis that addictions are rational in the sense of having behavior that is consistent with forward-looking maximization.

Substance abuse, education, health, and job stability

Labor market success is mainly, although not completely, determined by the accumulation of human capital. Health, education, and experience are the three major types of human capitals that determine the labor market success. However, we often observe that substance abuse interrupts the accumulation of these types of human capital. Many studies have shown that substance abuse is strongly associated with low educational attainment, job instability, and accelerated health depreciation, such as malnutrition and the development of cardiovascular disease, liver disease, and lung cancer.

Mullahy and Sindelar (1989) revealed that the early onset of alcoholism is related to lower schooling. Cook and Moor (1993) showed that heavy drinking in high school reduces the number of years of schooling completed and the likelihood of graduating from college. High school seniors who are frequent drinkers complete 2.3 fewer years of college than those who are not frequent drinkers. Yamada, Kendix, and Yamada (1996) used data from the National Longitudinal Survey of Youth (NLSY) to estimate the relationship between high school graduation and alcohol and marijuana use. They showed there are significant adverse effects of alcohol and marijuana use on the probability of high school graduation.

Frequent job changes and job losses result in lower job tenure and work experience. Kandel and Yamaguchi (1987) show that illicit drug use increases job turnover and decreases job tenure. Higher frequencies of job change and job loss are associated with current drug usage. Kandel and Davis (1990) investigated the role of illicit drugs on the labor force experiences of young men. They found that drug use lead to an increase in the number of job changes and the duration of unemployment. Mullahy and Sindelar (1996) applies a linear probability model and demonstrated that, for both sexes, problem drinking reduces employment and increases unemployment.

The long-term impact of harmful addiction on health can be found in the panel research of aging. Clark (1996) demonstrated that, for African American men between the ages 51 to 61, alcoholism is associated with a 25 percent greater likelihood of reporting difficulty in physical function. Using 1992 Health and Retirement Study (HRS), Wray (1996) showed that, among people between the ages 51 and 61, smokers and problem drinkers are more likely to be retired and not working. Shea, Miles, and Hayward (1996) indicated that smokers and drinkers have a lower level of wealth and health. These results suggest that substance abuse accelerates the depreciation of health and interrupts human capital accumulation.

Substance abuse and labor productivity

While the evidence regarding the adverse impact of substance abuse on human capital accumulation (health, education, and experience) is abundant, current economic literature fails to reach a consensus on the impact of substance abuse on labor productivity and the wage. Berger and Leight (1988) showed that alcohol use has a negative impact on an individual's wage. Kenkel and Ribar (1994) demonstrated a negative relationship between annual earnings and several heavy alcohol use measures for a male sample. Hamilton and Hamilton (1997) separated their sample into three drinking categories, non-drinker, moderate drinker, and heavy drinker. Annual earnings regressions were conducted for each group, respectively.

They found a flatter age-earnings profile for heavy drinkers. Heien (1996) and French and Zarkin (1995) confirmed the medical findings on moderate drinking by showing that moderate drinkers have higher annual earnings and hourly wages.

On the contrary, other recent studies using the National Longitudinal Survey of Youth Cohort (NLSY79; 1995 a,b) (Gill and Michaels, 1992; Kaestner, 1991, 1994; Register and Williams, 1992) found a positive relationship between an individual's wage and the consumption of illicit drugs. Zarkin, French, Mroz, and Bray (1998) intended to replicate their findings in 1995 using prime-age workers from National Household Surveys on Drug Abuse. However, they did not find evidence of an inverse U-shaped relationship between an individual's wage and intensity of alcohol use. Furthermore, their results also suggested that male alcohol users have higher wage rates than non-users and alcohol use in not associated with lower wages even at high levels of use.

It is difficult to believe that consistent long-term drug use, which causes health deterioration and personal upheaval, would increase labor productivity and wages. One difficulty in assessing the impact of substance abuse on socioeconomic status is that the impact varies not only from person to person, but also from drug to drug. An individual's reactions to a drug are heterogeneous, and each drug has a different addictive pattern. For instance, cigarettes and illicit drugs are much more addictive than alcohol. Most importantly, the adverse consequences of substance abuse frequently occur many years after the initiation of substance abuse. Consequently, the short run effect of substance abuse on labor productivity is uncertain.

Several potentially important factors contribute to the inconclusiveness of the impact of substance abuse on labor productivity. First, as emphasized in the previous section, health, education, and work experience are three main determinants of labor productivity, and substance abuse has direct and significant effects on them. Without taking into account these human capital effects, the analysis of the impact of substance abuse on wages is incomplete. This implies that the main effects of substance abuse on labor productivity are captured by human capital and other variables affected directly by substance abuse. The direct and instant effect of substance abuse on labor productivity is hard to evaluate.

The second factor is that individuals who have an early onset of substance abuse are more likely to drop out of school and enter the labor market earlier. Therefore, they accumulate more experience and earn a higher wage during their early working career than people staying in school. However, when people enter their prime working ages, continued substance abuse begins to show its impact on labor productivity through poor health, lower educational attainment, and job instability. People without drug problems will, on the average, experience greater wage growth and eventually surpass their counterparts.

This explanation is quite applicable to the research using the NLSY79 (The National Longitudinal Survey of Youth Cohort) because the respondents in the NLSY79 are young adults. In the latest 1996 survey, the oldest cohort is only 38 years old and most of the recent illicit drug studies use 1984 data. In fact, the NLSY79 data show that respondents, who are younger than 20 and report drug use in the last month, are more likely to work and receive a higher wage. The wage gap narrows gradually and the average wage of nonusers exceeds the average wage of drug users from 1989 on. It is possible to observe a positive relationship between drug use and the wage given that the analyses use only respondents in their early twenties. Kaestner (1994) added the 1988 NLSY wave to his analysis and found an insignificant negative effect of illicit drug use on the wage rate for males.

Unobserved heterogeneity may be the third factor. Kaestner (1991) used the wage decomposition approach to investigate the source of wage premiums for drug users. He concluded that the wage difference between users and nonusers does not come from differences in observed characteristics, such as education and experience, but is mainly due to unobserved characteristics. For instance, drug users have higher wage rates because they may have a higher innate ability than nonusers.

Substance abuse affects many socioeconomic variables, which determine labor market outcomes. Furthermore, its impact accumulates over time and may not be noticeable until many years after the initiation. Therefore, a panel survey, which is able to follow individuals and collect data on drug use and socioeconomic variables over their lifetime, will be ideal for understanding addiction and finding significant long-term effects.

Objectives of Current Research

The main objective of the current research is to model and estimate the long-term impact of heavy drinking on health and labor market indicators, such as wage rates and labor supply. While most of the previous literature emphasizes cross-sectional and single equation estimation (either wage or labor supply equation), this study recognizes the simultaneity and endogeneity of the choices to consume alcohol, to invest in health, to invest in labor productivity, and to participate in the labor market. Health is included in the model not only to test the rationality of the behavior of addiction, but also to capture the accumulated effect of addiction on labor market outcomes. The data for the empirical analysis are from the NLSY79 (1979–1994). The data set includes Geocode files, which permit merging separately collected state alcohol prices. The design of this survey provides sufficient information to control for significant unobserved heterogeneity across individuals.

Grossman's (1972 a,b) investment in health model and Becker and Murphy's (1988) rational addiction theory are combined and modified. The hybrid model provides a rational framework for examining the consumer's optimal intertemporal resource allocation among the consumption of alcohol, the investment in health and leisure when the cumulative effects of continued substance abuse on health, wage rates, and labor supply are explicitly incorporated. In particular, this model allows us to examine empirically how consumers choose optimally and 'rationally' between two temporally distinct goods, health capital and heavy drinking.

The resulting four–equation simultaneous econometric model is estimated by a two-stage procedure. Based upon the estimated coefficients, simulation is then conducted to evaluate the effectiveness of several policy variables, e.g., excise tax, minimum legal drinking age, and education. The long run and short run price elasticity with respect to heavy drinking, the demand for health, labor supply and wage are computed.

The second objective of this dissertation is to examine the occupational choice of individuals to identify how alcohol consumption, especially heavy drinking, affects their choice. The entire sample will be grouped into four mutually exclusive employment groups, unemployment, self-employment, working full-time for a wage, and working part-time for a wage. This analysis will apply the multinominal logit model. Furthermore, frequent heavy drinking seems to have a different impact on male and female's occupational choices. This issue and its explanations will also be addressed.

Historic Trends and Current Drug Use in the United States

This section provides additional background information on the historic trends and current drug use. It further documents the seriousness of the drug problem over time and across different demographic groups. We use data from the National Household Survey on Drug Abuse (NHSDA) in 1992, 1993 and 1996, which, like NLSY79, is a national representative sample. They provide information on national consumption trends for several common drugs by socioeconomic characteristics for different demographic groups. NHSDA also collects data on the perceived risk of substance abuse and the dependence symptoms for

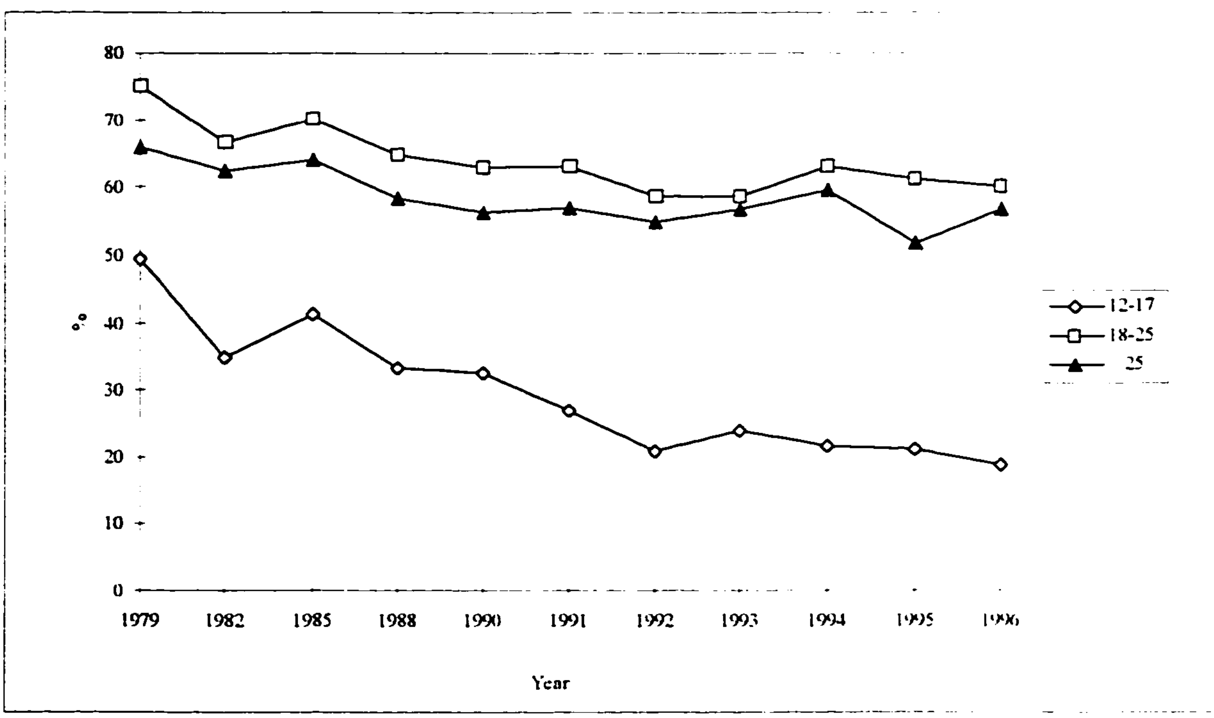

Figure 1.1. Trends in percentage of youth and young adults reporting alcohol use in the past month: 1979-1996

drug use. Because this study examines the behavior of alcohol abuse, the following discussion will mainly focus on alcohol consumption.

Figure 1.1 shows the percentage trend in of survey respondents who reported alcohol use in the past month from 1979 to 1996. It is clear that alcohol is the most frequently used drug in America. In 1996, more than 60 percent of respondents older than age 18 reported alcohol use in the past month. Once again, the 18-25 age group has highest prevalence rate. The trend peaked in 1979 and then decreased slightly over time. However, the rate of decrease was much less significant than that of illicit drugs. The percentage for the 18-25 and 26 or older age groups remain relatively stable over time, while the 12-17 age group experienced a greater decline in alcohol use in the past 30 days. Nonetheless, there are still nearly 20 percent of the 12-17 age group consuming alcohol during the past 30 days. In the U.S., the major public concern for drinking problems is the large share of underage individuals reporting alcohol consumption.

Alcohol is addictive and excessive consumption of it frequently increases the probability of becoming addicted. Binge drinking and heavy drinking are strongly related to alcohol addiction, and the trends of binge drinking and heavy drinking are informative to the understanding of the drinking problems faced by the nation. Figures 1.2 and 1.3 display the trends of reporting binge drinking and heavy drinking in the past 30 days, respectively. "Binge drinking" is defined as drinking five or more drinks on the same occasion on at least one day in the past 30 days. "Heavy drinking" is defined as drinking five or more drinks on the same occasion on each of five or more days in the past 30 days.

The 18-25 age group has the highest reported percentage in both binge drinking and heavy drinking. Binge drinking ranges between 30 and 35 percent, and heavy drinking fluctuates between 12 to 14 percent. For people older that 25, the percentage declined to 16 and 6 percent in 1996 for binge drinking and heavy drinking, respectively. The trends for both groups remain quite stable throughout the time. The high percentage for the 18-25 age group is attributed to the drinking culture in high schools and colleges. On the other hand, the percentages reporting binge drinking and heavy drinking for the 12-17 age group continued to decrease between 1985 and 1996. In 1996, the percentage of binge drinking and heavy drinking reached 7.2 and 2.9 percent, respectively, which are the lowest percentages in the past 17 years.

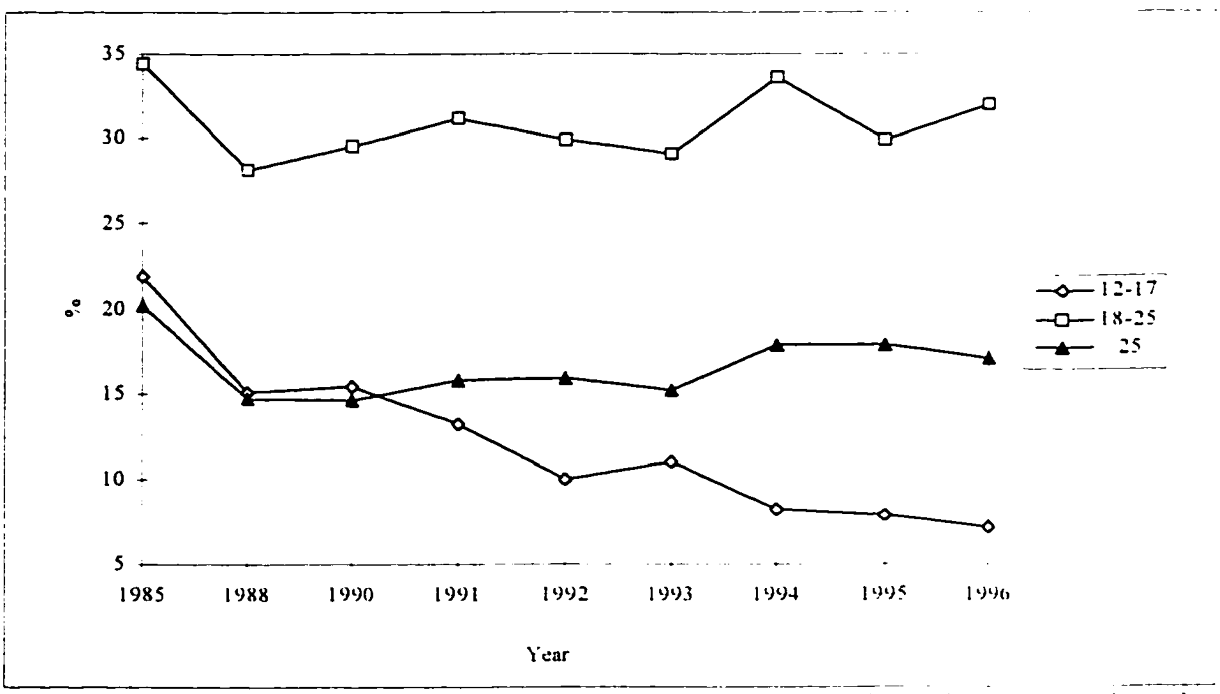

Figure 1.2. Trends in percentage of youth and young adults reporting "binge" alcohol use in the past month: 1985-1996

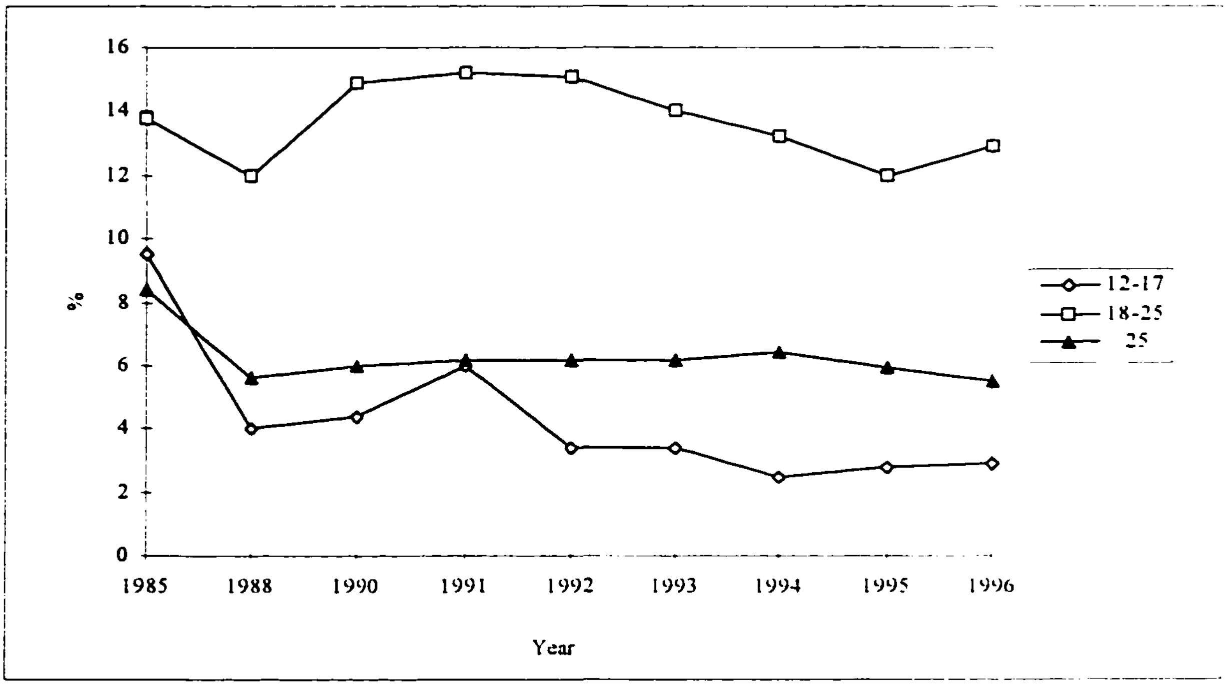

Figure 1.3. Trends in percentage of youth and young adults reporting heavy alcohol use in the past month: 1985-1996

The demographic characteristics for heavy alcohol use are displayed in Table 1.1. Heavy alcohol use is defined as drinking five or more drinks per occasion on 5 or more days in the past 30 days. The 18-25 age group had the highest prevalence of heavy alcohol use across all age groups and all demographic characteristics. As with marijuana use, males are six times more likely than female to report heavy alcohol use. Whites report a higher frequency of heavy drinking than Hispanics and blacks.

Although college graduates reported the highest prevalence of current alcohol use, they have the lowest prevalence of heavy alcohol use across all age groups. People without a high school diploma or with some college reported more heavy alcohol use. In terms of the labor market, current heavy alcohol users are more likely to be unemployed. The data on employment status also reveal that a high percentage of heavy drinkers are currently working.

Table 1.1. Percentage Reporting Heavy Alcohol Use[a] in the Past Month, by Age Group and Characteristics: 1996[b]

Demographic Characteristics	Age Group (Years)				
	12-17	18-25	26-34	>34	Total
Total	2.9	12.9	7.1	3.8	5.4
Sex					
Male	4.3	20.6	11.8	6.9	9.3
Female	1.4	5.4	2.6	1.1	1.9
Race					
White	3.2	14.9	7.9	3.6	5.5
Black	1.7	7.4	5.8	5.5	5.3
Hispanic	3.4	10.5	5.8	5.4	6.2
Adult education					
Less than high school	N/A[c]	14.4	10.0	4.4	6.8
High school graduate	N/A	11.8	8.8	4.4	6.2
Some college	N/A	14.1	6.0	3.7	6.2
College graduate	N/A	10.7	4.6	2.6	3.7
Current employment					
Full-time	N/A	16.1	7.8	4.9	7.1
Part-time	N/A	10.0	6.3	1.4	4.7
Unemployed	N/A	15.8	12.1	9.5	11.9
Other	N/A	8.1	2.7	2.6	3.2

[a]Heavy alcohol use: five or more drinks on 5 or more days in past 30 days.
[b]Source: National Household Survey on Drug Abuse (1996)
[c]Not applicable.

Particularly for individuals younger than 35, the combined percentage of heavy drinkers reporting currently working full-time and part-time is higher than that of unemployed.

Table 1.2 presents trends in the percentage of workers, aged 18-49, reporting drug use from 1985 to 1993. For illicit drug use, the percentage reporting drug use decreased from 16.5 percent in 1985 to 8.1 percent in 1993. On the other hand, heavy alcohol use decreased only slightly during this period. In fact, the percentage of workers reporting heavy alcohol use increased significantly after 1990 in the unemployed category. Table 1.2 also shows the impact of substance abuse on employment status. Workers who are current illicit drug users or heavy drinkers are more likely to be unemployed.

The key element of the rational addiction model is that the consumer has perfect information about adverse consequences of substance abuse. Some people have argued that consumers might not acknowledge the risk of over-consuming alcohol, illicit drugs, or cigarettes. Table 1.3 presents the percentage of population reporting a perception of great risk of using illicit drugs, alcohol, and cigarettes, by age group in 1992. More than sixty percent of the population reported realizing the potential risk of using illicit drugs regularly, having four or five drinks nearly every day, and smoking one or more packs per day. Although the 18-25 age group has the highest drug use percentage among all age groups, the percentage reporting perception of risk is not lower than other age groups except individuals older than age 34. The greater risk perception of substance abuse reported by the aged group $\geq$ 34 years may contribute to the lower occasion of substance abuse in this group.

Table 1.4 shows the percentage reporting dependence syndromes among heavy drug users by age group in 1992. Marijuana, alcohol, and cigarette are included for comparison.

Table 1.2. Trends in Percentage of Workers, Ages 18-49, Reporting Drug Use, by Employment Status 1985-1993[a]

	Current Illicit Drug Use						Heavy Alcohol Use					
Year	1985	1988	1990	1991	1992	1993	1985	1988	1990	1991	1992	1993
Total	16.5	10.2	8.9	8.9	8.0	8.1	8.5	6.5	6.8	7.6	7.0	7.0
Employment status												
Full-time	16.7	9.9	8.2	7.5	7.0	7.3	9.7	7.0	7.5	7.4	6.8	7.4
Part-time	15.3	11.7	10.3	10.5	8.4	10.3	6.8	6.7	6.2	6.3	7.4	5.9
Unemployed	27.9	20.7	15.7	18.9	16.8	14.1	8.2	9.3	7.6	13.1	12.7	13.7
Unemployment rate	7.2	5.5	5.5	6.7	7.4	6.8	7.2	5.5	5.5	6.7	7.4	6.8

[a]Source: National Household Survey on Drug Abuse (1993).

Table 1.3. Percentage Reporting Perceptions of Great Risk of Using Illicit Drugs, Alcohol and Cigarettes, by Age Group: 1992[a]

Risk Behavior	Age Group (Years)				Total
	12-17	18-25	26-34	>34	
Marijuana					
Smoke once or twice a week	35.9	22.0	23.7	43.2	35.9
Smoke occasionally	49.8	31.8	31.2	51.6	44.9
Smoke regularly	83.0	68.8	68.0	82.0	77.7
Cocaine					
Try once or twice a week	53.9	57.9	59.8	76.3	68.4
Use occasionally	75.3	77.8	75.9	86.6	82.2
Use regularly	92.1	94.5	95.7	97.7	96.3
Alcohol					
One or two drinks nearly every day	26.7	24.7	27.9	32.8	30.2
Four of five drinks nearly every day	61.2	64.1	66.9	76.2	71.3
Five or more drinks once or twice a week	58.4	50.8	54.0	67.5	61.8
Cigarettes					
Smoke one or more packs per day	48.7	58.0	64.3	68.2	64.1

[a]Source: National Household Survey on Drug Abuse (1992).

Table 1.4. Percentage Reporting Dependence in the Past Year Attributed to Marijuana, Alcohol and Cigarette Use, by Age Group: 1992[a]

	12-17	18-25	26-34	> 34	Total
Used Marijuana once a month or more often in the past year					
Tried to cut down	49.6	36.9	41.2	N/A[b]	39.0
Tried and failed	18.3	11.1	11.5	2.8	10.1
Larger amount	19.3	16.2	7.6	NA	12.8
Every day	18.9	30.3	27.9	NA	27.2
Dependent	15.3	17.1	15.9	10.1	15.0
Withdrawal	10.9	7.9	3.5	NA	5.4
Any of the above problems	57.2	53.4	57.0	NA	54.1
Five or more drinks on each of 5 or more occasions in the past 30 days					
Tried to cut down	NA	42.7	47.5	48.9	46.5
Tried and failed	NA	19.4	19.6	21.3	20.5
Larger amount	NA	28.3	16.1	13.5	19.9
Every day	NA	32.0	36.9	60.1	43.8
Dependent	9.6	15.6	25.7	36.3	26.3
Withdrawal	NA	8.0	7.5	8.0	7.7
Any of the above problems	NA	62.9	66.3	76.2	69.3
Currently smoke about a pack or more per day					
Tried to cut down	NA	65.8	65.1	59.7	61.9
Tried and failed	NA	55.7	54.3	46.3	49.6
Larger amount	NA	18.2	17.4	12.2	14.6
Every day	NA	90.1	86.3	82.7	84.5
Dependent	NA	78.3	81.7	75.4	77.3
Withdrawal	NA	33.6	32.9	25.3	28.3
Any of the above problems	NA	92.2	89.8	87.4	88.6

[a]Source: National Household Survey on Drug Abuse (1992).
[b]Not applicable.

Although the 18-25 age group has the highest prevalence rate of drug use in the nation, older cohorts seem to show more dependent symptoms than younger cohorts, particularly in heavy drinking. This finding implies that the dependence syndromes progress along with the continuation of substance abuse. When most of the young adults eventually give up their drug abuse habit after entering adulthood, people continuing the habit will result in greater drug dependence.

A large proportion of drug abusers uses several drugs at once. Table 1.5 shows the most common drug combinations are alcohol and cigarettes, and alcohol and marijuana. In particular, most of the illicit drug users reported heavy alcohol drinking in the past month. Cigarette smokers also have a higher incidence of heavy drinking. These patterns suggest that substitution and complementary effects between different drugs exist.

Table 1.5. Percentage Reporting Use of Selected Drugs in the Past Month, by Age Group and Alcohol Use: 1993[a]

Age Group/ Drugs Used in the Past Month	No Alcohol Used in the Past Month	Alcohol Used in the Past Month	Heavy Alcohol Used in the Past Month
Total			
Cigarettes	18.5	22.6	50.9
Marijuana	0.9	3.3	23.0
Cocaine	0.1	0.4	4.2
12-17 years old			
Cigarettes	5.1	9.0	*[b]
Marijuana	1.4	4.3	*
Cocaine	*	0.3	*
18-25 years old			
Cigarettes	16.9	26.1	52.3
Marijuana	2.2	7.3	42.8
Cocaine	0.2	0.9	7.0
26-34 years old			
Cigarettes	22.5	27.8	58.2
Marijuana	1.2	5.5	23.1
Cocaine	0.2	0.7	3.7
> 34 years old			
Cigarettes	21.6	22.7	47.0
Marijuana	0.5	1.5	10.8
Cocaine	0.1	0.2	2.7

[a] Source: National Household Survey on Drug Abuse (1993).
[b] Low precision; no estimate reported.

CHAPTER 2. THE ECONOMIC MODEL

The theoretical framework combines Grossman's (1972 a,b) demand for health and Becker and Murphy's (1988) rational addiction model. Three key elements of these models for being able to closely link them are the assumption of perfect foresight, intertemporal utility maximization, and health is a type of human capital. The demand for health and the consumption of drugs are interpreted as part of the choice of lifestyles. The dependence syndrome from substance abuse is explicitly incorporated into the consumer's utility function. Health status affects labor market outcomes, and excessive drug use accelerates the depreciation of health capital. Therefore, the long-term effect of excessive drug use on labor market outcomes is hypothesized to come from its effect on the health capital.

Let an individual have the following utility function:

$$U(t) = U[H(t), D(t), D(t-1), L(t), Z(t)] \quad . \tag{2.1}$$

H(t) is the health capital at period t. D(t) is the consumption of the addictive good (illicit drugs, alcohol, etc.) at period t. D(t-1) is the consumption of the addictive good at period t-1. L(t) is the leisure at period t. Z(t) is the composite good at period t and its price is normalized. Given that a consumer's choices have a major effect on the health capital, the consumer can choose to live up to period T, where the stock of health is below the minimum stock of health, H_{min}, and hence death takes place. This implies that period T is endogenous and determined by the consumer. Nonetheless, the determination of longevity is not considered in the economic model. For simplicity, the following discussion will assume period T is fixed and exogenous. To characterize the dependence syndromes, the drug tolerance effect is incorporated into the utility function in the following way:

$$U_{D(t)D(t-1)}(t) > 0,\ U_{D(t-1)}(t) < 0,\quad t=1,2,3,\ldots,T$$

$U_{D(t)D(t-1)}(t) > 0$ indicates that higher past consumption increases the marginal utility of current consumption. Holding other things constant, the consumer would increase his current consumption if he consumed more in the past. $U_{D(t-1)}(t) < 0$ represents that higher past consumption lowers current utility level. Combining both effects, tolerance refers to the need for an increase in the amount of substance to achieve the same level of utility.

In Becker and Murphy's (1988) rational addiction model, they used the concept of the stock of "consumption capital," which is the sum of each period's net consumption of the addictive good, to capture the severity of addiction. Net consumption is computed by subtracting the depreciation of the consumption capital from the current consumption. The depreciation rate is assumed to be a constant between 0 and 1. However, without loss of generality and for the ease of theoretical and empirical analyses, the depreciation rate is assumed to be 1 in the subsequent discussion. The resulting stock of consumption capital at period t is just the consumption at period t-1. Moreover, the utility function is continuously differentiable and, at each period t, the following conditions hold.

$$U_H(t) > 0,\ U_D(t) > 0,\ U_L(t) > 0,\ U_Z(t) > 0,\ U_{D(t-1)}(t) < 0,\ U_{ii}(t) < 0,$$

$$i = H,\ D,\ D(t-1),\ L,\ Z;\ \ t=1,2,3,\ldots,T \qquad (2.2)$$

Health is viewed as a form of capital. By definition, net investment is equal to the difference between gross investment and depreciation. The stock of health capital follows the health capital accumulation equation:

$$H(t+1) = \{1 - \delta[t, D(t)]\}\, H(t) + I(t) \qquad (2.3)$$

$I(t)$ is the gross investment or health production function and $\delta[t, D(t)]$ is the depreciation rate, which is a function of t and $D(t)$. To be consistent with human aging, the depreciation rate increases with age at an increasing rate. The derivative of the depreciation rate with respect to the consumption of the addictive good is further assumed to be a constant. That is, $\delta_D(i) = \delta_D(j) = \delta_D$ for i, j = 1, 2, 3,...,T. The gross investment is defined by the following health production function:

$$I(t) = I[M(t)\ ; ED] \quad . \tag{2.4}$$

$M(t)$ is the demand for medical care at period t and ED is the educational attainments, which are assumed to be positively related to non-market productivity. That is, more years of schooling will shift the production function upward. The production of health capital often requires inputs other than medical care, such as own time input and market inputs. However, the exclusion of time input and other market inputs from the health production function (2.4) results mainly from the lack of data and model simplification. Medical care, $M(t)$, is defined in a broader sense in the model. It includes not only the actual spending in medical care, but also contains the use of health information. In addition, the production function is assumed to be Cobb-Douglas and constant returns to scale. Therefore, the cost function can be expressed as:

$$C[I(t)] = \pi(t)\, I(t) \quad , \tag{2.5}$$

where $\pi(t) = \pi\left[P_M(t); ED\right]$ denotes the unit cost of producing $I(t)$. $P_M(t)$ is the price of medical care. Grossman's assumption that the wage rate is independent of health is relaxed here. The wage rate is assumed to be a function of the stock of health, the consumption of the addictive good, education, other personal characteristics, $Q(t)$ and unobserved innate productivity, Φ:

$$w(t) = w[H(t), D(t), Q(t), ED; \Phi] \quad . \tag{2.6}$$

Furthermore, the relationship between the wage and health, drug consumption, and unobserved innate productivity are as follows:

$$w_H(t) > 0, \ w_{HH}(t) < 0; \ w_{D(t)} < 0; \ w_{\Phi(t)} > 0 \quad .$$

The individual faces time and asset accumulation constraints. The total time available at each period is $\overline{T}$. It is exhausted by all possible uses:

$$\overline{T} = T_w(t) + L(t) + T_l(t) \quad . \tag{2.7}$$

where $T_w(t)$ is hours worked and $L(t)$ is leisure at time t. $T_l(t)$ is the time lost from market work and household production due to illness and injuries. Let $h(t) = h[H(t)]$ be the healthy days available for market and non-market work at period t. Its first and second derivatives are assumed to be $h'(t) > 0$ and $h''(t) < 0$. They indicate that the number of healthy days increase with health stock at a decreasing rate. Given the definition of $h(t)$, the following relationship can be easily derived: $h(t) = \overline{T} - T_l(t)$.

