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This dissertation investigates the effect of alcohol and marijuana use on Temporary Assistance for Needy Families (TANF) eligibility and participation among young adult women. The relationship between substance use and TANF participation has gained prominence because of recent legislation requiring drug testing for TANF participants. Much of the existing literature does not consider the effect of substance use on eligibility or participation. The studies that do incorporate substance use treat it as being exogenously determined. It may be the case, however, that characteristics such as preferences for leisure or mental health status affect eligibility for TANF, participation in TANF if eligible, and substance use. If this is the case then the assumption of exogeneity is violated. I use data from the National Longitudinal Survey of Youth 1997 to estimate a joint model of TANF eligibility, TANF participation, alcohol use, and marijuana use which allows the substance use variables to be endogenous. The outcomes are jointly determined due to the inclusion of a shared error term which is allowed to have a different effect on each outcome. This term is intended to capture woman-specific characteristics that may affect eligibility, participation, and substance use. The estimation results suggest that alcohol use is not a significant predictor of TANF eligibility or participation. Infrequent marijuana use, on the other hand, is positively related to both eligibility and participation while frequent marijuana use is positively related to eligibility. These results contribute to the understanding of TANF eligibility and participation and substance use.

SUBSTANCE USE AND TEMPORARY ASSISTANCE

FOR NEEDY FAMILIES

by

Joshua L. Price

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To Meggan, Evan, and Jaxon

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CHAPTER I

INTRODUCTION

Temporary Assistance for Needy Families (TANF) is a public assistance program that continues to receive considerable attention in the United States. TANF, also known as "welfare," had a monthly average participation of 3.8 million people in 2013 with a budget of $17.35 billion. Some believe the program should be expanded to serve more and provide greater benefits, while others believe the program should strive for smaller caseloads. Attempts to reduce caseloads have been a pervasive part of TANF since its inception, spawning numerous studies attempting to identify barriers to ending program participation.

One such barrier commonly cited by policy commentators but with surprisingly little empirical research is substance use. As once claimed by Joseph Califano, former U.S. Secretary of Health, Education, and Welfare, "all the financial lures and prods and all the job training in the world will do little to make employable the hundreds of thousands of welfare recipients who are addicts and abusers" (Califano 1995, 40–41). This 20-year-old claim has not lost its hold on the minds of the public.

Since the passage of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996, which established the TANF program, at least 12 states have passed legislation requiring drug screening or testing for TANF applicants and/or recipients, and at least 36 states have proposed such legislation since 2011 (National Conference of State Legislatures 2014). Given the increasing interest in implementing drug screening and

testing for TANF applicants and/or recipients, it is essential to understand how substance use affects TANF eligibility and/or participation.

The existing literature has investigated the prevalence of substance use—drug use that may include alcohol use—among Aid to Families with Dependent Children (AFDC; TANF's predecessor) participants, and the association between substance use and participation. Existing estimates of prevalence rates of alcohol use among participants are as high as 67 percent, and prevalence rates of drug use are estimated to range between about four percent and 16 percent.

Mixed results have been found when researchers have investigated the association between substance use and participation. Studies that reported statistically significant estimates have found a modest association between substance use and participation, with one study concluding that "if marijuana use among [AFDC] participants was reduced to the level of nonparticipants, [AFDC] participation would decline by approximately 5 percent among nonblacks and 3 percent among blacks" (Kaestner 1998, 514).

The existing literature, however, has not addressed the potential endogeneity of substance use. Endogeneity may exist in statistical analyses for several reasons. One of these is through omitted variables that affect both the dependent variable and an independent variable. For example, in the present context, the unobserved characteristic "preference for leisure" may be correlated with both substance use and participation. Statistically, this means that the effect of "preference for leisure" will be absorbed into the coefficient on substance use in a model of participation, which means the estimated effect is not the true, or causal, effect. The existing literature typically assumes that substance use is uncorrelated with

unobserved characteristics. If this is not true, then the estimates of the effect of substance use on participation are biased.

Moreover, the existing literature does not allow for the possibility that substance use affects TANF eligibility. Studies typically compare recipients to non-recipients without regard for the eligibility of non-recipients. The concern with this approach is that the group of all non-recipients is not the correct control group for recipients. The correct control group is eligible non-recipients. One possible solution is to treat eligibility as given and examine the relationship between TANF and substance use. However, TANF eligibility requires individuals to have a child and low-income. Thus, eligibility is the result of women's choices, and eligibility may be affected by substance use through its effect on fertility, employment, or income. Similar to the argument above, substance use may be endogenous to eligibility if an unobserved variable like "preference for leisure" affects eligibility and substance use.

The goal of this dissertation is to estimate the effect of alcohol and marijuana use on TANF eligibility and participation while addressing the potential eligibility of non-participants and the endogeneity of substance use. The primary contributions of this dissertation are addressing eligibility and endogeneity. Eligibility is addressed by modeling it rather than ignoring or conditioning on it. Endogeneity is addressed by allowing for the unobserved determinants of eligibility, participation, and substance use to be correlated.

To address the issues described, I estimate a model of TANF eligibility, TANF participation among eligible women, alcohol use, and marijuana use where eligibility and participation are allowed to depend on alcohol and marijuana use. Each of these outcomes depends on a woman's observed characteristics, a person-specific unobserved variable

(frequently referred to as "unobserved heterogeneity") meant to capture things like "preference for leisure", and an idiosyncratic variable that varies across women and over time for a woman which is meant to capture random events in life. The choices are modeled jointly by allowing the effect of the person-specific unobserved variable to be correlated across the outcomes. After assuming specific distributions for the unobserved variables, maximum likelihood is used to estimate the parameters of the model.

In order to account for the unobserved characteristics and to address the potential endogeneity of substance use, I need longitudinal data. My analysis sample consists of female respondents to the National Longitudinal Survey of Youth 1997 (NLSY97) who are at least 18 years old. The NLSY97 collects information annually, including information on alcohol use, marijuana use, TANF participation, and other characteristics necessary to determine TANF eligibility status. These data cover the TANF period only.

The remainder of this dissertation is organized as follows. Chapter II reviews the institutional background pertaining to TANF, including a discussion of the AFDC program and current policy trends. Chapter III reviews the literature that has investigated the association between substance use and TANF. Chapter IV discusses the data used in this dissertation and presents descriptive statistics for the analysis sample. Chapter V discusses how substance may affect TANF eligibility and/or participation and develops an econometric model that addresses the possible endogeneity of substance use through a joint model of eligibility, participation, and substance use. Chapter VI presents the results of the econometric model developed in Chapter V. Chapter VII concludes the dissertation with a discussion of key findings, limitations, and future research avenues.

CHAPTER II

INSTITUTIONAL BACKGROUND

The provision of cash benefits ("welfare") has a long history in the US. In fact, the history of public assistance can be traced back to the colonial period. A complete history of public assistance in the US would require its own book (e.g., Katz 1996; Trattner 1998; Stern and Axinn 2011). The relevant history for this dissertation begins with TANF's predecessor and program changes up to 1960. I next discuss program changes occurring between the 1960s and the 1990s, which led to the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), commonly referred to as welfare reform. This chapter ends with a discussion of efforts to impose drug-testing requirements. Table 1 presents a legislative timeline of AFDC/TANF from 1911 through 2014, and this chapter discusses the main provisions and outcomes of each piece of legislation and noteworthy event listed in Table 1.

AFDC: The Great Depression to 1960

Aid to Families with Dependent Children (AFDC), TANF's predecessor, began as mothers' pensions programs. In 1911, Illinois created the first mothers' pension program called the "Funds to Parents Act." These types of programs were designed to provide financial assistance to mothers with children who no longer had a breadwinner. During this period, households typically lost their breadwinner through death, but losses also occurred through injury, divorce, or unemployment. The purpose of these pensions was to allow mothers to raise their children instead of working. During the Great Depression, state and

local costs increased rapidly with the increase in unemployment, leading to the creation of AFDC by the federal government.

The Social Security Act of 1935 established AFDC, originally called Aid to Dependent Children. AFDC was a grant program designed to cover one-third of mothers' pension costs. State participation in AFDC was voluntary, and eight states—Connecticut, Illinois, Iowa, Kentucky, Mississippi, Nevada, South Dakota, Texas, and the territory of Alaska—had no AFDC program in 1939 (Coll 1995, 104; Gordon and Batlan 2011). States set benefit levels and eligibility criteria, subject to the federal criteria that restricted eligibility to single-parent families with dependent children. AFDC remained largely unchanged at the national level until the 1960s.

AFDC: Reforms from 1960 to 1995

The first significant change to AFDC occurred in 1961 when Congress created the AFDC-UP program. AFDC-UP ("unemployed parent") operated like the basic AFDC program with respect to benefits and income and asset eligibility tests. AFDC-UP differed in that the program covered two-parent families with both parents present in which the primary earner was employed less than 100 hours per month. AFDC-UP was optional for states, and 25 states had created such programs by 1970 (Moffitt 2003).

In the beginning, the purpose of AFDC was to provide assistance. By the 1960s, the political objectives of AFDC had shifted to providing assistance while promoting work. This was largely due to changes in the workforce composition with women becoming a larger proportion. This led to policy changes in 1967 which "included both 'carrots' and 'sticks' to promote employment" (Grogger and Karoly 2005). The carrot took the form of a new benefit reduction rate. Prior to 1967, an AFDC recipient's earned income decreased her

benefits at a one-to-one rate. The new benefit reduction rate disregarded the first $30 of earnings per month and one-third of the remainder (known as the "$30-and-a-third" rule).

The stick took the form of the Work Initiative (WIN) program. "WIN required states to register nonexempt recipients for work-related activities that focused on training and education. But the legislation exempted recipients with children under age six, and [such recipients] accounted for a substantial fraction of the caseload. As a result, relatively few recipients registered, and ever fewer took part in the programs" (Grogger and Karoly 2005).

In the late 1960s, a number of US Supreme Court cases changed how states determined AFDC eligibility. The first case, King v. Smith (1968), challenged an Alabama regulation allowing benefits to be terminated for women who were cohabiting with a man. Several other states with similar regulations included casual relationships as cohabitation (Gordon and Batlan 2011). This regulation, called the "man-in-the-house" rule, was found to violate the Social Security Act's stipulation that eligibility be based on the absence of the natural father. A year later, Shapiro v. Thompson (1969) challenged residency requirements preventing benefits from being awarded to families that had recently relocated to a new state. These residency requirements, which required families to live in the new state for at least one year before eligibility could be determined, were found to have violated the 14th Amendment's equal protection clause and to have restricted freedom of residential movement.

The Nixon and Carter administrations attempted to reform AFDC to balance providing better living standards with promoting work, changes did not occur until 1981 under the Reagan administration. The Omnibus Budget Reconciliation Act (OBRA) of 1981 reversed earlier policy and increased the benefit reduction rate to 100 percent, as was the

case before 1967, after the first four months of work. This change in the benefit reduction rate departed from the trend of using incentives and work requirements to promote work, and OBRA reduced AFDC rolls by about 400,000 recipients (Grogger and Karoly 2005).

Financial incentives and work requirements returned with the enactment of the Family Support Act of 1988 (FSA). The Job Opportunities and Basic Skills Training program (JOBS) created by the FSA replaced the WIN program. Similar to WIN, the purpose of JOBS was to promote a transition from AFDC to work. One difference between JOBS and WIN was that JOBS only exempted recipients with children under age three (compared to age six under WIN). The FSA also required states to provide childcare and other services (e.g., medical care) when necessary for participation in JOBS.

In the early 1990s, states began to take advantage of section 1115 of the Social Security Act. This particular section had existed since 1962 and allowed the states to "petition the U.S. Department of Health and Human Services (DHHS) to implement experimental, pilot, or demonstration projects they believed would result in a more effective welfare program" (Grogger and Karoly 2005). States taking advantage of these waivers were able to implement AFDC programs that deviated from the legislative requirements. The most commonly changed policies were the earned income disregard rule, age-related exemptions, work requirements, the inclusion of benefit time limits. Waivers were also used to introduce "family caps," which are described below.

The earned income disregard determined how much benefits were reduced with respect to the individual's income. Waivers to the earned income disregard rule were used to encourage work by allowing recipients to earn income without said income reducing their

benefits at a one-to-one rate. For example, Michigan disregarded the first $200 and then 20 percent of the remaining.

As discussed with WIN and JOBS, women with children under a federally determined age were exempt from work requirements. The age-related exemption waivers allowed states to modify who was exempt from work requirements based on the youngest child's age. Typically, states applying for these waivers reduced the threshold. For example, recipients living in New Jersey were exempt from work requirements when their youngest child was under age 2. While most states reduced the threshold, a few states increased the age-related threshold. For example, recipients living in Massachusetts were exempt from work requirements while their youngest child was under age 6.

Work-requirement waivers imposed stricter sanctions for JOBS noncompliance. For example, Massachusetts dropped the adult's portion of the benefits after the first violation, and their maximum sanction dropped the entire family's benefits (referred to as full-family sanctions). Depending on the state, full-family sanctions lasted for either a fixed time period or until compliance was met.

Benefit time limit waivers changed the benefits received after a specified date. Some states imposed lifetime limits, while others imposed intermittent time limits. For example, Indiana imposed a 24-month lifetime limit. After 24 months of benefits (continuous or intermittent) the adult portion of benefits was terminated (referred to as adult-only time limits). Nebraska imposed intermittent time limits where cases could receive benefits for 24 out of 48 months after which the entire case's benefits were terminated. The case could begin receiving benefits after the 48-month period expired.

Family cap waivers affected benefit changes when a new child was born to the family. AFDC benefits increased with family size. Thus, AFDC benefits increased when new children were born to an AFDC recipient. This benefit structure led to a perception that AFDC incentivized having more children while participating. Motivated by this perception, New Jersey implemented the first family cap, which did not increase benefits for new children born into the family.

PRWORA and TANF

The state waiver-based reforms of the 1990s led to reform at the national level with the enactment of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (Public Law 104-193 1996). The goals of PRWORA as stated in its preamble are to:

> increase the flexibility of States in operating a program designed to—
> 1. provide assistance to needy families so that children may be cared for in their own homes or in the homes of relatives;
> 2. end the dependence of needy parents on government benefits by promoting job preparation, work, and marriage;
> 3. prevent and reduce the incidence of out-of-wedlock pregnancies and establish annual numerical goals for preventing and reducing the incidence of these pregnancies; and
> 4. encourage the formation and maintenance of two-parent families.

With the enactment of PRWORA, the entitlement program AFDC became the transitional program called the Temporary Assistance to Needy Families program. The key features of TANF that distinguish it from AFDC are lifetime benefits limits and work requirements.

TANF limits the receipt of federally funded benefits to at most 60 months. States have the option to impose stricter limits or to use state funds to continue providing benefits after the benefits time limit. By July 2000, eight states had implemented shorter time limits, 13 states had imposed intermittent time limits, and six states had adult-only time limits

(Grogger and Karoly 2005). States may also exempt up to 20 percent of the caseload from this time limit. States can determine which recipients fall into this 20 percent. Some states exempt individuals receiving substance dependence treatment or who have a mental health disorder (e.g., depression).

TANF also requires recipients to work or participate in work-related activity after 24 months of benefits receipt. Again, states have the option to impose a stricter time frame. By fiscal year 1999, 25 percent of all cases must have had an adult working or engaging in work-related activity, and the rate rose to 50 percent by fiscal year 2002. Ninety percent of two-parent cases were required to have an adult working or engaging in work-related activity by fiscal year 1999. By fiscal year 2000, single-parent cases were required to have an adult working or engaging in work-related activity at least 30 hours per week, and single parents with children under age 6 were required to be working or engaging in work-related activity at least 20 hours per week. For two-parent cases, the parents were required to be working or engaging in work-related activity at least a total of 35 hours per week—this could have been achieved through one or both parents' employment. Single parents with children under age 6 who could not find childcare were exempt from the work requirement, and states may exempt single parents with children under one year of age.

Work-related activities include education, on-the-job training, community service, and vocational training. Job search for up to 6 weeks but no more than 4 consecutive weeks is considered a work-related activity. High school attendance counts for case heads who are teenagers, but no more than 20 percent of the state caseload can count vocational training or high school attendance.

The creation of TANF introduced new rules and granted states more flexibility with respect to determining eligibility. While PRWORA defines work requirement and benefit time limits, states are permitted to shorten these time limits. PRWORA also grants states permission to use drug testing as an eligibility criteria, which is the current legislative trend.

Current Reforms: Substance Use and Drug Testing

Section 902 of the PRWORA grants states permission to use drug testing as an eligibility criteria for TANF participation. Furthermore, the Gramm Amendment of 1996 imposed a lifetime ban on total benefits from TANF or from the Food Stamps Program (renamed Supplemental Nutritional Assistance Program in 2008) to individuals with felony convictions for illegal drug possession, use, or distribution. The TANF ban applies to convictions after April 1, 2002. States, however, are allowed to revoke or ease the TANF ban. As of 2014, 31 states have revoked the ban, and four states have modified the ban to require individuals convicted of felony drug charges to comply with drug testing requirements to receive benefits (Urban Institute 2015).

Looking at Table 1, we see that the two events following the Gramm Amendment deal with drug testing in two states in 1999, only three years after states were granted permission to use drug testing as an eligibility criteria. Florida began a demonstration project in 1999 to "answer two fundamental questions: (1) 'Are the individuals who apply for temporary cash assistance or services under the state's welfare program likely to abuse drugs?' and (2) 'Does such abuse affect employment and earnings and use of social services benefits?'" (Crew and Davis 2003, 41). Individuals who applied for TANF benefits were required to complete a paper-and-pencil test, called the Substance Abuse Subtle Screening Inventory (SASSI), which is designed to predict the probability that the applicant had a

substance dependence disorder. If the SASSI determined the applicant likely had a substance dependence disorder, then the applicant was required to immediately submit to a urine test. Applicants testing positive were referred to a substance abuse treatment provider for assessment and treatment. While the SASSI determined the probability of a substance dependence disorder, alcohol included, the urinalysis tested for illicit drugs only. According to Crew and Davis (2003), only 5.1 percent of their sample (N = 6,462) had positive urinalyses. The authors concluded that the screening and testing procedures "were not an efficient way to assess the extent of drug use within the state's TANF population" (46).

Later in 1999, Michigan became the first state to enact legislation requiring drug testing as a TANF-eligibility criterion. Michigan's law required all applicants to be tested, and 20 percent of recipients were to be randomly tested every six months. Drug testing in Michigan lasted only five weeks and tested 258 recipients before the courts blocked its enforcement. "Over the short life of this intervention, individuals testing positive for illicit substances remained eligible for welfare receipt but were subject to progressive sanctions if they failed to comply with a mandated treatment plan" (Pollack et al. 2002). Of the 258 recipients tested, 21 tested positive for illicit substance use (8.1 percent). Eighteen of the 21 positive results were for marijuana use only (Pollack et al. 2002).

After the failed experiment in Michigan, state attempts to pass drug-testing legislation ceased until 2009 when states began again to consider drug-testing legislation. It took another two years before drug testing was enacted again. Since 2011, at least 36 States have proposed and at least 12 States have enacted drug testing legislation. These are Alabama, Arizona, Florida, Georgia, Kansas, Michigan, Mississippi, Missouri, North Carolina, Oklahoma, Tennessee, and Utah (National Conference of State Legislatures 2014).

A timeline of TANF drug-testing legislation is presented in Table 2 A "P" indicates that the state proposed drug-testing legislation in that year, and an "*E*" indicates that the state enacted drug-testing legislation in that year. Seven states and the District of Columbia did not propose or enact legislation between 2011 and 2014. The drug-testing legislation here are different from the Gramm Amendment modifications. The Gramm Amendment and its modifications only apply to convicted drug felons. The drug-testing legislation presented in Table 2 are not restricted to convicted drug felons.

Currently, blood or urine tests on individuals for whom there is no "reasonable suspicion" of drug use are prohibited as violating the Constitutional protection against unreasonable searches. The only state laws that now permit such tests require the tested individuals to first have been identified by a screening process. Those testing positive are required to attend an approved rehabilitation program or become ineligible to receive benefits for six months.

In 2012, Congress enacted legislation prohibiting purchases made with TANF benefits at liquor stores, casinos, and strip clubs. States were responsible for implementing the restrictions by 2014. States that failed to implement this policy by 2014 had their annual state TANF grant reduced by up to five percent until they implement the policy.

The legislative changes presented in this chapter indicate a trend of progressively stricter policies and rules on applicants and recipients. AFDC began to help families without a primary breadwinner. Program changes eventually led to a temporary assistance program. Now, applicants and participants experience more scrutiny as states adopt drug-testing requirements. I next turn to the literature to explore what is known about substance use among welfare recipients and its effect on participation.

Table 1. AFDC/TANF Timeline

Date	Legislation/Event	Main Provision or Outcome
1911	Illinois "Funds to Parents Act"	First mothers' pension program, the predecessor of AFDC
1935*	Social Security Act (Public Law 74-271 1935)	Created the AFDC program for low-income children without a parent present in household*
1961*	Amendments to the Social Security Act	Created AFDC-UP program for children in two-parent families where primary earner is unemployed*
1967*	Amendments to the Social Security Act	Lowered the benefit reduction rate to two-thirds; created the WIN program*
1968	Supreme Court Case *King v. Smith*	Overturned "man-in-the-house" rule.
1969	Supreme Court Case *Shapiro v. Thompson*	Overturned residency requirements.
1981*	Omnibus Budget Reconciliation Act (Public Law 97-35 1981)	Increased the benefit reduction rate to 100 percent; imposed a gross income limit; counted income of stepparents; expanded waiver authority*
1988*	Family Support Act (Public Law 100-485 1988)	Created the JOBS program for education, skills training, job search assistance, and other work activities; created transitional child care and Medicaid programs; mandated AFDC-UP in all states*
1996*	Personal Responsibility and Work Opportunity Reconciliation Act (Public Law 104-193 1996)	Abolished the AFDC program and created the TANF program*
1996	Gramm Amendment	Imposed a lifetime ban on Food Stamps and TANF aid to individuals with felony convictions for illegal drug possession, use, or distribution
1999		Florida began a demonstration project to assess (1) if TANF applicants are likely to abuse drugs, and (2) if such abuse affects employment, earnings, and use of benefits.
1999		Michigan passed first law requiring drug testing of all TANF applicants. The law only lasted five weeks.

Date	Legislation/Event	Main Provision or Outcome
2011		At least 36 states put forth proposals in 2011 for drug testing TANF and SNAP recipients. Three states passed legislation (Arizona, Florida, Missouri).
2012	Middle Class Tax Relief and Job Creation Act (Public Law 112-96 2012)	Prevents TANF benefits from being spent in liquor stores, casinos, or strip clubs
2012		At least 28 states put forth proposals requiring drug testing for public assistance applicants or recipients. Four states passed legislation (Georgia, Oklahoma, Tennessee, Utah).
2013		At least 29 states put forth proposals requiring drug testing or screening for public assistance applicants or recipients. Two states passed legislation (Kansas, North Carolina).
2014		At least 18 states introduced proposals or had carryover bills that would require drug screening or testing for public assistance applicants or recipients in 2014. Three states passed legislation (Alabama, Michigan, Mississippi).

* Source: Direct quote from Table 5.1 in (Moffitt 2003).

Table 2. TANF Drug-testing Legislation History by State

State	2011	2012	2013	2014
Alabama		P	P	*E*
Alaska			P	
Arizona	*E*			
Arkansas			P	
California		P		
Colorado		P		
Connecticut		P	P	
Delaware				
District of Columbia				
Florida	*E*[***]			
Georgia		*E*		
Hawaii		P	P	
Idaho				
Illinois		P[**]	P	
Indiana		P	P	
Iowa		P[**]	P	
Kansas		P	*E*	*E*
Kentucky		P[**]	P	
Louisiana		P		
Maine[*]			P	
Maryland		P	P	
Massachusetts			P	
Michigan		P[**]	P	*E*
Minnesota[*]		P		
Mississippi		P	P	*E*
Missouri	*E*			
Montana			P	
Nebraska		P		
Nevada			P	
New Hampshire			P	
New Jersey		P	P	
New Mexico				
New York		P	P	
North Carolina			*E*	*E*
North Dakota			P	

State	2011	2012	2013	2014
Ohio				
Oklahoma		*E*		
Oregon				
Pennsylvania*			P	
Rhode Island				
South Carolina		P**	P	
South Dakota		P**		
Tennessee		*E*		
Texas			P	
Utah		*E*	*E*	*E*
Vermont			P	
Virginia*		P	P	
Washington		P	P	
West Virginia		P	P	
Wisconsin				
Wyoming		P		

"P" denotes a year when drug testing/screening legislation was proposed.

"*E*" denotes a year when drug testing/screening legislation was enacted.

* These states have modified the Gramm Amendment ban to "require those convicted of drug felony charges to comply with drug testing requirements as a condition of receiving benefits" (National Conference of State Legislatures 2014). These states are not counted as having drug-testing laws because the modifications to the Gramm Amendment still apply to convicted drug felons.

** These states proposed legislation requiring drug testing for SNAP applicants, in addition to TANF applicants.

*** Halted due to judge's order over concerns about constitutionality. Florida abandoned appeals in 2015.

CHAPTER III

THE LITERATURE ON SUBSTANCE USE AND AFDC/TANF ELIGIBILITY AND PARTICIPATION

This chapter examines the existing literature on the relationship between substance use and the participation in the AFDC and TANF programs. The discussion begins with a summary of what we know about the prevalence of substance use among recipients of the programs. Exploring prevalence rates is a necessary first step in understanding the potential importance of the issue, but for purposes of making or amending policy it is necessary to investigate the causal relationships between drug use and eligibility or participation. The literature confronting these issues is reviewed in the second section of this chapter and is found to have two shortcomings. First, much of the literature has examined the correlational, rather than causal, linkages between substance use and AFDC/TANF participation as these studies have not addressed the potential endogeneity of substance use. Second, the literature thus far has paid little attention to the important interplay between substance use and program eligibility. These two generalizations indicate that there is an important gap in the literature—a careful study of substance use, TANF eligibility, and TANF participation that confronts the potential endogeneity of substance use. This chapter ends with a discussion highlighting the importance of eligibility when investigating participation and providing a framework within which to examine TANF eligibility and substance use.