The lifetime budget constraint is presented in terms of full-income budget constraint:

$$V(0) + \sum_{t=0}^{T} b^t h(t) w(t) = \sum_{t=0}^{T} b^t [\pi(t) I(t) + w(t) L(t) + P_D(t) D(t) + Z(t)] \tag{2.8}$$

$V(0)$ is the non-wage income at period 0. b is a discount factor that equals $\frac{1}{(1+r)}$. r is the interest rate and is assumed to be constant over time. Furthemore, personal rate of time preference is set to equal the interest rate. Finally, the lifetime utility maximization problem can be summarized as follows:

$$\underset{H(t),D(t),L(t),Z(t)}{\mathrm{MAX}} \sum_{t=0}^{T} b^{t}\, U[H(t), D(t), D(t-1), L(t), Z(t)] \quad , \tag{2.9}$$

subject to (2.3), (2.6), (2.7), and (2.8). The Lagrange function and equilibrium conditions can be derived, respectively:

$$\begin{aligned}\zeta = {} & \sum_{t=0}^{T} b^{t}\, U[H(t), D(t), D(t-1), L(t), Z(t)] + \lambda\{V(0) + \sum_{t=0}^{T} b^{t} h(t)\, w(t) - \\ & \sum_{t=0}^{T} b^{t}[\pi(t)\, I(t) + w(t)\, L(t) + P_D(t)\, D(t) + Z(t)]\} \quad .\end{aligned} \tag{2.10}$$

$$\begin{aligned}\frac{\partial \zeta}{\partial I(t)} : & \left\{ b^{t+1}\, U_H(t+1) + \sum_{i=t+1}^{T-1} b^{i+1} U_H(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] \right\} \\ & + \lambda \left\{ b^{t+1} T_w(t+1) w_H(t+1) + \sum_{i=t+1}^{T-1} b^{i+1} T_w(i+1) w_H(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] \right\} \\ & + \lambda \left\{ b^{t+1} h_H(t+1) w(t+1) + \sum_{i=t+1}^{T-1} b^{i+1}\, h_H(i+1)\, w(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] \right\} \\ & = \lambda\, b^{t}\, \pi(t) \quad .\end{aligned} \tag{2.11}$$

$$\begin{aligned}\frac{\partial \zeta}{\partial D(t)} : & \; b^{t}\, U_{D(t)}(t) + b^{t+1} U_{D(t)}(t+1) + \lambda b^{t}[T_w(t) w_D(t)] \\ & - \left\{ b^{t+1}\, \delta_D\, U_H(t+1)\, H(t) + \sum_{i=t+1}^{T-1} b^{i+1} \delta_D\, U_H(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] H(j) \right\} \\ & - \lambda \left[b^{t+1}\, \delta_D\, w_H(t+1)\, H(t)\, T_w(t+1) \right] \\ & - \lambda \left\{ \sum_{i=t+1}^{T-1} b^{i+1} \delta_D w_H(i+1)\, T_w(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] H(j) \right\} \\ & - \lambda \left[b^{t+1}\, \delta_D\, h_H(t+1)\, H(t)\, w(t+1) \right] \\ & - \lambda \left\{ \sum_{i=t+1}^{T-1} b^{i+1} \delta_D\, h_H(i+1)\, w(i+1) \prod_{j=t+1}^{i} [1-\delta(j)] H(j) \right\} \\ & = \lambda\, b^{t} P_D(t) \quad .\end{aligned} \tag{2.12}$$

$$\frac{\partial \zeta}{\partial L(t)} = b'U_{L(t)} - b'\lambda w(t) = 0 \quad . \tag{2.13}$$

$$\frac{\partial \zeta}{\partial Z(t)} = b'U_{Z(t)} - b'\lambda = 0 \quad , \tag{2.14}$$

where λ is the marginal utility of initial wealth, V(0). It is assumed to be constant over time.

The first-order conditions have their standard explanations. The left-hand side of Equation (2.11) is the discounted sum of future benefits resulting from one additional unit of health investment at period t. These future benefits include increased utility or satisfaction from health, higher labor productivity, and less time lost due to illness and injuries. The right-hand side of Equation (2.11) is the discounted cost of producing one unit of health capital. The rational consumer will continue to invest in health until the marginal cost equals its marginal benefit.

Equation (2.12) is the equilibrium condition for the consumption of the addictive good. It shows that the consumers will continue to consume the addictive good until the discounted net benefits from consuming one more units of addictive goods equal to the discounted cost of consuming the addictive goods. The discounted net benefits are the difference between the discounted increased utility gained from the consumption and the discounted costs resulted from the consumption. These costs consist of a decreased future utility or satisfaction, longer sick days due to illness, and lower labor productivity. The future costs, which capture the long run effect of substance abuse, come from the deteriorated health capital resulting from substance abuse. The full price of the addictive good is defined as the sum of the discounted market price of the addictive good and the discounted future costs. Equation (2.13) indicates the marginal utility of leisure equals the value of time, the wage.

Equation (2.14) shows that the marginal utility derived from the composite good is equal to its market price which has been normalized.

Equations (2.11) and (2.12) can be further simplified by applying the equilibrium conditions of the investment in health and the consumption of the addictive good at period t-1. Following the same utility maximization framework, the first order conditions with respect to I(t-1) and D(t-1) are as follows:

$$
\begin{aligned}
\frac{\partial \zeta}{\partial I(t-1)} &: \left\{ b^{t} U_{H}(t) + \sum_{i=t}^{T-1} b^{i+1} U_{H}(i+1) \prod_{j=t}^{i} [1-\delta(j)] \right\} \\
&\quad + \lambda \left\{ b^{t} T_{w}(t) w_{H}(t) + \sum_{i=t}^{T-1} b^{i+1} T_{w}(i+1) w_{H}(i+1) \prod_{j=t}^{i} [1-\delta(j)] \right\} \\
&\quad + \lambda \left\{ b^{t} h_{H}(t) w(t) + \sum_{i=t}^{T-1} b^{i+1} h_{H}(i+1)\, w(i+1) \prod_{j=t}^{i} [1-\delta(j)] \right\} \\
&= \lambda\, b^{t-1} \pi(t-1) \quad .
\end{aligned}
\tag{2.15}
$$

$$
\begin{aligned}
\frac{\partial \zeta}{\partial D(t-1)} &: b^{t-1} U_{D(t-1)}(t-1) + b^{t} U_{D(t-1)}(t+1) + \lambda b^{t-1} \left[T_{w}(t-1) w_{D}(t-1) \right] \\
&\quad - \left\{ b^{t} \delta_{D} U_{H}(t) H(t-1) + \sum_{i=t}^{T-1} b^{i+1} \delta_{D} U_{H}(i+1) \prod_{j=t}^{i} [1-\delta(j)] H(j) \right\} \\
&\quad - \lambda \left[b^{t} \delta_{D} w_{H}(t) H(t-1) T_{w}(t) \right] \\
&\quad - \lambda \left\{ \sum_{i=t}^{T-1} b^{i+1} \delta_{D} w_{H}(i+1) T_{w}(i+1) \prod_{j=t}^{i} [1-\delta(j)] H(j) \right\} \\
&\quad - \lambda \left[b^{t} \delta_{D} h_{H}(t) H(t-1) w(t) \right] \\
&\quad - \lambda \left\{ \sum_{i=t}^{T-1} b^{i+1} \delta_{D} h_{H}(i+1)\, w(i+1) \prod_{j=t}^{i} [1-\delta(j)] H(j) \right\} \\
&= \lambda\, b^{t-1} P_{D}(t-1) \quad .
\end{aligned}
\tag{2.16}
$$

Substituting Equations (2.15) and (2.16) into (2.11) and (2.12) respectively and rearranging terms, then Equations (2.11) and (2.12) become

$$\begin{aligned} & b^t U_H(t) + \lambda b^t T_w(t) w_H(t) + \lambda b^t h_H(t) w(t) - \lambda b^{t-1} \pi(t-1) \\ & + \lambda b^t \pi(t)[1-\delta(t)] = 0 \quad . \end{aligned} \tag{2.17}$$

$$\begin{aligned} & \frac{1}{\lambda}\left[b^{-1} U_{D(t-1)}(t-1) + U_{D(t-1)}(t)\right] + \frac{1}{b}\left[T_w(t-1) w_D(t-1) - P_D(t-1)\right] \\ & - \delta_D H(t-1)\left[\frac{1}{\lambda} U_H(t) + w_H(t) T_w(t) + h_H(t) w(t)\right] \\ & - \frac{b[1-\delta(t)]}{\lambda} U_{D(t)}(t+1) - [1-\delta(t)][T_w(t) w_D(t) - P_D(t)] \\ & = \frac{[1-\delta(t)]}{\lambda} U_{D(t)}(t) \quad . \end{aligned} \tag{2.18}$$

Equation (2.17) can be further simplified as:

$$\frac{1}{\pi(t-1)}\left[\frac{1}{\lambda} U_H(t) + T_w(t) w_H(t) + h_H(t) w(t)\right] = \{r - \tilde{\pi}(t-1) + \delta[t, D(t)]\} \quad . \tag{2.19}$$

where $\tilde{\pi}(t-1)$ is defined as $\dfrac{\pi(t) - \pi(t-1)}{\pi(t-1)}$ and $r\,\tilde{\pi}(t-1)$ is assumed to be zero.

This modified first-order condition, which is an extension of Grossman's optimal condition for health capital, determines the optimal stock of health demanded at period t. Its interpretation is in terms of the demand for health. The right-hand side of Equation (2.19) is the net rental price (or net cost) of holding one unit of health capital, which consists of three components: interest rate, capital depreciation and capital gains. Given that health is viewed as a capital, $\pi(t)$ can be explained as the market price of health capital. Therefore, the cost of holding one unit of health capital for one period is the forgone interest income and the depreciation, while the monetary rewards are the potential capital gains from holding it for one more period, $\tilde{\pi}(t-1)$.

The interest rate has been assumed constant over time in the current model, so its effect will not vary across individuals. The depreciation rate is a function of time and drug use. It implies that aging and heavy drug use accelerate the depreciation of health capital and raise the cost of holding one unit of health capital. The left-hand side includes the monetary value of psychic return to an additional unit of health capital, the earnings return due to the effect of health on the wage, and the earnings return due to the effect of health on the number of healthy days. Equation (2.17) does not have a different interpretation than Equation (2.12). The substitution is mainly to obtain an estimable demand equation for the addictive good.

Under the discrete time framework, there will be a time lag between changes in gross investment and changes in the health capital. To avoid the complication in the empirical analysis, the econometric model presented in the next chapter adopts the continuous time equilibrium conditions. The continuous time version of Equation (2.19) can be shown as the following [for derivation detail, see Muurinen (1982) and Wagstaff (1986)].

$$\frac{1}{\pi(t)}\left[\frac{1}{\lambda}U_H(t) + T_w(t)w_H(t) + h_H(t)w(t)\right] = \{r - \tilde{\pi}(t) + \delta[t, D(t)]\} \quad , \qquad (2.20)$$

where $\tilde{\pi}(t)$ is defined as $\dfrac{\dot{\pi}(t)}{\pi(t)}$ and $\dot{\pi}(t)$ is the instantaneous rate of change of capital gains.

Although Equations (2.18) and (2.20) are the first-order conditions for health and the addictive good, they can be viewed as the structural demand equations for health and the addictive good, respectively. Furthermore, given the time constraint, Equation (2.13) can be rearranged to derive the structural labor supply equation. These three equations along with the wage equation, (2.6), comprise the simultaneous model in the following empirical analysis. This economic model shows that individual's lifestyle choices could provide an explanation to the distribution of health, income, and wage outcomes in the population. People, who choose to continue their unhealthy lifestyle (substance abuse) eventually become addicted and their health deteriorates in the long run. On the other hand, maintaining a healthy lifestyle slows down the depreciation of health capital and enhances labor productivity.

The economic model provides a general framework. It can be modified as a pure investment model or a pure consumption model defined in Grossman's (1972) paper. A pure investment model assumes that good health only increases labor productivity and healthy days. Health does not enter the utility function as a consumption good. Hence, the only benefit from investing in health is the potential financial reward. A pure consumption model assumes that good health has no effect on labor productivity and healthy days. Like other consumption goods, health is demanded because people gain utility and satisfaction from it.

Apparently, good health does improve labor productivity and increase healthy days and utility simultaneously. The general model should be preferred to pure investment or pure consumption models. However, the main difficulty in applying the general model for economic analysis comes from the sign prediction. The sign prediction can be obtained only after making assumptions about the relationships between health, leisure, past drug use, and current drug use in the utility function. Simplifying the general model to a pure investment or pure consumption model is attractive because we can identify the structural relationship between key variables without making these assumptions. Since the labor market outcomes are the focus of this study, pure investment model is more appropriate under the current context.

Given the pure investment model, there is no need to assume the association between health and drug use in the utility function. The first-order condition for the demand for health becomes relatively simple because the marginal utility of health is zero. We are able to predict that the relationship between health and drug use in the structural demand for health is negative because the wage and healthy days are concave functions in health, and drug use is part of the cost of holding the health capital. Conversely, the pure investment assumption does not help greatly in identifying the structural relationships in the demand for binge drinking equation. The relationships between drug use, labor supply and health remain ambiguous. More assumptions and simplifications are needed. They will be covered in greater detail in the next chapter.

CHAPTER 3. ECONOMETRIC MODEL

The econometric specifications follow directly from the first-order conditions derived in the economic model. The optimal conditions in (2.13), (2.18), and (2.20) are treated as structural demand equations for leisure, the occasions of binge drinking, and health, respectively. As a result, they are estimated as a simultaneous equation system. The purpose of the estimation is to investigate the structural relationships between health, drug use, labor supply, and wage. Moreover, the estimated coefficients will be used in simulations to evaluate likely effects of changing governmental policies and other demographic variables. Before proceeding further, several assumptions and simplifications must be made to obtain a testable econometric model. First of all, the utility function is assumed quadratic:

$$\begin{aligned}U(t) = {} & k_Z Z(t) + k_D D(t) + k_H H(t) + k_L L(t) + k_{D(t-1)} D(t-1) + \tfrac{1}{2} a_{ZZ} Z(t)^2 \\ & + \tfrac{1}{2} a_{DD} D(t)^2 + \tfrac{1}{2} a_{HH} H(t)^2 + \tfrac{1}{2} a_{LL} L(t)^2 + \tfrac{1}{2} a_{D(t-1)D(t-1)} D(t-1)^2 \\ & + a_{ZD} Z(t)D(t) + a_{ZH} Z(t)H(t) + a_{ZL} Z(t)L(t) + a_{ZD(t-1)} Z(t)D(t-1) \\ & + a_{DH} D(t)H(t) + a_{DL} D(t)L(t) + a_{D(t)D(t-1)} D(t)D(t-1) + a_{HL} H(t)L(t) \\ & + a_{HD(t-1)} H(t)D(t-1) + a_{LD(t-1)} L(t)D(t-1)\end{aligned} \tag{3.1}$$

For simplicity, D(t), H(t), L(t), and D(t-1) are assumed to have no effect on the marginal utility of the composite good Z(t). That is, $a_{ZD} = a_{ZH} = a_{ZL} = a_{ZD(t-1)} = 0$. This assumption implies that the consumption of the composite good is independent of others. Therefore, the structural demand equation for the composite good can be excluded from the simultaneous system. Furthermore, a_{DL} and $a_{LD(t-1)}$ are assumed to be positive because substance abuse is a relatively time consuming activity. More frequent substance abuses would require more leisure time. Imposing this assumption would allow us to verify if excessive drug use and leisure are complements.

The first-order conditions obtained in the previous chapter are nonlinear. To simplify the econometric estimation and the policy simulation, a linear approximation will be applied to these optimal conditions. Several explanatory variables are added to the estimation because they have been shown to be important determinants in earlier literature. A majority of the sign predictions in the structural equations are ambiguous largely because of the nonlinearity. The quadratic assumption on the utility function provides limited help to sign predictions. The following sign predictions come from the general findings in related studies. The main goal of this econometric model is to characterize the interrelationship among health, addictive good, labor supply, and wage. Consequently, not every single variable appearing in the equilibrium conditions is included in the empirical analysis.

The structural demand for leisure in equation (2.13) is converted to the labor supply equation by applying the time constraint, $L(t) = h(t) - T_w(t)$. Given the assumptions on the quadratic utility function, the predicted signs for health and drug use in the labor supply equation are listed as follows:

$$T_w(t) = T_w[\underbrace{H(t)}_{+}, \underbrace{D(t)}_{-}, \underbrace{D(t-1)}_{-}, R(t)] \tag{3.2}$$

R(t) is a vector of other exogenous variables, such as gender, race, education, number of children, non-wage income, local labor market conditions, and the region of residence. The predicted sign on health is consistent with previous empirical studies. Wolfe and Steven (1995) show that single mothers' health is positively associated with hours worked. However, the effect of substance abuse on labor supply is inconclusive. Zarkin et al. (1992) found a slight negative effect of illicit drug use on weeks worked per year, while Kaestner (1994 a) showed that the negative impact of illicit drug use on annual hours worked was only significant in the cross-sectional analysis. The longitudinal results suggested no impact on the labor supply.

Given the perfect foresight framework, the rational consumer knows that health is the main determinant of labor productivity and he/she has already taken this into account when maximizing his/her lifetime utility. Hence, H(t) in Equation (2.13) summarizes two effects of health on the labor supply–the effect on the production of healthy days for market and non-market activities, and the effect on labor productivity. In the labor economic literature, the wage rate is the value of time and has been demonstrated to be a key determinant in labor supply decision. Thus, the following empirical labor supply equation will include wage as an explanatory variable. This specification can separate the wage effect from the total effect of health on labor supply. Moreover, it will be consistent with other empirical labor supply literature. The linear approximation of Equation (3.2) is given as:

$$T_w(t) = \alpha_1 + \alpha_2 w(t) + \alpha_3 OI(t) + \alpha_4 H(t) + \alpha_5 D(t) + \alpha_6 D(t-1) + \alpha_7 R'(t) + u_1 \qquad (3.3)$$

where u_1 is a standard normal random error and OI is the non-wage income.

The structural demand function for health is very similar to the one in Grossman's (1972, a,b) analysis. The major differences are that the current model treats the wage as endogenous and includes the impact of harmful addiction on health. Solving for Equation (2.20), the demand function for health and its predicted signs are as follows:

$$H(t) = H[\underbrace{BED(t)}_{-}, \underbrace{DOC(t)}_{-}, \underbrace{D(t)}_{-}, \underbrace{T_w(t)}_{+}, \underbrace{ED}_{+}, \underbrace{t}_{-}, Y(t)] \qquad (3.4)$$

BED and DOC represent the number of hospital beds and the number of doctors per 100,000 population in the respondent's residence area, respectively. Y(t) is a vector of other exogenous variables including family income, education, gender, race, marital status, neighborhood characteristics, and urbanization.

The costs of medical care are difficult to obtain because the health care system is complicated and the medical costs vary from person–to–person. Therefore, two local environmental variables are used to approximate the costs of medical care. The number of doctors per 100,000 population and the number of hospital beds per 100,000 population can capture the degree of scarcity in medical resources and partially reflect the medical costs in the residence area. More physicians and hospital beds indicate lower medical costs. As a result, less health capital is demanded. On the other hand, these two local variables may represent the local environment that affects the consumer's health production. If medical resources are positively related to the efficiency of health production, positive signs should be expected for hospital beds and the doctors.

The prediction for AGE, ED, BED(t), and DOC(t) are consistent with Grossman's sign predictions. Haveman, Wolfe, Kreider, and Stone (1994), and Wagstaff (1986) also showed that good health is positively associated with education and negatively related to age. D(t) is part of the full price of holding the health capital. An increase in excessive drug use leads to higher costs for the health capital and results in a lower health capital demanded. Labor supply is positively related to the demand for health because longer hours worked increase the monetary benefits from investing an additional unit of health. The linear empirical specification for the demand for health is the following:

$$\begin{aligned} H(t) = {} & \eta_1 + \eta_2 BED(t) + \eta_3 DOC(t) + \eta_4 FI(t) + \eta_5 ED + \eta_6 t + \eta_7 T_w(t) \\ & + \eta_8 D(t) + \eta_9 D(t-1) + \eta_{10} Y(t)' + u_2 \quad , \end{aligned} \tag{3.5}$$

where FI(t) is the net family income at period t.

The structural demand function for the addictive good is more complicated than Becker's (1988) demand function because health and labor supply are explicitly modeled as choice variables. The structural demand equation for the addictive good and its predicted signs can be expressed as:

$$D(t) = D[\underbrace{P_D(t)}_{-}, \underbrace{ED}_{-}, \underbrace{H(t)}_{\pm}, \underbrace{D(t-1)}_{+}, \underbrace{D(t+1)}_{+}, \underbrace{T_w(t)}_{-}, \underbrace{P_D(t-1)}_{+}, X(t)] \quad , \qquad (3.6)$$

where X(t) is a vector of other exogenous variables. It includes family income, marital status, urbanization, gender, race, minimum legal drinking age, start drinking before age 18, illegal activity reported in the 1980 survey, neighborhood characteristics, family members with drinking history, lag health, lead health, lag hours worked, and lead hours worked.

The positive association between current, past, and future consumption comes from the definition of addiction, particularly the tolerance syndrome. The definition of addiction for current analysis is that a person is potentially addicted to a good if an increase in the current consumption of the good increases his/her future consumption of the same good. This is equivalent to saying that current and past, and current and future consumption are adjacent complements. The inclusion of future consumption in Equation (3.6) distinguishes the rational addiction model from the myopic model.

Education increases the efficiency of health production and labor productivity. In equation (2.12), loss of healthy days and labor productivity are the components of the full price of consuming the addictive good. Hence, an increase in educational attainment raises the full price and reduces the consumption of the addictive good. Since leisure and the addictive good are complements, longer hours worked would decrease the consumption of the addictive good.

The sign on the demand for health can be positive or negative. Since health drops out of the utility function in the pure investment model, the demand for health affects the consumption of the addictive good through the full price of drug use. However, an increase in the demand for health lowers the marginal product of healthy days and marginal wage of health because both wage and health production are concave in health capital. The overall effect of an increase in the demand for health on the full price of drug use is undetermined. The empirical model for the demand of the addictive good is:

$$\begin{aligned} D(t) = {} & \beta_1 + \beta_2 P(t) + \beta_3 FI(t) + \beta_4 D(t-1) + \beta_5 D(t+1) + \beta_6 T_w(t) + \beta_7 H(t) \\ & + \beta_8 P_D(t-1) + \beta_9 ED + \beta_{10} X(t)' + u_3 \end{aligned} \tag{3.7}$$

To account for the endogeneity of the wage in the labor supply equation, the structural wage equation, Equation (2.6), is included in the simultaneous system. The empirical specification and its sign predictions for wage equation are expressed as:

$$\begin{aligned} w(t) = {} & \upsilon_1 + \upsilon_2 \underbrace{ED}_{+} + \upsilon_3 \underbrace{Age(t)}_{+} + \nu_4 \underbrace{Age\ Square\ (t)}_{-} + \nu_5 \underbrace{D(t)}_{-} + \upsilon_6 \underbrace{H(t)}_{+} \\ & + \upsilon_7 \underbrace{AFQT}_{+} + \upsilon_8 Q(t)' + u_4 \quad , \end{aligned} \tag{3.8}$$

where Q(t) is a vector of other personal and environmental variables including race, region of residence, marital status, race, union status, occupational dummy, and local labor market conditions. Age(t) is the respondent's age at period t. Age Square(t) is the square of the respondent's age at period t.

The literature on the return to education (Becker, 1993; Psacharopoulos, 1985; Mincer, 1974) shows that education has strong positive effect on the wage. The wage premium derived from job tenure and work experience also provides evidence of the beneficial effect of learning by doing, on-the-job training, and job stability on productivity. Age and Age Square are used to approximate the work experience. AFQT (Armed Forces Qualifications Test) percentile is included to control for the respondent's unobserved ability. This is particularly important when the unobserved ability is positively correlated to education. Without controlling for the unobserved ability, the return to education will be overestimated.

The empirical four-equation simultaneous framework can be obtain by pulling Equations (3.3), (3.5), (3.7), and (3.8) together:

$$\begin{aligned} D_i^*(t) = {} & \beta_1 + \beta_2 P_i(t) + \beta_3 FI_i(t) + \beta_4 D_i(t-1) + \beta_5 D_i(t+1) + \beta_6 T_{wi}(t) + \beta_7 H_i(t) \\ & + \beta_8 P_D(t-1) + \beta_9 ED_i + \beta_{10} X_i(t)' + u_{1i} \quad . \end{aligned}$$

$$\begin{aligned} \text{where } D_i(t) &= 1 \text{ if } D_i^*(t) \le 0 \\ &= 2 \text{ if } 0 < D_i^*(t) \le \mu_2 \\ &= 3 \text{ if } \mu_2 < D_i^*(t) \quad . \end{aligned}$$

$$\begin{aligned} H_i^*(t) = {} & \eta_1 + \eta_2 BED_i(t) + \eta_3 DOC_i(t) + \eta_4 FI_i(t) + \eta_5 ED_i + \eta_6 t_i + \eta_7 T_{wi}(t) \\ & + \eta_8 D_i(t) + \eta_9 D_i(t-1) + \eta_{10} Y_i(t)' + u_{2i} \quad . \end{aligned}$$

$$\begin{aligned} \text{where } H_i(t) &= 1 \text{ if } H_i^*(t) > 0 \\ &= 0 \text{ otherwise} \quad . \end{aligned}$$

$$T_{wi}(t) = \alpha_1 + \alpha_2 W_i(t) + \alpha_3 OI_i(t) + \alpha_4 H_i(t) + \alpha_5 D_i(t) + \alpha_6 D_i(t-1) + \alpha_7 R_i'(t) + u_{3i} \quad ,$$

$$\begin{aligned} w_i(t) = {} & \upsilon_1 + \upsilon_2 ED_i + \upsilon_3 Age_i(t) + \nu_4 \text{Age Square}_i(t) + \nu_5 D_i(t) + \upsilon_6 H_i(t) \\ & + \upsilon_7 AFQT_i + \upsilon_8 Q_i(t)' + u_{4i} \quad , \end{aligned}$$

where $i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T$.

$T_{wi}(t)$ is labor supply.

$W_i(t)$ is wage rate.

$H_i(t)$ is health.

$D_i(t)$ is alcohol consumption.

AFQT is Armed Forces Qualifications Test percentile.

DOC(t) is number of doctors per 100,000 population.

BED(t) is number of hospital beds per 100,000 population.

FI(t) is net family income.

OI(t) is non-wage income.

EXP(t) is the actual work experience.

ED is the years of schooling.

$P_D(t)$ is the price of the addictive good at period t.

R(t), Y(t), X(t), Q(t) are personal characteristics.

μs are the unknown threshold parameters separating the adjacent categories.

CHAPERT 4. ESTIMATION METHODS AND ISSUES

Two-stage Procedure

The dependent variables in the simultaneous equations are health, hours worked, hourly wage, and two alcohol measure–total alcohol consumption and the number of occasions of binge drinking in the past 30 days. Health is a binary variable, and the occasions of binge drinking are ordered responses. In addition, more than 50% of the total observations have zero occasions of binge drinking in past 30 days. Alcohol consumption, hours worked, and the wage are usual continuous variables.

Given the nature of the data, the ordinary method for simultaneous-equation estimation can not be applied. The procedures for estimating the simultaneous equations with limited dependent variables can be found in several economic studies (Amemiya, 1974, 1978, 1979; Lee, 1982b). Nelson and Olson (1978) proposed an alternative estimation method for a simultaneous equation model in which some or all endogenous variables are limited dependent variables. It is a two-stage estimation procedure, which is similar to two-stage least squares. At the first stage, each dependent variable is regressed on a set of instrumental variables, respectively. The instruments consist of all exogenous variables in the model, the first lead and first lag of real beer prices, the first lead and first lag of minimum legal drinking age, and the first lead and first lag of two time-varying socioeconomic variables–real net family income and marital status. The exogenous variables include education, race, parents' education, marital status, urban residence, alcohol price, gender, illegal activity in 1980, age, age square, local unemployment rate, alcoholic parent, legal drinking age, number of children, family income, non-wage income, drinking before age 18, AFQT percentile, and state higher education per capita expenditure. The predicted value of each dependent variable is calculated. The first-stage estimation in the two-stage procedure is equivalent to the reduced-form estimation.

Given the current setting, wage and labor supply equations are estimated by OLS. The structural demand for health can be estimated by Probit. The OLS is applied to estimate the demand for alcohol when total alcohol consumption is used as the measure of alcohol demand. On the other hand, since occasions of binge drinking have been converted to ordinal responses, the ordered Probit is appropriate. The predicted values obtained in the first-stage for the limited dependent variables, health and occasions of binge drinking, are the predicted latent values, $X'\hat{\beta}$, rather than its predicted probability.

The second-stage procedure is to substitute all endogenous variables on the right hand side of the system by their predicted counterparts. Then the simultaneous system can be estimated equation-by-equation. The structural parameters in the wage, labor supply, and total alcohol consumption equations are estimated by OLS. The demand for health equation is estimated by Probit. The ordered Probit is applied to the occasions of binge drinking. Nelson and Olson have shown that the estimates obtained by this two-stage procedure are consistent and asymptotically normal, although the procedure is not the most efficient.

An important assumption behind Nelson and Olson's (1978) model is that the error terms, ε_{jit}, $i = 1,\ldots,n; j = 1, 2, 3, 4,; t = 1,\ldots,T$, are correlated across equations in the same time period, but uncorrelated across different periods. If this assumption is satisfied, the existence of lag or lead dependent variables on the right-hand side should not cause any problems and can be treated as exogenous variables in the first-stage estimation. The lead and lag dependent variables at period t are defined as the values of the dependent variables at period t+1 and period t-1. However, alcohol consumption is habit forming and, moreover, health, labor supply, and wage are also likely to be correlated across different time periods. The assumption on the error terms is violated when lagged dependent variables are presented in the current model and the resulting estimates will not be consistent. In fact, the Durbin-Watson statistics suggest the existence of autocorrelation for all dependent variables in the current system.

The traditional method for estimating simultaneous equations with autocorrelation involves data transformation, derived by Hatanaka (1974). Unfortunately, this approach is valid only when the dependent variables are continuous. A minor adjustment to the Nelson-Olson two-stage procedure in handling autocorrelation is to view the right-hand side lag and lead dependent variables as endogenous and use other exogenous variables to obtain their predicted values in the first-stage. The second-stage procedure remains the same except that the lag and lead dependent variables are also substituted by their predicted values.

Maddala (1983) shows that if a dependent variable in a simultaneous system is dichotomous, the reduced-form and structural parameters associated with this variable can only be identified up to a proportionality factor. The value of the proportionality factor is the inverse of the standard error of the reduced-form residual for that dichotomous variable. Health and the occasions of binge drinking are dichotomous and ordinal, respectively, in this study. Hence, the structural estimates of the demand for health and the demand for binge drinking obtained from the two-stage procedure are not the true structural parameters. The solution to this problem is to normalize the standard errors of the reduced-form residuals to one.

Bootstrap Procedure for Estimating Variances of the Parameters

Since the simultaneous system includes the limited-dependent variables, the variance-covariance matrix reported by the statistical software is not correctly estimated. Amemiya (1979) derived the asymptotic variance-covariance matrix for Nelson-Olson's two-stage estimator. Although the same derivation logic can be applied to the current model, the asymptotic variance-covariance matrix is still difficult to obtain mainly due to the following two reasons. The major difficulty comes from the autocorrelation in the error terms, which is assumed to be independent across different periods in Nelson-Olson's framework. The second reason is the derivation process becomes tedious because the simultaneous system has four equations with lag and lead dependent variables.

The alternative to estimate the variance-covariance matrix is the bootstrap procedure. Bootstrap is a computer-based nonparametric method of statistical inference. It was first developed and introduced by Efron (1979). The classical situation is that a random sample, X, of size n is observed from an unknown probability distribution F. We are interested in the distribution of a random variable Y(X, F), which possibly is a function of X and the unknown distribution F. The sampling distribution of Y is estimated on the basis of the observed data X.

The bootstrap method begins first by treating the sample X as an empirical population or the sample probability distribution $\hat{F}$. Given the sample probability distribution, a random sample, X^*, of size n is drawn with replacement from $\hat{F}$. We call this random sample the bootstrap sample. At last, we can approximate the sampling distribution of Y(X, F) by the bootstrap distribution of $Y^*(X^*, \hat{F})$. The next step is to obtain the bootstrap distribution. The Monte Carlo method is used to approximate the bootstrap distribution. Repeated bootstrap samples are generated by taking random samples of size n from $\hat{F}$, say $X^*_1, X^*_2, X^*_3, \ldots, X^*_N$. The histogram of the $Y^*(X^*_1, \hat{F}), Y^*(X^*_2, \hat{F}), Y^*(X^*_3, \hat{F}), \ldots, Y^*(X^*_N, \hat{F})$ is taken as the approximation of the bootstrap distribution of $Y^*(X^*, \hat{F})$.