The Prevalence of Substance Use in AFDC/TANF

As we begin the discussion about substance use, it is helpful to define some terminology used in the literature. The consumption of substances has been described with a number of different terms: use, abuse, addiction, dependence, and alcoholism. The term "use" is simply use of a substance. The terms "abuse," "addiction," "dependence," and "alcoholism" refer to diagnosable mental health disorders based on the Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association 2013). The difference between abuse and addiction, where dependence is synonymous with addiction, is in the number of diagnostic criteria, with addiction being more severe than abuse. The term "alcoholism" refers to alcohol use disorder, with three levels of severity (mild, moderate, or severe).[1] Similar to abuse and addiction, the severity of alcohol use disorder depends on the number of diagnostic criteria.

Estimates of prevalence rates for AFDC recipients supported the popular opinion leading up to "welfare reform," as embodied in PRWORA, that hundreds of thousands of AFDC recipients were drug addicts and abusers (see Califano 1995). Early estimates of the prevalence rates of alcohol and drug abuse/dependence were 7.6 percent and 3.6 percent, respectively (Grant and Dawson 1996). However, these rates were similar to national rates for alcohol and drug abuse/dependence of 7.4 percent and 1.5 percent, respectively (Grant and Dawson 1996).While these prevalence rates did not represent most of the participants, further investigation is required to understand if the prevalence rates of substance use among AFDC/TANF participants changed.

[1] The current edition of the Diagnostic and Statistical Manual of Mental Disorders no longer uses the terms "abuse" or "dependence." Instead, each substance is discussed in terms of "use disorders," such as alcohol use disorder. These substance use disorders vary in severity based on the number of diagnostic criteria present.

To begin, Schmidt, Weisner, and Wiley (1998) examined data drawn from the Welfare Client Longitudinal Study (WCLS). The WCLS collected its data from a large California county, using a time-line follow-back method to gather six years of data from 1989 to 1995, limiting the sample to respondents who were recipients in 1989.[2] They found that the proportion of AFDC recipients considered problem drinkers was not different from that of the general population (12.2 percent and 11.3 percent, respectively). Heavy drug use and substance dependence were more prevalent among AFDC recipients than the general population (15.9 percent and 5.5 percent for heavy drug use, respectively, and 10.5 and 2.8 percent for substance dependence, respectively). Unfortunately, this study analyzing data from the WCLS was unable to report prevalence rates for eligible non-participants.

Some studies have used cross-sectional data to estimate prevalence rates. Jayakody, Danziger, and Pollack (2000) used the 1994 and 1995 National Household Survey on Drug Abuse (NHSDA). Their sample consisted of 2,728 single mothers who were at least 18 years old. The authors tested the difference in means between mothers who received AFDC in the past year and mothers who did not. The prevalence of alcohol use was not statistically significantly different between recipients and non-recipients (67 percent and 70 percent, respectively), but the prevalence of marijuana use was greater for recipients than non-recipients (16 percent and 10 percent, respectively). Jayakody, Danziger, and Pollack considered a sample of single mothers who were at least 18 years old, which is a reasonable proxy for eligibility status.

[2] The time-line follow-back method presents the respondent with a personal calendar covering the observation period. The interviewer works with the respondent to record memory-triggering events, including births, deaths, and other memorable events. Then, these events are used to recall their histories over the observation period. In these studies, the researchers are interested in determining the respondents' history of public aid receipt and the reasons for each time participation ended.

Pollack et al. (2002) used data from the 1990 to 1998 NHSDA to summarize trends in substance use among unmarried women between 18 and 54 years old. The authors reported that the prevalence of illegal drug use including marijuana was greater among AFDC/TANF recipients than non-recipients, and the prevalence of illegal drug use other than marijuana was also greater among AFDC/TANF recipients than non-recipients. Based on the 1998 NHSDA, the authors reported that illicit-drug dependence was about twice as common among past year TANF recipients than past year non-recipients (4.5 percent versus 2.1 percent). While it was a statistically insignificant difference, alcohol dependence was greater among past year TANF recipients than past year non-recipients (7.5 percent versus 4.6 percent). The authors expressed concerns that substance use and dependence might be more prevalent in the smaller TANF caseloads of the 2000s than in the late 1990s. Pollack et al. made comparisons between recipients and non-recipients, but the non-recipients are not necessarily eligible. Thus, they could not estimate the prevalence rate of substance use among AFDC/TANF eligible women.

Revisiting the study discussed in Chapter II, Crew and Davis (2003) estimated the prevalence of substance abuse among TANF applicants.[3] This study used data on substance abuse generated by a screening and testing demonstration in Florida. In this project 6,462 applicants were screened and received benefits, and 1,477 of these individuals had to submit to a drug test.[4] In all, 335 individuals tested positive for illicit substance use, which

[3] Recall that Crew and Davis (2003) used data from a Florida demonstration project that required TANF applicants to go through a substance abuse screening test to assess the probability of a substance use disorder. Applicants whose test suggested the presence of a substance use disorder were required to submit to a urinalysis.

[4] In the Florida demonstration program, all applicants responded to a drug-screening instrument. The instrument, a paper and pencil test, is called the Substance Abuse Subtle Screening Inventory. If the drug-

represented 5.1 percent of the entire sample. The authors claimed to investigate the prevalence of substance abuse among TANF applicants, but the sample actually consists of TANF applicants who received TANF, Food Stamps, or Medicaid. The authors drop 2,335 individuals from the analysis who did not receive TANF, Food Stamps, or Medicaid during their time frame. By dropping these individuals, the authors could only make statements about TANF applicants who received government benefits instead of statements about TANF applicants in general. Also, the authors could not discuss prevalence rates with respect to TANF eligible non-participants.

The evidence discussed in this section tells us that substance use/abuse was not widespread among AFDC/TANF participants, contrary to the popular opinion of researchers and policymakers. Joseph Califano expressed this position, saying, "Today the bulk of mothers on welfare—perhaps most—are drug and alcohol abusers and addicts, often suffering from serious mental illness and other ailments" (Califano 2002, A29). Although the evidence contradicts this negative picture, substance use is frequent enough within these programs to warrant a careful consideration of its impact on AFDC/TANF recipients.

Linkages between Substance Use and AFDC/TANF Participation

A number of papers explore the relationship between substance use and the AFDC/TANF programs using multivariate methods. Much of the literature has treated substance use as exogenously determined and thus can best be thought of as exploring correlational rather than causal relationships between substance use and welfare participation—a fact generally acknowledged by the researchers. Also, little research has

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screening inventory indicated a probability of substance abuse, the applicant was required to submit to a urinalysis.

estimated the association between substance use and participation using the appropriate control group of eligible non-participants. This is important because substance use may affect eligibility for AFDC/TANF. These gaps are identified below and help frame the research agenda of this dissertation.

Kaestner (1998) was one of the first researchers to empirically investigate the relationship between substance use and AFDC participation. He used eight years of data from the 1979 National Longitudinal Survey of Youth (NLSY79) to estimate a linear probability model of past year marijuana and cocaine use and past month alcohol use on future AFDC participation. Past year marijuana and cocaine use were indicators (yes/no) and past month alcohol use was measured as the number of drinks. Information on these substances was gathered in years 1984 and 1988. Due to the frequency at which substance use data were collected, future AFDC participation was an indicator equal to one if the "woman participated in AFDC at any time in the four-year period following the 1984 and 1988 interviews" (502).

Given these variable definitions, Kaestner estimated four sets of models. One was for black women in 1984; one was for black women in 1988; one was for nonblack women in 1984; and the last is for nonblack women in 1988.[5] For each of these groups, he estimated separate models for all women, never-married women, and women with no prior receipt of AFDC.

These models estimated the effect of substance use by interacting past year marijuana and cocaine use with lifetime use indicators representing moderate lifetime use

[5] Hispanic women are included in the nonblack subsample.

and heavy lifetime use.[6] Based on these models, Kaestner's preferred results are from all black women in 1984 and all nonblack women in 1988, which suggested that marijuana use (with moderate lifetime use) increased the mean probability of future AFDC participation by about 33 percent for black women and by about 50 percent for nonblack women. Kaestner argued that the effect of past year marijuana use is modest, calculating that "if marijuana use among [AFDC] participants was reduced to the level of nonparticipants, [AFDC] participation would decline by approximately 5 percent among nonblack and 3 percent among blacks" (Kaestner 1998, 514).

There were some results, however, that Kaestner did not highlight. Based on his results, marijuana use (with heavy lifetime use) increased the mean probability of future AFDC participation for black women with no prior AFDC receipt by about 121 percent. Also, marijuana use (with moderate lifetime use) increased the mean probability of future AFDC participation for nonblack women with no prior AFDC receipt by about 45 percent. These were interesting results which suggested that marijuana use might increase the probability of participation substantially, especially among black women.

In addition to providing the first systematic analysis of the association between substance use and AFDC participation, Kaestner recognized that there are unobserved characteristics correlated with both substance use and AFDC participation, stating, "to many, drug use and [AFDC] participation are behaviors that stem from the same underlying fundamental problems" (495). There are three unobserved characteristics discussed by

[6] Lifetime cocaine use between 1 and 39 times denotes moderate lifetime cocaine use, and lifetime cocaine use more than 39 times denotes heavy lifetime cocaine use. Lifetime marijuana use between 1 and 99 times denotes moderate lifetime marijuana use, and lifetime marijuana use more than 99 times denotes heavy lifetime marijuana use.

Kaestner: "welfare stigma," preferences for leisure, and physical/mental ability.[7] To the extent that substance use and welfare participation are both partially determined by an unobserved common factor, substance use is endogenous in the welfare participation equation. In an attempt to address this issue, Kaestner included some variables as proxies for these unobserved factors, including the frequency of religious attendance (measured in 1979), a self-esteem index (measured in 1980), and the number of illegal acts (measured in 1980).

There are several limitations to Kaestner's approach. First, at the time of the article, the NLSY79 only contained substance use information only for the years 1984, 1988, and 1992, which limited the analysis. Second, Kaestner's definition of AFDC participation as any participation in the four-year period following the observed substance use restricted his analysis to two estimation years. Based on this definition, marijuana and cocaine use in 1983 was allowed to affect a woman's AFDC participation decision in 1987, even if she did not use marijuana or cocaine since 1983. Third, drug use was defined as use in the past year. This is a weak measurement of drug use behavior because it is impossible to know when the individual used drugs over the past year. She could have used drugs at the beginning of the year, and then abstained for the rest of the year. Alternatively, she could have used drugs consistently throughout the year, which would have represented a more direct linkage between drug use and program participation than the previous scenario. There are also issues of recall over that time period.

Dooley and Prause (2002) also used data from female respondents to the NLSY79 to estimate the association of depression and alcohol abuse with entry into and exit from

[7] "Welfare stigma" is the disutility of AFDC participation (Moffitt 1983).

AFDC. Using a logistic regression model, the number of drinks per drinking day was not a significant predictor of entry into or exit from AFDC participation. One limitation of this study was the small number of years that were used in the analyses of alcohol use on AFDC status. Like other substance use studies using the NLSY79, the authors only had limited substance use information. Another limitation was that this study did not limit the sample to a reasonable comparison group. That is, the authors were comparing participants to non-participants instead of participants to eligible non-participants. A final limitation to this study was that they did not consider the potential endogeneity of substance use, which was introduced by the unobserved characteristics discussed by Kaestner (1998).

Schmidt, Weisner, and Wiley (1998) used longitudinal data from the WCLS (years 1989–1995) to examine substance use as a determinant of AFDC dependency. The authors considered three different AFDC participation patterns. A "continuous stay" was characterized by continuous AFDC participation over the entire time frame. A "single stay" was characterized by AFDC recipients who stopped participating at some point in the sample period and did not return to the program. "Multiple stays" was characterized by AFDC participation that ended at some point during the time frame and began again during the time frame.[8] Only one substance use variable—an indicator for problem drinking or heavy drug use—was included in their logistic models. The outcome variable for one model was an indicator for continuous stays (compared to any other participation pattern), and the outcome for the other model was an indicator for multiple stays (compared to any other

[8] This process of participation ending and beginning again could occur more than once for the "multiple stays" category.

participation pattern). Substance use was not a statistically significant predictor in either model.

Schmidt et al. (2002) also used data from the WCLS to investigate pathways by which substance dependence was associated with AFDC dependency. Results from a multinomial logistic model suggested that being substance dependent at AFDC entry increased the probability that an individual would exit AFDC through family reasons or administrative reasons, compared to not exiting. Family exits included changes in marital status, changes in number of children, or a residential move. Administrative exits included being transferred to another program, going to jail/prison, or being cut off for failing to meet requirements. The authors also found that individuals with substance use difficulties at initial exit were more likely to return to AFDC if they exited through family reasons or administrative reasons. The results of this study did not show a statistically significant relationship between substance use and exits through work reasons (mean hours worked per week, median annual pay, or mean months employed).

Schmidt et al. (2007) used newer data from the WCLS, gathered from 2001 to 2003, to investigate how substance use affected transitions from TANF to work and the ability to remain employed after TANF. Substance use in 2001 was not a statistically significant predictor of a first exit from TANF in a Cox proportional hazard model, and substance use in 2001 was not a statistically significant predictor in a logit model of leaving TANF for a job on the first exit. Substance use at the time of exit was not a statistically significant predictor in either a Cox proportional hazard model of reentering TANF following an exit or a logit model of reentering TANF due to job loss. These results were contrary to the authors' predictions. The authors argued that the absence of a substance use effect could occur

because of short-term and low-wage employment opportunities for TANF mothers, which might not have allowed sufficient time for substance use to "impact work performance and, ultimately, job retention" (Schmidt et al. 2007, 1080).

There are limitations to these three studies that used the WCLS, of which the first two were acknowledged by the authors. First, the sample was restricted to a single county, which limited generalizability of results. Second, the time-line follow-back interview process may have had inaccurate self-reports over the long time frame, especially with respect to the data gathered between 1989 and 1995. As the authors stated, "although the time-line follow-back approach improves the reliability of retrospective self-reports, concerns about accurate recall, particularly among those with addiction problems, place constraints on the analysis" (Schmidt et al. 2002, 228). Third, these studies did not address the issue of eligibility. While some of the individuals who exit AFDC/TANF might remain eligible, these analyses did not compare participants to eligible non-participants. Instead, they compared participants to formerly participating non-participants. Moreover, substance use may affect eligibility. Finally, these three studies did not consider the possible endogeneity of substance use which may result if unobserved characteristics are correlated with both substance use and AFDC/TANF participation.

Jayakody, Danziger, and Pollack (2000) used cross-sectional data on single mothers who were at least 18 years old from the 1994 and 1995 NHSDA to estimate the association between substance use and AFDC receipt using a logistic regression model. The authors used four past year substance use measures in their multivariate analysis: (1) cocaine/crack use, (2) any other illicit substance use, (3) alcohol dependence, and (4) cigarette use. Among these measures, past year cocaine/crack use and cigarette use were statistically significant and

positive predictors of past year AFDC receipt. The authors did not include proxies that might control for unobserved characteristics, like those discussed by Kaestner (1998). Their sample of single mothers, however, reasonably proxied for eligibility status—the only study reviewed in this chapter to do so. Even so, they treat eligibility as given when it may be influenced by substance use.

Like all empirical work, there are limitations to Jayakody et al. (2000). First, substance use and AFDC receipt were measured over the past year, which makes it impossible to know the timing of these two events. Based on these measures, substance use could precede, follow, or occur simultaneously with AFDC receipt. Ultimately, as acknowledged by the authors, these data cannot allow the researchers to make any causal statements about how substance use affects AFDC receipt. Second, the combined measure of any other illicit substance use—which grouped marijuana use with other drugs including heroin—assumed that all of these substances would have the same type of effect on AFDC receipt. Third, while the authors admitted that there is stigma associated with AFDC receipt and substance use, they did not make any attempt to address this issue.

The studies discussed in this section tell us two things. One, while some authors alluded to potential endogeneity of substance use, the existing literature has not addressed it except by including variables meant to proxy for unobserved factors. Two, much of the existing literature has not addressed the eligibility status of non-participants and its relationship with substance use. Based on these two shortcomings, there is a need for studies that estimate the causal relationship between TANF eligibility, TANF participation, and substance use.

AFDC Eligibility and Participation

Given the lack of literature investigating the association or relationship between substance use and TANF eligibility, the best guidance for an empirical analysis is the general literature on AFDC eligibility. When considering participation, studies typically restrict the data to individuals who are or appear to be eligible, or they incorporate some elements of eligibility into a model of participation (e.g., Moffitt 1983; Hoynes 1996; Swann 2005). Blank and Ruggles (1996) is one exception to this approach. They analyzed the determinants of AFDC eligibility and participation. This section discusses their approach for approximating eligibility status and their analysis of determinants of AFDC participation.

Their analysis used the 1986 and 1987 panel files of the Survey of Income and Program Participation (SIPP) to investigate the determinants of AFDC and Food Stamps eligibility and participation among unmarried mothers. They were specifically interested in whether spells of eligibility and participation begin and end at the same time or whether eligible women begin participation sometime after becoming eligible, end participation while remaining eligible, or simply choose not to participate through being eligible.

During the data's observation period, initial AFDC eligibility was determined by income and asset tests. Empirically, Blank and Ruggles compared three definitions of eligibility. The first definition was based on current cash income only. The second definition was based on current cash income and total wealth (this is their preferred definition). The third definition was based on current cash income, total wealth, and included vehicle asset test rules.[9] Based on these definitions, they estimated eligibility rates between 35 and 40

[9] During the time period the data were collected, if the woman owned a car, then its equity value must have been less than $1,500.

percent. They estimated AFDC take-up rates among eligibility women of between 62 and 70 percent.[10]

Based on their spells analysis, there were about twice as many eligibility spells as participation spells. Comparing the characteristics of participants to eligible non-participants, participants appeared to be more disadvantaged than eligible non-participants. Blank and Ruggles stated "AFDC recipients are more likely to be black, never married, disabled, have less education, and to have younger children and more children than are eligible nonrecipients. They are also far less likely to be working" (67).

The authors used competing risks models to estimate characteristics that affected the probability of exiting eligibility or participation spells through family composition changes or income/other changes. AFDC eligible women were less likely to end an eligibility spell with family composition changes if they were black, younger, never married, disabled, or had more children. AFDC eligible women were less likely to end an eligibility spell with income/other changes if they were black, disabled, or had younger children. Older women with more years of education were more likely to end an eligibility spell with income/other changes. AFDC participants were less likely to end a participation spell if they were older, never married, had more years of education, or had younger children. AFDC participants were more likely to end a participation spell if they had more years of education. These competing risk models also included other geographic covariates—such as the state unemployment rate and the share of rural population in the state—although these covariates were not generally statistically significant.

[10] These take-up rates were similar to estimated take-up rates in Ruggles, Lamas, and Eargle (1992).

While this study did not include substance use as a covariate, it did highlight the complexity of adequately addressing TANF eligibility. Considerable research has considered AFDC/TANF participation dynamics, such as entries onto and exits off of the program, but few studies analyzed eligibility or its dynamics. Substantially fewer studies have addressed eligibility when estimating the relationship between substance use and AFDC/TANF participation. This emphasizes the importance of estimating eligibility and the relationship between substance use and eligibility in this dissertation. Blank and Ruggles also identified the directional associations between demographic variables and eligibility and participation, which are benchmarks for gauging my statistical results.

The literature reviewed in this chapter tells us a several things. First, contrary to the popular opinion, most AFDC/TANF recipients were not substance abusers. There was evidence suggesting substance use is more prevalent among AFDC/TANF recipients than in the general population, but the literature did not provide information about a comparison between recipients and eligible non-recipients. Second, the literature investigating the relationship between substance use and AFDC/TANF participation, rarely considered eligibility, often used pre-TANF era data, and did not address the potential endogeneity of substance use. In the absence of literature on substance use and eligibility, Blank and Ruggles (1996) guide my empirical analysis by providing a starting point for estimating eligibility and a set of covariates to include when estimating the relationship between substance use, eligibility, and participation. This review also highlights the key variables needed for my analysis. Specifically, I require information on TANF eligibility—or the variables required to impute eligibility—TANF participation, substance use, and socioeconomic controls.

CHAPTER IV

DATA

The discussion in Chapter III provides insight into the data needed to investigate the relationship between substance use, TANF eligibility, and TANF participation. First, I need longitudinal data on TANF eligibility and participation and substance use collected during the TANF era (1997 and later). Although the methods discussed in Chapter V will allow me to address endogeneity without exclusion restrictions for the eligibility and participation equations, instruments will provide an additional source of identification. Thus, I also require data on state policies that may be used as instruments. This chapter begins with a general discussion of possible data sources on program participation and substance use. I next discuss the construction of my analysis sample. Then I discuss the policy variables to be used as instruments. This chapter ends with a description of the analysis sample.

TANF Participation and Substance Use Data

Several publicly available datasets are commonly used in the public assistance and/or substance use literature, such as the Survey of Income and Program Participation (SIPP), the Panel Study of Income Dynamics (PSID), the National Survey on Drug Use and Health (NSDUH), the Welfare Client Longitudinal Survey (WCLS), and the National Longitudinal Survey of Youth.

The SIPP, administered by the US Census Bureau, consists of a series of nationally representative panels that last between two-and-a-half to four years each. The SIPP is one of the best sources for program participation data. The purpose of the SIPP is to provide data

for evaluation of government programs and investigation of the effects of changes to those programs. Unfortunately, the SIPP contains no information on substance use and so cannot support the proposed analyses.

Like the SIPP, the PSID contains information on program participation. The PSID is a survey administered by the Institute for Social Research at the University of Michigan. The PSID was an annual survey from 1968 until 1997 and became biennial thereafter. The PSID consists of a nationally representative sample and a poverty oversample. The PSID follows the original sample members as well as their children, grandchildren, and so forth, and it is commonly used to investigate labor market outcomes and poverty. Unlike the SIPP, the PSID contains some information about substance use. Unfortunately, the PSID only contains one year of information about substance use. Thus, the PSID does not have enough substance use data to support this dissertation.

The NSDUH is an annual, national survey sponsored by the Substance Abuse and Mental Health Services. The NSDUH is an excellent source of substance use information, providing data on tobacco use, alcohol use, illicit drug use and mental health in the US. The NSDUH also has information on the number of months of "welfare receipt" by the household. While the NSDUH collects relevant data for this dissertation, the cross-sectional nature of the data cannot address the concerns about unobserved characteristics raised in Chapter III.

The WCLS, introduced in Chapter III, collected data from a large California county, using a time-line follow-back method to gather six years of data from 1989 to 1995 on individuals who were AFDC/TANF or General Assistance recipients in 1989. The same method was used for a separate panel to gather three years of data from 2001 to 2003 on

recipients in 2001. The WCLS contains information on AFDC/TANF participation and substance use. While these data contain valuable information for this dissertation, I do not have access to the data. Moreover, these data do not allow for researchers to consider eligible non-participants other than former participants. Thus, the WCLS cannot support this dissertation.

The Bureau of Labor Statistics (BLS) administers numerous surveys, one of which (the NLSY79) was used by two studies discussed in Chapter III. The NLSY79 is an annual survey of men and women that began in 1979. As discussed in Chapter III, the NLSY79 contains information on AFDC participation and substance use. Unfortunately, the substance use information is relatively sparse. Moreover, the respondents were at least 30 years old when TANF was enacted in 1996. While the NLSY79 could be used to estimate the effect of substance use on TANF eligibility and participation, a more recent data source administered by the BLS contains annual substance use information, which would allow for more usable years of data. This data source is the National Longitudinal Survey of Youth 1997 (NLSY97).

The NLSY97 is an annual survey of men and women that began in 1997 and includes longitudinal data on program participation and substance use. The NLSY97 collects past month substance use information every year and contains monthly information on program participation. Moreover, the longitudinal nature of the data makes it possible to allow for person-specific unobserved heterogeneity. For these reasons, the NLSY97 is the preferred data source for this dissertation.

National Longitudinal Survey of Youth 1997

The NLSY97 is an annual survey administered by the BLS. The sampling frame was individuals born between January 1, 1980 and December 31, 1984. The round 1 data consist of 8,984 individuals, and the oldest respondents (17 and 18 year olds) represented six percent of the total sample.

The original NLSY97 sample consists of two subsamples. The first is a nationally representative sample of people living in the US during 1997 and born between 1980 and 1984, and the second is a supplemental sample designed to oversample Hispanic or Latino and black people living in the US during 1997 and born between 1980 and 1984. The retention rate for females in the cross-sectional sample was 93.2 percent in round 2, declining to 84.5 percent in round 13, and the retention rate for females in the in the supplemental sample was 94.6 percent in round 2, declining to 90.9 percent in round 13.

Youth are interviewed annually, with the first interview round beginning in February 1997. Respondents answer questions in person through a computer-based system. If they cannot respond in person, then a telephone interview is conducted. During round one, 96.8 percent of respondents responded in person, and 3.2 percent responded via telephone. Each round is fielded for about seven months. The youth questionnaire collects data on schooling, employment activities, financial characteristics, family background, social behavior, and health status.