In the regression context, there are two ways of generating random samples from the sample probability distribution $\hat{F}$–bootstrapping pairs vs bootstrapping residuals. Bootstrapping pairs assumes that the pairs (d_i, e_i) in the original sample come from an unknown multivariate distribution. d_i represents the dependent variable and e_i is a vector explanatory variable. Bootstrapping pairs is conducted by resampling the dependent and independent variables simultaneously. On the other hand, bootstrapping residuals requires a stronger assumption that the error between the observed dependent variable and its mean (or predicted value) is independent of the explanatory variables. That is, the error comes from the same distribution no matter what the explanatory variables would be. The residual is the difference between the observed dependent variable and its predicted value computed from the regression. Since the explanatory variables are assumed to be nonrandom, we only resample the dependent variable. The bootstrap dependent variables are obtained by adding the randomly selected residuals to their predicted values.

Efron (1993) shows that the outcomes from bootstrapping pairs are less sensitive to assumptions than bootstrapping residuals. Furthermore, the stronger assumption in bootstrapping residuals may fail to hold. The current model includes lag and lead dependent variables in the vector of explanatory variables. It is hard to believe that the error term is independent of the lag and lead explanatory variables. Also, it is difficult to apply bootstrapping residuals on limited dependent variables. Most importantly, bootstrapping residuals violate the basic idea of nonparametric analysis behind the bootstrap method because distribution assumptions must be made to compute the residuals of the limited dependent variables. In conclusion, bootstrapping pairs are more appropriate than bootstrapping residuals for the current model.

NLSY79 is a panel data that has the properties of both time-series and cross-section data. It is unacceptable to assume that the observations across different years from the same respondent are independent draws from an unknown distribution, although the independence assumption between different respondents is reasonable. The method of bootstrapping time-series will be different from that of bootstrapping cross-section data because the error terms are autocorrelated in time-series data. Instead of resampling one pair at a time, a block of pairs is chosen with replacement from all possible contiguous blocks. The choice of the length of the block is conditional on how strong is the autocorrelation. The current analysis chooses three as the length of the block because the estimation requires only one-year lead and lag variable.

Once the bootstrap sample is generated, the two-stage procedure is conducted to obtain the bootstrap structural estimates. To obtain the bootstrap distribution for the bootstrap structural estimators, the Monte Carlo method is performed–repeating the bootstrapping pairs procedure N times to get N bootstrap samples and N bootstrap structural estimates. At last, the variances of the two-stage estimates are approximated by the variances of the N bootstrap structural estimates. The bootstrap t statistics are computed for the first-stage and second-stage estimates, respectively. In the following empirical analysis, 1000 bootstrap samples are generated to approximate the variances of the structural estimates.

Sample Selection

By 1994, the NLSY79 had 16 waves of data. Alcohol-related questions were only asked in 7 of the 16 waves. On the other hand, health, hours worked, wage, and other socioeconomic variables are collected in all 16 waves. To fully utilize the information available in the data set, all sixteen panels are used to estimate the demand for health, labor supply, and wage equations in the first-stage. For total alcohol consumption and the occasions of binge drinking, both are estimated using 7 panels. Moreover, the predicted values of the total alcohol consumption and the occasions of binge drinking in the years in which alcohol questions were not surveyed are computed using the coefficients from the regression. In the second stage, the sample includes only respondents who are employed. The common problem in using household data for the economic analysis is the presence of missing values. The procedures to compensate missing values in the independent variables are demonstrated in Appendix A.

Since the econometric model consists of one-year lead and lag variables, the estimation requires data that the respondents had participated in at least three consecutive surveys. The sample used in the two-stage procedure is chosen by the following additional criteria: (1) respondents who miss at least three consecutive surveys are deleted, (2) respondents who work more than 75 hours a week are excluded, (3) observations with hourly wage higher than $ 30 are excluded, (4) observations which have missing values on real alcohol prices are excluded, (5) those who are currently enrolled in school or serve in the armed forces are deleted, and (6) self-employed and working on the family farm or family business are also excluded.

The Correction for Self-selection Bias

Since only respondents who are working for a wage are included in the second-stage estimation, the inverse Mill's ratio is computed to correct for self-selection bias. The computation of the inverse Mill's ratio is based on Heckman's (1976) two-stage estimation method. Additionally, as discussed in the previous chapter, it is common to have unit non-response and attrition in panel surveys. If the unit non-response and attrition occur randomly, the correction for self-selection will be sufficient and the estimates from the two-stage procedure will be unbiased and consistent. However, a review of the data suggests that respondents who miss more waves of surveys are more likely to be unemployed and have health problems. This suggests that the unit non-response occurs non-randomly and the second Mill's ratio correction for the non-randomness is necessary.

To obtain the second Mill's ratio for non-randomness of unit non-response, we need to calculate the probability of participating in the survey (Ziliak and Kniestner, 1998; Zabel, 1998). Because data are unavailable in the year where unit non-response or attrition occurred, first-year lag explanatory variables are used to predict the probability of participating in the current survey. The explanatory variables include age, years of schooling, region of residence, urbanity, gender, race, local unemployment rate, and a dummy which is equal to one if the respondent moved during the year, or zero otherwise.

The decision of employment status and participation in the survey may be jointly determined. For example, unemployed respondents may also be more likely to withdraw from the survey. To investigate if they are joint decisions, a bivariate probit model is applied, assuming a bivariate normal distribution between the error terms, and the correlation coefficient is estimated. The results show that the correlation coefficient is -0.23 and is not significant at the 5 percent level. Therefore, the two inverse Mill's ratios will be estimated separately in the following empirical analysis.

Multicollinearity

When two explanatory variables are highly intercorrelated, it becomes difficult to distinguish the separate effect of each explanatory variable on the dependent variable. This is called multicollinearity in econometrics. It is particularly common in the dynamic model, whereby the current, lead and lag values of the same variable are included as explanatory variables. The statistical inference based upon these highly intercorrelated variables is unreliable because both variables basically contain the same information. However, as mentioned by Maddala (1988), including highly intercorrelated variables in the equation need not necessarily create a problem. There are several other criteria to detect if multicollinearity causes any serious problems other than correlation between explanatory variables. The major symptoms of multicollinearity include: (1) the standard errors of the estimated coefficients are large, (2) the parameter estimates are very sensitive to minor additions or deletions of observations, and (3) the model prediction is less precise.

The current model includes current, one-year lead and lag dependent variables in the equation. Some of them are highly correlated simply because one year is not long enough to show the separate effects of the lead and lag variables. The following empirical estimation uses the above three criteria to determine if multicollinearity is serious in the model and whether lead and lag variables should be maintained or deleted.

CHAPTER 5. DATA AND EMPIRICAL DEFINITIONS OF VARIABLES

This section presents the data and variables used in the empirical analysis. The definition of variables and their measurements are discussed. The data used in this study are from the National Longitudinal Survey of Youth Cohort 1979-1994 (NLSY79). It is a nationally representative sample of 12,686 young men and women who were 14 to 21 years of age when they were first surveyed in 1979. Surveys are conducted on an annual basis. The NLSY focuses mainly on the labor market experiences of American young adults and oversamples blacks, Hispanics, and economically disadvantaged white youth. Drug related questions were added to the survey in selected years. Alcohol consumption questions were included in the survey conducted in 1982-1985, 1988, 1989, 1992, and 1994.

Two measures of alcohol consumption are available in the data set, the number of occasions having six or more drinks in a row in the past 30 days and the total number of drinks consumed in the past 30 days. The definition of "a drink" in the survey includes a can of beer, a glass of wine, or a glass of hard liquor. "Binge drinking" is defined as having five or more drinks on the same occasion at least one day in the past 30 days. "Heavy drinking" is defined as drinking five or more drinks on the same occasion on each of five or more days in the past 30 days. "Occasion" is meant at the same time or within a couple hours of each other. Therefore, an individual will be categorized as a "heavy drinker" if he/she has five or more days of having 5 or more drinks on the same occasion in the past 30 days.

The occasions of binge drinking in the past 30 days in the data set are categorized into seven levels, which take values from 0 to 6 with respect to the following category: 0 occasion, 1 occasion, 2-3 occasions, 4-5 occasions, 6-7 occasions, 7-8 occasions, and 10 or more occasions. The occasions of binge drinking are available in 1982-1985, 1988, 1989, and 1994. To investigate the long-term effect of heavy drinking on health, labor supply, and wages, these seven panels of alcohol data are included in the analysis. The distribution of the occasions of binge drinking is skewed toward zero, and contains a very thin tail when the distribution approaches greater occasions of binge drinking. Table 5.1 displays the distribution of occasions of binge drinking in the data set. Because of the nature of the data, regrouping the occasions of binge drinking is necessary. Otherwise, it will be difficult to identify the impact of independent variables on some categories when these categories have

Table 5.1. Frequency, Percentage and Cumulative Percentage of the Distribution of the Occasions of Binge Drinking

Occasions of Binge Drinking	Frequency	Percentage	Cumulative Percentage
0 occasion	48792	66.7	66.7
1 occasion	6827	9.3	76.1
2-3 occasions	8246	11.3	87.3
4-5 occasions	4050	5.5	92.9
6-7 occasions	1805	2.5	95.3
8-9 occasions	921	1.3	96.6
10 or more occasions	2492	3.4	100.0
Total	73133	100.0	100.0

relatively few observations. In the following empirical model, the occasions of binge drinking are further converted into ordinal responses. The occasions of binge drinking is reassigned to 1 if the original response was 0, 2 if the original response was 1 or 2, and 3 if the original response was at least 3. The renumbered values are interpreted as no binge drinking, binge drinking, and heavy drinking.

The reliability of self-reported alcohol consumption has been a major concern for most drug-related studies. This is because substance abuse is not an acceptable behavior society.

Respondents have an incentive to underreport their actual level of consumption particularly when the interviewer or other people are present during the interview. The problem of underreporting is more likely to happen for teenage respondents because underage drinking is illegal.

Although the intention of underreporting cannot be controlled and verified in the NLSY data, it has been shown that the alcohol data from the NLSY are consistent with those obtained from other nationally representative surveys (Lorraine, 1988; Pacula, 1995). Variables such as whether parents or friends were present during the survey is included in the analysis to reduce the underreporting bias. Hoyt (1992) shows that respondents are more likely to underreport when parents are present during the survey and to exaggerate their actual consumption when friends are present.

The health section of the survey does not provide information on the respondents' health and medical histories in great detail. Good health is simply defined as "no limitation" on the *amount* or *kind* of work the respondent can do at work. Hence, health is a binary variable, and is equal to one if the respondent has a health limitation or zero otherwise. The main disadvantage for this definition is that it does not precisely capture the respondent's true health status. In particular, substance abuse frequently is related to the development of chronicle diseases, which may not affect people's daily functioning in the short run. It is very likely to categorize any two people as healthy even when one of them has a health problem, as long as the health problem does not prevent the respondent from working. In the NLSY79, the respondents are in their twenties or early thirties. Many major health problems associated with substance abuse or other unhealthy lifestyles may still be at the early stage of development. The health outcomes of substance abuse are difficult to identify for young adults without a comprehensive health survey. In fact, for people who are employed, the NLSY79 reveals there are only 2,504 out of 80,441 observations indicating health limitations at work.

Labor supply is defined as the actual hours worked at all jobs during the last week. Wage is the hourly rate of pay at the main job. Although the survey does not provide information on actual hours worked at each job, a majority of the respondents do hold only one job. Hence, the estimation of labor supply based on the hourly rate of pay at the main job should not cause serious bias.

Information on the state of current residence, MSA, and PMSA are used to merge the sample with local and state real alcohol prices, and state minimum legal drinking age. Alcohol prices come from *the Cost of Living Index* published quarterly by the American Chamber of Commerce Researchers Association (ACCRA). The living index has different names in various years: Inter-city Cost of Living Index or Inter-city Cost of Living Indicator. The ACCRA collects information on the prices of a number of consumer goods including beer, liquor, and wine for more than 300 cities in the states. The price of beer is selected as the measure of the price of alcohol in this study because beer is the most common alcoholic beverage consumed, especially among young adults. *The price of alcohol is defined as the price of a six-pack canned low- alcohol beer, e.g., Budweiser.* Since the cost of living index displays that the price of beer does not vary much across different quarters in the same year, the prices reported in the third quarter are chosen as the annual price of alcohol. This is because most of the NLSY79 survey periods cover the third quarter. Furthermore, the prices of alcohol will be deflated in terms of the 1994-dollar.

The *Cost of Living* Index only provides the price of liquor in the surveys before 1982. Regression analysis is applied to obtain the price of beer before 1982. The sample used for the regression includes the prices of beer from 1982 to 1996 and the independent variables include state excise tax, region of residence, and a time trend. The data on state excise tax come from the *Brewers Almanac*. The predicted value is then taken as the price of beer. For respondents who do not live in these 300 surveyed cities, the state average price is used as the price of beer. The state average price at year t is the average predicted price of the surveyed cities in that state at year t. Moreover, the lead (year t+1) and lag (year t-1) alcohol prices are defined as the price of alcohol at period t+1 and period t-1. If the respondents do not live in the same state or the same city in adjacent years, the lead and lag prices are simply calculated as the average of the alcohol prices in two different residence areas.

The minimum legal drinking age can be viewed as part of the full price of alcohol consumption, particularly for underage youths. The data on the minimum legal drinking age come from the *Book of the States* (1978-1996). A higher minimum drinking age increases the probability of being caught and discourages underage drinking. Instead of using the minimum legal drinking age alone, an alternative to evaluate the effect of the minimum legal drinking age on alcohol consumption is to multiply the minimum legal drinking age by a dichotomous variable which equals 1 if the respondents are younger than the minimum legal drinking age, or 0 otherwise. For people who are older than the minimum legal drinking age, the legal drinking age restriction will not have any effect on their alcohol consumption. The coefficient of this interaction term is expected to be negative, which implies that underage youths are less likely to obtain alcohol in states with a higher minimum legal drinking age than in states with a lower minimum drinking age. Alternatively, given the minimum drinking age, older underage youths have more access to alcohol than their counterparts.

AFQT (Armed Forces Qualifications Test) percentile is a composite score derived from selective sections in the Armed Services Vocational Aptitude Battery (ASVAB) tests. The ASVAB consists of ten tests which measure knowledge and skills in the following areas: (1) general science, (2) arithmetic reasoning, (3) word knowledge, (4) paragraph comprehension, (5) numerical operation, (6) coding speed, (7) auto and shop information, (8) mathematics knowledge, (9) mechanical comprehension, and (10) electronics information.

AFQT scores are a general measure of trainability and a primary criterion of enlistment eligibility for the armed forces. The AFQT percentile is constructed based on the scores from section 2, 3, 4, and one-half of the scores from section 5. It provides a measure of the respondent's innate ability. The AFQT percentile is included in the wage equation to control for unobserved ability. This is potentially important because the return to education may be overestimated if education is positively correlated with unobserved ability. Blackburn and Neumark (1995) indicate an upward bias of nearly 40 percent in the OLS estimation on the return to education if one ignores unobserved ability.

A group of independent variables are constructed from the socioeconomic and local environmental information collected in the NLSY. They include gender, race, age, highest grade completed, parents' education, real net family income, non-wage income work experience, height, number of children younger than five, twelve, and eighteen years old, marital status, local unemployment rate, local hospital beds per 100,000 population, local physicians per 100,000 population, living with parents at the age of fourteen, alcoholic parents, started drinking before 18, illegal activities in 1980, and parent or friend present during the survey. Table 5.1 contains the definitions, means, and standard deviations of variables. Table 5.2 gives a comparison on personal characteristics, local environment, and family backgrounds for heavy drinkers and non-heavy drinkers. Recall that heavy drinker is defined as people who have 5 or more occasions of binge drinking in the past 30 days.

The descriptive statistics presented in Table 5.2 show that heavy drinkers are more likely to be male, white, single, and surprisingly, working longer hours. They come from less educated families and are two times more likely than non-heavy drinkers to engage in illegal activities. Additionally, heavy drinkers have lower AFQT percentiles. Their educational attainments and work experience indicate that frequent heavy drinking is associated with interrupted schooling and job instability, which result in lower wages and family incomes. Heavy drinkers are also more likely to work than their counterparts. However, we have to be cautious when making this conclusion. The NLSY79 includes many young adults who are still in school. If heavy drinkers are more likely to drop out of school and enter labor market earlier, we will find this positive relationship between working status and heavy drinking, while the relationship between heavy drinking and working status may indeed be negative.

Respondents who have alcoholic parents are more likely to become heavy drinkers. Furthermore, state excise tax and minimum legal drinking age are not very effective in discouraging excess alcohol consumption. The real alcohol price and minimum legal drinking age are almost identical in the residences of both heavy and non-heavy drinkers. Heavy drinkers are more likely to reside in states where the expenditures per pupil in public elementary school and secondary school are lower. It implies that increasing investment in education could reduce the incidence of heavy drinking.

The finding that a young, heavy drinker is healthier than a non-heavy drinker may be inconsistent with our intuition that heavy drinking accelerates the depreciation of health. This finding should not be interpreted as an increase in heavy drinking improves health status. On the contrary, it is the outcome resulted from the adjustment in the consumption decision. If people choose to reduce their occasions of heavy drinking when health status deteriorates, we are likely to observe that non-heavy drinkers have a lower health status than heavy drinkers. In fact, the data show that people who move from healthy status to unhealthy status do reduce their frequencies of heavy drinking, and increase the occasions of binge drinking when their health status improves. Consequently, the cause-effect relationship between health and heavy drinking is difficult to identify from the data summary.

Table 5.1. Definitions, Means, and Standard Errors of Variables

Variable	Mean (Standard Error)	Definition
Health limitation	0.066 (0.248)	Dichotomous variable equals 1 if health limits the amount and kind of work the respondent can do
Frequency of binge drinking	0.866 (1.506)	Number of occasions of having 6 or more drinks in a row in the past 30 days
Hours worked	38.51 (12.79)	Actual hours worked at all jobs last week
Log wage	2.15 (0.165)	Natural log of hourly wage
Education	12.346 (2.288)	Highest grade completed
Age	25.281 (4.268)	Age of the respondent
Black	0.27 (0.444)	Dichotomous variable equals 1 if respondent is African American
Hispanic	0.172 (0.378)	Dichotomous variable equals 1 if respondent is Hispanic
Father's education	10.734 (3.952)	Highest grade completed by respondent's father
Mother's education	10.721 (3.188)	Highest grade completed by respondent's mother
Married	0.405 (0.491)	Dichotomous variable that equals 1 if respondent is married
Urban	0.8 (0.4)	Dichotomous variable that equals 1 if respondent lives in urban area
Dage	20.229 (1.168)	State minimum legal drinking age
Real alcohol price	4.185 (0.408)	Real market price of 6 packed beer
AFQT	38.601 (28.496)	AFQT test percentile
Age14	0.675 (0.468)	Dichotomous variable equals 1 if respondent lives with parents at age of 14
Eduspend	3179.75 (1586.36)	Real state expenditures per pupil in public elementary and secondary day schools
Work experience	259.78 (186.649)	Accumulated work experience in weeks between 1979 and 1994
Less5	0.473 (0.757)	Number of children who are younger than 5 years old at home

Table 5.1. (continued)

Variable	Mean (Standard Error)	Definition
Less12	0.249 (0.607)	Number of children who are older than 5 years old, but younger than 12 years old
Less18	0.039 (0.278)	Number of children who are older than 12 years old, but younger than 18 years old
Male	0.471 (0.499)	Dichotomous variable equals 1 if respondent is male
Ill80	0.102 (0.303)	Dichotomous variable equals 1 if the respondent had been charged with illegal activity by the police in 1980
Unemployment rate	3.102 (1.074)	Local unemployment rate
Northeast	0.182 (0.386)	Dichotomous variable equals 1 that if respondent lives in the northeast region
North central	0.24 (0.427)	Dichotomous variable equals 1 if respondent lives in the north central region
West	0.195 (0.396)	Dichotomous variable equals 1 if respondent lives in the west region
Parents present	0.052 (0.221)	Dichotomous variable equals 1 if parents were present in the interview
Friends present	0.026 (0.16)	Dichotomous variable equals 1 if friends were present in the interview
Alcoholic parents	0.24 (0.427)	Dichotomous variable equals 1 if respondent has alcoholic parents
Hospital beds per 100,000 population	6258.36 (4623.92)	Hospital beds per 100,000 population at current residence
Physicians per 100,000 population	1812.32 (1285.28)	Physicians per 100,000 population at current residence
Real net family income	37961.8 (64741.09)	Real total net family income including assets
Real other income	22080.11 (59508.67)	Non-wage income
Working	0.689 (0.455)	Dichotomous variable that equals 1 if currently working for a wage
Lambda1	0.058 (0.037)	Inverse Mill's ratio: correction for unit non-response
Lambda2	0.506 (0.27)	Inverse Mill's ratio: correction for employment status

Table 5.2. Means and Standard Deviation for Heavy Drinker and Non-heavy Drinker

Variable	Heavy Drinker Mean (Standard Error)	Non-heavy Drinker Mean (Standard Error)
Health limitation	0.048	0.069
	(0.213)	(0.253)
Frequency of binge drinking	4.19	0.394
	(1.25)	(0.72)
Hours worked	39.191	38.055
	(13.111)	(13.035)
Log wage	2.114	2.125
	(0.454)	(0.471)
Education	11.876	12.459
	(1.987)	(2.265)
Age	24.484	24.985
	(4.065)	(4.23)
Black	0.2	0.271
	(0.4)	(0.445)
Hispanic	0.174	0.166
	(0.379)	(0.372)
Father's education	10.817	10.776
	(3.814)	(3.972)
Mother's education	10.8	10.754
	(3.011)	(3.2)
Married	0.23	0.414
	(0.421)	(0.493)
Urban	0.81	0.795
	(0.392)	(0.403)
Hospital beds per 100,000 population	6285.9	6240.76
	(4634.9)	(4660.49)
Physicians per 100,000 population	1733.01	1786.12
	(1237.31)	(1291.11)
Real alcohol price	4.146	4.166
	(0.45)	(0.432)
Dage	19.98	20.083
	(1.216)	(1.177)
Age14	0.662	0.675
	(0.473)	(0.468)
Less5	0.28	0.485
	(0.618)	(0.766)

Table 5.2. (continued)

Variable	Heavy Drinker Mean (Standard Error)	Non-heavy Drinker Mean (Standard Error)
Less12	0.145	0.228
	(0.479)	(0.582)
Less18	0.025	0.039
	(0.181)	(0.231)
Working	0.726	0.684
	(0.446)	(0.464)
Work experience	234.543	241.871
	(174.547)	(185.311)
Eduspend	2946.89	3022.58
	(1427.81)	(1515.47)
Male	0.761	0.437
	(0.427)	(0.496)
Ill80	0.21	0.089
	(0.407)	(0.285)
Start drinking before age 18	0.701	0.406
	(0.458)	(0.491)
Unemployment rate	3.323	3.236
	(1.191)	(1.188)
Northeast	0.205	0.182
	(0.403)	(0.386)
North central	0.273	0.231
	(0.446)	(0.421)
West	0.182	0.196
	(0.386)	(0.397)
Parents present	0.06	0.045
	(0.238)	(0.206)
Friends present	0.043	0.022
	(0.202)	(0.146)
Alcoholic parents	0.268	0.235
	(0.443)	(0.424)
Real net family income	36064.88	39151.26
	(60629.09)	(73435.64)
Real other income	20058.18	23748.15
	(57388.93)	(67639.8)
AFQT	37.238	39.35
	(28.022)	(28.704)
Number of observations	8399	57630

CHAPTER 6. EMPIRICAL RESULTS AND MODEL SIMULATIONS

This chapter presents the empirical results of the simultaneous system when the occasions of binge drinking are the measure of the alcohol consumption. In the preliminary estimation, The inclusion of lag and lead dependent variables in the equation do not change the sign and the magnitude of other coefficient estimates obtained from excluding the lag and lead dependent variables. Furthermore, the coefficient on the lag (lead) dependent variable has almost an identical magnitude as its current counterpart except with a different sign. This finding indicates that the separate effects of the current and lag (lead) dependent variables on the left-hand side dependent variable cannot be identified when including them simultaneously in the same equation. Hence, it is difficult to interpret the coefficient on current and lag (lead) variables. Since multicollinearity appears to affect the estimation significantly, the right-hand side lead and lag dependent variables are dropped from the following estimation except for lag and lead binge drinking in the demand for binge drinking equation. The first-stage estimation is presented in Table 6.1.

The Demand for Health

Table 6.2 presents the structural estimates of the demand for health. Both heavy drinking and age are the main components of the full price of acquiring one additional unit of health capital. An increase in either raises the cost of the health capital, and hence, decreases the demand for health. The coefficient on heavy drinking has the predicted sign, but insignificant at the 5 % level and marginally significant at 10 % level. On the other hand, the age effect is statistically significant at the 5% level. It shows that the health capital declines over the life cycle because the health capital becomes more expensive when people age.

Table 6.1. First-stage Estimation: Health, Occasions of Binge Drinking, Labor Supply Log Wage, Lag Occasions of Binge Drinking, Lead Occasions of Binge Drinking

	Demand for Health	Occasions of Binge Drinking	Labor Supply
Education	0.03	-0.045	-0.296
	(5.747)[a]**	(-13.278)**	(-5.873)**
Black	0.064	-0.352	-0.157
	(3.636)**	(-20.229)**	(-0.747)
Hispanic	0.084	-0.03	-0.057
	(4.038)**	(-1.554)*	(-0.523)
Father's education	0.005	0.006	-0.032
	(2.427)**	(3.333)**	(-2.254)**
Mother's education	-0.01	0.01	-0.058
	(-4.032)**	(4.348)**	(-3.268)**
Male	0.165	0.573	3.177
	(4.599)**	(44.247)**	(12.739)**
Married	-0.129	-0.219	-0.832
	(-4.645)**	(-8.907)**	(-3.802)**
Urban	-0.017	0.119	-0.426
	(-0.994)	(7.173)**	(-3.336)**
Hospital beds per 100,000	-3.21E-6	3.09E-6	-0.00003
population	(-2.153)**	(2.026)**	(-2.542)**
Physicians per 100,000	0.00002	-0.00003	0.00005
population	(3.226)**	(-4.839)**	(1.19)
Living with parents at age	0.073	0.03	-0.004
14	(3.931)**	(1.974)**	(-0.035)
Age	-0.047	0.14	4.588
	(-1.943)**	(5.054)**	(20.274)**
Age xx 2	-0.0002	-0.003	-0.082
	(-0.446)	(-5.379)**	(-20.76)**
Local unemployment rate	0.003	0.024	-0.04
	(0.297)	(2.874)**	(-0.442)
Northeast	-0.091	0.178	-1.39
	(-3.906)**	(8.036)**	(-8.54)**
North central	-0.157	0.129	-0.996
	(-8.177)**	(7.104)**	(-6.955)**
West	-0.148	-0.032	-0.733
	(-7.749)**	(-1.711)*	(-5.495)**

[a]Bootstrap t statistics are in the parentheses.
**Statistically significant at the 5 % level.
*Statistically significant at the 10 % level.

Log Wage	Lag Occasions of Binge Drinking	Lead Occasions of Binge Drinking
0.019	-0.048	-0.046
(7.539)[a]**	(-14.089)**	(-13.71)**
0.007	-0.367	-0.322
(0.861)	(-20.18)**	(-19.053)**
0.034	-0.038	-0.037
(7.441)**	(-1.945)*	(-2.102)**
0.001	0.005	0.005
(2.237)**	(2.66)**	(2.994)**
0.0003	0.009	0.011
(-0.508)	(3.676)**	(4.937)**
0.108	0.55	0.581
(7.505)**	(41.509)**	(46.111)**
0.005	-0.1	-0.029
(0.689)	(-3.982)**	(-1.18)
0.04	0.1	0.098
(-10.526)**	(5.78)**	(5.768)**
-0.000004	1.375E-6	2.761E-6
(-13.33)**	(0.902)	(1.93)*
0.00002	-0.00002	-0.00004
(14.286)**	(-3.278)**	(-7.018)**
0.018	0.013	0.017
(5.099)**	(0.844)	(1.133)
0.067	0.117	0.085
(6.504)**	(4.163)**	(4.775)**
-0.001	-0.002	-0.002
(-5.747)**	(-3.636)**	(-5.747)**
-0.007	0.024	0.048
(-2.336)**	(2.684)**	(5.783)**
0.057	0.154	0.177
(11.594)**	(7.007)**	(8.863)**
0.018	0.122	0.127
(4.391)**	(7.056)**	(7.147)**
0.076	-0.034	-0.026
(17.447)**	(-1.925)*	(-1.481)

Table 6.1. (continued)

	Demand for Health	Occasions of Binge Drinking	Labor Supply
Parents present	-0.166	-0.028	-1.055
	(-6.173)**	(-1.086)	(-4.579)**
Friends present	-0.078	0.28	-0.03
	(-2.281)**	(8.892)**	(-0.102)
Real alcohol price	0.004	-0.029	0.002
	(0.161)	(-1.518)	(0.011)
Legal drinking age x age >minimum drinking age	0.006	-0.005	-0.072
	(2.83)**	(-2.915)**	(-4.286)**
Alcoholic parents	-0.155	0.061	0.323
	(-7.346)**	(2.796)**	(1.852)*
Living with alcoholic parents at 14	0.111	0.046	-0.07
	(3.908)**	(1.612)	(-0.331)
Number of children < 5 years old	0.052	-0.058	-0.036
	(3.91)**	(-6.236)**	(-0.241)
Number of children between 6 and 12	0.053	-0.002	-0.145
	(4.344)**	(0.152)	(-1.436)
Number of children older than 12	-0.064	-0.001	0.816
	(-2.832)**	(0.023)	(4.206)**
Real non-wage income	-0.00002	-2.26E-6	-0.0001
	(-3.774)**	(-5.333)**	(-7.692)**
Real net family income	0.00002	2.164E-6	0.0001
	(3.704)**	(5.328)**	(7.752)**
Started drinking before 18	0.07	0.516	0.278
	(5.512)**	(44.56)**	(2.951)**
Illegal activities in 1980	-0.099	0.196	0.415
	(-4.714)**	(10.739)**	(2.068)**
AFQT percentile	0.003	-0.0005	-0.015
	(6.289)**	(-1.812)*	(-6.667)**
Eduspend	2.91F-6	-0.00003	-0.00005
	(0.351)	(-3.371)**	(1.109)
Lag real alcohol price	-0.018	-0.029	0.124
	(-0.773)	(-1.385)	(0.777)
Lead real alcohol price	0.015	-0.027	0.101
	(0.696)	(-1.357)	(0.66)

Log Wage	Lag Occasions of Binge Drinking	Lead Occasions of Binge Drinking
-0.033	-0.046	-0.026
(-5.03)**	(-1.489)	(-1.131)
0.019	0.102	0.095
(2.369)**	(2.684)**	(-2.962)**
0.012	-0.019	-0.038
(2.43)**	(-0.856)	(-1.786)*
-0.0005	0.002	-0.001
(-1.155)	(1.01)	(-0.648)
0.013	-0.091	-0.034
(2.394)**	(-9.96)**	(-3.8)**
-0.022	0.003	0.012
(-5.995)**	(0.245)	(0.965)
-0.031	0.008	0.041
(-5.363)**	(0.211)	(1.486)
-0.00001	-3.84E-6	-1.69E-6
(-8.333)**	(-7.761)**	(-4.143)**
0.00001	3.187E-6	1.55E-6
(7.692)**	(6.812)**	(3.9)**
-0.0005	0.514	0.494
(-0.186)	(43.596)**	(45.825)**
0.01	0.2	0.202
(1.471)	(10.629)**	(12.875)**
0.002	-0.0003	-0.001
(18.536)**	(-1.087)	(-3.776)**
0.00001	-0.00002	-0.00002
(6.25)**	(-2.5)**	(-2.899)**
-0.008	0.055	0.05
(-1.541)	(2.429)**	(2.433)**
-0.004	0.057	0.042
(-0.61)	(2.059)**	(1.634)
0.004	-0.039	-0.042
(-0.861)	(-1.875)*	(-2.02)**
-0.0001	-0.045	-0.028
(-0.023)	(-2.124)**	(-1.563)

Table 6.1. (continued)

	Demand for Health	Occasions of Binge Drinking	Labor Supply
Lag real net family income	3.18E-7	8.09E-8	0.000003
	(1.562)	(-1.096)	(3.75)**
Lead real net family income	3.26E-7	-9.71E-8	0.000002
	(2.207)**	(-0.482)	(2.857)**
Lag legal drinking age x age >minimum drinking age	0.0001	-0.002	-0.026
	(0.063)	(-1.439)	(-1.967)**
Lead legal drinking age x age >minimum drinking age	0.001	0.002	-0.043
	(0.455)	(1.023)	(-2.396)**
Lag marital status	0.118	-0.038	-0.49
	(5.3)**	(-1.827)*	(-3.322)**
Lead marital status	0.032	-0.18	1.093
	(1.368)	(-9.212)**	(7.153)**
Lag local unemployment rate	0.009	-0.001	0.081
	(1.059)	(-0.144)	(1.311)
Lead local unemployment rate	-0.01	0.021	-0.092
	(-1.205)	(2.783)**	(-1.562)
Intercept	1.802	-2.825	-19.0
	(5.331)**	(-8.019)**	(-4.791)**
Intercept2	N/A	-1.998	N/A
		(2.832)**	
Lambda1	-0.107	-0.128	-3.273
	(-0.444)	(-0.713)	(-2.021)**
Lambda2	N/A	N/A	-5.475
			(-5.209)**
Chi-Square Statistics (Degree of fredoom=43)	3886.209	9452.44	N/A
F statistics	N/A	N/A	351.73
Adjusted R square	N/A	N/A	0.167
Number of observations	111941	51335	77008

N/A Not available.