During the first round, one parent of each youth, who must reside in the household, was asked to participate in an interview. If the youth did not live with a parent-type figure, then there was not a parent questionnaire administered for that youth. The parent questionnaire was completed in person through a computer-based system. If a parent did

not respond in person, then a telephone interview was conducted for the parent. The parent questionnaire collected data on marital status, employment histories, family characteristics, and information on the NLSY97-eligible children.

Much of the NLSY97 data are publically available, but there is a restricted use portion of data that includes geographic information, referred to as the geocode data. The geocode data are collected during the main data collection and include county unemployment rates, state and county FIPS codes, and other state and county level data. Researchers in the US may request access to the geocode data by submitting an application to the BLS. To protect the confidentiality of respondents, researchers must agree to adhere to the BLS confidentiality policy. The application must include a clear description of the research project and an explanation of how the geocode data are essential to the project. The geocode data are necessary for the project so that I may use state specific information on TANF and other policies. Permission was sought and received to use the geocode data.

Analysis Sample

I apply several sample restrictions before conducting analyses. Table 3 contains information on sample size changes resulting from these restrictions. The full NLSY97 includes 8,984 individuals and 116,792 person-years from round 1 through round 13 (survey waves 1997 through 2009). First, I restrict my sample to female respondents because the majority of TANF case heads are female. After dropping the male respondents, the sample decreases by 4,599 women and 59,787 person-years (51.19 percent reduction of the original person-years). Second, I treat the first non-interview as attrition from the panel. Explicitly, I drop the non-interview year and every following year for the woman even if the woman returns to the sample. This is necessary because information on TANF eligibility,

participation, and substance use are not available for the time the woman is out of the sample. Dropping these observations reduces the sample by 12,419 person-years (10.63 percent reduction relative to the original sample). Third, I drop observations occurring after September 2009. This sample restriction is based on the NLSY97's program participation variables, which end in September 2009. This restriction reduces the sample by 2,162 person-years (1.85 percent reduction relative to the original sample). Fourth, I treat leaving the country as attrition from the panel because I cannot match TANF eligibility tests to women that are outside of the country. Dropping these observations reduces the sample size by 219 person-years (0.19 percent reduction relative to the original sample). Finally, I drop observations when the woman is under the age 18. This restriction ensures that my analysis is conducted for young adults. There are 541 women without any observations at, or after, age 18. This is a reduction of 12,411 person-years (10.63 percent reduction relative to the original sample). After all of the sample restrictions, my sample includes 3,844 women and 29,794 person-years.

NLSY97 Variable Definitions

The primary variables of interest for this dissertation are TANF eligibility, TANF participation, alcohol use, and marijuana use. TANF eligibility requires the woman to be the parent of a minor child and to have low enough income to qualify for the program. I use one of the NLSY97 created variables to create an indicator for whether or not the woman is the parent (biological or adoptive) of a minor child. The NLSY97 created variable used counts the number of children living in the household of the woman at the time of the interview, where women who are not the parent of a minor child have a missing value for that year. Minor children not living in the household are, therefore, not considered in my definition of

eligibility. If the count is greater than or equal to one, then I consider the woman to be the parent of a minor child. There are some missing values for the NLSY97 variable. If the woman has a child in the years immediately preceding and following the missing observation, I consider the woman to have a child in the household. Pregnant women can also be eligible for TANF. Women who do not have a child in one year but who have a child in the household in the next year are assumed to be pregnant during the first year.

Total income is equal to the woman's earned income if she is not married or the sum of the woman's earned income and her spouse's earned income if she is married. Here, earned income includes annual income gained from salaries and wages. If the woman does not provide a continuous earned income measure, then the NLSY provides a bracketed measure of income, and I use the midpoint of the appropriate income interval. For example, consider a woman who did not provide a continuous earned income and who reported her income to be between $1 and $5,000. This woman's earned income would be imputed as $2,500 for that survey wave. The BLS makes this imputation when constructing several of its own created variables. For comparability with the TANF income thresholds, I divide this annual income measure by 12 to approximate the woman's average monthly income. This same process was applied to create spouse's earned income.

There are 362 person-years that did not have a valid response for continuous or bracketed income. For these observations I used data on the most recent or current jobs to calculate the average weekly earnings (average hours worked per week multiplied by wage). This approach calculates monthly income by multiplying the average weekly earnings by four, while the approach in the previous paragraph calculated monthly income by dividing annual income by 12. The variables I use to calculate weekly earnings are measured for each

job the woman has had over the year preceding the survey year (e.g., 1996 for the first round). This imputation uses three variables. The first variable identifies the woman's current or most recent job as of the survey. The second variable identifies the average number of hours worked per week at that job. The third variable identifies the hourly pay for that job (excluding overtime and performance pay). If the woman did not have a current job, then her income was imputed as zero for that survey year. If she had at least one current job, then her income was imputed as the hourly pay multiplied by the average hours worked per week multiplied by four weeks, and summed over all current jobs. This approximates the woman's average monthly income.

Since the employment measures described in the previous paragraph are only collected for the respondent, I cannot make this same imputation for spouse's income if spousal income is missing. Instead, I use the spouse's income data in the year preceding and the year following the missing observation. This is done after imputing the midpoint of the spouse's interval income response. If the spouse has an income measure in both the year immediately preceding and following the missing observation, then I use the average of these two values. If the spouse only has an income measure in one of the years (preceding or following), then I use that value. If neither year contains an income value, then I assume zero dollars.

Finally, TANF income eligibility thresholds are required to determine if women are TANF eligible. TANF income eligibility thresholds vary by state, and the threshold typically varies depending on the household size. Urban Institute's Welfare Rules Database Project (WRD) is a longitudinal database that tracks state AFDC/TANF policies, currently covering

1996 through 2014. The WRD is the sole source for TANF income eligibility thresholds used in this work (see Huber et al. 2015 for the most recent Databook).

The income considered for eligibility varies across states and years. Specifically, states may use gross or net earnings or gross or net income. For example, from 1997 to 2009 Alabama had a net income threshold, while Alaska had a gross income threshold.[11] States may also change the type of income threshold over time. For example, Washington had a gross income threshold from 1997 to 1998, and the state had a gross earnings test from 1998 to 2009.[12]

The most common income eligibility threshold considers gross income. This is the preferred income threshold to use because most state-year combinations have a gross income threshold. When appropriate, this is the income eligibility threshold used. For state-years that did not have a gross income eligibility threshold, I use the gross earnings threshold. Consider Washington as an example. I use the gross income threshold for Washington for years 1997 and 1998. I use the gross earnings threshold for Washington for years 1999 through 2009. For state-years that did not use a gross income or earnings threshold, I use the net income threshold. An example of this is California, which used a gross income test in 1997 and a net income test from 1998 to 2009.

Finally, some states do not have a formal income eligibility threshold. Instead, these states calculate the individual's benefit award as the difference between the maximum benefit and net income. If the calculated award is negative, then the individual is ineligible. In this case I use the maximum benefit as the income eligibility threshold. For example, Nebraska

[11] Net income is gross income less certain allowable exemptions and deductions.

[12] Gross income is total income, which includes earnings and income from other sources. "Gross earnings" refers to the woman's earnings only.

used a gross income threshold in 1997, but from 1998 to 2009, the state did not have a formal income threshold.

TANF eligibility is based on the three variables described above: whether or not the woman is the parent (biological or adoptive) of a minor child, total income, and the TANF income eligibility threshold. A woman is TANF eligible if she is the parent of a minor child and has total income less than her state's TANF income eligibility threshold. Otherwise she is assumed to be ineligible.

Participation is based on three variables. The first variable is program eligibility. The second variable indicates if the woman and/or her spouse received program benefits, referred to as "program status." The third variable identifies which persons are covered by the program payments received, referred to as "the payments variable." The second and third variables are collected at the monthly level. Program status is an indicator equal to one if the woman and/or her spouse received benefits, and equal to zero otherwise (with exception of any missing values). The payments variable is a discrete variable identifying which persons were covered by the payments: (1) respondent only; (2) spouse/partner only; (3) child only; (4) respondent and spouse/partner; (5) respondent and child; (6) spouse/partner and child; (7) respondent and spouse/partner and child; or (8) other.

Participation is conditional on program eligibility. If the woman is ineligible, then she may not participate. A woman is a participant if program status is equal to one and she is one of the persons covered by the payments (cases 1, 4, 5, and 7). A woman is not a participant if program status is equal to zero or if it is one and she is not one of the persons covered by the payments (cases 2, 3, 6, and 8). Thirteen person-years are imputed as participant using information for either the program status variable or the payments variable.

Five person-years were imputed as participant when program status was one and the payments variable was missing. The remaining eight imputed person-years were imputed as participant when program status was missing and the payments variable was equal to either one or five. Any remaining missing values for participation are imputed using the previous year's value.

For this dissertation, alcohol and marijuana use are conceptualized as ordered discrete variables representing no use, infrequent use, and frequent use. Frequency of use is based on the number of days of use in the last 30 days, ranging from 0 to 30 days. No use occurs when the woman did not use any in the last 30 days. To distinguish infrequent and frequent users, I first find the median number of days of use for users separately for alcohol and marijuana. These values are 3 and 4 for alcohol and marijuana, respectively. Infrequent use occurs when the days of use is at least 1 day and no more than the median days of use. Frequent use occurs when the days of use is more than the median days of use. Missing values are imputed as infrequent use.

In addition to eligibility, participation, and substance use, I also use demographic and geographic characteristics. Race/ethnicity is separated into four categories: white, black, Hispanic, and other. Age is measured at the time of the interview. I create indicators for urban residence and living in the South region to control for geographic trends. The county-level unemployment rate, available as a variable in the NLSY97 geocode data, is included to control for local labor market conditions. In a number of cases, the county-level unemployment rate is not available. In these cases, the county unemployment rate is imputed using the state unemployment rate. Education is measured as the highest degree completed:

did not graduate high school, high school diploma or GED, and a Bachelor's degree or higher (referred to as "4-year college degree").

State-level Policy Data

In addition to the individual-level data in the NLSY97, this dissertation requires state-level policy data that will be used to explain alcohol and marijuana use but will be omitted from the eligibility and participation equations. In other words, these policy data are used to help address the potential endogeneity of substance use, and they include information on marijuana decriminalization laws, medical marijuana laws, beer taxes, cigarette taxes, and spirits taxes.

The marijuana policies for this dissertation are on marijuana decriminalization laws and medical marijuana laws. Decriminalization laws remove the criminal status of possession of small amounts (up to 1 ounce) of marijuana. Data on medical marijuana laws indicate if the state provides legal protection (medical necessity defense) for possession and/or cultivation of marijuana for medical purposes. These laws reduce the full price of marijuana use. These data are from the RAND Marijuana Policy Data set (Pacula, Chriqui, and King 2003; Pacula, Boustead, and Hunt 2014; Pacula et al. 2015).

I also use alcohol and cigarette taxes. The Beer Institute collects a wealth of information annually including state beer taxes. The state beer taxes are found in the Beer Institute's Brewers Almanac, covering years 1997 through 2012. I obtained spirits taxes from the Tax Foundation for years 2000 through 2009. Because spirits taxes are only available beginning in the year 2000, I imputed values for the years 1998 and 1999. Because they remain relatively stable within a state, the 2000 taxes are imputed for the missing years. I obtained cigarette taxes from the Center for Disease Control and Prevention (CDC). The

CDC's cigarette taxes are measured in the fourth quarter and cover year 1995 through 2009. State cigarette taxes are measured as dollars per pack of 20 cigarettes. I then normalized beer taxes, cigarette taxes, and spirits taxes to 2015 dollars.

Descriptive Statistics

Table 4 presents descriptive statistics for the entire sample of 29,794 person-years. Eighteen percent of the person-years are TANF eligible, and 12 percent of TANF eligible person-years (5,398) are TANF participating. Using a slightly different measure of eligibility, Blank and Ruggles (1996) find that about 40% of single mother person-years are AFDC eligible. They find a much higher participation rate—women participate in about two-thirds of the person-years in which they are eligible. This is similar to other estimates of AFDC participation (e.g., Moffitt 1983). However, there is evidence that the take-up rate for TANF is significantly lower than for AFDC. For example, Loprest (2012) found that the TANF take-up rate in 2007 was 36%. Although not exactly a take-up rate among eligible families, the Center on Budget and Policy Priorities (2015) found that the number of families receiving TANF per 100 poor families with children fell from 68 in 1996 to 26 in 2013.[13]

More than half of the person-years have any alcohol use, with 29 percent for both infrequent and frequent use. Less than 15 percent of the person-years have any marijuana use, with seven percent for both infrequent and frequent use. The equal proportions for infrequent and frequent use is expected because the variables are based on a median split.

To assess the extent to which the substance use behaviors in my sample are representative, I use data from the 2003 through 2005 NSDUH. The NSDUH is the best

[13] Although lower than take-up rates for AFDC, these estimates are still higher than the 12 percent take-up calculated in my sample. It is possible that my method of inferring eligibility may overstate the number of eligible person-years by, for example, attributing eligibility to teen moms who live at home. Issues with eligibility calculation are discussed in Chapter VI.

data source for nationally representative substance use information. NSDUH frequencies can be restricted by sex and age range, with the most appropriate range for this comparison being 18 to 25 years old. The most comparable years based on this age range are 2003 through 2005. The age range for women in the NLSY97 is 18 to 24 in 2003, 19 to 25 in 2004, and 20 to 26 in 2005. Table 5 displays the proportion of any alcohol or marijuana use for women between the age ranges discussed. My sample has a greater prevalence of substance use than the NSDUH in every year. There are only two years, however, that seem to have similar rates: alcohol use in 2003 and 2004. The remaining substance use rates seem very different between the NLSY97 and the NSDUH.

For alcohol use in 2005, my sample has a 63.43 percent rate, and the NSDUH has a 56.1 percent rate. While this is a difference of about seven percentage points, I expect my sample to have a greater prevalence rate. The age range for my sample is 20 to 26 in 2005, which means more people in my sample, in percentage terms, are able to use alcohol legally than in the NSDUH. For marijuana use, the prevalence rates from my sample are consistently three to five percentage points greater than the rates in the NSDUH. This difference might be attributable to sample size differences, where my sample is about one-third the size of NSDUHs for 18 to 25 year old women.

Turning to the policy variables, and returning to Table 4, we also see that 20 percent of the person-years are in states with medical marijuana laws, 36 percent are in states with marijuana decriminalization laws. The average state beer tax is $0.31 and varies from $0.02 to $1.53. The average state cigarette tax is $0.97 and varies from $0.03 to $3.33. The average state spirits tax is $4.56 and varies from $0.00 to $29.32.

About half of the person-years are from women who are white, 28 percent black, 21 percent Hispanic, and three percent other races. The average age for the sample is about 22 years, ranging from 18 to 29. Most of the person-years are from women with a high school diploma (72 percent), with 17 percent having less than a high school diploma, and 11 percent having at least a four-year college degree. The average unemployment rate is 5.64 percent, but it varies greatly from 1.40 percent to 20.2 percent. Seventy-seven percent of the person-years are from women who live in an urban residence, and 40 percent live in the South.

While these descriptive statistics give us some information about the included person-years, these statistics cannot tell us about how these characteristics vary over time. Figures 1 through 6 present trend lines depicting changes over women's ages for sample size and the endogenous variables eligibility, participation, and substance use. Figure 1 plots the number of women at each age. The number of women begins with 3,844 at age 18, and slowly declines to about 3,000 women at age 24. The sample size declines quickly after age 24, dropping below 1,000 after age 27. The number of women at age 29 is the smallest (81 women). These women were the oldest during the first interview, which was the smallest age subgroup during the first interview. As we look at the remaining figures, there is expected to be greater volatility in the measurements at ages 28 and 29 because of the small sample sizes.

Figure 2 plots the proportion of TANF eligible women. The proportion of eligible women has some variation by age, but it stays between 15 and 20 percent. At age 18, about 15 percent of women are eligible—the smallest proportion of eligible women by age. Eligibility reaches 20 percent at age 20 and remains at that level through age 22. From age 23 to age 29, eligibility varies between 15 and 18 percent.

Because participation is conditional on eligibility, the sample size relevant for participation is less than the full sample. Figure 3 plots the number of eligible women at each age. There are fewer than 1,000 women at all ages. The number of eligible women begins at about 570 at age 18, reaches a maximum of about 725 women by age 20, and drops to a minimum 15 women at age 29.

Figure 4 plots the proportion of participating women conditional on eligibility. The proportion of participating women has some variation by age, but stays between about eight percent and about 16 percent. Participation begins at around nine percent at age 18 and slowly increases to about 16 percent by age 25. In terms of women, there are about 50 participating women at age 18, about 65 participating women at age 25, and 2 participating women at age 29. While the proportion of participating women reaches a maximum at age 25, the count of participating women reaches a maximum at age 20 (about 83 women).

Figure 5 plots the proportion of women in each alcohol use category by age. The line with round bullets represents no alcohol use. The line with diamond-shaped bullets represents infrequent alcohol use. The line with triangular bullets represents frequent alcohol use. The proportions for these three categories will sum to one at each age because these three categories are mutually exclusive. At age 18, about 55 percent of women did not drink alcohol in the past month. For every age after 18, more than half of women drank at least one drink in the past month. Relative to infrequent and frequent use, no use is the most common alcohol use group at every age. No alcohol use reaches its minimum at age 24 with about 35 percent. Infrequent alcohol use reaches its maximum of about 31 percent at age 22, declining to about 26 percent at age 29. Frequent alcohol use is about 20 percent at age 20,

and reaches a maximum of about 34 percent at age 21. Frequent use is more prevalent that infrequent use at every age after 20.

Figure 6 plots the proportion of women in each marijuana use category. The line with round bullets represents no marijuana use. The line with diamond-shaped bullets represents infrequent marijuana use. The line with triangular bullets represents frequent marijuana use. Again, the proportions for these three categories will sum to one at each age because these three categories are mutually exclusive. Marijuana use is less prevalent than alcohol use at every age. Unlike alcohol use, marijuana gradually decreases as age increases. No marijuana use begins at about 84 percent at age 18 and increases to about 90 percent at age 29. Infrequent and frequent marijuana use have about the same prevalence at every age. Infrequent marijuana use begins at about nine percent at age 18 and gradually declines to about 4 percent at age 29. Frequent marijuana use begins at about seven percent at age 18 and drops to about 6 percent at age 29.

Now that the data are prepared for analysis, we are ready to discuss how to estimate the relationship between substance use, eligibility, and participation. The next chapter discusses the econometric model I will use in my analysis.

Table 3. Sample Restrictions

	Sample Size				% Δ Person-Years	
Restriction	**Persons**	**Δ Persons**	**Person-Years**	**Δ Person-Years**	**… relative to previous row**	**… relative to the original sample**
None (Original Sample, 1997-2009 survey waves)	8,984	-	116,792	-	-	-
Drop male respondents	4,385	-4,599	57,005	-59,787	51.19%	51.19%
Attrition: non-interview	4,385	0	44,586	-12,419	21.79%	10.63%
No program participation information	4,385	0	42,424	-2,162	4.85%	1.85%
Attrition: leave the country	4,385	0	42,205	-219	0.52%	0.19%
Drop age < 18 observations	3,844	-541	29,794	-12,411	29.41%	10.63%

Table 4. Description Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
TANF State				
Eligibility	0.18	0.39	0	1
Participation conditional on eligibility (n = 5,398)	0.12	0.32	0	1
Substance Use				
No alcohol use+	0.42	0.49	0	1
Infrequent alcohol use	0.29	0.45	0	1
Frequent alcohol use	0.29	0.46	0	1
No marijuana use+	0.87	0.34	0	1
Infrequent marijuana use	0.07	0.25	0	1
Frequent marijuana use	0.07	0.25	0	1
Policy Variables				
Medical marijuana legal	0.20	0.40	0	1
Marijuana decriminalized	0.36	0.48	0	1
Beer tax	$0.31	$0.26	$0.02	$1.53
Cigarette tax	$0.97	$0.70	$0.03	$3.33
Spirits tax	$4.56	$3.91	$0.00	$29.32
Demographic Characteristics				
White+	0.48	0.50	0	1
Black	0.28	0.45	0	1
Hispanic	0.21	0.41	0	1
Other race	0.03	0.18	0	1
Age	21.90	2.77	18	29
Less than high school diploma+	0.17	0.37	0	1
High school diploma or GED	0.72	0.45	0	1
4 yr. college or more	0.11	0.32	0	1
Geographic Characteristics				
Unemployment rate (%)	5.64	2.30	1.40	20.20
Urban residence	0.77	0.42	0	1
Lives in the South	0.40	0.49	0	1
Sample Size (person-years)	29,794			

Note: Proportions for categorical variables may not sum to one due to rounding error. + Omitted category in analysis.

Table 5. Comparison of Substance Use Variables between NLSY97 and NSDUH

Variable	Year	NLSY97	NSDUH*
Alcohol use (any)	2003	57.21%	55.80%
	2004	58.00%	55.90%
	2005	63.43%	56.10%
Marijuana use (any)	2003	13.86%	9.70%
	2004	13.94%	9.00%
	2005	12.29%	8.40%

Notes: The age range for women in the NLSY97 is 18 to 24 in 2003, 19 to 25 in 2004, and 20 to 26 in 2005. The age range for women in the NSDUH is 18 to 24 in all three years.

* Source: National Survey on Drug Use and Health (2003; 2004; 2005).