Log Wage	Lag Occasions of Binge Drinking	Lead Occasions of Binge Drinking
0.000001	6.33E-8	3.78E-7
(9.733)*	(0.842)	(1.778)*
0.0000003	-1.24E-7	-1.34E-8
(7.642)**	(-1.17)	(0.191)
-0.026	0.017	-0.075
(-14.138)**	(2.241)**	(-10.908)**
0.003	0.006	0.041
(1.675)*	(0.677)	(5.84)**
-0.001	-0.008	-0.002
(-2.814)**	(-5.333)**	(-1.613)
0.0006	-0.003	-0.005
(1.318)	(1.147)	(-3.157)**
0.021	-0.238	-0.068
(4.302)**	(-11.333)**	(-3.276)**
0.049	-0.092	-0.345
(9.665)**	(-4.6)**	(-18.098)**
0.447	-2.46	-1.926
(2.523)**	(-6.734)**	(-7.871)**
N/A	-1.633	-1.108
	(-4.478)**	(-4.53)**
-0.242	0.041	-0.03
(-5.013)**	(0.224)	(-0.178)
-0.074	N/A	N/A
(-1.897)*		
N/A	9366.07	10023.36
1315.22	N/A	N/A
0.436	N/A	N/A
75029	50961	56899

Table 6.2. Structural Estimates of The Demand for Health (Probability of Being Healthy)

Explanatory Variables	Dependent Variable: Health Limitation
Age	-0.018
	(-4.675)[a]**
Education	0.055
	(7.432)**
Predicted binge drinking[b]	-0.032
	(-1.013)
Predicted hours worked	0.026
	(3.768)**
Married	0.068
	(2.698)**
Black	-0.024
	(-0.737)
Hispanic	0.085
	(2.972)**
Male	0.18
	(5.59)**
Urban	0.006
	(0.225)
Real net family income	3.81E-7
	(1.346)
Physicians per 100,000 population.	0.00001
	(1.099)
Hospital beds per 100,000 population	1.76E-6
	(0.705)
Intercept	0.16
	(0.458)
Lambda1	0.344
	(1.072)
Lambda2	0.382
	(3.708)**
Chi-Square statistics(Degree of freedom =14)	266.358
Number of observations	77929

[a]Bootstrap t statistics are in the parentheses.
[b]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in the past 30 days.
**Statistically significant at the 5 % level.

Education is assumed to be positively associated with the efficiency of market and non-market production. Higher educational attainment will shift the demand function for health outward and result in higher levels of health capital demanded. Hours worked has a positive and significant coefficient. Longer hours worked increase the benefits of holding health capital because the hourly wage is a function of health and the total wage income will increase if the consumer is healthier. Net family income captures the income effect on the demand for health. The positive coefficient on net family income shows that health is a normal good. An increase in family income results in higher level of health capital.

Physicians and hospital beds per 100,000 population are used to approximate the cost of medical care. Both coefficients on physicians and hospital beds are positive, but insignificant. The economic model predicts a negative sign on both variables because medical costs are viewed as the market price of health capital. Higher medical costs imply a greater capital gain of holding the health capital and lead to more health capital demanded. An increase in the physicians and hospital beds per 100,000 population may indicate lower medical costs because health care resources are less scarce. We would expect a decrease in the health capital demanded.

Nonetheless, the number of physicians and hospital beds per 100,000 population may not be closely related to medical costs. Instead, it may represent the local health facility and health care environment. In the economic model, medical care in the health production function is defined in a broader sense to include health information. If physicians and hospital beds are positively correlated with health information, the positive sign in Table 6.2 simply indicates that health production will be more efficient if medical resources are more abundant.

The dummy variable for urban in the structural health demand equation is also a proxy for medical costs. If transportation cost is included in the medical costs, people living in rural areas face a higher market price for health capital than people living in urban areas. Therefore, people in the rural area will demand more health. However, the results in table 6.2 show that the location of residence does not significantly affect the decision on health demanded.

Males have significantly higher health capital than females. The reasons may be that males demand more health capital because traditionally, males are the breadwinners of the household, or males are more efficient health producers than females. Another potential explanation is that women often report more health problems after the birth of a child. As a result, women's health status is worse than men's health status. Blacks demand less health capital than whites. On the other hand, Hispanics have a greater health capital than whites. Married people demand more health capital than their counterparts.

The Demand for Binge Drinking

The structural estimates of the demand for binge drinking are presented in Table 6.3. The occasions of binge drinking have three ordinal responses, which imply two thresholds. The first threshold is normalized to zero. The second threshold is the difference between intercept 2 and intercept 1. Real alcohol price and minimum legal drinking age are part of the full price of binge drinking. Unlike the conclusions in the earlier economic literature, the alcohol price does not seem to have a significant effect on the occasions of binge drinking. If frequent binge drinking is more likely to lead to addiction, we would expect that heavy drinkers are not as sensitive to price fluctuation as social drinkers.

On the contrary, minimum legal drinking age has a significant effect on the occasions of binge drinking among underage youths, although its magnitude is almost equal to that of the real alcohol price. Particularly, the coefficient of the interaction term between minimum drinking age and the respondent's age indicates that respondents who are younger than the minimum drinking age have fewer occasions of binge drinking than their counterparts. Since early initiation of alcohol use is strongly related to the development of alcoholism, preventing underage youth from an early experience of alcohol use seems fruitful.

Like the health capital, binge drinking is also a normal good. The coefficient of net family income is positive, although it is not statistically significant. Under the forward-looking framework, the demand for health should have an effect on the occasions of binge drinking. However, the results in Table 6.3 suggest that in these data the demand for health does not significantly affect the occasions of binge drinking. The insignificance could be a result of the sample being relatively young. Recall that more than 95 percent of the observations do not have a health limit. The lack of variations in health status could lead to a failure to identify the "true" effect of the occasions of binge drinking on the demand for health.

Lag and lead binge drinking are positively and significantly correlated to current binge drinking. Both coefficients have much greater magnitudes and statistical significance than other coefficients. This indicates not only that current, past and future binge drinking are complements, but also that frequent binge drinking is addictive and habit-forming. Furthermore, the statistically significant coefficient on lead binge drinking supports the rational addiction model in the sense that heavy drinkers are not myopic, instead they are forward-looking.

Table 6.3. Structural Estimates of The Demand for binge drinking (Probability of Having More Occasions of Binge Drinking)

Explanatory Variables	Dependent Variable: Occasions of Binge Drinking
Real alcohol price	-0.005
	(-0.317)[a]
Real net family income	2.32E-7
	(1.557)
Legal drinking age x age >minimum drinking age	-0.006
	(-3.158)**
Predicted health[b]	0.011
	(0.306)
Predicted hours worked	-0.012
	(-2.222)**
Predicted lag binge drinking[c]	0.463
	(6.182)**
Predicted lead binge drinking[d]	0.389
	(6.224)**
Age	0.002
	(0.462)
Education	-0.028
	(-3.59)**
Black	-0.073
	(-2.517)**
Hispanic	-0.021
	(-0.977)
Married	-0.102
	(-3.806)**
Urban	0.028
	(1.458)
Male	0.111
	(3.24)**

[a]Bootstrap t statistics are in the parentheses.
[b]Predicted health limit is the predicted latent value of being healthy.
[c]Predicted lag occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in past 30days.
[d]Predicted lead occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in the past 30 days.
*Statistically significant at the 10 % level.
**Statistically significant at the 5 % level.

Table 6.3. (continued)

Explanatory Variables	Dependent Variable: Occasions of Binge Drinking
Illegal activity in 1980	0.096
	(3.478)**
Unemployment rate	0.016
	(1.928)*
Alcoholic parents	0.015
	(0.898)
Start drinking before age 18	0.072
	(2.416)**
Lambda1	-0.015
	(-0.068)
Lambda2	-0.08
	(-0.916)
Intercept 1	0.49
	(2.145)**
Intercept 2	1.356
	(5.921)**
Chi-Square statistics (Degree of freedom=20)	6470.82
Number of observations	35308

In the economic model, binge drinking and leisure are viewed as complements in the sense that more occasions of binge drinking increase the marginal utility of leisure, and vice versa. Hours worked is predicted to have a negative sign. The empirical result in Table 6.3 is significant at the 5 % level and consistent with the prediction–leisure and binge drinking are complements. However, the relationship between leisure and the occasions of binge drinking may not be *perfect* complements as defined in the economic model. People can always substitute beer by hard liquor and reach the same level of satisfaction in a shorter time.

The age effect is not significant, and a positive sign on age does not support the maturing-out hypothesis that young adults will reduce the occasions of binge drinking when they accept the adult role. Since the NLSY79 does not have a broad age distribution, it is not too surprising that the age effect cannot be identified. Additional schooling significantly reduces occasions of binge drinking. This is consistent with previous findings that college graduates have the fewest occasions of binge drinking.

Family backgrounds and personal characteristics are strongly associated with occasions of binge drinking. Having alcoholic parents, committing illegal activity in 1980, or star drinking before the age of 18 increases the occasions of binge drinking. In particular, if an individual initiated drinking before the age of 18, he/she is more likely to develop dependence syndromes, which lead to more occasions of binge drinking. Along with lag and lead binge drinking, starting drinking before the age of 18 also leads to habit formation.

The coefficient of the urban dummy suggests that people living in the urban area demand more occasions of binge drinking, although it is not significant at the 5 % level. The explanation may be that alcohol is more accessible in urban areas. Another perspective is that if transportation cost is included in the price of binge drinking, people living in rural areas have higher costs of binge drinking. Therefore, they demand fewer occasions of binge drinking.

The hypothesis that poor economic conditions are related to higher alcohol consumption is supported in Table 6.3. A higher local unemployment rate means more unemployment and longer duration of unemployment. The added available time and anxiety from unemployment may cause the demand for binge drinking to increase. Last, males have more occasions of binge drinking, whereas married people, black, and Hispanic have fewer occasions of binge drinking.

Labor Supply Equation

Table 6.4 contains the structural estimates of the labor supply equation. Most of the coefficients are consistent with the findings in the economics literature. Although wage is endogenized in the economic model, the labor supply equation nevertheless includes the predicted wage as the explanatory variable to comply with the economic literature. However, the coefficient of the wage has a predicted sign, but it is insignificant. The effect of wage–the value of time, has been captured in the health, education, and age variables. The coefficients of age and age square show a life-cycle pattern of labor supply where labor supply is concave in age. Health is positively correlated with the labor supply because higher health capital increases the number of health days for market work and improves labor productivity.

Binge drinking has a positive, but statistically insignificant coefficient in the structural labor supply equation. The instant impact of substance abuse may not be evident because we do see people with alcohol problems working as normally as their counterparts. The long run effect of substance abuse, on the other hand, is captured in the health variable, which is an important determinant in labor supply. People with lower educational attainment are more likely to be blue-collar workers. The results in Table 6.4 supports the observation that the blue collars work more hours than the white collars. The urban dummy shows that people living in the urban area work fewer hours. It is because people who live in the rural area are more likely to be farmers or self-employed who usually work long hours.

Males work longer hours in the labor market than females because of the traditional role taken by the males in the households. Married people work fewer hours, although the coefficient is not statistically significant. The explanation may be that married couples pool

Table 6.4. Structural Estimates of The Labor Supply Equation

Explanatory Variable	Dependent Variable: Hours Worked
Predicted wage	0.589
	(0.309)
Age	5.96
	(24.776)[a]**
Age xx 2	-0.104
	(-26.735)**
Predicted health[b]	4.552
	(6.68)**
Predicted binge drinking[c]	0.087
	(0.433)
Education	-0.689
	(-9.387)**
Urban	-0.71
	(-2.896)**
Male	2.31
	(6.992)**
Married	-0.2
	(-1.1)
Black	0.696
	(2.636)**
Hispanic	0.322
	(2.161)**
Non-wage income	-0.00001
	(-10.00)**
Number of children < 5 years old	-0.3
	(-2.288)**
Number of children between age 5 and 12	-0.387
	(-2.879)**

[a]Bootstrap t statistics are in the parentheses.
[b]Predicted health limit is the predicted latent value of being healthy.
[c]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in the past 30 days.
**Statistically significant at the 5 % level.

Table 6.4. (continued)

Explanatory Variable	Dependent Variable: Hours Worked
Number of children >12 years old	1.3
	(5.591)**
Lambda1	-3.79
	(-2.191)**
Lambda2	-5.91
	(-7.652)**
Intercept	-41.8
	(-11.857)**
Adjusted R-square	0.1587
F statistics	855.78
Number of observations	77008

their resources together and each person's time is a nearly perfect substitute for their spouse's time. Hence, married people can jointly allocate their time more efficiently. Hours worked differ significantly across races. The coefficients on blacks and Hispanics show that blacks and Hispanics work longer hours. People with more children less than 12 years old work fewer hours, but work more when children are older than 12 years old. Non-wage income captures the income effect on the demand for leisure. The empirical result indicates that leisure is a normal good.

Wage Rates

The empirical results for the log wage equation are presented in Table 6.5. Consistent with expectations, health is positively and significantly related to labor productivity. More importantly, binge drinking *does* significantly impair labor productivity and lowers the wage. The results also suggest that frequent binge drinking have both a significant direct effect and indirect effect–through health, on the wage. Health captures the long run impact of frequent binge drinking on labor productivity.

Table 6.5. Structural Estimates of the Log Wage Equation

Explanatory Variables	Dependent Variable: Log Wage
Predicted health[a]	0.498
	(5.259)[b]**
Predicted binge drinking[c]	-0.021
	(-1.747)*
Age	0.088
	(8.461)**
Age xx 2	-0.001
	(-5.102)**
Education	0.003
	(1.98)**
Male	0.029
	(2.26)**
Black	-0.018
	(-1.54)
Hispanic	-0.022
	(-1.461)
Unemployment rate	-0.022
	(-5.867)**
Urban	0.065
	(7.412)**
Married	0.042
	(4.213)**
Northeast	0.141
	(12.261)**
North central	0.098
	(5.414)**

[a]Predicted health limit is the predicted latent value of being healthy.
[b]Bootstrap t statistics are in the parentheses.
[c]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in the past 30 days.
*Statistically significant at the 10 % level.
**Statistically significant at the 5 % level.

Table 6.5. (continued)

Explanatory Variables	Dependent Variable: Log Wage
West	0.161
	(9.2)**
AFQT percentile	0.001
	(2.326)**
Lambda1	-0.182
	(-3.618)**
Lambda2	-0.178
	(-5.798)**
Intercept	-0.304
	(-1.538)
Adjusted R-square	0.4163
F Statistics	3149.25
Number of observations	75029

Age and age square are used to approximate the work experience. A negative coefficient on age square reveals the life-cycle profile of the real wage, wage is concave in age. Along with health and work experience, education is another important human capital variable that determines labor productivity. The results indicate that education increase the labor productivity, even when AFQT percentile is included to control for the unobserved ability. The positive coefficient implies that unobserved ability also plays an important role in determining the wage, although the magnitude of its effect is small. The results also suggest that, without controlling for the unobserved ability, the estimated coefficients of other variables, especially education, will be biased.

The findings on other variables are consistent with most of the economic studies. Males and married people earn a higher wage rate. The blacks and Hispanics earn a lower wage than the whites, although the coefficients are not statistically significant. Holding human capital and other variables constant, a higher local unemployment rate indicates a lower labor demand faced by individuals, which results in a lower wage. Individuals living in an urban area have a higher wage than those living in a rural area.

Model Simulations

Theil (1971) showed it is better to use structural equations than reduced-form equations to make policy recommendations when lag dependent variables are present. In particular, if we are interested in the long-term impact of the government policies, dynamic structural equations can show how the impact carries over time.

Before evaluating the model's performance and conducting policy simulations, it is essential to obtain the reduced form equation for each dependent variable in the model. They are then used to derive the short run and long run alcohol price elasticity with respect to health, binge drinking, labor supply, and the wage. The procedures for solving the simultaneous system and deriving price elasticities are included in Appendix B

Because the model is dynamic, the simulations only include respondents participating in at least 11 surveys between 1979 to 1994 to minimize the effect of unit non-response on the simulated results. Moreover, the reduced-form solutions are functions of current, past and future values of exogenous variables in the system. Because the time horizon of these exogenous variables goes forward and backward to infinity, it is necessary to make assumptions about years outside of the sample period analyzed. The following simulations use data in 1979 and 1994 for years before 1979 and after 1994, respectively.

The computations of the reduced-form solutions also depend on how quickly the effects of the past and future variables on current dependent variable diminish. The current system has two characteristic roots taking values of 1.96 and 0.61. The unstable root, 1.48, implies that the effects of future variables are approximately zero after 18 years. The stable root, 0.41, suggests that the effects from past variables will approach zero in 10 years. Therefore, the calculation of the reduced-form solution for each year uses the values of future variables for 18 years ahead and the values of variables 10 years in the past. In addition, a stability condition is needed for the system to derive the long run price elasticities.

Groups of simulation results are presented in Figures 6.1 to 6.4 covering ages 15 to 37. To compare actual health status and actual occasions of binge drinking with the predicted latent values of the health capital and of the occasions of binge drinking, the latter two variables are converted to predicted binary and ordinal response variables, respectively. The predicted health status equals zero if an individual has no health limit, or it is one otherwise. The predicted occasions of binge drinking is assigned a value from one to three with the severity of binge drinking indicated by a large number. For the predicted latent value of health capital, a larger number implies better health status.

Actual health status (baseline) is very stable before age 26 and experiences a small deterioration thereafter. Due to the narrow age range and imprecise health measure, the effect of aging is insignificant. For the entire sample period, predicted health is zero, indicating that in simulations, the representative individual does not have any health limit during the entire period. Although it appears unreasonable at first, the chance of obtaining such extreme predictions is fairly high, given the fact that more than 95 percent of the sample does not have any health problem. On the other hand, a simulated latent value of health capital shows a slight concavity in age, which is more consistent with the actual health status.

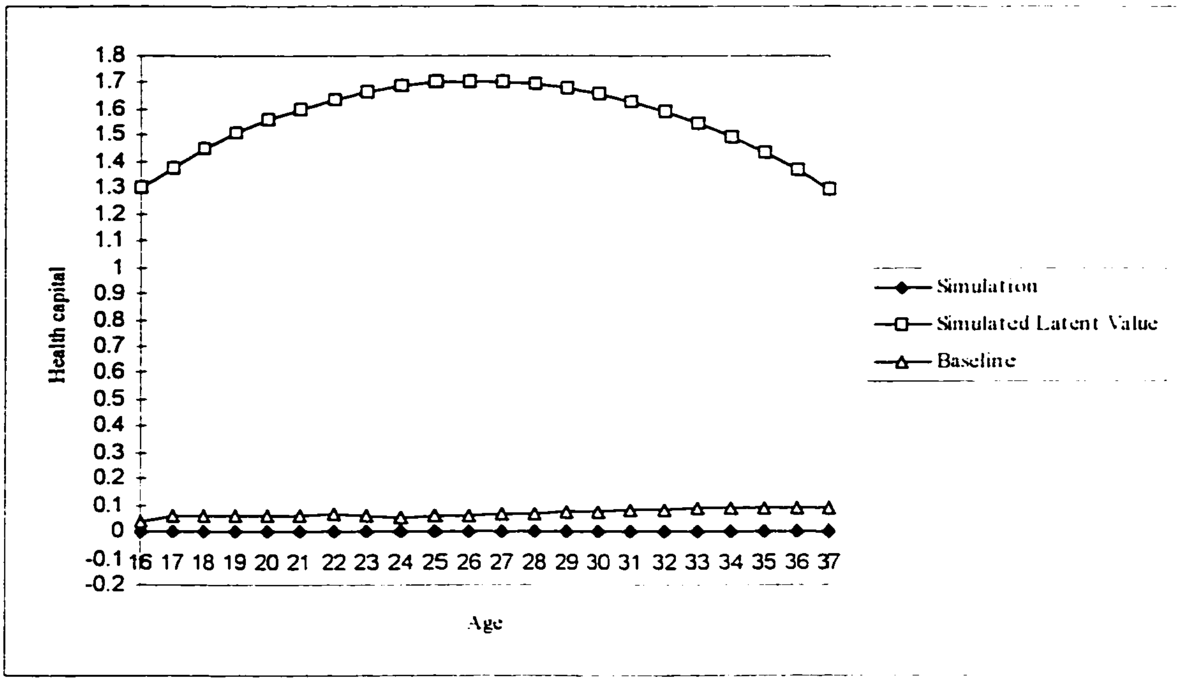

Figure 6.1. Simulated health capital, age 16-37. Baseline indicates the actual health capital. Simulation represents the converted simulated latent values of health capital

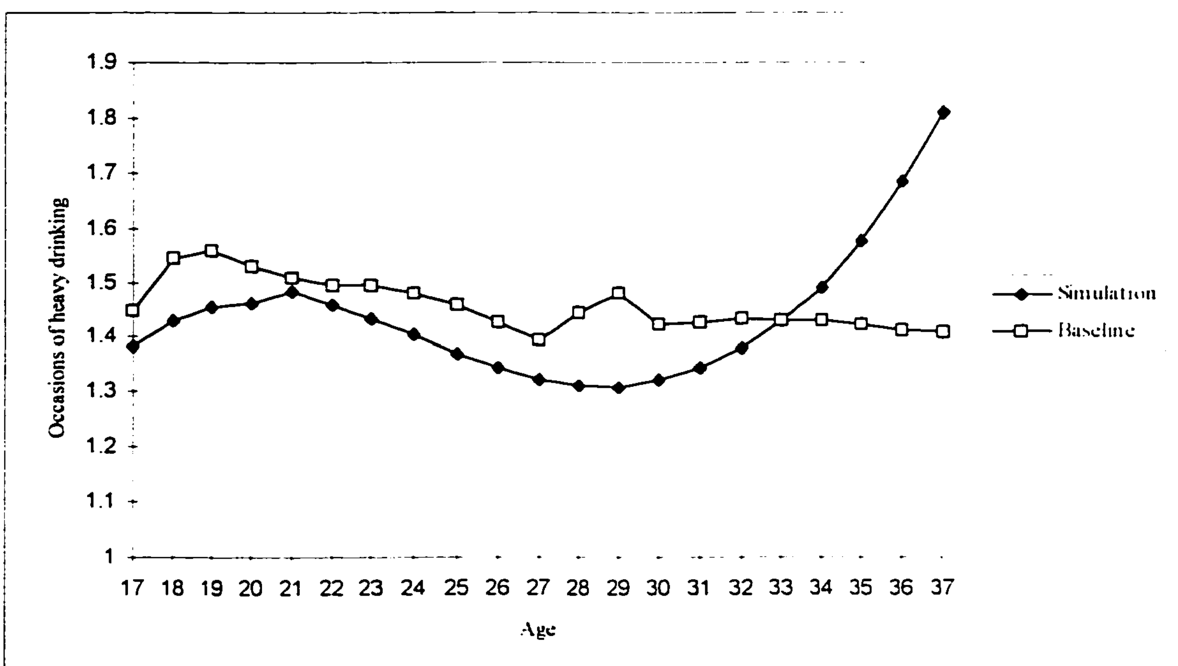

Figure 6.2. Simulated occasions of binge drinking, age 17-37. Baseline indicates the actual occasions of binge drinking. Simulation represents the simulated occasions of binge drinking

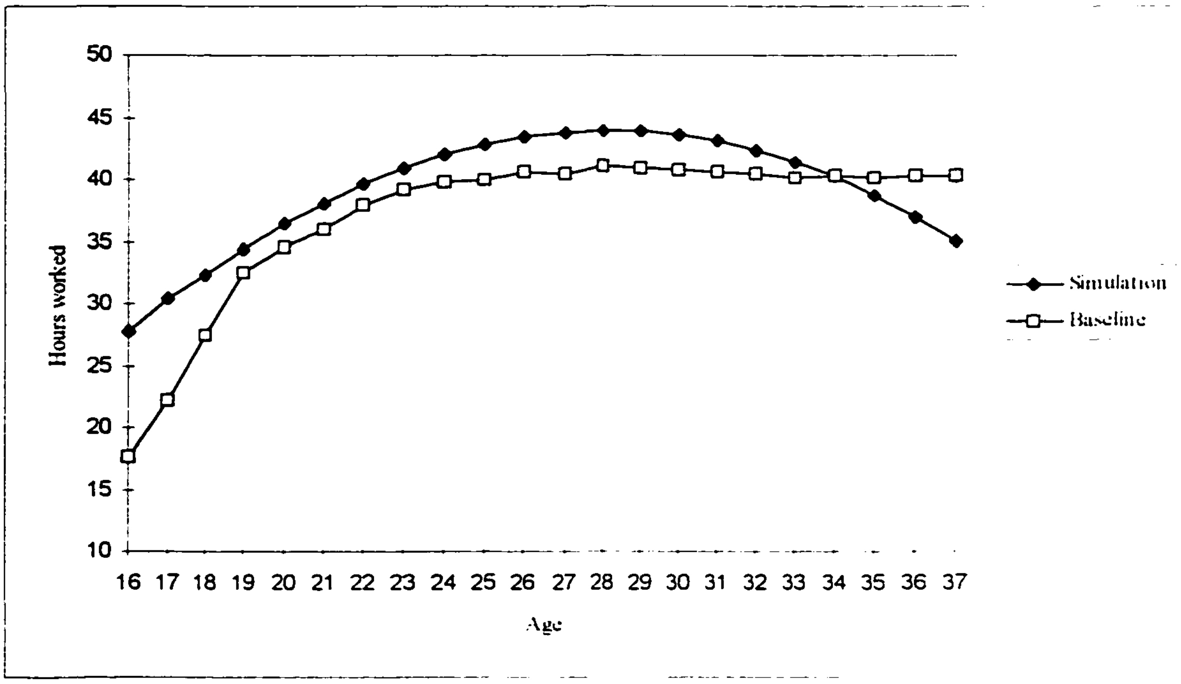

Figure 6.3. Simulated hours worked, age 16-37. Baseline indicates the actual weekly hours worked in the data set. Simulation represents the simulated weekly hours worked

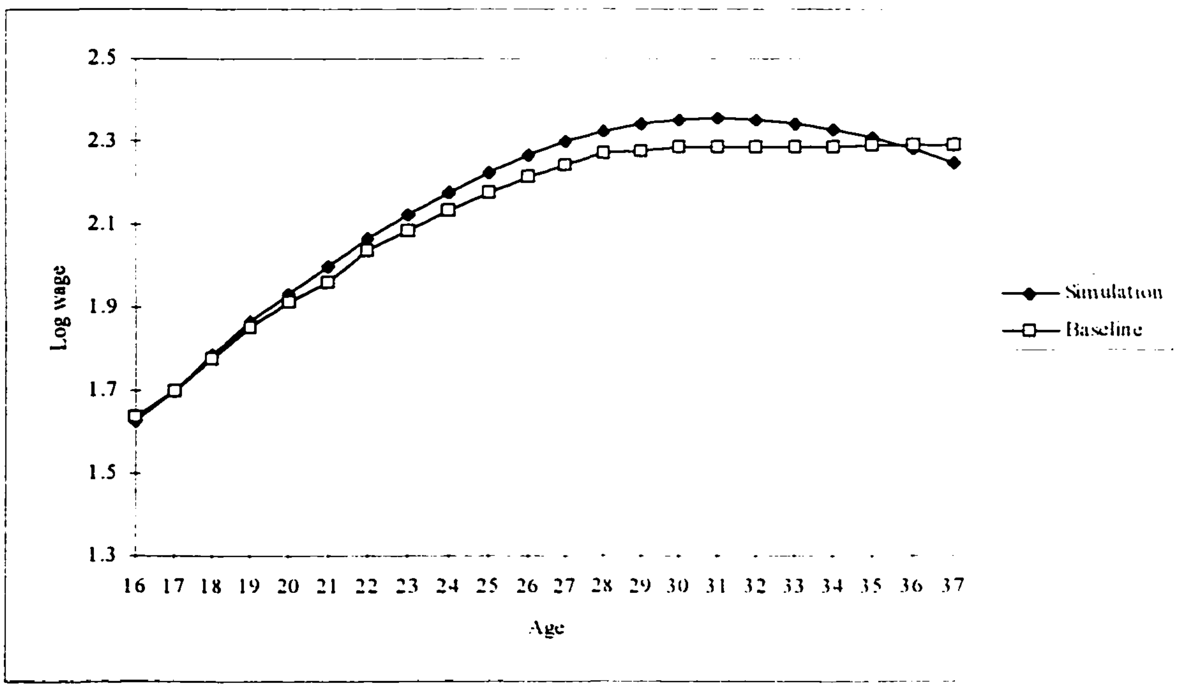

Figure 6.4. Simulated log wage, age 16-37. Baseline indicates the actual log hourly wage in the data set. Simulation represents the simulated log hourly wage

The predicted occasions of binge drinking are quadratic in age and peak around ages 21 and 37. The increasing trend for the predicted occasions of binge drinking after age 33 mainly results from the combined effects of assumptions made for observations outside the sample period and the estimated coefficient of age in the structural demand for the binge drinking equation.

Data in 1994 are used for periods after 1994 and age is the only variable that changes after year 1994. Because of the narrow range in age in the sample, the estimated coefficient of age in the structural demand for binge drinking equation fails to identify the effect of "maturing-out" on the demand for binge drinking. The resulting positive coefficient of age implies that binge drinking increases with age. In addition, given that aging increases the price of health capital, the price of the occasions of binge drinking becomes relatively lower. As a result, the demand for binge drinking increases with age. The actual sample mean for the occasions of binge drinking peaks around age 19, then it decreases only slightly and remains relatively stable across the entire sample period. If we had a wider age distribution in the sample, the effect of "maturing-out" can be captured and the demand for binge drinking may decline with age. For weekly hours worked and log wage, the simulation results track the actual data fairly well. Both simulated and actual values are concave in age and peak at age 29.

The trade-off between health and the occasions of binge drinking can be seen in Figures 6.1 and 6.2. When the representative individual is in his late teens and early twenties, his health capital is high and wage is relatively low. As a result, the full price of frequent binge drinking is low, and he demands more occasions of binge drinking and reduces his demand for health. However, the cost of frequent binge drinking increases during the prime age mainly because the value of time becomes more expensive, while the financial rewards from holding health capital become greater. Consequently, as the representative individual gets older, the demand for health increases and the frequency of binge drinking decreases.

When an individual approaches retirement age, his/her wage begins to decrease with age and health depreciation accelerates. Both lead to an increase in the price of health capital and a decrease in the price of frequent binge drinking. Furthermore, when they retire, the hours of wage work are reduced to zero. This further reduces the cost of binge drinking in retirement. This could partially explain the drinking problem among the elderly.