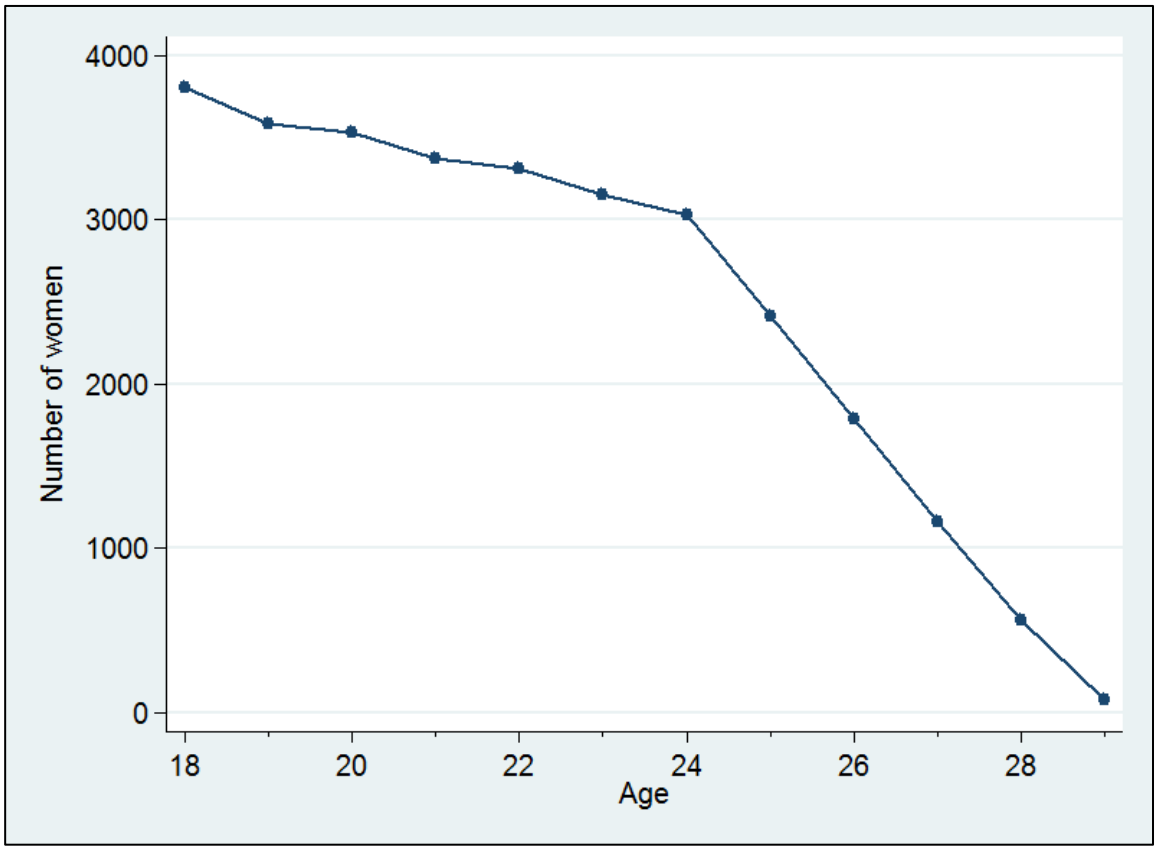

Figure 1. Sample Size

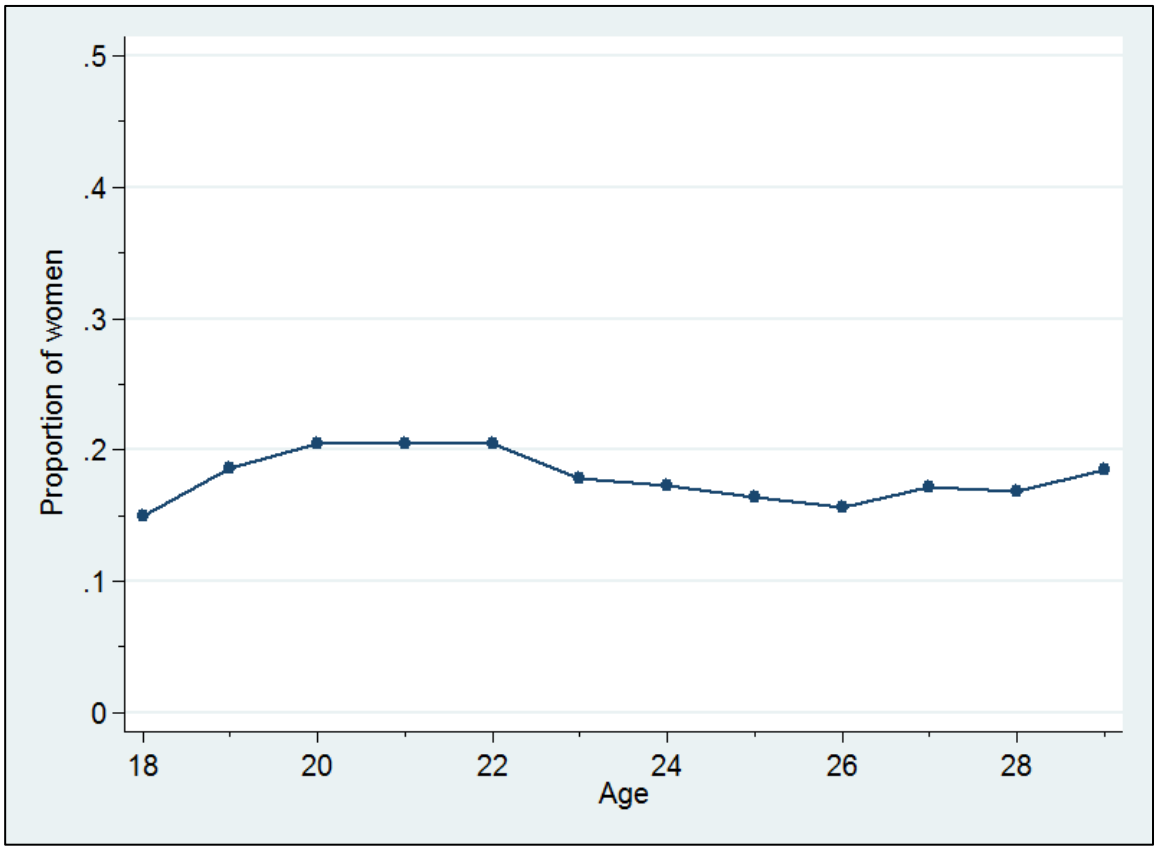

Figure 2. Proportion of TANF Eligible Women

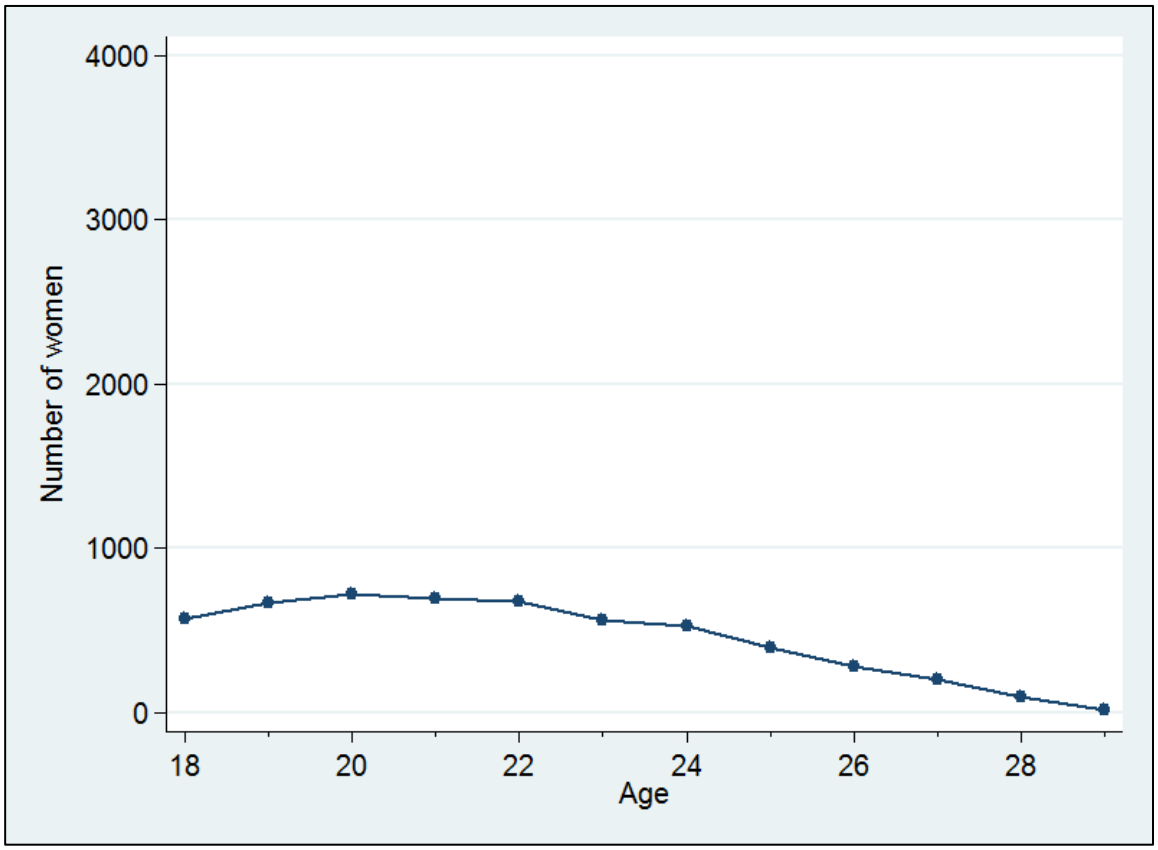

Figure 3. Sample Size of TANF Eligible Women

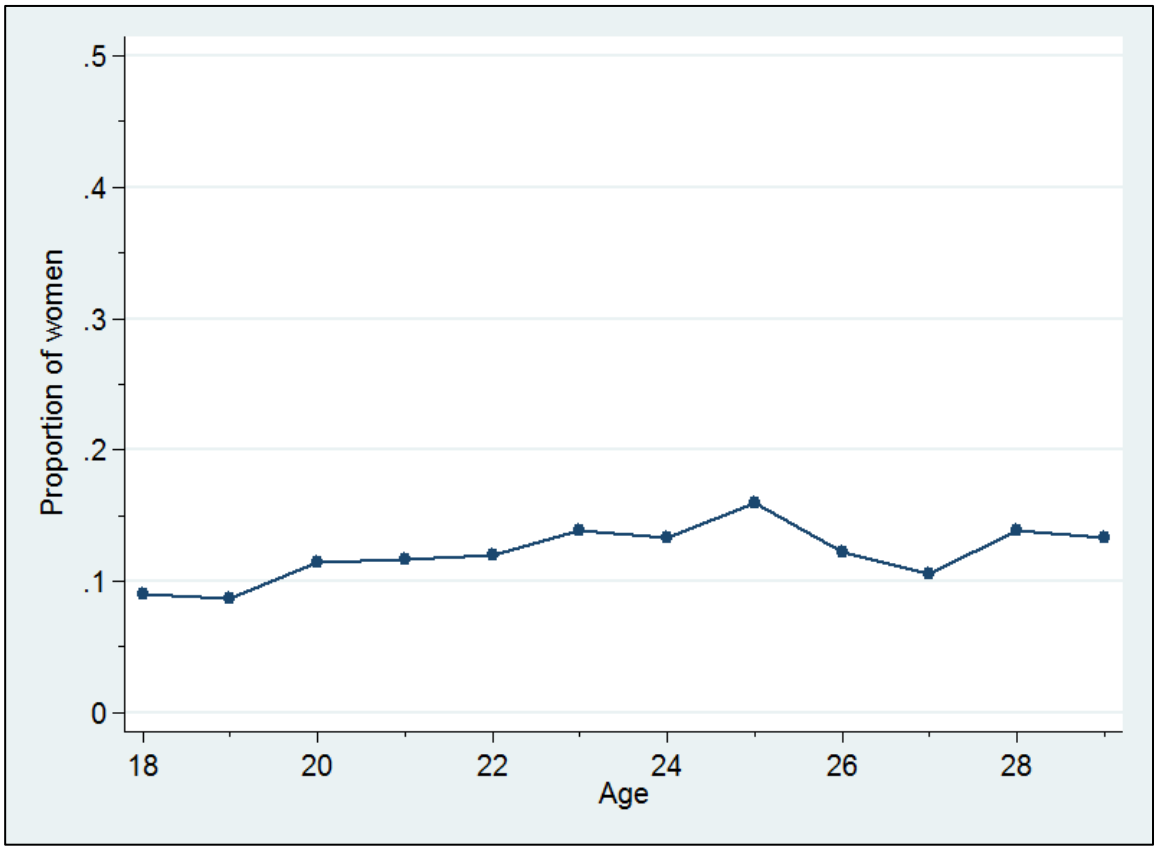

Figure 4. Proportion of TANF Participating Women

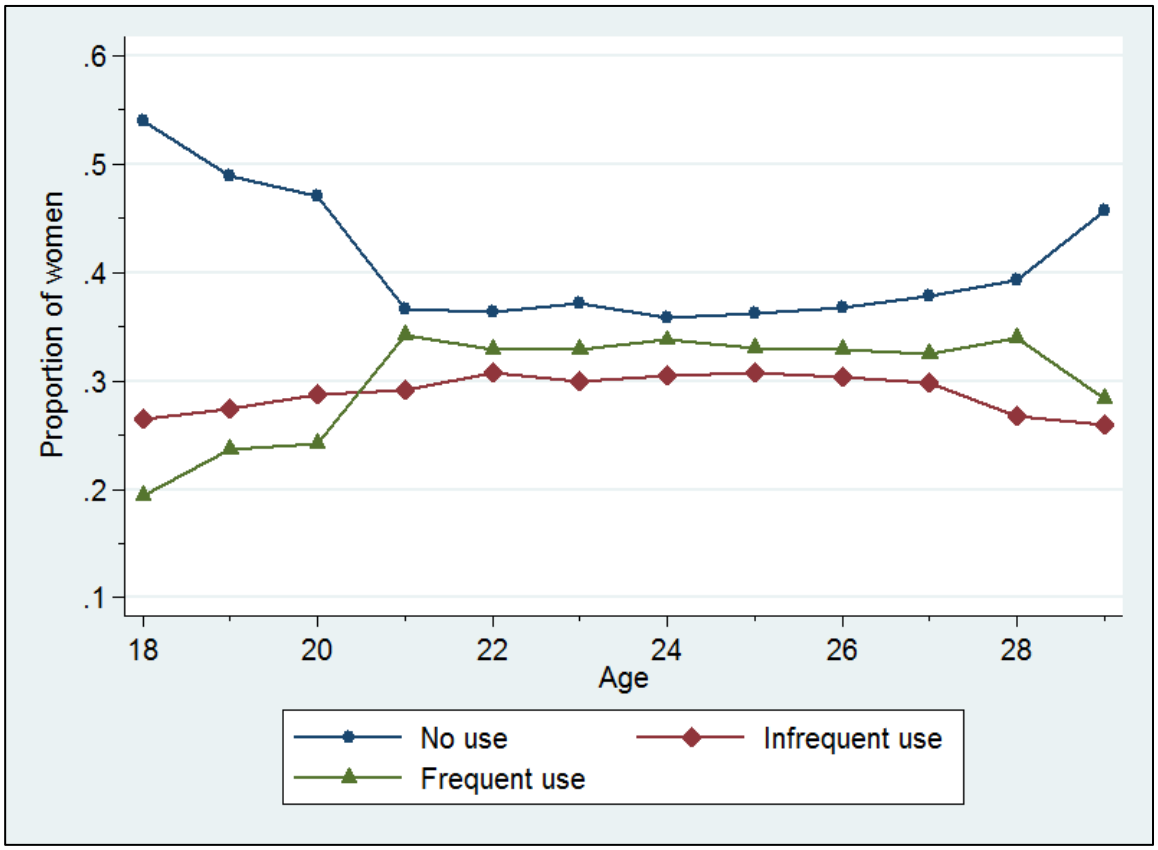

Figure 5. Proportion of Women in each Alcohol Use Categories

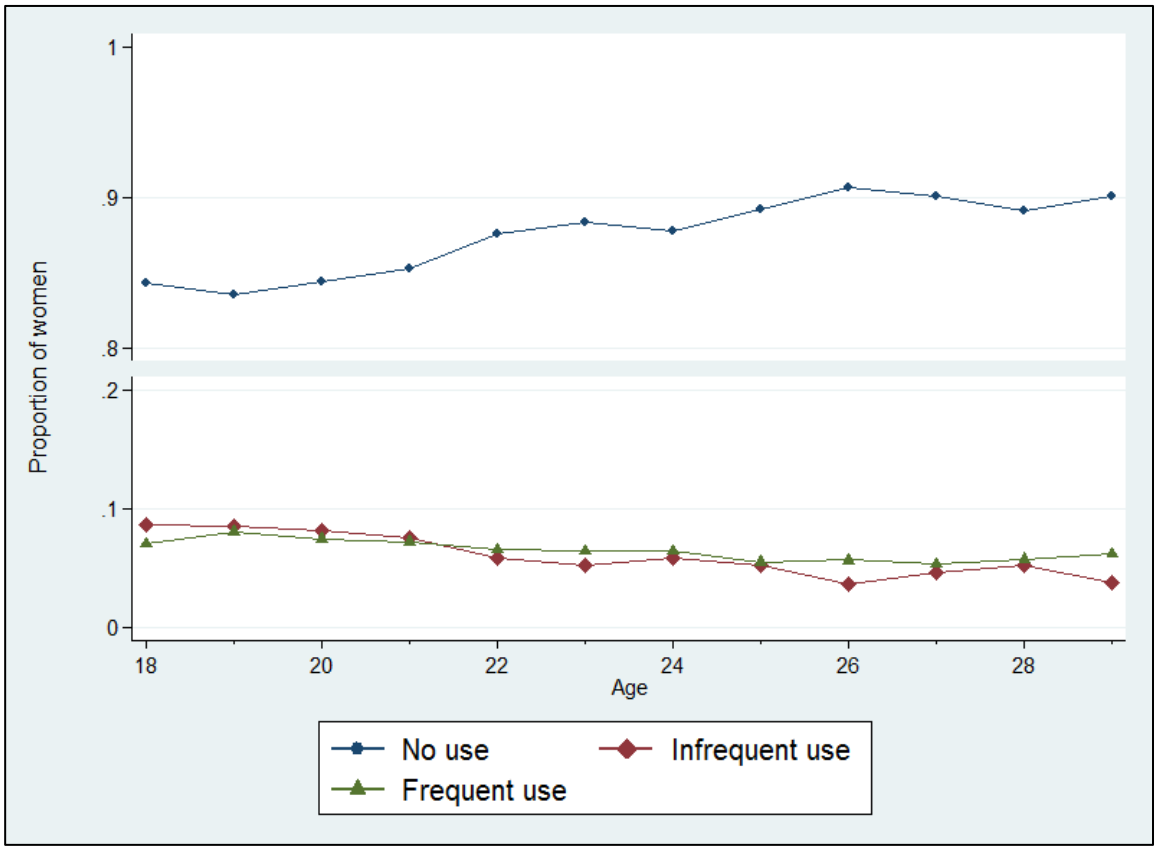

Figure 6. Proportion of Women in each Marijuana Use Categories

CHAPTER V

ECONOMETRIC MODEL

While sample means and trend lines provide an idea about variation in the data, those statistics do not identify a causal relationship between substance use, TANF eligibility, and TANF participation. Identifying a causal relationship requires more sophisticated techniques. This chapter begins with a conceptual discussion about how substance use may affect eligibility and/or participation, including a discussion of possible mechanisms through which substance use may act. The remainder of the chapter builds up the econometric models that I apply to the data discussed in Chapter IV.

Theoretical Considerations

Before we consider the econometric models, we should have a conceptual understanding of how eligibility, participation, alcohol use, and marijuana use should be modeled. This section discusses how eligibility is determined, how participation is typically modeled, and the ways through which substance use may affect eligibility and participation. Moving forward, "participation" should be understood to be "participation conditional on eligibility."

As was discussed in the context of data construction, eligibility depends on fertility and income, and there is evidence that substance use affects these behaviors. Substance use may affect fertility by increasing the probability of unprotected sex or out-of-wedlock births, which increases the probability of eligibility (Yamaguchi and Kandel 1987; Mensch and Kandel 1992; Kaestner 1996; Cooper 2002; Leigh 2002; Kingree and Betz 2003; Brown and

Vanable 2007; Scott-Sheldon, Carey, and Carey 2010). Substance use may also affect income by acting as a barrier to employment by decreasing job performance and the motivation to work which decreases income or the probability of employment (Aaronson and Hartmann 1996; Bloom 1997; Schmidt et al. 2002). Having less income increases the probability of eligibility.

In economics, participation is typically modeled as a utility maximization problem, where the woman participates if the utility of participating is greater than the utility of not participating (Moffitt 1983; Blank and Ruggles 1996; Hoynes 1996; Swann 2005). As described below, I take a non-structural approach to the participation decision and will not explicitly model utility. The remainder of this section discusses possible mechanisms through which substance use may affect participation.

The existing literature that has estimated the relationship between substance use and participation has considered several mechanisms. One hypothesized relationship is that substance use alters welfare stigma, or the distaste for participation. If substance use reduces stigma, then the probability of participation will increase. Some authors attempted to address this issue through the use of covariates that may be related to stigma. As discussed by Kaestner (1998), young adult substance users "have greater peer than parental influences, are less likely to attend religious services, have greater attitudinal tolerance for deviance, are more likely to participate in illegal activities, and are more likely to have low self-esteem" (see also Kandel 1980; Kandel 1982; Rosenbaum and Kandel 1990). These correlates would likely decrease the effect of stigma, which decreases the disutility of participation and increases the probability of participation. Another possibility is that these correlates increase the woman's

penchant for behaviors such as unprotected sex which would increase the probability of eligibility.

Kaestner (1998) also acknowledged the possibility of unobserved characteristics that are correlated with both substance use and participation. One unobserved characteristic that he discussed was preference for leisure. Substance use and leisure are complements (Kaestner 1994; Alexandre and French 2004; Cook and Peters 2005; West and Parry 2009; French et al. 2011), which means if one increases then the other increases as well. This suggests that substance use would increase the probability of eligibility through preferences for leisure.[14] Also, TANF benefits may allow a woman to have the same budget constraint, yet work less, which would grant her greater utility through a labor-leisure tradeoff. Given the correlation of the unobserved preference for leisure with both substance use and participation, substance use is likely to be endogenous in any model of participation.

Substance use may also affect human capital and/or market opportunities (Kaestner 1998; Schmidt et al. 2002). This follows from the argument above that substance use is a barrier to employment. While this is a popular argument, there are mixed results with respect to the relationship between substance use and job performance (Berger and Leigh 1988; French and Zarkin 1995; Ettner, Frank, and Kessler 1998; Bray 2005). Substance use may also affect the woman's motivation to search for employment. Based on the discussion in Schmidt et al. (2002), if there is an effect, then substance use would increase the probability of eligibility through human capital and/or market opportunities.[15]

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[14] Since income is a determinant of eligibility, leisure affects the eligibility outcome through changes in hours worked.

[15] Schmidt et al. (2002) actually stated that "the human capital perspective would lead us to hypothesize that, as compared with other welfare recipients, addicted recipients will have a lower probability of exiting welfare

Another mechanism discussed in Schmidt et al. (2002) is based on social capital, which they define as "the capacity to accumulate resources through membership in durable social networks in which money and resource-generative skills are shared" (223). The argument is that low-income households survive through social networks of family and friends that provide economic and in-kind support such as pooling income or helping with childcare (Stack 1974; Edin and Lein 1997; Edin and Harris 1999). Substance users are unlikely to maintain such social networks, "having exhausted their moral credit with family and friends" (Schmidt et al. 2002, 224). The discussion in Schmidt et al. (2002) suggested that substance use would increase the probability of participation through changes in social capital.