A reasonable question to ask is that what will the profiles of health capital, hours worked, and the wage become if the representative individual remained no binge drinking, binge drinking, and binge drinking, respectively, throughout his/her life cycle. The results for health capital, hours worked, and the wage, are presented in Figures 6.5 to 6.7. The simulation results indicate that frequent binge drinking results in a lower health capital and wage profiles. The percentage decline ranges from 4 percent to 5 percent if the representative individual becomes heavy drinker, and 2 percent to 3 percent if he/she moves from no binge drinking to binge drinking. On the other hand, hours worked do not seem to be affected by the change in the occasions of binge drinking. The magnitudes of the decline are lower than 1 percent for either case. The long run and short run price elasticity for occasions of binge drinking, the demand for health, hours worked, and log wage are presented in Table 6.6. The short run price elasticity measures the effect of an unanticipated permanent increase in the alcohol price starting from period t, on the occasions of binge drinking in period t. The long

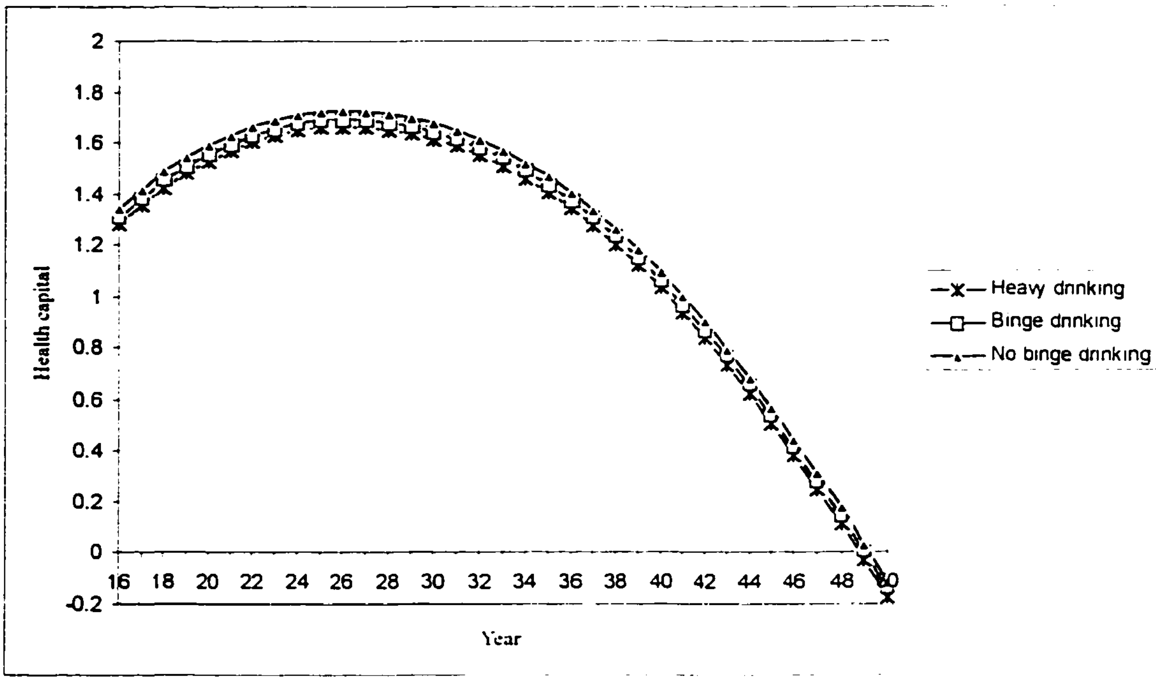

Figure 6.5. Simulated latent values of health capital, age 16-50. Simulations hold everything else constant except occasions of binge drinking

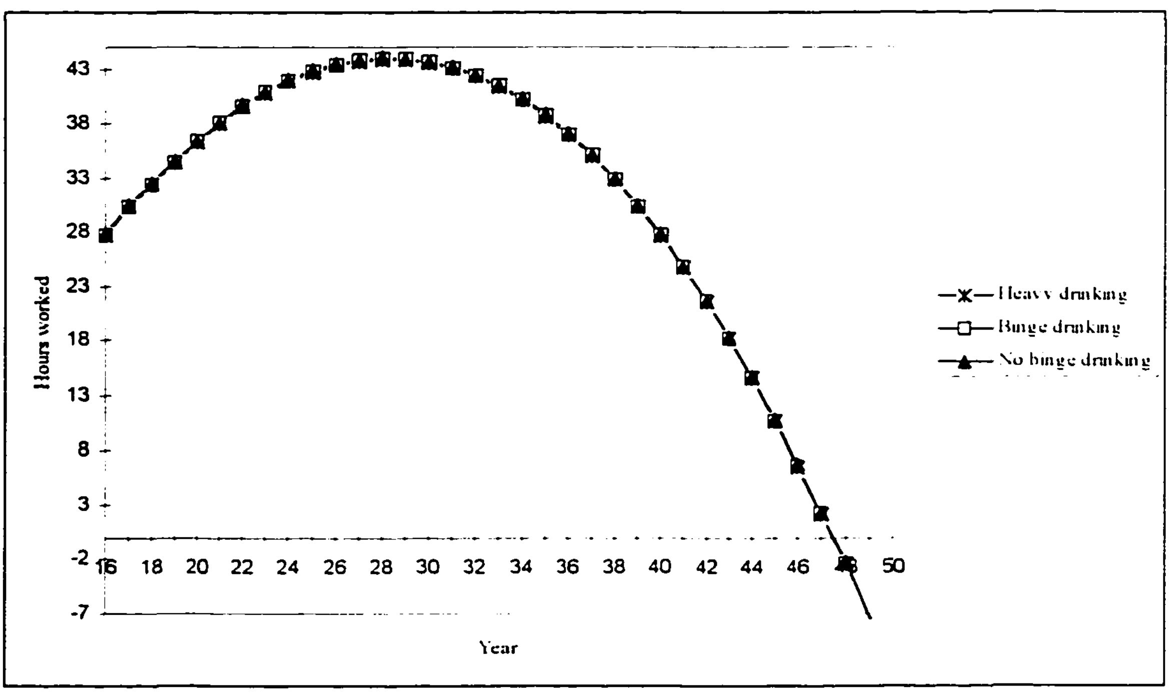

Figure 6.6. Simulated hours worked, age 16-50. Simulations hold everything else constant except occasions of binge drinking

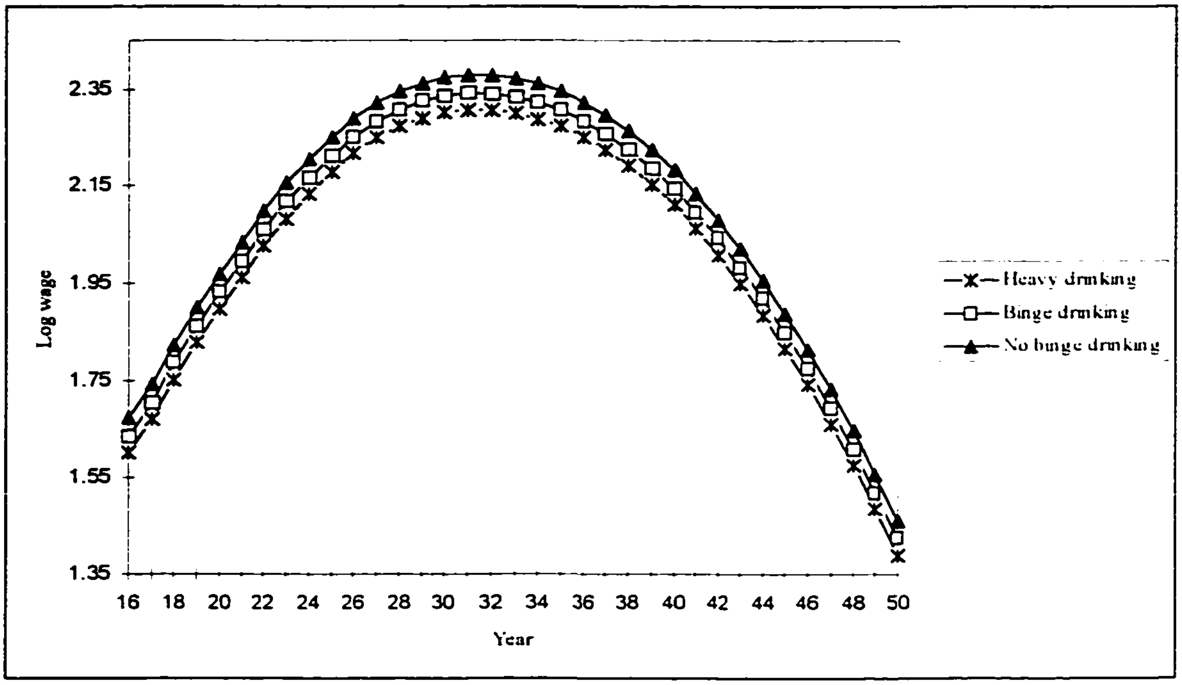

Figure 6.7. Simulated log wage, age 16-50. Simulations hold everything else constant except occasions of binge drinking

run price elasticity estimates the effect of an anticipated permanent change in the alcohol price in all periods on occasions of binge drinking in period t.

The alcohol price elasticity for occasions of binge drinking has different interpretations given the nature of the data. There are three ordinal categories for the occasions of binge drinking: no occasion of binge drinking, binge drinking, and heavy drinking. Given that a person is in the heavy drinking category (more than four occasions in past 30 days), the price elasticity shows the effect of raising the alcohol price on the probability of being in heavy drinking group, binge drinking group, and no binge drinking group.

The price elasticity for binge drinking is inelastic both in the short run and in the long run. See Table 6.6. They are -0.09 and -0.24 respectively, which are consistent with the

Table 6.6. Short run and Long run Price Elasticity of Demand for Health, Demand for Binge drinking, Labor Supply, and Wage (Labor Productivity)

		Price Elasticity
Demand for health (probability of being healthy)	short run	0.0002
	long run	0.0006
Demand for binge drinking (probability of being in heavy drinking group)	short run	-0.09
	long run	-0.24
Demand for binge drinking (probability of being in binge drinking group)	short run	0.01
	long run	0.03
Demand for binge drinking (probability of being in no binge drinking group)	short run	0.08
	long run	0.21
Hours worked (labor supply)	short run	0.0001
	long run	0.0003
Log wage (labor productivity)	short run	0.001
	long run	0.003

standard economic theory that the long run price elasticity is greater than the short run price elasticity. Both long run and short run price elasticity estimates are smaller than those reported in other economic literature where total alcohol consumption in the past 30 days is the measure of the alcohol consumption rather than the occasions of binge drinking. Furthermore, the short run price elasticity is more than two times smaller than the log-run price elasticity. This finding may suggest that alcoholics are less sensitive to a price change because of the addiction and alcohol dependence.

The long run and short run price elasticities for binge drinking (one to three occasions in past 30 days) are also less than one, and their magnitudes are smaller than those estimated for the heavy drinking group. Since the sum of the elasticities of heavy drinking, binge drinking, and no binge drinking should be one, the elasticity of no binge drinking can be easily obtained by subtracting the elasticities of heavy drinking and binge drinking from one.

Given that an increase in the alcohol price decreases the probability of being in the heavy drinking group, a heavy drinker is nearly three times more likely to move to the no binge drinking group than to the binge drinking group. This finding indicates that for heavy drinkers who are responsive to alcohol price fluctuation, an increase in the alcohol prices is more likely to reduce their occasions of binge drinking to no occasion.

The alcohol price elasticity for the demand for health, labor supply, and log wage are all positive, although their magnitudes are fairly small, particularly hours worked. If we had a better health measure and greater age variations in the data set, the price effect might be more significant. Because binge drinking is closely related to these labor market indicators, the results suggest that an increase in the alcohol price not only reduces occasions of binge drinking, but also promotes public health and increases labor productivity. It also implies that continued binge drinking is harmful to the health and labor productivity.

The effects of a change in the alcohol price on health, occasions of binge drinking, hours work, and wage rate are conducted by increasing the alcohol price by 100 percent. These results are presented in Figures 6.8 to 6.11. Consistent with the predicted short run and long run price elasticities in Table 6.6, the simulation shows that an increase in the real alcohol price has almost no impact on health capital, hours worked, and the wage. The magnitude of change ranges between 0.02 percent to 0.3 percent. On the other hand, the demand for occasions of binge drinking experiences approximately a 5 percent decrease.

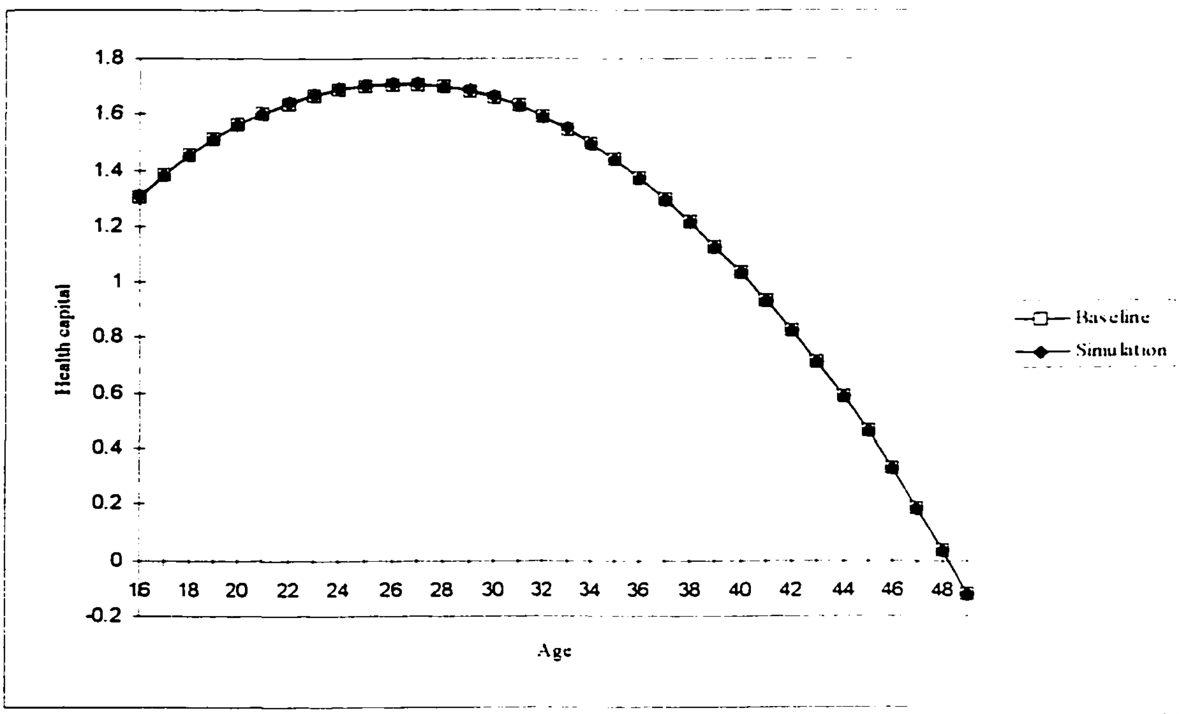

Figure 6.8. Simulated latent values of health capital, age 16-49. Simulations hold everything else constant except real alcohol price

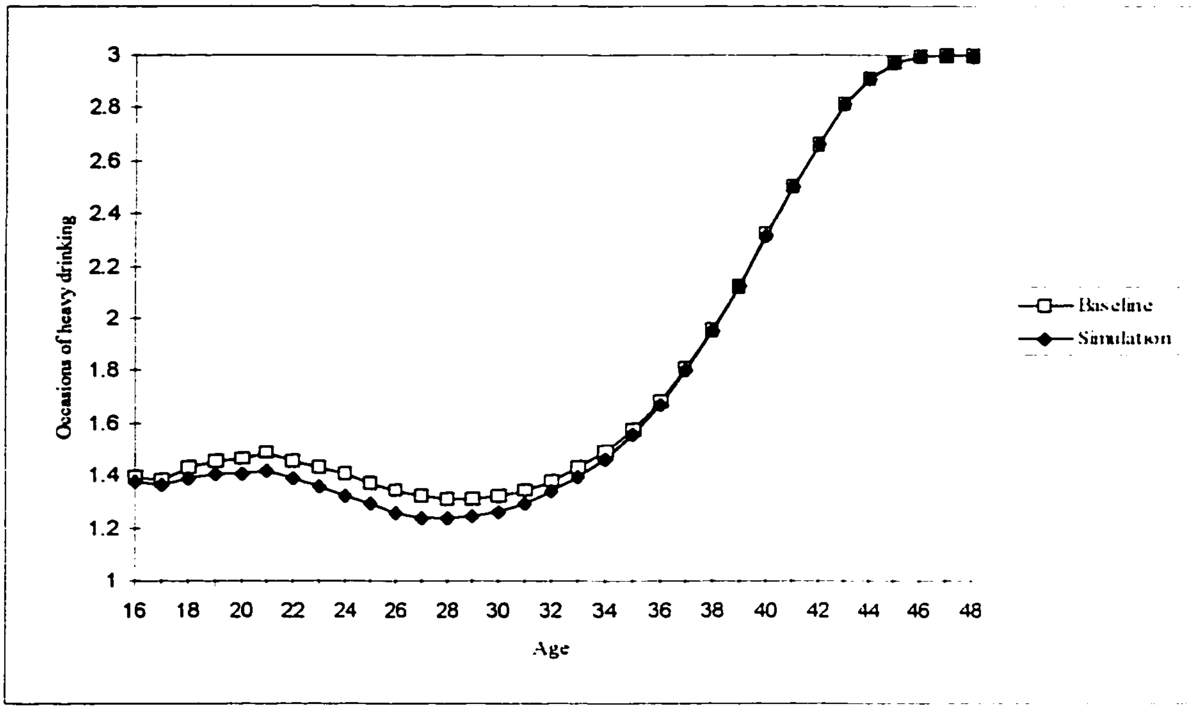

Figure 6.9. Simulated occasions of binge drinking, age 16-48. Simulations hold everything else constant except real alcohol price

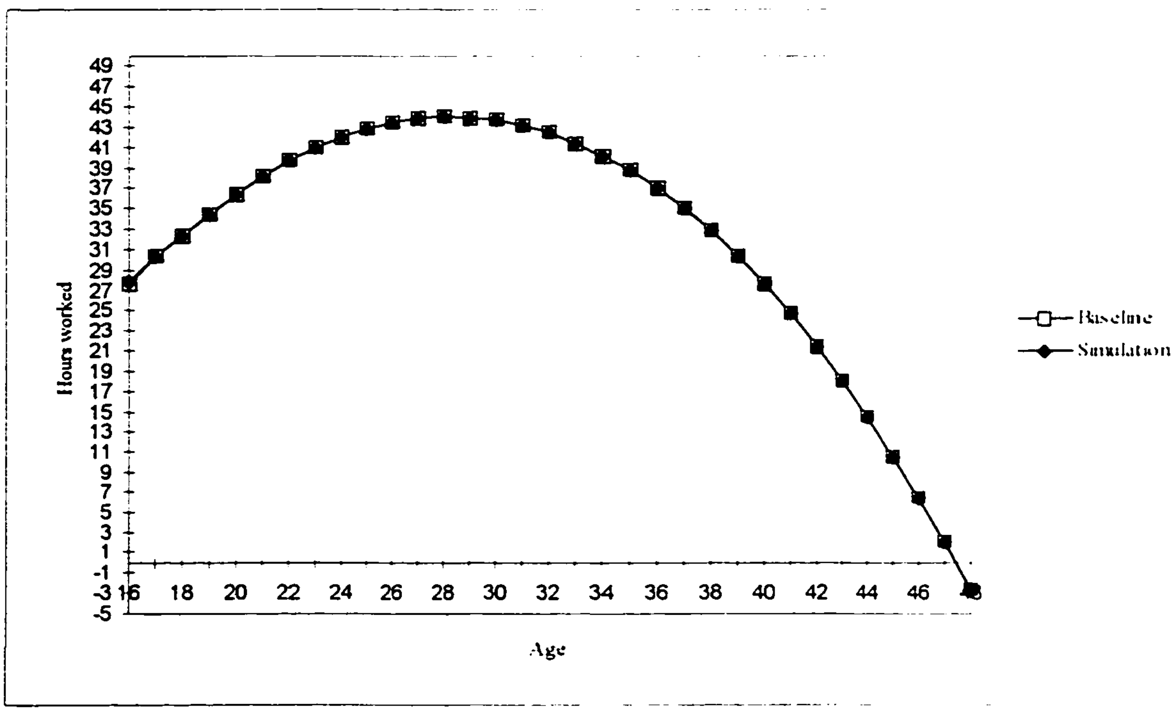

Figure 6.10. Simulated hours worked, age 16-48. Simulations hold everything else constant except real alcohol price

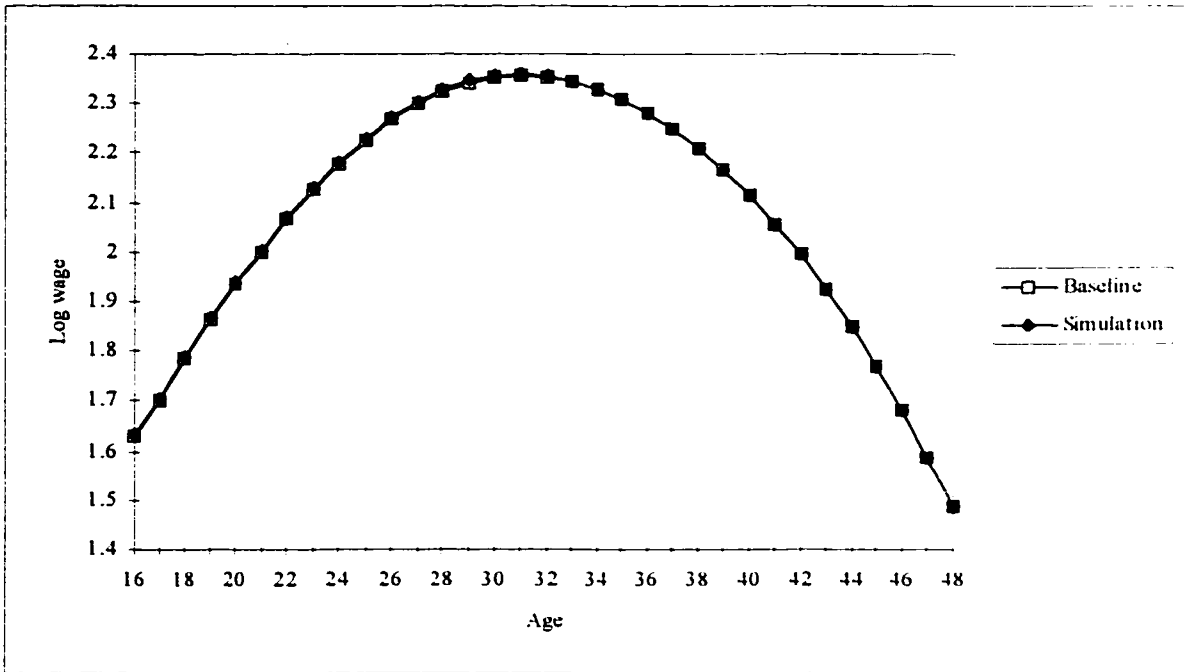

Figure 6.11. Simulated log wage, age 16-48. Simulations hold everything else constant except real alcohol price

The minimum legal drinking age is another government policy for discouraging underage drinking. The simulation examines the effect of increasing minimum drinking age by one year and the results are displayed in Figures 6.12 to 6.15. Figure 6.13 shows that an increase in the minimum legal drinking age reduces the occasions of binge drinking for young adults younger than 24, and the magnitudes of reduction range from 4 percent to 5 percent. Youths between 18 to 21 years old are usually illegal to drink, and, furthermore, they are also the group in higher risk of binge drinking. These results suggest that the minimum legal drinking age is effective in reducing the occasions of binge drinking among underage youths. Figures 6.12, 6.14, and 6.15 show that the effect of increasing minimum drinking age on health capital, hours worked, and wage are positive. However, their magnitudes are fairly small.

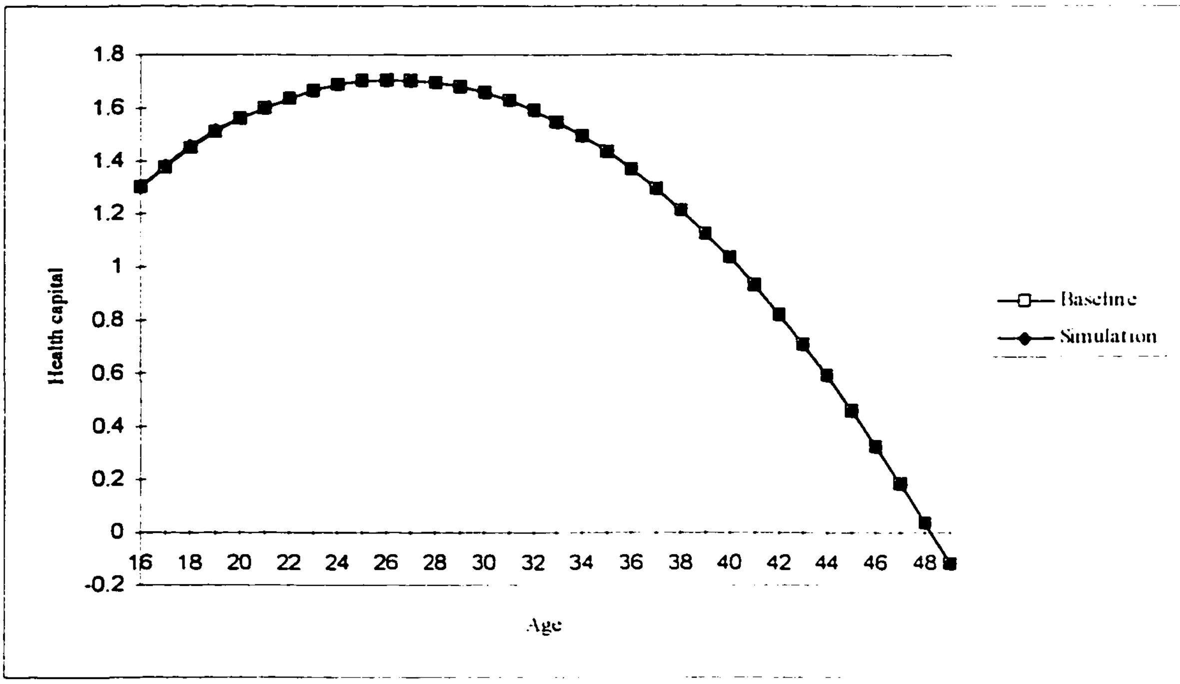

Figure 6.12. Simulated latent values of health capital, age 16-50. Simulations hold everything else constant except minimum legal drinking age

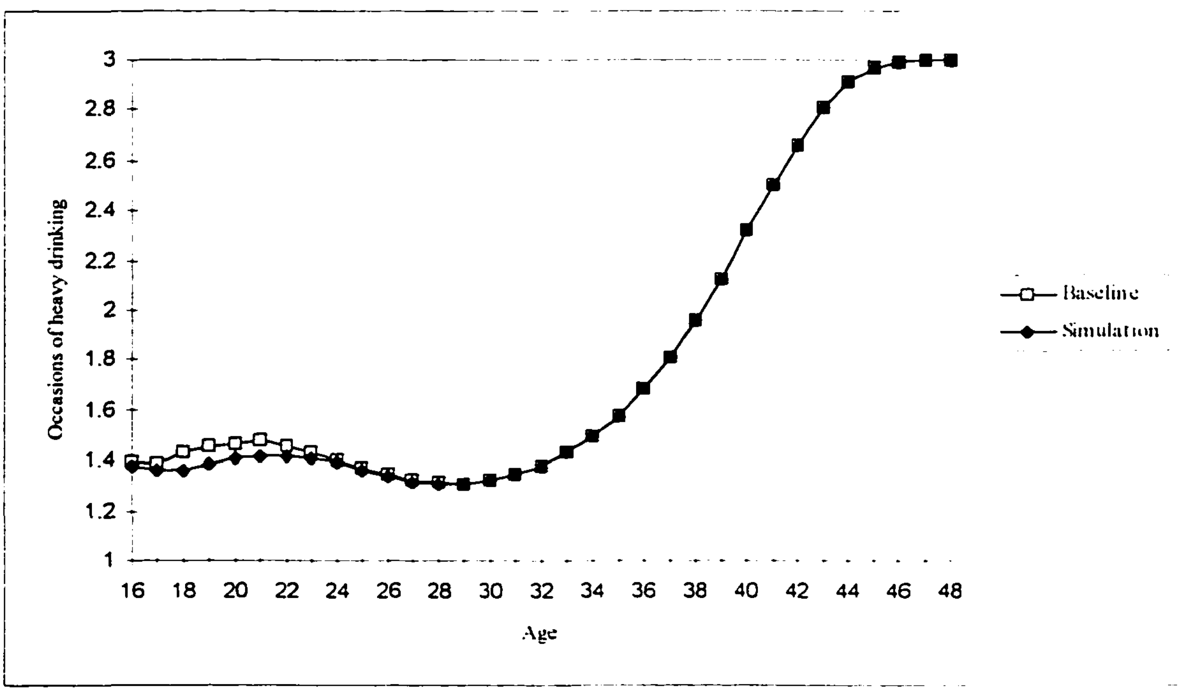

Figure 6.13. Simulated occasions of binge drinking, age 16-48. Simulations hold everything else constant except minimum legal drinking age

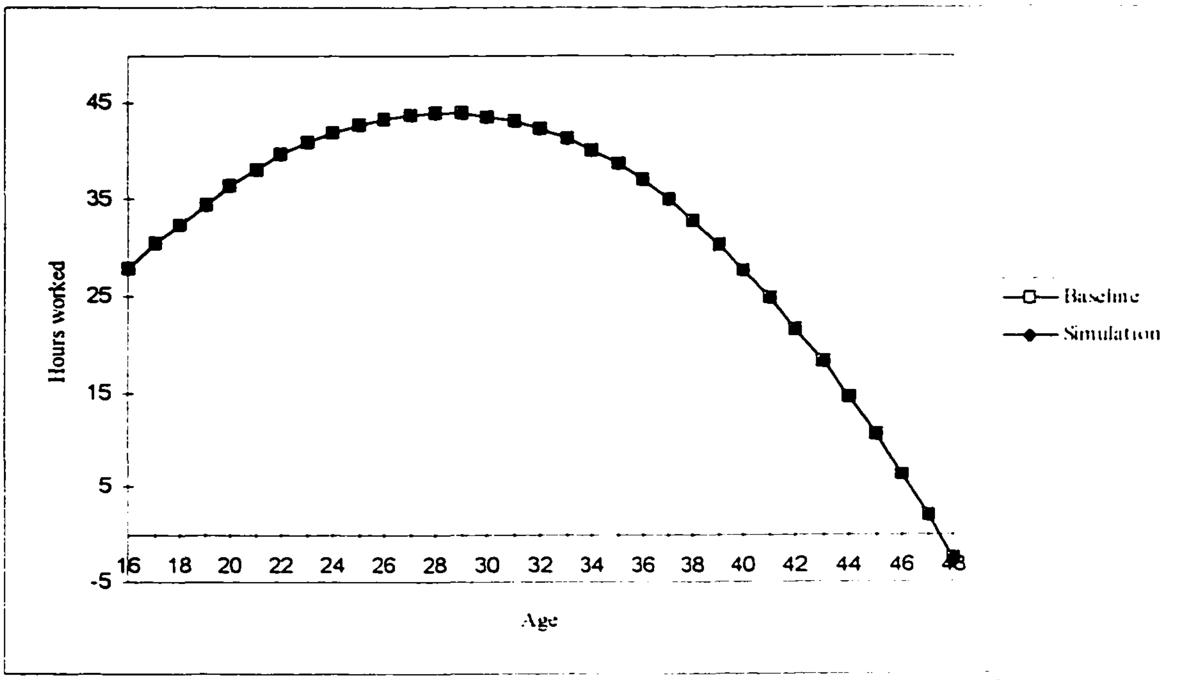

Figure 6.14. Simulated hours worked, age 16-48. Simulations hold everything else constant except minimum legal drinking age

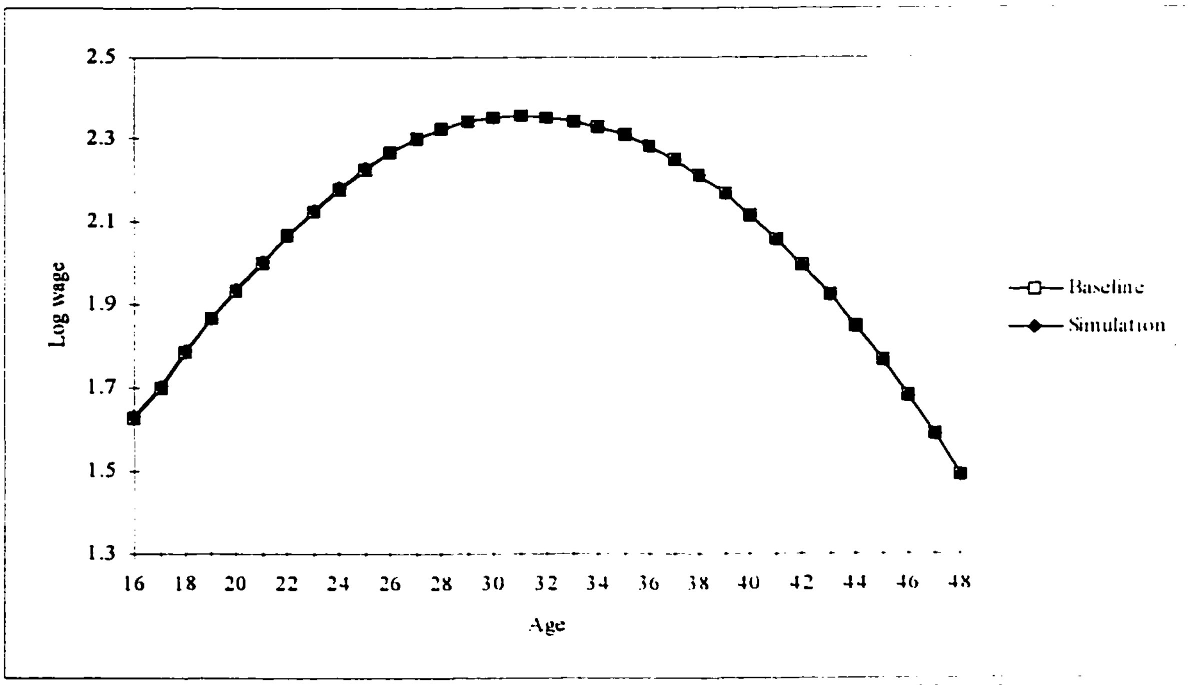

Figure 6.15. Simulated log wage, age 16-48. Simulations hold everything else constant except minimum legal drinking age

When an individual starts drinking before age 18, he/she is more likely to develop alcoholism. The following simulation demonstrates the predicted outcomes for the demand for health, the occasions of binge drinking, hours worked, and log wage if an individual started to drink before the age of 18. The baseline group includes only respondents who began drinking after age 18. The demand for health reported in the figure is its predicted latent value. The advantage of using the predicted latent value is that it allows observation in the change of health capital over time and avoids the situation in which everyone is healthy after the conversion. The baseline group only includes respondents who did not start drinking before age 18. The results are presented in Figures 6.16 to 6.19.

The impact of starting to drink before age 18 on the trajectory of health capital over the life cycle is apparent in Figure 6.16. On the average, health capital is nearly 1 percent to 2 percent lower if an individual starts drinking before age 18. The convergence of the simulation line to the baseline in the late forties arises primarily from the stability condition imposed when solving the set of simultaneous equations. Without loss of the generality, the result suggests that if we can prevent an early initiation of alcohol consumption by youth, public health can be improved. In Figure 6.17, the results suggest that early initiation of alcohol consumption results in more occasions of binge drinking in the past 30 days in current and future periods. The percentage increase ranges between 12 percent and 30 percent. Figures 6.18 and 6.19 show the labor market outcomes, given the baseline group started drinking before 18. The percentage decrease in hours worked ranges from 0.08 percent to 0.7 percent. The effect of frequent binge drinking on annual labor supply is almost negligible, which is consistent with the findings in earlier economic studies.

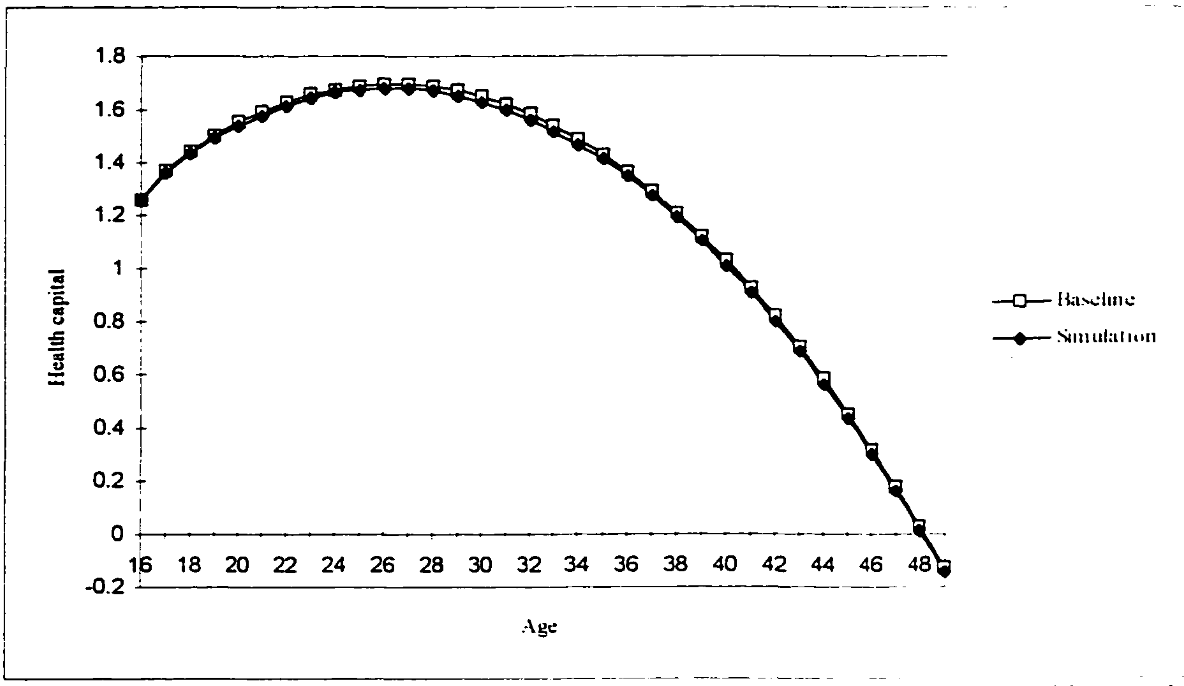

Figure 6.16. Simulated latent values of health capital, age 16-48. Simulations hold everything else constant except started drinking before age 18

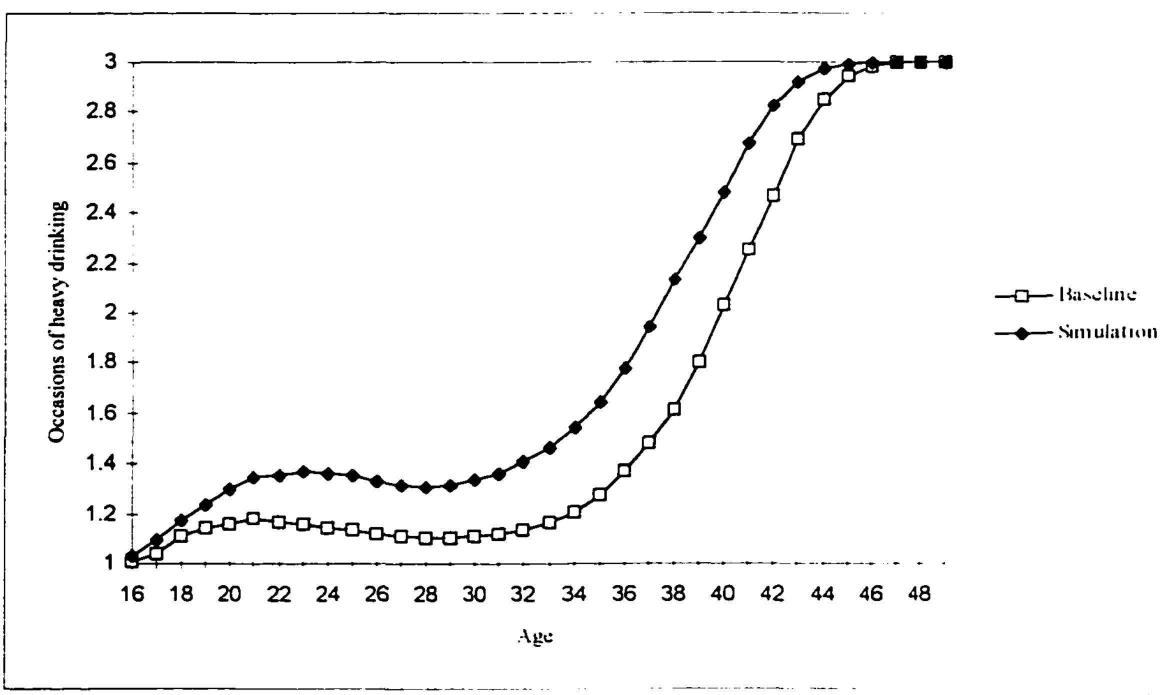

Figure 6.17. Simulated occasions of binge drinking, age 16-49. Simulations hold everything else constant except started drinking before age 18

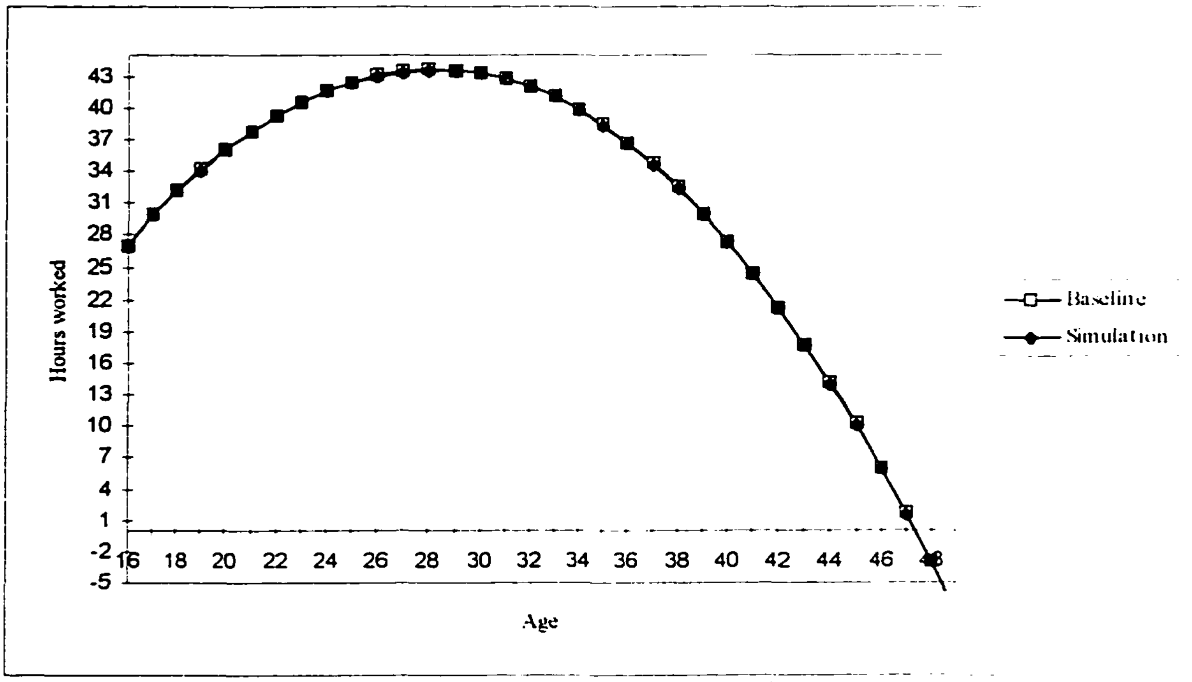

Figure 6.18. Simulated hours worked, age 16-49. Simulations hold everything else constant except started drinking before age 18

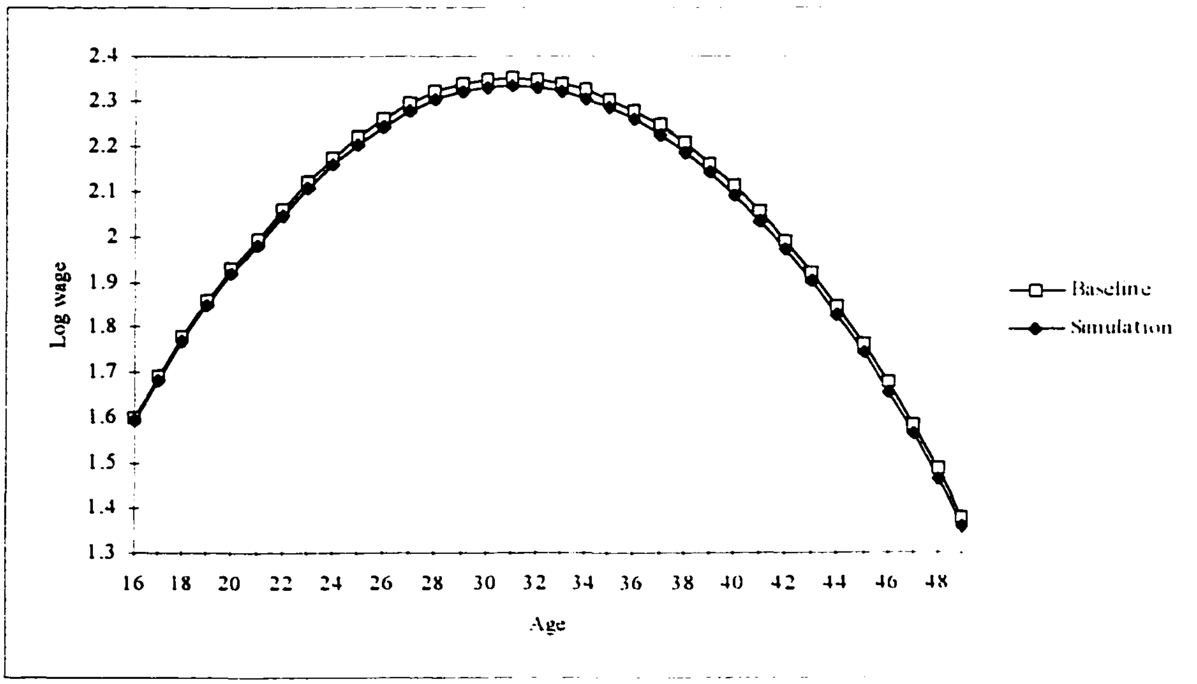

Figure 6.19. Simulated log wage, age 16-49. Simulations hold everything else constant except started drinking before age 18

On the other hand, the impact on log wage is of much greater magnitude ranging from 0.5 percent to an almost 1.5 percent decline. The decreased wage is the result of lower health capital and direct negative effect of more frequent binge drinking. Overall, the simulated results imply that starting to drink before age 18 leads to a later frequent binge drinking problem, poorer health, and lower wage rates.

Frequent occasions of binge drinking have been shown to strongly increase the risk of an individual becoming an alcoholic. Consider the impact of increasing the initial frequency of binge drinking by 100 percent on the demand for health, the occasions of binge drinking, hours worked, and wage. In Figure 6.20, if the initial frequency of binge drinking is doubled, the health capital of a representative individual is lower. However, the decrease in health capital converges from nearly 2 percent to zero later in life. As in the simulation for starting to drink before age 18, the convergence is the consequence of the stability assumption imposed when solving the simultaneous system. If the convergence assumption is relaxed, the effect of the unstable root could dominate that of the stable root and results in an increasing demand for binge drinking later in life. Figure 6.21 suggests that the demand for occasions of binge drinking increases significantly after the change in the initial occasions of binge drinking. It implies that binge drinking is habit-forming. For hours worked, Figure 6.22 shows that doubling initial occasions of binge drinking do not have significant effect on an individual's hours worked. The wage profiles in Figure 6.23 indicate that young adults engaging in frequent binge drinking can be expected to experience a lower wage profile later in life. The reduction in the log wage is nearly 2 percent.

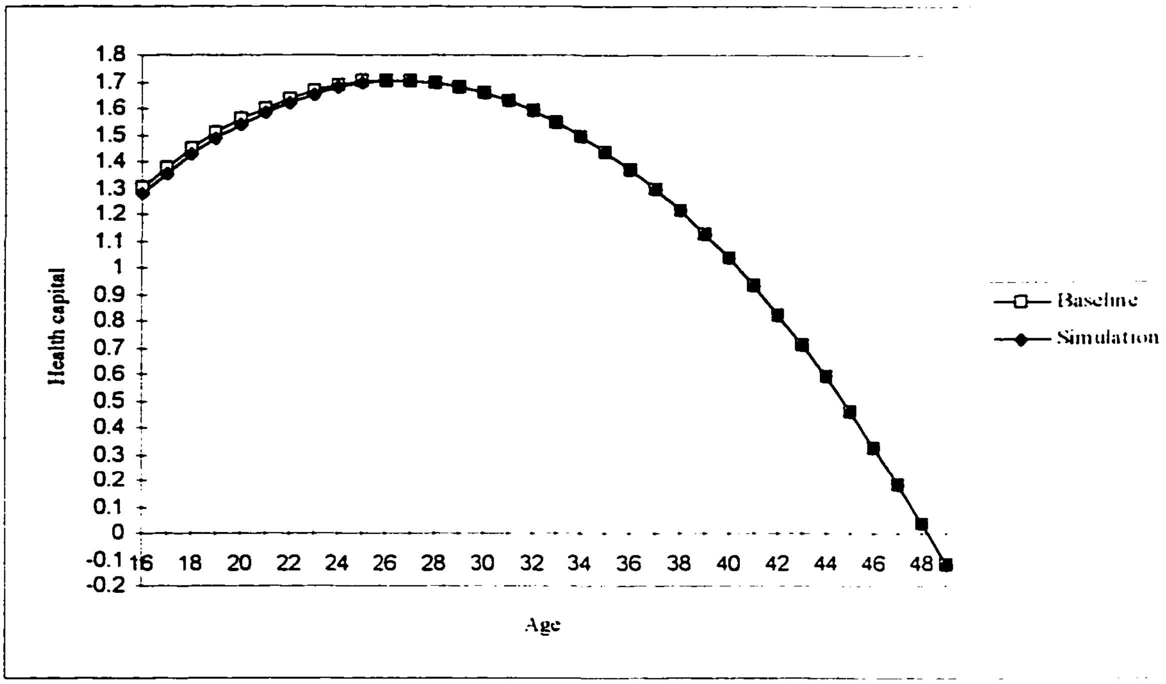

Figure 6.20. Simulated latent values of health capital, age 16-49. Simulations hold everything else constant except the initial occasions of binge drinking

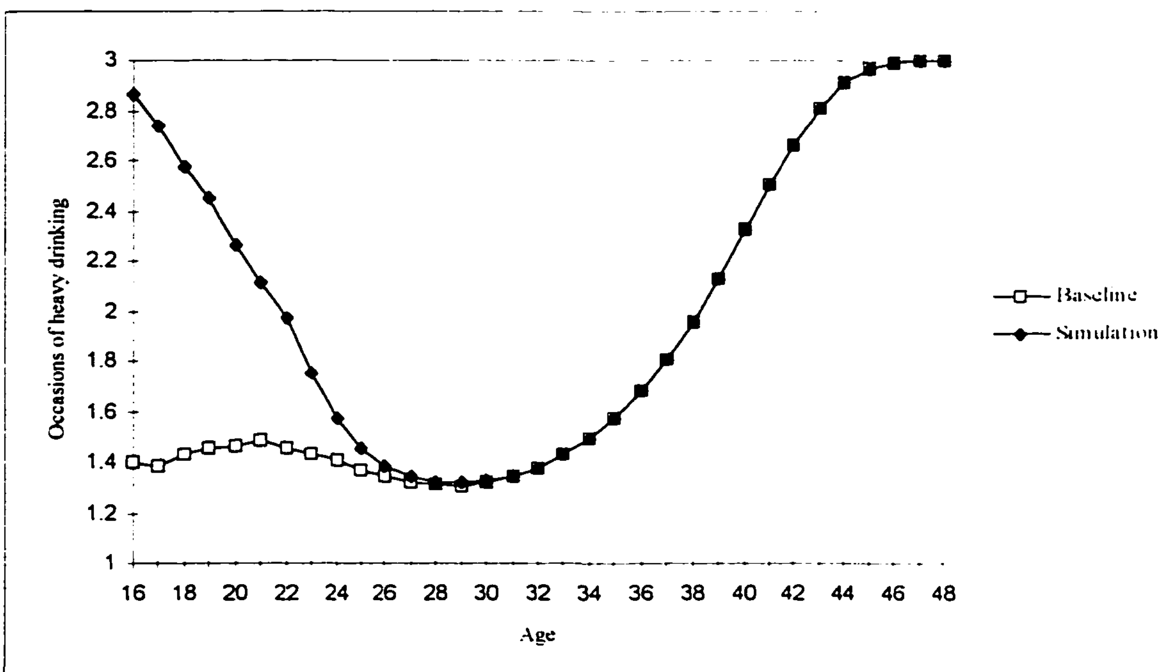

Figure 6.21. Simulated occasions of binge drinking, age 16-48. Simulations hold everything else constant except the initial occasions of binge drinking

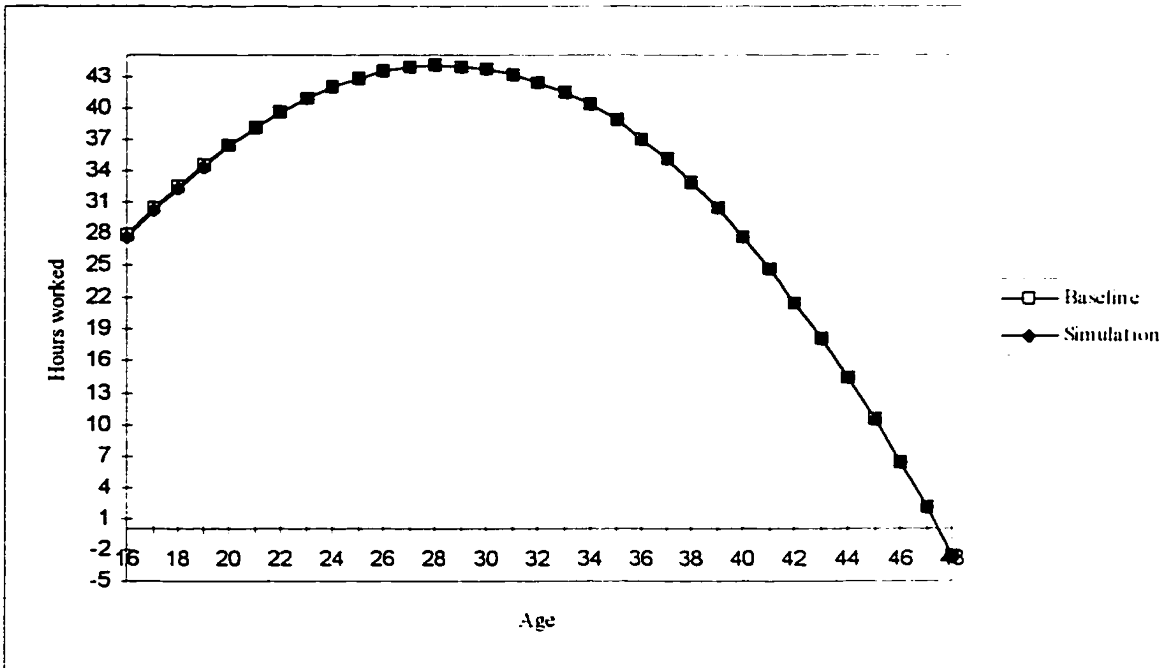

Figure 6.22. Simulated hours worked, age 16-48. Simulations hold everything else constant except the initial occasions of binge drinking

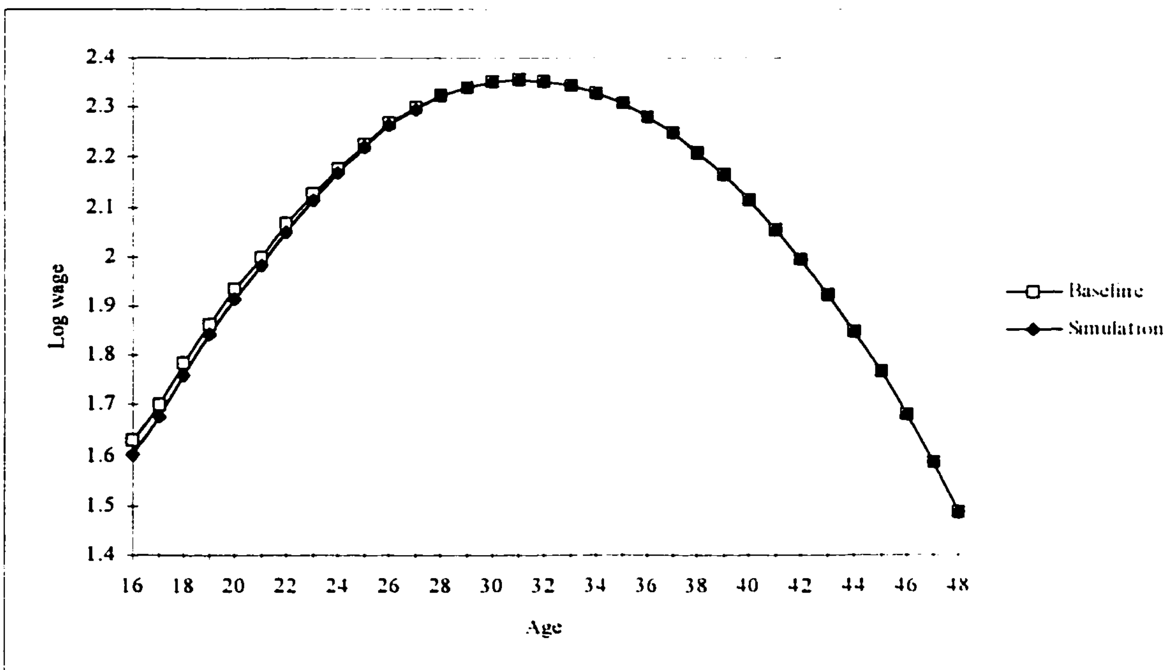

Figure 6.23. Simulated log wage, age 16-48. Simulations hold everything else constant except the initial occasions of binge drinking

Education not only has been the key determinant of the labor market success, but also is strongly related to the behavior of binge drinking. The following simulation examines the effect of one-year increase in schooling. Figure 6.24 suggests an increase in health capital, ranging from 2 percent to 3 percent, if the representative individual has one more year of schooling. The effect of education on the occasions of binge drinking is more significant. Figure 6.25 shows a 2 percent to 6 percent decline in the demand for the occasions of binge drinking. For hours worked, Figure 6.26 demonstrates that the representative individual decreases his/her labor supply by1 percent to 2 percent. In Figure 6.27, more years of schooling improve labor productivity and the wage by nearly 2%. The simulation suggests that an increase in the investment of education reduces the occasions of binge drinking, enhances public health, and increases the wage rate.

Figure 6.24. Simulated latent values of health capital, age 16-49. Simulations hold everything else constant except years of schooling

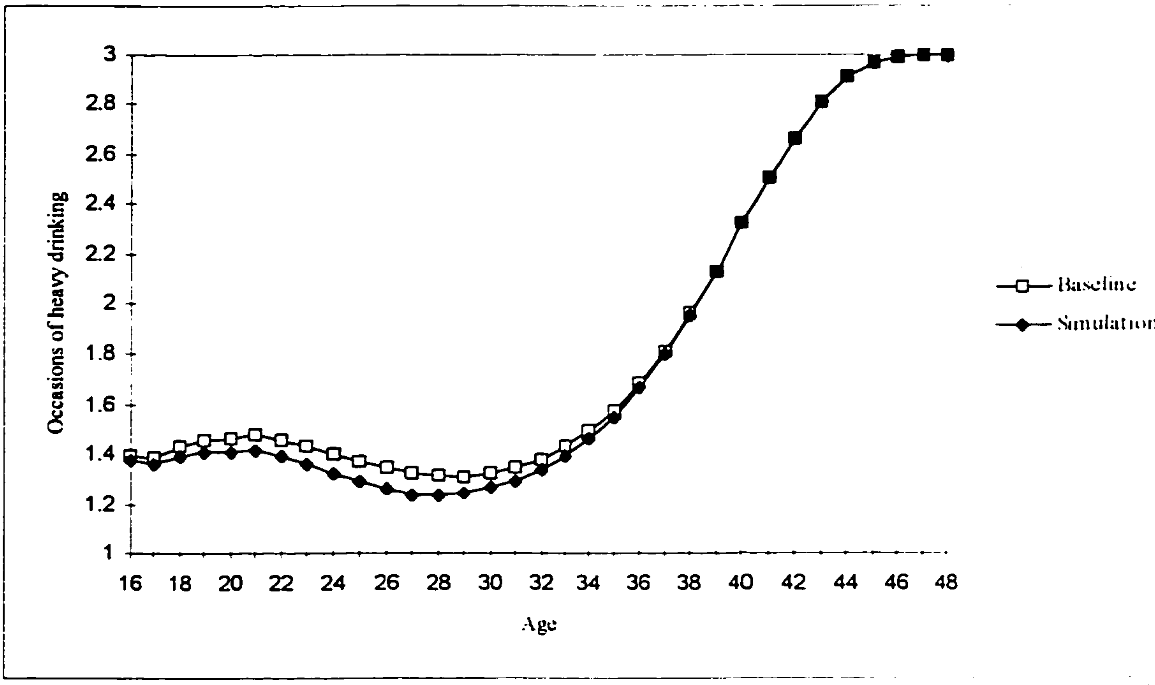

Figure 6.25. Simulated occasions of binge drinking, age 16-48. Simulations hold everything else constant except years of schooling

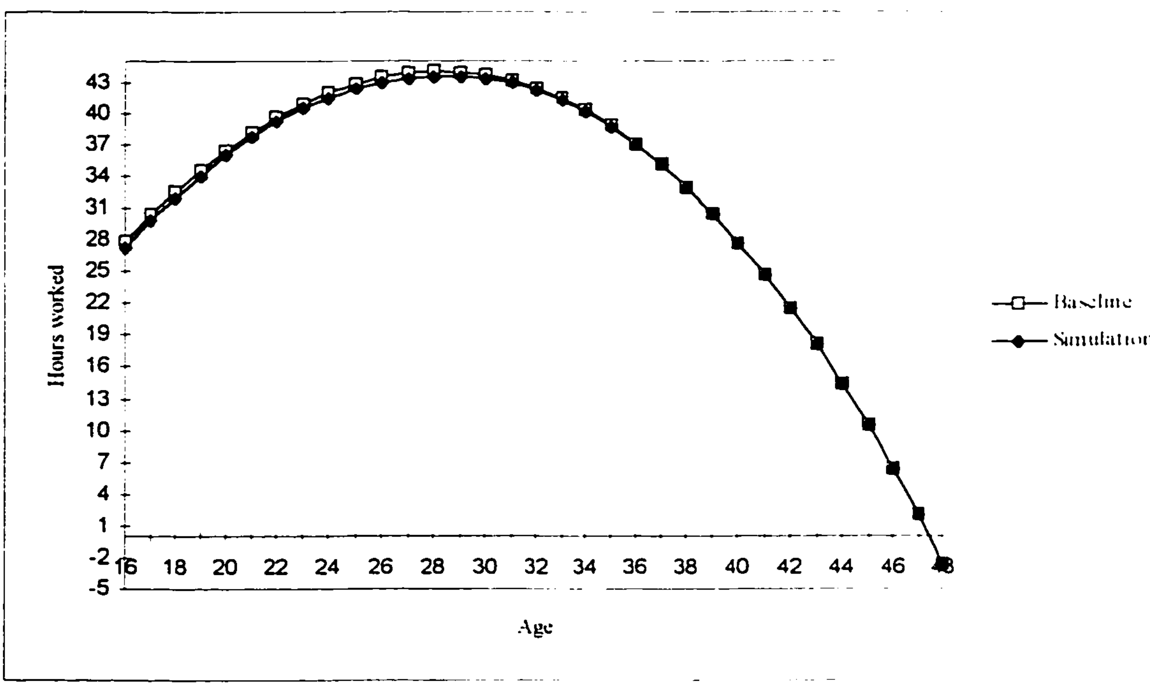

Figure 6.26. Simulated hours worked, age 16-48. Simulations hold everything else constant except years of schooling

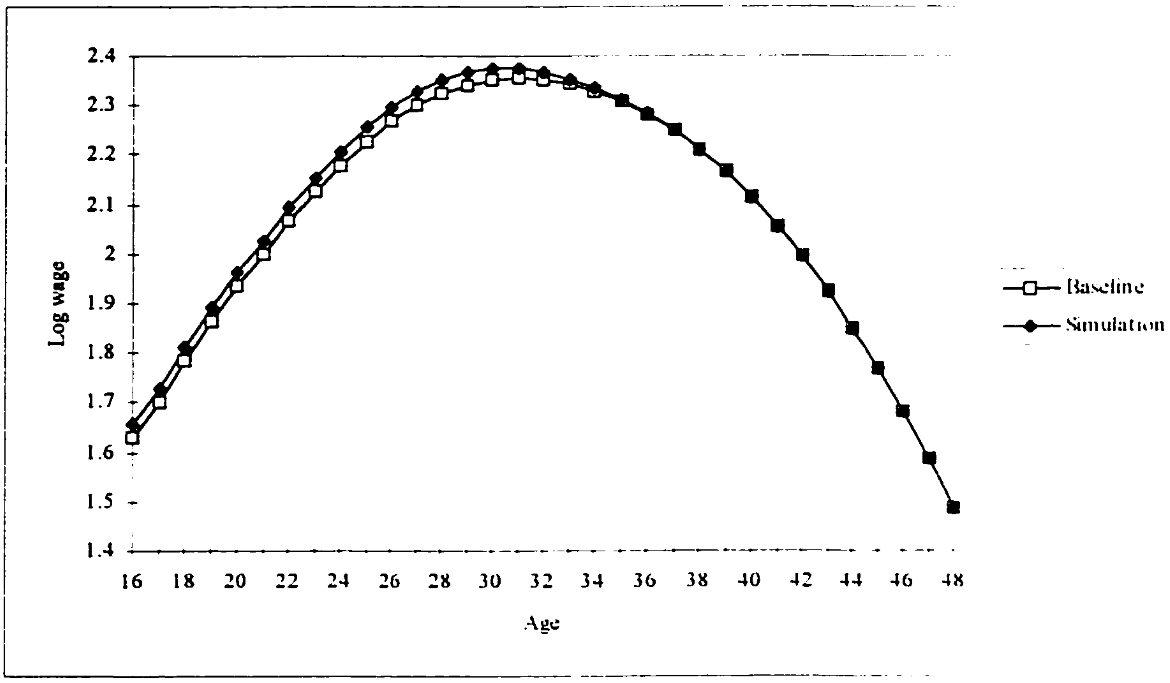

Figure 6.27. Simulated log wage, age 16-48. Simulations hold everything else constant except years of schooling

The simulation for the effect of an increase in the net family income is conducted by increasing the net family income by 50 percent, and the results are shown in Figures 6.28 to 6.31. The simulation suggests that an increase in the net family income has very small effects on health capital, occasions of binge drinking, hours worked, and the wage rate. The magnitudes of the growth in health capital, occasions of binge drinking, hours worked, and the wage after the 50 percent increase in net family income are between 0.1 percent and 0.5 percent. Despite the change is very small, the results confirm that health capital and occasions of binge drinking are both normal goods.

The economic model here provides a framework for examining some of the economic impacts of frequent binge drinking. Although it is necessary to impose some assumptions to

Figure 6.28. Simulated latent values of health capital, age 16-49. Simulations hold everything else constant except net family income

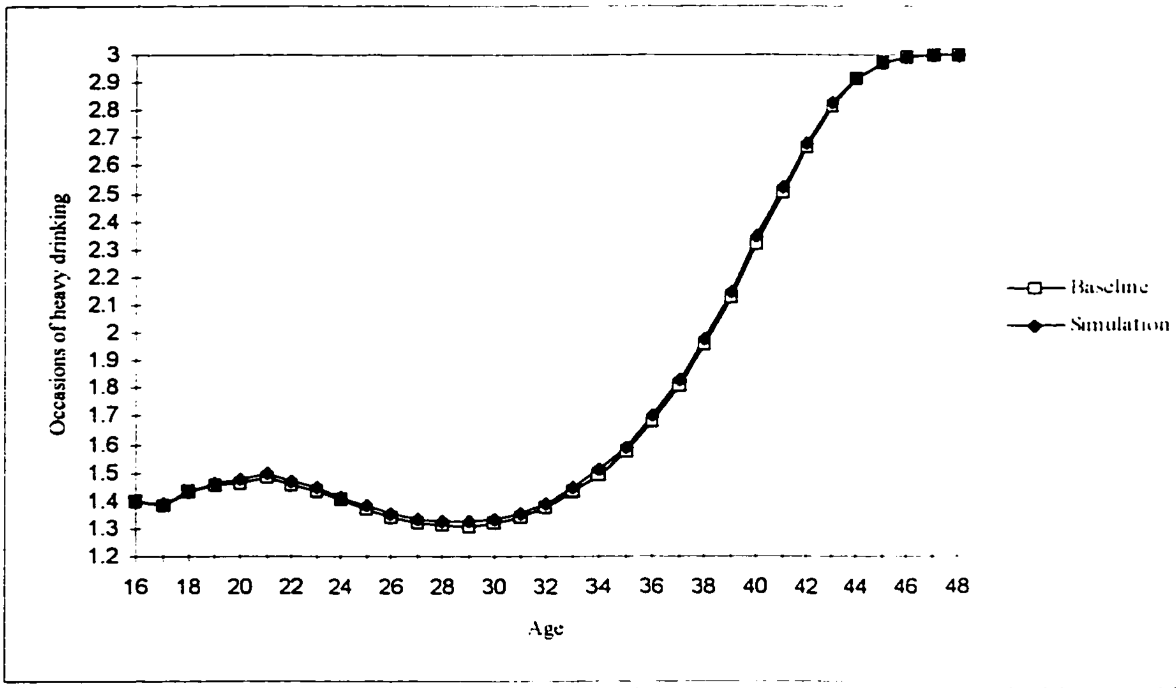

Figure 6.29. Simulated occasions of binge drinking, age 16-48. Simulations hold everything else constant except net family income

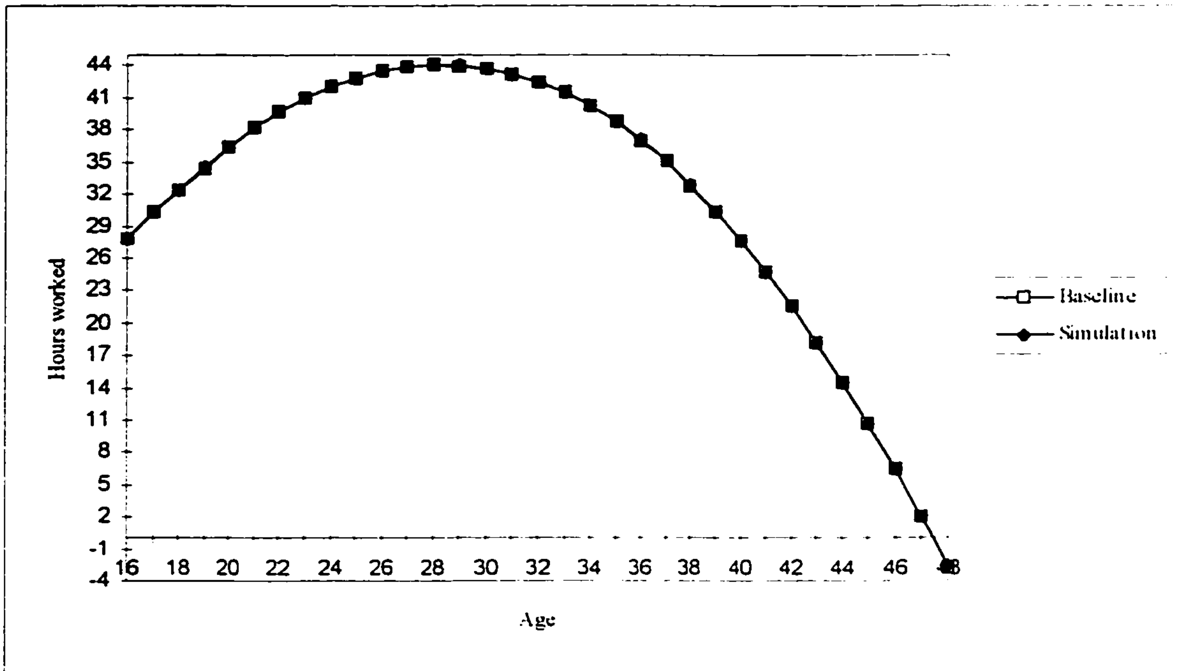

Figure 6.30. Simulated hours worked, age 16-48. Simulations hold everything else constant except net family income

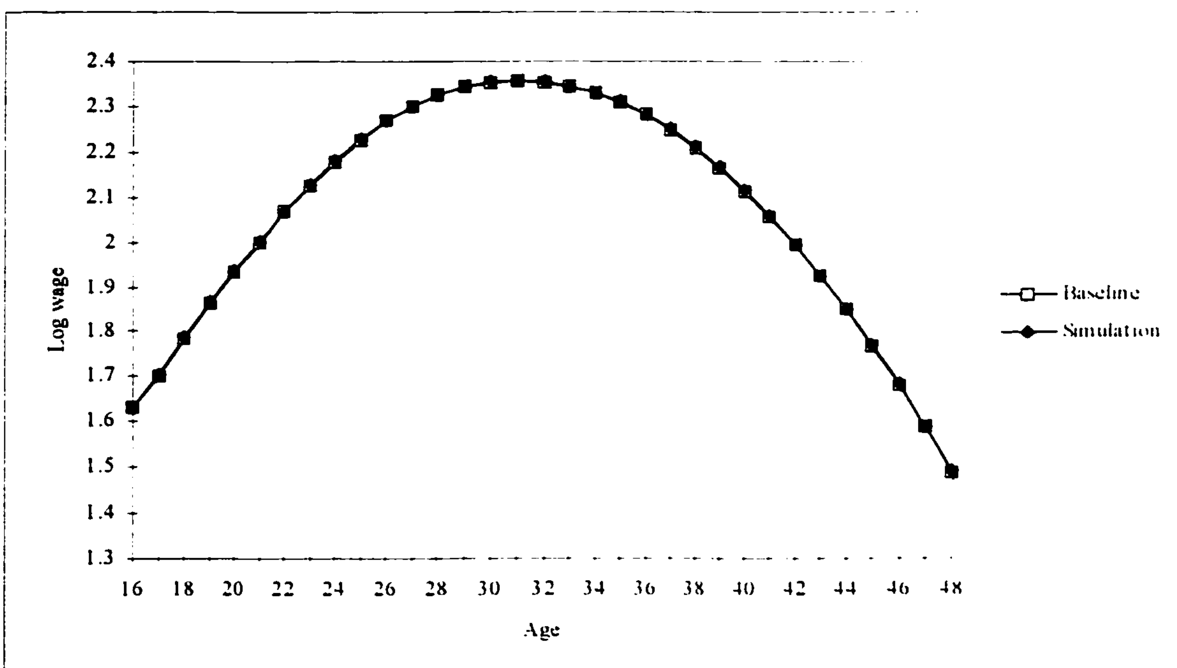

Figure 6.31. Simulated log wage, age 16-48. Simulations hold everything else constant except net family income

gain simplicity and mathematical tractability, the basic idea is that individuals choose a life style in the model, which then affects health and income inequality in the population. The policy implication can be drawn clearly. If we can reduce binge drinking among young adults and prevent teenagers from an early experience with alcohol, the negative economic impacts can be reduced, which implies savings in terms of health care expenditures and loss of labor productivity.

Although raising the alcohol tax is the most mentioned policy instrument in related literature, its effect is not very significant in discouraging binge drinking and heavy drinking in this research. Other policy variables that might be considered include the minimum legal drinking age and public campaign against heavy drinking. From an economic perspective, increasing the alcohol price may not be the best strategy, because it unfairly imposes extra costs on people who are social drinkers. The best method would be to change the perception of alcohol use in the public fundamentally, in particular, the drinking culture in college campuses. If the society as a whole can develop a strong disapproval towards heavy drinking, then the incidence of drinking problems might be diminished.

CHAPTER 7. BINGE DRINKING AND OCCUPATIONAL CHOICE

Previous chapters have examined the impact of frequent binge drinking on selected labor market indicators: health, labor supply, and wage. Because alcoholism has been shown in the literature to be strongly associated with job instability, it is important to examine the effect of frequent binge drinking on an individual's choice of occupation. Only a few studies (Kenek and Riber, 1994; Mullahy and Sindelar, 1996) examined the relationship between alcoholism and occupational choice. In the earlier literature, alcoholism seems to have different impacts on occupational choice for men and women. Alcoholism is negatively related to the employment status of prime-age men, but for women, the relationship is positive and the explanations for the positive association remains unclear.

Several socioeconomic factors have been proposed by others to explain the positive association between alcoholism and employment status among women. It could result from the stress involving role conflict, particularly the conflicting demands for work and family roles among married women. The type of job a woman is holding could also affect her drinking behavior. Women employed in male-dominated occupations or industries often report more problem drinking, seemingly due to peer influence, increased drinking opportunities, and stresses experienced by women in a male-dominated work environment. However, these explanations are rather difficult to measure and not testable with our data.

The latest research from Mullahy and Sindelar (1997) provides a new explanation for the positive relationships between alcoholism and employment outcomes among women. They showed the positive association is confined to white women only. In addition, alcoholism is associated with more schooling, fewer young children, and a smaller probability of being married. These characteristics are usually associated with an increased female's labor supply.

This chapter examines the effect of frequent binge drinking on occupational choice and provides an explanation for differences in the occupational choice between males and females. As for the puzzling positive association between alcoholism and employment status among women, two variables–marital status and children younger than 5 years old–are used to identify the unobserved adjustment behind the decision of occupational choice. These two variables are potentially important because they significantly affect women's labor force participation decision.

The empirical measure of occupational choice consists of four categories: (1) no employment, (2) working full-time for a wage, (3) working part-time for a wage, and (4) being self-employed. The no employment group includes the unemployed and individuals who are out of the labor force. The sample for the analysis consists of survey observations in 1982-1985, 1988, 1989, and 1994 in which data on binge drinking are available. One modeling strategy is to model the occupational choice as sequential decision making. In the first stage, an individual makes a labor force participation decision, work or no work. This sequential decision making corresponds to an econometric model of the nested logit model type. However, the nested logit model requires attributes for each occupation, but the NLSY79 does not collect attributes for each occupation. The main alternative to the nested logit model is the multinominal logit model. The only disadvantage of applying mutinominal logit is that it assumes the decision for each occupational choice is independent of the other choices.

In addition to the occasions of binge drinking, marital status, and the presence of children younger than age 5, a set of socioeconomic and demographic variables also are included in the analysis–age, health status, gender, race, educational attainment, and non-wage income. Although binge drinking may affect occupational choice, reverse causality could exist in the sense that occupational choice (or working environment) also has an impact on the occasions of binge drinking. This type of feedback violates the independence assumption between regressors and the error term. To minimize the problem of reverse causality in the occupational choice model, the multinominal logit model is estimated with instrumental variables.

Empirical Results

The estimated coefficients for the multinominal logit model using the entire sample are displayed in Table 7.1. The omitted or reference category is no employment. The estimated coefficients are interpreted as the partial effects on the odds of falling into one category as opposed to the omitted category.

When an individual has a health limit, it reduces significantly the likelihood of being employed in each category. Relative to no employment, an increase in the occasions of binge drinking increases the odds of working full time at wage work and being self-employed. On the other hand, frequent binge drinking reduces the odds of working part time relative to no employment. If working full time at wage work is chosen as the omitted category, the results imply that increasing the occasions of binge drinking increases the odds of being self-employed and reduces the odds of working part time. The findings suggest that many individuals frequently engaged in binge drinking are currently working and they are

Table 7.1. Multinominal Logit Regression: Employment Outcomes and Coefficients

	Self-employed	Full-time	Part-time
Health limit	-0.861	-1.388	-1.037
	(-9.07)[a]**	(-29.9)**	(-15.49)**
Predicted occasions of binge drinking[b]	0.701	0.433	-0.292
	(13.654)**	(15.79)**	(-8.132)**
Education	0.152	0.192	0.207
	(13.29)**	(29.29)**	(23.68)**
Age	0.166	0.106	-0.53E-1
	(27.95)**	(30.69)**	(-11.18)**
Black	-0.88	-0.184	-0.601
	(-12.28)**	(-5.66)**	(-14.02)**
Hispanic	-0.49	0.19E-1	-0.234
	(-7.01)**	(0.54)	(-5.03)**
Married	0.619	0.418	-0.301
	(10.3)**	(12.62)**	(-6.82)**
Children less than 5 years old	-0.243	-0.312	-0.201
	(-0.73)	(-16.12)**	(-7.45)**
Non-wage income	0.852E-6	-0.13-5	-0.56E-7
	(3.295)**	(-5.61)**	(-0.22)
Chi-Square statistics	7693.48	7693.48	7693.48
Number of observations	53941	53941	53941

[a]t statistics are in the parentheses.
[b]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in past 30days.
**Statistically significant at the 5 % level.

more likely to choose to work full time at wage work and be self-employed.

In general, blacks and the Hispanics are more likely to be unemployed. Being married decreases the odds of working part-time and increases the odds of being self-employed and working full-time at wage work relative to being unemployed. Having children younger than 5 years old requires more time for childcare. As a result, parents with young children are more likely to withdraw from the labor market. An increase in non-wage income increases the likelihood of being self-employed relative to no employment. On the other hand, higher non-wage income decreases the odds of an individual working full time at wage work or part time.

The marginal effect of an increase in the occasions of binge drinking on occupational choice categories are computed and presented in Table 7.2. The results show that frequent binge drinking increases the probability of working full time by 9.7 percent and being self-employed by 1.6 percent. In addition, the probabilities of no employment and working part-time decrease 4.1 percent and 7.1 percent, respectively. There is a little evidence showing that individuals, who frequently engage in binge drinking, choose to become self-employed to accommodate their drinking habits because the majority of them still choose to work full time. In other words, most individuals who frequently engage in binge drinking can manage their full time job and drinking habits.

Table 7.2. Marginal effects of Frequent Binge Drinking on Employment Outcomes: Full Sample

	No employment	Self-employed	Full-time	Part-time
Occasions of binge drinking	-0.041 (0.0001)[a]	0.016 (0.0001)	0.097 (0.0001)	-0.071 (0.0001)

[a]P values are in the parentheses.

Because males and females have different experiences in the labor market, Tables 7.3 and 7.4 present the multinominal estimates for males and females, respectively. The omitted occupational category is no employment. Using the likelihood ratio test, the null hypothesis that the coefficients are identical for men and women is rejected. The sample value of the test statistic is 2087.6 with 27 degrees of freedom is greater than a 0.01 critical value of 12.88. It indicates that the structure of the occupational choice differs significantly by gender.

Table 7.3. Multinominal Logit Regression for Men: Employment Outcomes and Coefficients

	Self-employed	Full-time	Part-time
Health limit	-0.935	-1.27	-0.759
	(-6.512)[a]**	(-16.59)**	(-6.41)**
Predicted occasions of binge drinking[b]	-0.185	-0.216	-0.515
	(-1.84)*	(-3.6)**	(-6.27)**
Education	0.121	0.147	0.258
	(7.9)**	(15.33)**	(18.28)**
Age	0.188	0.129	-0.122
	(22.86)**	(23.78)**	(-14.06)**
Black	-1.32	-0.572	-0.64
	(-13.66)**	(-11.14)**	(-8.98)**
Hispanic	-0.763	-0.129	-0.173
	(-8.01)**	(-2.45)**	(-2.38)**
Married	0.538	0.688	-0.564
	(5.82)**	(11.34)**	(-5.81)**
Children less than 5 years old	0.49E-1	-0.62E-1	-0.234
	(0.91)	(-1.65)*	(-3.33)**
Non-wage income	0.15E-5	-0.835E-6	-0.103
	(3.74)**	(-2.265)**	(-0.211)
Chi-squared	5131.31	5131.31	5131.31
Number of observations	27855	27855	27855

[a]t statistics are in the parentheses.
[b]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in past 30days.
*Statistically significant at the 10-percent level.
**Statistically significant at the 5-percent level.

The most significant differences appear to be due to the effects of binge drinking and marital status. For men, an increase in the frequency of binge drinking decreases significantly the likelihood of being in each category relative to no employment. In contrast, for women, an increase in the occasions of binge drinking increases her likelihood of being in each of the three employment categories, relative to no employment. However, only the coefficient for working full time at wage work is statistically significant at the 5 % level. If working full time at wage work is chosen to be the omitted category, the results suggest that, for men, the

Table 7.4. Multinominal Logit Regression for Women: Employment Outcomes and Coefficients

	Self-employed	Full-time	Part-time
Health limit	-0.65	-1.42	-1.18
	(-5.035)[a]**	(-23.58)**	(-14.52)**
Predicted occasions of binge drinking[b]	0.148	0.253	0.673E-1
	(1.16)	(4.178)**	(0.92)
Education	0.11	0.203	0.197
	(5.87)**	(21.36)**	(16.71)**
Age	0.148	0.86E-1	-0.288E-1
	(16.35)**	(18.64)**	(-4.84)**
Black	-1.148	-0.154	-0.422
	(-8.76)**	(-2.96)	(-6.55)**
Hispanic	-0.431	0.99E-2	-0.22
	(-4.0)**	(0.2)	(-3.53)**
Married	0.49	-0.703E-1	-0.23
	(4.88)**	(-1.524)	(-3.99)**
Children less than 5 years old	0.11E-1	-0.543	-0.253
	(0.23)	(-22.19)**	(-8.3)**
Non-wage income	0.221E-6	-0.1E-5	-0.238E-7
	(0.48)	(-3.3)**	(-0.07)
Chi-squared	3609.73	3609.73	3609.73
Number of observations	26086	26086	26086

[a]t statistics are in the parentheses.
[b]Predicted occasions of binge drinking is the predicted latent value of having more than 4 occasions of binge drinking in past 30days.
*Statistically significant at the 10-percent level.
**Statistically significant at the 5-percent level.

occasions of binge drinking is positively associated with the odds of being self-employed and negatively related to the odds of working part time. As for women, the occasions of binge drinking are positively associated with the odds of working full time. Marital status has a different impact on the probability of working full time at wage work for men and women. Relative to no employment, married men are more likely to work full time than their counterparts. Married women are more likely to withdraw from the labor market, although the coefficient of the marital status in column 3, Table 7.4, is not statistically significant. A woman having a child less than 5 years old significantly decreases her odds of working full time relative to no employment among women. For men, the odds of working full time relative to no employment are not affected significantly at the 5 percent level by the presence of young children.

The marginal effects of an increase in the occasions of binge drinking on occupational choice for men and women are reported in Table 7.5. The major difference is that, for men, frequent binge drinking significantly increases the probability of being unemployed by 2.4 percent. The decline in the probability of working full time for a wage is nearly 0.5 percent and is insignificant. On the contrary, for women, frequent binge drinking increases the probability of working full time by 4.8 percent and reduces the probability of becoming unemployed by almost 3 percent. An increase in the occasions of binge drinking reduces the

Table 7.5. Marginal Effects of Frequent Binge Drinking on Employment Outcomes: Male and Female Samples

		No employment	Self-employed	Full-time	Part-time
Male	Occasions of	0.024	0.0012	-0.005	-0.019
	binge drinking	(0.0001)[a]	(0.77)	(0.496)	(0.0001)
Female	Occasions of	-0.028	-0.0008	0.048	-0.019
	binge drinking	(0.0003)	(0.8)	(0.0001)	(0.02)

[a]P values are in the parentheses.

probability of working part time for both men and women by 1.9 percent. The effect of frequent binge drinking on the probability of being self-employed is insignificant for both men and women.

The different experience in occupational choice between men and women seems to reflect the traditional role of men and women in the U.S. households. Being married and the presence of young children usually are the turning points in women's working careers and typically affect women's labor force participation. Women usually withdraw, at least temporarily, from the labor market after they are married or/and have young children. Conversely, men remain employed after they get married. Even having young children only slightly affects men's employment status because their wives are the main childcare givers.

Table 7.6 shows how marital status and having young children affect men's and women's employment outcomes. The value of the dependent variable is 1 if the respondent is currently working, or 0 otherwise. The results in Table 7.6 strongly support the argument that the traditional roles of men and women in the family affect women's and men's labor force participation. Having children less than 5 years old decreases the probability of working for both men and women. However, its impact on women is about 19 times greater than for men. More importantly, marital status has different impacts on the employment status for men and women. Men choose to participate in work more frequently because they are the "breadwinners" of the families. Women withdraw from the labor market and become the homemakers and childcare givers.

To explain the positive relationship between the occasions of binge drinking and occupational choice for women reported in Table 7.4, it is essential to identify the effects of marital status and the presence of young children on the occasions of binge drinking. Table 7.7 displays the ordinal probit estimates of the occasions of binge drinking for man and women, respectively.

The results indicate that, for both men and women, being married reduces the occasions of binge drinking significantly. However, having children less than 5 years old has a significant negative effect on women only. Men's drinking behavior does not change significantly with the presence of young children. Both men and women working in male dominated occupations have more occasions of binge drinking than their counterparts. The magnitude of coefficient for women is more than two times greater than the coefficient for men. The hypothesis that women working in male-dominated occupations have more occasions of binge drinking is supported, although the coefficient is not statistically significant.

For men, employment status does not significantly affect on the occasions of binge drinking. However, the employment status is positively and significantly related to the

Table 7.6. Probit Regression: Employment Status and Coefficients for Men and Women Respectively

Explanatory Variable	Dependent Variable: Employment Status	
	Male	Female
Predicted occasions of binge drinking	-0.174	0.064
	(0.0001)[a]	(0.04)
Health limit	-0.647	-0 769
	(0.0001)	(0.0001)
Education	0.08	0.103
	(0.0001)	(0.0001)
Age	0.052	0.0345
	(0.0001)	(0.0001)
Black	-0.366	-0.17
	(0.0001)	(0.0001)
Hispanic	-0.116	-0.06
	(0.0001)	(0.02)
Married	0.26	-0 07
	(0.0001)	(0.0038)
Urban	0.084	0.063
	(0.0005)	(0.006)
Children less than 5 years old	-0.021	-0.39
	(0.4865)	(0.0001)
Log likelihood	-11024.44	-12141.98
Number of observations	30193	28107

[a]P values are in the parentheses.

Table 7.7. Ordinal Probit Regression: Occasions of Binge Drinking and Coefficients

Explanatory Variable	Dependent variable: Occasions of Binge Drinking	
	Male	Female
Education	-0.04	-0.065
	(0.0001)	(0.0001)[a]
Age	0.0006	-0.006
	(0.76)	(0.026)
Black	-0.4	-0.433
	(0.0001)	(0.0001)
Hispanic	-0.064	-0.252
	(0.0011)	(0.0001)
Married	-0.36	-0.431
	(0.0001)	(0.0001)
Started drinking before age 18	0.51	0.512
	(0.0001)	(0.0001)
Real alcohol price	-0.087	-0.033
	(0.0001)	(0.089)
Children less than 5 years old	-0.027	-0.21
	(0.20)	(0.0001)
Working	0.0085	0.054
	(0.67)	(0.019)
Working in male-dominated occupations	0.146	0.32
	(0.0001)	(0.20)
Log likelihood	-27813.34	-16350.02
Number of observations	28659	20866

[a]P values are in the parentheses.

occasions of binge drinking for women. The results show there exists a reversed causality between binge drinking and the employment status among women.

It is clear that the positive relationship between the occasions of binge drinking and the employment status among women could be attributed to marital status and the presence of young children. The following analysis provides additional evidence to support this argument by comparing the characteristics of the following groups. Males and females are separated into four mutually exclusive groups, respectively, single and working, single but not working, married and working, and married but not working. The results are presented in Tables 7.8 and 7.9.

The common characteristics include both employed men and women are healthier and have more years of schooling than their counterparts. Among single men and women, the occasions of binge drinking do not differ by their employment status. Moreover, both single men and women have more occasions of binge drinking than married men and women, and employed men and women drink more than the unemployed, except for married men. The greater occasions of binge drinking among men who are married and unemployed provide some evidence for the difference in the decision of occupational choices between men and

Table 7.8. Means and Standard Deviation of Women in Four Demographic Groups–Single and Working, Single but not Working, Married and Working, and Married but not Working

	Single and Working	Single but not Working	Married and Working	Married but not Working
Occasions of binge drinking	1.36	1.34	1.18	1.15
	(0.625)[a]	(0.64)	(0.45)	(0.42)
Health limit	0.04	0.14	0.047	0.161
	(0.2)	(0.35)	(0.21)	(0.37)
Education	13.04	12.01	12.95	12.0
	(2.0)	(1.85)	(2.13)	(2.31)
Age	24.31	23.24	26.48	25.21
	(4.11)	(4.09)	(4.01)	(4.11)
Black	0.273	0.403	0.16	0.14
	(0.44)	(0.49)	(0.37)	(0.35)
Hispanic	0.148	0.161	0.16	0.19
	(0.36)	(0.37)	(0.37)	(0.39)
Children less than 5 years old	0.174	0.34	0.49	0.66
	(0.38)	(0.47)	(0.5)	(0.47)
Started drinking before 18	0.366	0.387	0.31	0.338
	(0.48)	(0.48)	(0.46)	(0.47)
Number of observations	13271	2598	9766	2472

[a]Standard deviation statistics are in the parentheses.

Table 7.9. Means and Standard Deviation of Men in Four Demographic Groups–Single and Working, Single but not Working, Married and Working, and Married but not Working

	Single and Working	Single but not Working	Married and Working	Married but not Working
Occasions of binge drinking	1.75	1.74	1.54	1.66
	(0.81)[a]	(0.83)	(0.72)	(0.78)
Health limit	0.034	0.08	0.03	0.1
	(0.18)	(0.27)	(0.16)	(0.3)
Education	12.45	11.56	12.57	11.31
	(2.2)	(1.97)	(2.46)	(2.23)
Age	24.15	22.9	27.02	24.77
	(3.99)	(3.76)	(3.94)	(3.67)
Black	0.27	0.37	0.15	0.17
	(0.45)	(0.48)	(0.36)	(0.37)
Hispanic	0.16	0.17	0.18	0.21
	(0.36)	(0.37)	(0.38)	(0.41)
Children less than 5 years old	0.052	0.05	0.568	0.625
	(0.22)	(0.22)	(0.50)	(0.48)
Started drinking before 18	0.55	0.59	0.55	0.59
	(0.49)	(0.49)	(0.5)	(0.49)
Number of observations	16060	3301	10015	817

[a]Standard deviation statistics are in the parentheses.

women. It is possible that women quit their jobs mainly because of the traditional female role in the family. On the other hand, no employment for men is attributed to other factors, such as a drinking problem. As for the presence of young children, the percentage difference is substantial between employed and unemployed women for both single and married categories. The percentage difference is much smaller or close to zero for men. The finding indicates that the traditional roles of men and women in the family influence the decision for labor market participation and their drinking behavior.

Mullahy and Sindelar (1997) show that for women, educational attainment is positively related to alcoholism. They use this finding to explain the positive relationship between alcoholism and employment status. However, many related studies have shown that the early onset of alcohol consumption is strongly associated with fewer years of schooling. Table 7.7 suggests a negative relationship between the occasions of binge drinking and educational attainment for women. Therefore, educational attainment cannot be the main determinant of the puzzle.

A more convincing explanation is the positive relationship between the employment status and the occasions of binge drinking mainly results from the traditional roles which men and women take, and an increased drinking opportunity when women work. Women withdraw from the labor market after they are married and/or have young children. At the same time, women also reduce the occasions of binge drinking because they assume family and childcare responsibility, and their drinking opportunities are reduced. As a result, women staying in the labor market generally have more occasions of binge drinking than their counterparts.

On the other hand, in general, men do not quit their jobs after they are married or have young children. In fact, they work more when they become the breadwinners of the family. Furthermore, unlike women, employment status does not affect men's drinking behavior very much. Therefore, the impact of frequent binge drinking on the employment outcomes will not be distorted by the labor market withdrawals originated from the social norm. The effect of frequent binge drinking on women's employment outcomes will be misleading if we fail to consider the impact of the "unobserved" traditional roles of men and women on the labor force participation.

Since men and women have different structures of occupational choices, the discussion of the impact of frequent binge drinking on the employment outcomes should be separated for men and women. For men, an increase in the occasions of binge drinking increases the probability of no employment and self-employed, but decreases their probability of working both full time and part time for a wage. As for women, an increase in the occasions of binge drinking increases the probability of being a full-time wage worker relative to no employment. However, the real relationship between the occasions of binge drinking and employment outcomes may be distorted by the traditional roles of women in the family.

CHAPTER 8. CONCLUSIONS

This research focused on the drinking behavior among the American young adults between age 14 to 37. There were four goals to achieve. The first was to test the forward-looking hypothesis of drug use by combining the rational addiction model and the investment in health model. In general, the empirical results supported the hypothesis that the behavior of binge drinking is rational in the sense that heavy drinkers take the adverse impact of frequent binge drinking into account when making their consumption decisions. The model was simulated using the simultaneous framework, and it predicted the actual values of health status, occasions of binge drinking, hours worked, and log wage fairly well. The hypothesis that the demand for health, occasions of binge drinking, and labor supply were jointly determined, was supported by the empirical results.

The results were most likely affected by the deficiencies in the data. Several drawbacks of the NLSY79 should be pointed out. First, the NLSY79 has a narrow age distribution ranging between ages 17-37, and health status is improperly measured. Their combined effect results in more than 95 percent of the sample has no health problem during the entire sample period. Hence, the impact of frequent binge drinking on health and other labor market indicators was not estimated precisely. An ideal data set would have both a broader age range and objective measure of health status. Second, in the first stage of the two-stage estimation, dependent variables are regressed on a set of instrumental variables to obtain their predicted values. Most of the instrumental variables are time invariant, which may cause muticollinarity in the second stage.

The second goal of this research was to examine the impact of frequent binge drinking on health, labor productivity, and labor supply. Health status was shown to be negatively affected by the occasions of binge drinking. The fitted wage equation showed that frequent binge drinking reduces the wage rate significantly. In addition, health also captures the long-term impact of frequent binge drinking on labor productivity through faster health depreciation. Nonetheless, the simulation showed that frequent binge drinking did not significantly affect hours worked, given the individual was working.

The third goal was to evaluate the effectiveness of the government's policies, especially of a tax on alcohol. The purpose of the government's interventions is to discourage underage drinking and binge drinking. The model simulation showed the predicted benefits of increasing the alcohol price on occasions of binge drinking, health, labor supply, and wage. The results suggested that the occasions of binge drinking is price inelastic and its magnitude is smaller than those using total alcohol consumption as the measure of alcohol consumption, as reported in the earlier literature. It implies that frequent binge drinking is more likely to develop dependence symptoms, which results in a smaller price elasticity.

The unanticipated short run price elasticities for more than 4 occasions of binge drinking in the past 30 days, one to three occasions of binge drinking in the past 30 days, and no occasions of binge drinking in the past 30 days were estimated to be -0.09, 0.01, and 0.08, respectively. The anticipated long run price elasticities were estimated to be -0.24, 0.03, and 0.21, respectively. An increase in the alcohol price was shown to decrease the probability of an individual being in the group of more than 4 occasions of binge drinking and increases the probability of him/her being in the other two groups. Moreover, the increased probability for the group of no occasions of binge drinking was shown to be greater than in the group of one to three occasions of binge drinking.

An increase in the alcohol prices has positive short run and long run effects on health, labor supply, and wage, although the magnitudes are relatively small. The short run alcohol price elasticity for the demand for health, labor supply, and the wage rate were estimated to be 0.0002, 0.0001, and 0.001, respectively. The long run price elasticities were 0.006, 0.0003, and 0.003, respectively. By increasing the alcohol price, the government can discourage binge drinking, improve public health and labor productivity.

Unlike previous studies, this research also compares the effectiveness of several policy variables on the occasions of binge drinking, health status, hours worked, and wage. The simulation results suggest that preventing youths from starting drinking young has significant impact on the occasions of binge drinking, health status, hours worked, and labor productivity in their adulthood. For instance, having alcoholic parents, started to drink before age 18, and having illegal activities at a young age were shown to have strong effect on the occasions of binge drinking. This finding implies that binge drinking is closely related to an individual's early experiences with alcohol.

Increasing either minimum drinking age or investment in education has greater effect on binge drinking among young adults than increasing the alcohol price. Because binge drinking is price inelastic, the effect of increasing excise tax on binge drinking will be small unless the increase is significant. However, it would be politically difficult to increase excise tax by a great magnitude. Government intervention should focus on preventing early initiation of alcohol use among youths by altering the drinking culture among teenagers, educating young adults to drink responsibly, and giving our children a caring home. These efforts are more likely to effectively prevent youths from becoming alcoholics or heavy drinkers, promote public health, and increase labor productivity.

The last objective is to examine the relationship between binge drinking and occupational choices. The occasions of binge drinking were shown to have different impacts on the occupational choices of men and women. Frequent binge drinking was shown to be negatively and significantly related to employment status of men. On the other hand, the occasions of binge drinking were shown to be positively related to employment status of women. The explanation comes from the traditional roles which men and women take in the family. Particularly, most of the women choose to withdraw from the labor market after they are married and have young children. Men remain in the labor market or even increase their labor force participation after they assume family responsibilities. As a result, women show a positive relationship between occasions of binge drinking and employment status. The results suggest that it is important to consider the effect of traditional gender role in the family on male and female's occupational choice, when examining the impact of frequent binge drinking on occupational choices.

APPENDIX A. IMPUTATION PROCEDURE TO COMPENSATE FOR MISSING RESPONSES

An imputation procedure is a statistical procedure, which is applied to compensate for the missing data in a survey. Non-response is common in sample surveys and occurs for a variety of reasons. Missing survey data can be classified as arising from two main sources. The most recognized source is unit non-response, which occurs when no survey data are collected for a unit included in the sample. The unit can refer to a person, a household, or a firm, depending upon the survey. Unit non-response usually results from refusals to participate in the survey. Compensation for unit non-response is made by means of weighting adjustment. Respondents are assigned greater weight to represent the non-respondents.

A second source of missing data is item non-response. It occurs when a sampled unit participates in the survey but fails to provide acceptable responses to one or more survey questions. Item non-response may arise because a respondent refuses to answer the question, does not know the answer to the question, or gives an answer that is inconsistent with the answers to other questions. The compensation for item non-response is imputation, which involves assigning a value to the missing response.

There are quite a few imputation procedures to choose from. The following methods are commonly used in the literature (Brick and Kalton, 1996). Among many methods dealing with missing data, the simplest method is "no-imputation" procedure, which ignores the missing data. Non-respondents are not included in the analysis and the estimates are computed solely from the respondent data. The effectiveness of the no-imputation procedure depends upon the extent of the missing data and the degree to which non-respondents as a group differ from respondents as a group. When the level of missing data is large e.g. many survey participants refuse to provide correct family income information, or non-respondents have different characteristics than respondents, imputation for missing data can improve the accuracy of the estimates based only upon respondent data.

Most importantly, complex analyses, such as multiple regression analysis, usually use many variables. The effect of item non-response will be cumulative in the sense that the no-imputation procedure may result in fewer data records with complete responses to all variables. Under these circumstances, imputation provides an alternative to resolve the missing data problem. Otherwise, valuable information will be lost and the regression results may be biased.

There are four major methods of imputation to item non-response. The simplest and most widely used imputation procedure is the "mean-value imputation" procedure. This method replaces the missing data with the mean of the respondent data. However, the main drawback of mean value imputation is that replacing missing data with the mean usually distorts the distribution of the represented population. For example, when the income distribution is estimated, mean value imputation will overestimate the percentage falling into the middle of the distribution and underestimate the percentage with high and low income.

The second method is "hot deck imputation." First, the auxiliary variables (gender, race, age, etc.) are used to divide the sample into a set of classes and then the imputation is performed within the classes. The more auxiliary variables used, the more homogeneous people become in each class. Missing data are assigned values from the respondents in the same class.

The early version of hot-deck imputation is also known as sequential hot-deck imputation. It is performed in the following way. After the imputation classes are formed, an initial value of the variable to be imputed is determined and stored for each class. As the data are processed sequentially, the imputation class to which each record belongs is determined. If a record has a value for the variable, then that value replaces the value previously stored in the imputation class. On the other hand, if a record has a missing value, it is assigned the value currently stored in the imputation class. The main disadvantage of the sequential hot-deck imputation is that when two or more missing values occur in sequence in a given imputation, these missing data receive the same value from the previous responding record (donor). Multiple use of donors would result in an increase in imputation variance.

Hierarchical hot-deck method is devised to resolve the disadvantage of sequential hot deck imputation. With this method, all of the survey records are divided into respondent records and non-respondent records within each imputation class. Respondent records are randomly selected to replace non-respondent records. Generally, selecting donors by simple random sampling without replacement is preferred to sampling with replacement because sampling without replacement minimizes the multiple use of donors.

The third method, which is most familiar to economists, is "regression imputation." The respondent records are used to fit a linear model. The regression approach requires that both non-respondent and respondent records have complete data for the right-hand side explanatory variables in the regression. Deterministic regression imputation simply replaces the missing value with the predicted value from the regression. Although often used, deterministic regression imputation, like mean value imputation, has the disadvantage of distorting the distribution because the predicted values are actually mean values.

Stochastic regression imputation is developed to minimize the distribution distortion. Stochastic regression imputation is conducted by taking the residual from a respondent who has a similar predicted value to the non-respondent. Then, we add the residual to the predicted value of the non-respondent. However, when the residual is added to the non-respondent's predicted value, non-feasible value may occur, such as negative incomes. An alternative is to assign the *actual* value from the matched respondent, rather than just the residual. This alternative method is termed as "predicted mean matching." It has the attraction that the imputed values are all feasible values because they are actual values from the respondents.

Hot Deck Imputation for NLSY1979

The econometric model discussed in the previous chapter uses many variables in the estimation. The "no-imputation" procedure is inappropriate because it reduces the sample size too much. The imputation methods applied to the current data set, NLSY1979 (National Longitudinal Survey of Youth Cohort, 1979-1994), combine the hierarchical hot-deck imputation and the deterministic-regression imputation. Imputations are performed on the following variables–education, net family income, annual wage income, marital status, occupation, class of worker, AFQT percentile, and the number of children less than 5 years old.

Because NLSY79 is panel data, imputation is performed annually and, within each year, gender, race, and age are the three main auxiliary variables chosen to form imputation classes. Race contains three categories–black, Hispanic, and others. Age consists of two groups–a young cohort and an older cohort. The medium age in 1979 is chosen as the dividing age. The young cohort includes people between ages14 to 17 and the older cohort contains respondents between ages 18 to 21 in 1979.

A missing education value is handled by the carry-over method. When a respondent has a missing value for education in year t, the missing value is replaced with the educational achievement reported by the same respondent in year t-1. If education is missing for two or more consecutive years, the latest education reported in the past will be used to substitute for these consecutive missing values of education.

Annual wage income and net family income have the highest rate of item non-response among all variables, particularly net family income. Since net family income includes wage and all other sources of income. Non-wage income is defined as the difference between net family income and wage income. Hence, it would be more reasonable to perform imputation for wage and net family income simultaneously. Otherwise, it would be possible to obtain non-feasible results, for instance, annual wage income could be greater than annual net family income.

The patterns of missing net family income and wages income include net family income missing only, wage income missing only, and both missing. The entire sample is separated into employed and unemployed groups. The following imputation procedures are conducted for each group. For the case with both missing, the hierarchical hot-deck imputation is straightforward. The missing data are replaced with randomly sampled respondent data (with complete information on both wage and net family income).

In the case of net family income missing only, race and annual wages income are used to form imputation classes. Wage incomes are separated into three groups–less than $20,000, between $20,000 and $40,000, and more than $40,000. Missing non-wage income is compensated by the non-wage income randomly selected from the respondent data. Missing net family income can be computed indirectly by adding non-wage income to wages income. If only wage income is missing, race and the net family income are the auxiliary variables for forming imputation classes. Net family income also is divided into three groups–less than $15,000, between $15,000 and $50,000, and more than $50,000. Missing non-wage income is substituted with the non-wage income randomly sampled from the respondent data. The missing annual wage income can be obtained by subtracting non-wage income from the net family income.

Although it is possible to result in a negative annual wage income from the hotdeck imputation, the use of net family income as a stratifying variable reduces the probability of having non-feasible outcomes. In addition, more than 90 percent of the respondents who have missing data in wage income, also have missing data in net family income in NLSY1979. This further lowers the probability of having a negative wage income. Even it does occur, the number of occasions will be very small and we can delete them without seriously affecting parameter estimates.

Since the net family income and wage income for year 1994 are unavailable in the survey, the hot-deck imputation cannot be performed. Regression imputation is the alternative to compute the predicted family and wage income. The entire sample is grouped into employed and unemployed groups. To avoid the non-feasible outcomes, annual wage income and non-wage income are regressed on explanatory variables, respectively, for each group, using data from 1979 to 1993. The explanatory variables for annual wage income include age, gender, race, region, education, health status, marital status, urban, AFQT percentile (explained in Chapter 6), and occupations. For non-wage income, the explanatory variables comprise all the variables in the annual wage income equation, and the number of children less than five years old, and being charged with illegal activity in 1980. In each group, both annual wage income and non-wage income equation also consist of a self-selection corrector, the inverse Mill's ratio. Given the predicted annual wage income and non-wage income, the predicted annual net family income is the sum of the predicted annual wage income and predicted non-wage income.

APPENDIX B. SOLUTIONS TO THE THIRD-ORDER DIFFERENCE EQUATIONS

The simultaneous system can be represented as:

$$H_t = aC_t + bC_{t-1} + dL_t + X_{1t} \quad . \tag{1}$$

$$C_t = eH_t + fH_{t-1} + gC_{t+1} + iC_{t-1} + jC_{t-2} + kL_{t+1} + mL_t + nL_{t-1} + X_{2t} \quad . \tag{2}$$

$$L_t = oH_t + qC_t + rC_{t-1} + sW_t + X_{3t} \quad . \tag{3}$$

$$W_t = yH_t + hC_t + X_{4t} \quad , \tag{4}$$

where L_t is labor supply at period t,

W_t is wage rate at period t,

H_t is health status at period t,

C_t is binge drinking at period t, and

X_{it}, i=1, 2, 3, 4 is sum of the exogenous variables.

Substituting (4) into (3) and rearranging terms, we can obtain the following equation.

$$L_t = (o + sy)H_t + (q + sh)C_t + rC_{t-1} + (sX_{4t} + X_{3t}) \quad . \tag{5}$$

Using Equation (1), Equation (5) can be further simplified as a function of X's and C's.

$$\begin{aligned} L_t &= (o + sy)[aC_t + bC_{t-1} + dL_t + X_{1t}] + (q + sh)C_t + rC_{t-1} + (sX_{4t} + X_{3t}) \\ &= (q + sh + ao + asy)C_t + (r + bo + bsy)C_{t-1} + (do + dsy)L_t + (o + sy)X_{1t} \\ &\quad + sX_{4t} + X_{3t} \quad . \end{aligned} \tag{6}$$

$$\begin{aligned} L_t &= \frac{(q + sh + ao + asy)}{(1 - do - dsy)} C_t + \frac{(r + bo + bsy)}{(1 - do - dsy)} C_{t-1} + \frac{(o + sy)}{(1 - do - dsy)} X_{1t} \\ &\quad + \frac{s}{(1 - do - dsy)} X_{4t} + \frac{1}{(1 - do - dsy)} X_{3t} \\ &= uC_t + vC_{t-1} + \delta X_{1t} + \sigma X_{4t} + \eta X_{3t} \quad , \end{aligned} \tag{7}$$

where $u = \dfrac{(q + sh + ao + asy)}{(1 - do - dsy)}$,

$$v = \frac{(r + bo + bsy)}{(1 - do - dsy)} \quad ,$$

$$\delta = \frac{(o + sy)}{(1 - do - dsy)} \quad ,$$

$$\sigma = \frac{s}{(1 - do - dsy)} \quad , \text{ and}$$

$$\eta = \frac{1}{(1 - do - dsy)} \quad .$$

Let L be the lag operator defined by

$$L^n X_t = X_{t-n} \qquad \text{for } n = \ldots, -2, -1, 0, 1, 2, \ldots \quad . \tag{8}$$

If n<0, the effect of multiplying X_t by L^n will be to shift X forward in time by –n periods. Multiplying both sides of Equation (7) by L^1 and L^{-1} respectively, we can obtain the labor supply equation at period t-1 and t+1.

$$L_{t-1} = uC_{t-1} + vC_{t-2} + \delta X_{1t-1} + \sigma X_{4t-1} + \eta X_{5t-1} \quad . \tag{9}$$

$$L_{t+1} = uC_{t+1} + vC_t + \delta X_{1t+1} + \sigma X_{4t+1} + \eta X_{5t+1} \quad . \tag{10}$$

Substitute Equation (9) into Equation (1) to get the demand equation for health at period t in terms of the demand for binge drinking and other exogenous variables:

$$\begin{aligned} H_t &= aC_t + bC_{t-1} + d(uC_t + vC_{t-1} + \delta X_{1t} + \sigma X_{4t} + \eta X_{5t}) + X_{1t} \\ &= (a + du)C_t + (b + dv)C_{t-1} + (1 + \delta d)X_{1t} + d\sigma X_{4t} + d\eta X_{5t} \quad . \end{aligned} \tag{11}$$

The demand for health at period t-1 is obtained by applying lag operator on Equation (11)

$$H_{t-1} = (a + du)C_{t-1} + (b + dv)C_{t-2} + (1 + \delta d)X_{1t-1} + d\sigma X_{4t-1} + d\eta X_{5t-1} \quad . \tag{12}$$

To solve for the reduced form for the demand for binge drinking, we use Equations (9), (10), (11), (12), and (2). The resulting demand equation for binge drinking is a third-order difference equation:

$$
\begin{aligned}
C_t = {} & e[(a+du)C_t + (b+dv)C_{t-1} + (1+\delta d)X_{1t} + d\sigma X_{4t} + d\eta X_{3t}] \\
& + f[(a+du)C_{t-1} + (b+dv)C_{t-2} + (1+\delta d)X_{1t-1} + d\sigma X_{4t-1} + d\eta X_{3t-1}] \\
& + gC_{t+1} + iC_{t-1} + jC_{t-2} \\
& + k[uC_{t+1} + vC_t + \delta X_{1t+1} + \sigma X_{4t+1} + \eta X_{3t+1}] \\
& + m[uC_t + vC_{t-1} + \delta X_{1t} + \sigma X_{4t} + \eta X_{3t}] \\
& + n[uC_{t-1} + vC_{t-2} + \delta X_{1t-1} + \sigma X_{4t-1} + \eta X_{3t-1}] + X_{2t}
\end{aligned}
\tag{13}
$$

$$
\begin{aligned}
= {} & (g+ku)C_{t+1} + (ea+edu+kv+mu)C_t \\
& + (eb+edv+fa+fdu+i+mv+nu)C_{t-1} + (fb+fdv+j+nv)C_{t-2} \\
& + k\delta X_{1t+1} + (e+e\delta d+m\delta)X_{1t} + (f+f\delta d+n\delta)X_{1t-1} \\
& + k\eta X_{3t+1} + (ed\eta+m\eta)X_{3t} + (fd\eta+n\eta)X_{3t-1} \\
& + k\sigma X_{4t+1} + (ed\sigma+m\sigma)X_{4t} + (fd\sigma+n\sigma)X_{4t-1} + X_{2t}
\end{aligned}
$$

Rearranging terms, Equation (13) can be presented as the following:

$$
\begin{aligned}
C_{t+1} = {} & \frac{(1-ea-edu-kv-mu)}{(g+ku)}C_t \\
& - \frac{(eb+edv+fa+fdu+i+mv+nu)}{(g+ku)}C_{t-1} - \frac{(fb+fdv+j+nv)}{(g+ku)}C_{t-2} \\
& - \frac{k\delta}{(g+ku)}X_{1t+1} - \frac{(e+e\delta d+m\delta)}{(g+ku)}X_{1t} - \frac{(f+f\delta d+n\delta)}{(g+ku)}X_{1t-1} \\
& - \frac{k\eta}{(g+ku)}X_{3t+1} - \frac{(ed\eta+m\eta)}{(g+ku)}X_{3t} - \frac{(fd\eta+n\eta)}{(g+ku)}X_{3t-1} \\
& - \frac{k\sigma}{(g+ku)}X_{4t+1} - \frac{(ed\sigma+m\sigma)}{(g+ku)}X_{4t} - \frac{(fd\sigma+n\sigma)}{(g+ku)}X_{4t-1} - \frac{1}{(g+ku)}X_{2t} \\
= {} & z_1C_t + z_2C_{t-1} + z_3C_{t-2} + P(t+1) \quad ,
\end{aligned}
\tag{14}
$$

where $z1 = \dfrac{(1-ea-edu-kv-mu)}{(g+ku)}$,

$$z2 = -\frac{(eb+edv+fa+fdu+i+mv+nu)}{(g+ku)} \quad ,$$

$$z3 = -\frac{(fb+fdv+j+nv)}{(g+ku)} \quad \text{, and}$$

$$P(t+1) = -\frac{k\delta}{(g+ku)}X_{1t+1} - \frac{(e+e\delta d+m\delta)}{(g+ku)}X_{1t} - \frac{(f+f\delta d+n\delta)}{(g+ku)}X_{1t-1}$$
$$-\frac{k\eta}{(g+ku)}X_{3t+1} - \frac{(ed\eta+m\eta)}{(g+ku)}X_{3t} - \frac{(fd\eta+n\eta)}{(g+ku)}X_{3t-1}$$
$$-\frac{k\sigma}{(g+ku)}X_{4t+1} - \frac{(ed\sigma+m\sigma)}{(g+ku)}X_{4t} - \frac{(fd\sigma+n\sigma)}{(g+ku)}X_{4t-1} - \frac{1}{(g+ku)}X_{2t}$$

Because of the multicollinearity, the empirical estimation does not include lead and lag dependent variables in the structural equations except lead and lag occasions of binge drinking. To be consistent with the empirical analysis, the coefficients of one-year lead and lag of health capital, hours worked, and two-year lag of occasions of binge drinking are set to equal zero in the following derivation. This implies that f, j, k, n, and r are zeros. Applying the lag operator on both sides of Equation (14), we can get the third-order difference equation

$$C_t = z_1 C_{t-1} + z_2 C_{t-2} + P(t) \quad . \tag{15}$$

Solution to the Second-order Difference Equation

Using the lag operator, we can write Equation (15) as

$$(1 - z_1 L - z_2 L^2)C_t = P(t) \quad . \tag{16}$$

A solution to this difference equation is given by

$$C_t = \frac{1}{(1 - z_1 L - z_2 L^2)} P(t) \quad . \tag{17}$$

It is convenient to write the polynomial $1 - z_1 L - z_2 L^2$ in an alternative way,

$$\begin{aligned} 1 - z_1 L - z_2 L^2 &= (1 - \lambda_1 L)(1 - \lambda_2 L) \\ &= 1 - (\lambda_1 + \lambda_2)L + \lambda_1 \lambda_2 L^2 \quad , \end{aligned} \tag{18}$$

so that $\lambda_1 + \lambda_2 = z_1$, and $\lambda_1 \lambda_2 = -z_2$. λ_1 and λ_2 can be obtained from the following relation

$$(1-\lambda_1 x)(1-\lambda_2 x)=\lambda_1\lambda_2(\frac{1}{\lambda_1}-x)(\frac{1}{\lambda_2}-x) \quad . \tag{19}$$

If we set Equation (19) equal to zero, then the equation is satisfied at the two roots $x=\frac{1}{\lambda_1}$

and $x=\frac{1}{\lambda_2}$. Therefore, the two roots of x are found from solving the following characteristic

equation and λ_1 and λ_2 are the reciprocals of these two roots.

$$1-z_1x-z_2x^2=0$$

Assuming that $\lambda_1 \neq \lambda_2$, then we can write the general solution to the second-order difference

equation as

$$C_t=\frac{1}{(1-\lambda_1 L)(1-\lambda_2 L)}P(t)+w_1\lambda_1^t+w_2\lambda_2^t \quad , \tag{20}$$

where w_1 and w_2 are any constants which can be found by using two side conditions. Note

that

$$\frac{1}{(1-\lambda_1 L)(1-\lambda_2 L)}=\frac{k_1}{(1-\lambda_1 L)}+\frac{k_2}{(1-\lambda_2 L)} \quad ,$$

where $k_1=\frac{\lambda_1}{(\lambda_1-\lambda_2)}$ and

$$k_2=\frac{\lambda_2}{(\lambda_2-\lambda_1)}$$

Then Equation (20) can be rewritten as

$$C_t=\frac{k_1}{(1-\lambda_1 L)}P(t)+\frac{k_2}{(1-\lambda_2 L)}P(t)+w_1\lambda_1^t+w_2\lambda_2^t \quad . \tag{21}$$

Furthermore, we know that

$$\frac{1}{(1-\lambda L)} = 1 + \lambda L + \lambda^2 L^2 + \ldots$$
$$= -\frac{1}{\lambda} L^{-1} - (\frac{1}{\lambda})^2 L^{-2} - (\frac{1}{\lambda})^3 L^{-3} - \ldots \quad . \tag{22}$$

The estimated structural coefficients are used to compute two roots, λ_1 and λ_2. The results show that both roots are real and λ_1 is greater than one and λ_2 are less than 1. Using Equations (21) and (22), we can write the general solution to the third-order difference equation as

$$C_t = -k_1 \sum_{j=1}^{\infty} \lambda_1^{-j} P(t+j) + k_2 \sum_{j=0}^{\infty} \lambda_2^{j} P(t-j) + w_1 \lambda_1^{t} + w_2 \lambda_2^{t} \quad , \tag{23}$$

where w_1 and w_2 are the unknown constants, which can be found by two side conditions, one initial condition and one terminal condition. The initial condition includes the consumption level at period 0, C_0. The terminal condition requires that the marginal value of the addiction stock goes to zero when t approaches infinity. The stock equation is defined as:

$$S_{t+1} = C_t + (1-\pi) S_t \quad , \tag{24}$$

where S is the addiction stock and π is the exogenous depreciation rate of the addiction stock. Since the current model assumes that the depreciation rate of the addiction stock is equal to one, the addiction stock at period t is just the consumption level at period t-1. This terminal condition can be presented as the following:

$$\lim_{t \to \infty} \frac{dC_{t-1}}{dt} = \lim_{t \to \infty} [w_1 \lambda_1^{t-1} \ln(\lambda_1) + w_2 \lambda_2^{t-1} \ln(\lambda_2)] = 0 \quad . \tag{25}$$

For Equation (25) to hold, w_1 must be zero because λ_1 is greater than one and λ_2 is less than 1. By applying the initial conditions, w_2 can be obtained from solving Equation (26) and the results are presented in equation (27):

$$C_0 = -k_1 \sum_{j=1}^{\infty} \lambda_1^{-j} P(j) + k_2 P(0) + w_2 \quad . \tag{26}$$

$$w_2 = C_0 + k_1 \sum_{j=1}^{\infty} \lambda_1^{-j} P(j) - P(0) k_2 \quad . \tag{27}$$

The solutions to the demand for health, labor supply, and wage equations can therefore be solved accordingly, given the solution to the demand for binge drinking.

Short Run Price Elasticity and Long Run Price Elasticity

Equation (23) determines the sign and magnitude of the effects of changes in the government policy variables, such as alcohol price and minimum legal drinking age, in period τ on binge drinking, health status, labor supply, and wage in period t. These effects are temporary because the policy variables in other periods are held constant.

$$\left.\frac{dC_t}{dP_\tau}\right|_{\tau > t} = -(k_1 \lambda_1^{-(\tau+1-t)} z_4)\text{alhl} + (\lambda_2^{t} k_1 \lambda_1^{-(\tau+1)} z_4)\text{alhl} \quad . \tag{28}$$

$$\left.\frac{dC_t}{dP_\tau}\right|_{\tau < t} = (k_2 \lambda_2^{-(t-\tau-1)} z_4)\text{alhl} + (\lambda_2^{t} k_1 \lambda_1^{-(\tau+1)} z_4)\text{alhl} \quad . \tag{29}$$

$$\frac{dC_t}{dP_t} = -(k_1 \lambda_1^{-1} z_4)\text{alhl} + (\lambda_2^{t} k_1 \lambda_1^{-(t+1)} z_4)\text{alhl} \quad , \tag{30}$$

where alhl is the estimated structural coefficient of alcohol price. The effect on binge drinking in period t of a permanent change in alcohol price starting from period t can be derived, given that $\sum_{t=1}^{\infty} a^t = \frac{a}{1-a}$.

$$\begin{aligned} \frac{dC_t}{dP_t^{*}} = \sum_{\tau=t}^{\infty} \frac{dC_t}{dP_\tau} &= -(k_1 \lambda^{-1}{}_1 z_4)\text{alhl} + (\lambda_2^{t} k_1 \lambda_1^{-(t+1)} z_4)\text{alhl} \\ &- \frac{\text{alhl}(z_4)}{(\lambda_1 - \lambda_2)} \sum_{\tau=t+1}^{\infty} \lambda_1^{-(\tau-t)} + \frac{\text{alhl}(z_4)\lambda_2^{t}}{\lambda_1^{t}(\lambda_1 - \lambda_2)} \sum_{\tau=t+1}^{\infty} \lambda_1^{-(\tau-t)} \end{aligned} \tag{31}$$

$$= -(k_1\lambda_1^{-1}z_4)\text{alhl} + (\lambda_2^{t}k_1\lambda_1^{-(t+1)}z_4)\text{alhl}$$
$$-\frac{\text{alhl}(z_4)}{(\lambda_1-\lambda_2)(\lambda_1-1)} + \frac{\text{alhl}(z_4)\lambda_2^{t}}{\lambda_1^{t}(\lambda_1-\lambda_2)(\lambda_1-1)}$$

$$= -(k_1\lambda_1^{-1}z_4)\text{alhl} + (\lambda_2^{t}k_1\lambda_1^{-(t+1)}z_4)\text{alhl}$$
$$-\frac{\text{alhl}z_4}{(\lambda_1-1)}\left[\frac{(\lambda_1^{t}-\lambda_2^{t})}{\lambda_1^{t}(\lambda_1-\lambda_2)}\right] .$$

$$\frac{dC_{t-1}}{dP_t^{*}} = \sum_{\tau=t}^{\infty}\frac{dC_{t-1}}{dP_\tau} = -\frac{\text{alhl}(z_4)}{\lambda_1(\lambda_1-\lambda_2)}\sum_{\tau=t}^{\infty}\lambda_1^{-(\tau-t)}\left(1-\frac{\lambda_2^{t-1}}{\lambda_1^{t-1}}\right) \tag{32}$$

$$= -\frac{\text{alhl}(z_4)}{(\lambda_1-\lambda_2)(\lambda_1-1)}\left(1-\frac{\lambda_2^{t-1}}{\lambda_1^{t-1}}\right) .$$

By setting t equal to1, the equation gives the effect on binge drinking at period t and period t-1 of an unanticipated permanent change in alcohol price starting from period t. Since Equation (32) is equal to zero when t=1, the unanticipated price effect reduces to the following.

$$\left.\frac{dC_t}{dP_t^{*}}\right|_{\text{unanticipated}} = -\frac{z_4\,\text{alhl}}{(\lambda_1-1)} . \tag{33}$$

$$\left.\frac{dC_{t-1}}{dP_t^{*}}\right|_{\text{unanticipated}} = 0 . \tag{34}$$

Equation (33) and (34) define the short run price effect as the effect on the consumption in periods t and t-1 of a permanent change in alcohol price beginning from period t, while past consumption level is held constant. The short run effect on health status, labor supply, and wage in period t of an unanticipated permanent alcohol price change can be derived accordingly.

$$\frac{dH_t}{dP_t^*} = (a + du)\frac{dC_t}{dP_t^*} + (b + dv)\frac{dC_{t-1}}{dP_t^*} = (a + du)\frac{dC_t}{dP_t^*} \quad . \tag{35}$$

$$\frac{dL_t}{dP_t^*} = u\frac{dC_t}{dP_t^*} + v\frac{dC_{t-1}}{dP_t^*} = u\frac{dC_t}{dP_t^*} \quad . \tag{36}$$

$$\begin{aligned}\frac{dW_t}{dP_t^*} &= y\frac{dH_t}{dP_t^*} + h\frac{dC_t}{dP_t^*} = y\left((a + du)\frac{dC_t}{dP_t^*} + (b + dv)\frac{dC_{t-1}}{dP_t^*}\right) + h\frac{dC_t}{dP_t^*} \\ &= (ya + ydu + h)\frac{dC_t}{dP_t^*} \quad .\end{aligned} \tag{37}$$

The short run price elasticity with respect to health status, binge drinking, labor supply, and wage is as follows.

$$e_{HP}^* = P_t \frac{f(\overline{H_t})}{F(\overline{H_t})} \frac{dH_t}{dP_t^*} \quad . \tag{38}$$

$$e_{CP}^* = P_t \frac{f(\overline{C_t})}{F(\overline{C_t})} \frac{dC_t}{dP_t^*} \quad . \tag{39}$$

$$e_{LP}^* = \frac{P_t}{L_t} \frac{dL_t}{dP_t^*} \quad . \tag{40}$$

$$e_{WP}^* = \frac{P_t}{W_t} \frac{dW_t}{dP_t^*} \quad , \tag{41}$$

where $\overline{H_t}$ and $\overline{C_t}$ are the latent values of health capital and occasions of binge drinking, respectively, They are computed from the reduced form solutions of the simultaneous system, which are evaluated at the mean values of relevant exogenous variables. Furthermore, $f(\cdot)$ and $F(\cdot)$ are pdf and cdf of standard normal distribution, respectively. Since health and binge drinking are binary and ordered dichotomous variables, the interpretation of Equation (38) and (39) is the price elasticity with respect to the probability of being healthy and the probability of having at least 5 occasions of binge drinking in the past 30 days, respectively.

The effect of a permanent change in the alcohol price in all periods on binge drinking in period t is

$$\frac{dC_t}{dP} = -\mathrm{alhl}(k_1 z_4)\sum_{j=1}^{\infty}\lambda_1^{-j} + \mathrm{alhl}(k_2 z_4)\sum_{j=0}^{\infty}\lambda_2^{j} + \left[\mathrm{alhl}(k_1 z_4)\sum_{j=1}^{\infty}\lambda_1^{-j}\right]\lambda_2^{t} \quad . \tag{42}$$

The long run effect of a permanent change in alcohol price is derived by setting t to infinity in Equation (42). The last two terms in the equation will approach zero when t goes to infinity because λ_2 is less than one. Equation (46) is the long run effect of a permanent change in alcohol price.

$$\begin{aligned}\frac{dC_\infty}{dP} &= -\mathrm{alhl}(k_1 z_4)\sum_{j=1}^{\infty}\lambda_1^{-j} + \mathrm{alhl}(k_2 z_4)\sum_{j=0}^{\infty}\lambda_2^{j} \\ &= -\frac{\mathrm{alhl}(k_1 z_4)}{\lambda_1 - 1} + \mathrm{alhl}(k_2 z_4)\left(1 + \frac{\lambda_2}{1-\lambda_2}\right) \quad .\end{aligned} \tag{43}$$

The long run price effect will be greater than the short run price effect because the consumption level is allowed to change in all periods. At last, the long run effect on health status, labor supply, and wage is

$$\begin{aligned}\frac{dH_\infty}{dP} &= (a + du)\frac{dC_\infty}{dP} + (b + dv)\frac{dC_\infty}{dP} \\ &= (a + b + du + dv)\frac{dC_\infty}{dP} \quad .\end{aligned} \tag{44}$$

$$\frac{dL_\infty}{dP} = u\frac{dC_\infty}{dP} + v\frac{dC_\infty}{dP} = (u + v)\frac{dC_\infty}{dP} \quad . \tag{45}$$

$$\frac{dW_\infty}{dP} = y\frac{dH_\infty}{dP} + h\frac{dC_\infty}{dP} = (ya + yb + ydu + ydv + h)\frac{dC_\infty}{dP} \quad . \tag{46}$$

The long run price elasticity with respect to health status, binge drinking, labor supply, and wage is

$$e_{HP}^{\infty} = P_t \frac{f(\overline{H_t})}{F(\overline{H_t})} \frac{dH_{\infty}}{dP_t^{*}} \quad . \tag{47}$$

$$e_{CP}^{\infty} = P_t \frac{f(\overline{C_t})}{F(\overline{C_t})} \frac{dC_{\infty}}{dP_t^{*}} \quad . \tag{48}$$

$$e_{LP}^{\infty} = \frac{P_t}{L_t} \frac{dL_{\infty}}{dP_t^{*}} \tag{49}$$

$$e_{WP}^{\infty} = \frac{P_t}{W_t} \frac{dW_{\infty}}{dP_t^{*}} \tag{50}$$

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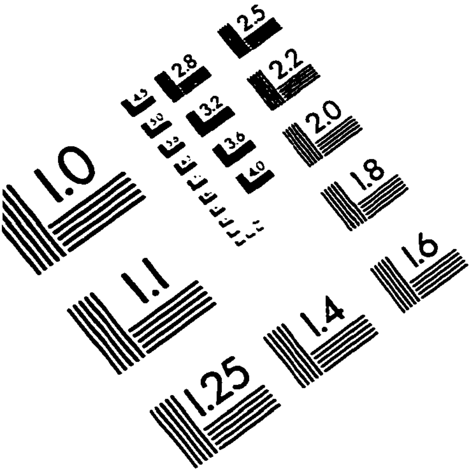
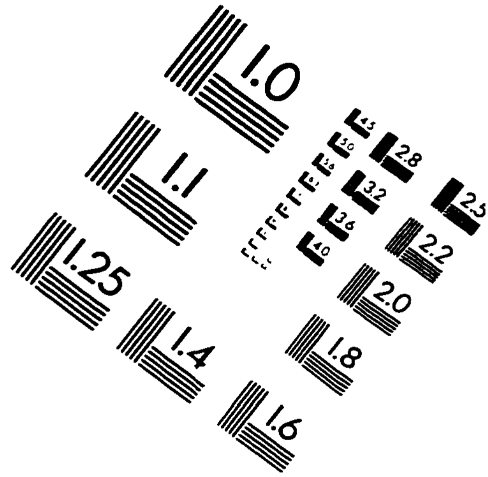
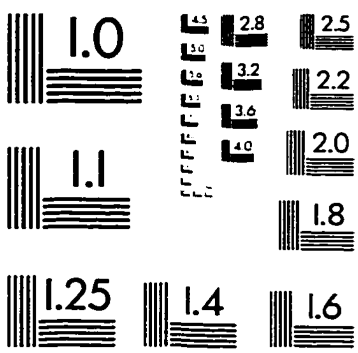
IMAGE EVALUATION TEST TARGET (QA-3)







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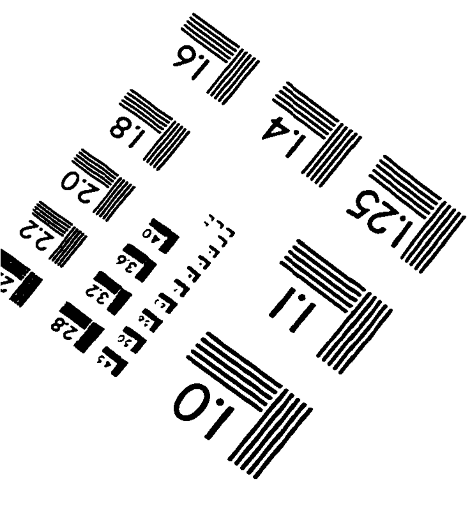

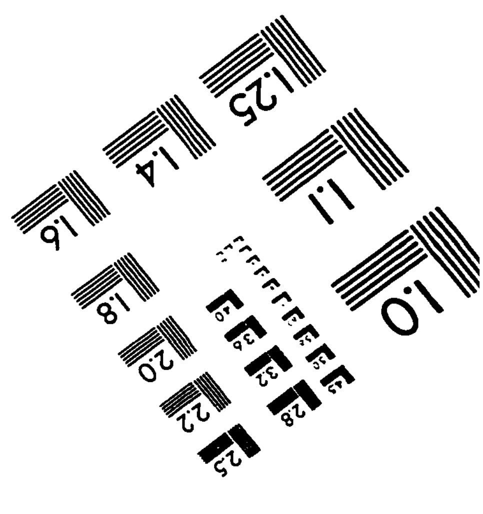

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