Schmidt et al. (2002) discussed one final mechanism, which was based on labeling and societal reaction theory. This argument states "substance abusers are more prone to repeat welfare dependency because welfare agencies and caseworkers who are less hospitable to people with alcohol and drug problems make their existence on welfare more precarious" (224). Here, substance use affects participation through the bureaucracy of TANF which requires the participant's adherence to program rules such as filing paperwork and participating in work-related activities. Substance users may actively resist or have difficulty adhering to these rules (Schmidt 1990; Schmidt et al. 2002). The discussion in Schmidt et al. (2002) suggested that substance use may decrease the probability of participation through labeling or societal reaction theory.

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for work reasons…" (223). This implied that substance use would increase the probability of "participation" in their study, but their definition of participation is not conditional on eligibility.

While the discussion so far has discussed several possible mechanisms through which substance use may affect eligibility and/or participation, I do not model these mechanisms explicitly. Instead, I estimate the effect of substance use on eligibility and participation using a non-structural approach, similar to the approach in Fitzgerald and Ribar (2004).

As discussed above and in Chapter III, there is concern that substance use may be endogenous in models of eligibility and participation due to the existence of unobserved characteristics (i.e., unobserved heterogeneity) that are correlated with substance use, eligibility, and participation. In my preferred specification (referred to as the "joint model" below), I address the potential endogeneity of substance use by jointly estimating models of eligibility, participation, alcohol use, and marijuana use and allowing the error term to be correlated across equations. While the joint model derived below is identified on functional form, the policy variables defined in Chapter IV are used as instruments in the substance use equations for additional identification. The models discussed below, including the joint model, are estimated using the aML software package (www.applied-ml.com).[16]

Outcome Variables

The two outcomes of interest for this dissertation are TANF eligibility $\left(E_{it}\right)$ and TANF participation conditional on being eligible $\left(P_{it}\right)$. Let E_{it} be a variable that equals 1 if woman *i* is eligible for TANF in period *t*. Let P_{it} be a variable that equals 1 if woman *i* is participating in TANF in period *t*, conditional on eligibility.

[16] Fitzgerald and Ribar (2004) use a similar approach to control for unobserved heterogeneity and address endogeneity. They also use aML to estimate their model of four equations as a system.

As described in previous chapters, I am interested in the effects of alcohol use and marijuana use on these outcomes. As discussed in above, alcohol and marijuana use are potentially endogenous. I address the potential endogeneity by jointly modeling eligibility, participation, alcohol use $\left(A_{it}\right)$ and marijuana use $\left(M_{it}\right)$. As described in Chapter IV, both alcohol use and marijuana use are modeled as ordered variables equal to 0 if no use, 1 if infrequent use, or 2 if frequent use for woman *i* in period *t*.

Eligibility and Participation

Although eligibility depends on fertility and income, I use a non-structural approach where I model eligibility without modeling fertility or income. To do this, I will use a latent variable framework. Let E_{it}^{*} be a latent index that represents woman *i*'s propensity to be program eligible in period *t* and is assumed to be a linear function of alcohol use, A_{it}, marijuana use, M_{it}, observed characteristics, X_{it} (k-by-1 vector), and unobserved characteristics, ε_{Eit}^{*}, such that

$$E_{it}^{*} = \alpha_{E1}1\left(A_{it}=1\right)+\alpha_{E2}1\left(A_{it}=2\right)+\beta_{E1}1\left(M_{it}=1\right)+\beta_{E2}1\left(M_{it}=2\right)+\gamma_{E}^{'}X_{it}+\varepsilon_{Eit}^{*}, \quad (1)$$

where 1(.) equals 1 if the condition in the parentheses is true and equals 0 otherwise. We assume that we observe $E_{it}=1\left(E_{it}^{*}>0\right)$. $\alpha_{E1}, \alpha_{E2}, \beta_{E1}, \beta_{E2}$ and the vector $\gamma_{E}^{'}$ are parameters to be estimated.

Conditional on being eligible, a woman may choose to participate in TANF or not, and this decision is assumed to depend on the net benefits of participation.[17] Let P_{it}^{*} be a latent index that represents woman *i*'s net benefit of participating in period *t*. This latent index is assumed to be a linear function of alcohol use, A_{it}, marijuana use, M_{it}, observed characteristics, X_{it} (k-by-1 vector), and unobserved characteristics, ε_{Pit}^{*}, such that

$$P_{it}^{*} = \alpha_{P1} 1\left(A_{it} = 1\right) + \alpha_{P2} 1\left(A_{it} = 2\right) + \beta_{P1} 1\left(M_{it} = 1\right) + \beta_{P2} 1\left(M_{it} = 2\right) + \gamma_{P}^{'} X_{it} + \varepsilon_{Pit}^{*}. \quad (2)$$

We assume that we observe $P_{it} = 1\left(P_{it}^{*} > 0\right)$. $\alpha_{P1}, \alpha_{P2}, \beta_{P1}, \beta_{P2}$ and the vector $\gamma_{P}^{'}$ are parameters to be estimated.

Substance Use

The decisions to use alcohol and marijuana may depend on unobserved characteristics (e.g., taste for leisure, motivation) that also determine eligibility and participation. If this is true, then they are endogenous variables. To allow for this possibility, I model alcohol and marijuana use.

The outcome of the decision to not use alcohol, to use alcohol infrequently, or to use alcohol frequently is modeled as an ordered choice. Let A_{it}^{*} be a latent index that represents woman *i*'s propensity to use alcohol in period *t* and is assumed to be a linear function of observed characteristics, X_{it} (k-by-1 vector), instruments, W_{it} (m-by-1 vector), and unobserved characteristics, η_{Ait}^{*}, such that

[17] Although I do not model it directly, the net benefit from participation can be thought of as equal to the utility when participating less the utility when not participating.

$$A_{it}^{*} = \delta_{A}^{'} Z_{it} + \eta_{Ait}^{*} , \tag{3}$$

where $Z_{it} = \begin{bmatrix} X_{it} & W_{it} \end{bmatrix}$. We observe

$$A_{it} = \begin{cases} 0 & if \quad 0 \le A_{it}^{*} < 1 \\ 1 & if \quad 1 \le A_{it}^{*} \le 3 \\ 2 & if \quad 3 < A_{it} \le 30 \end{cases} . \tag{4}$$

Typically, the cut points are unknown in an ordered logit model. However, in this case, the cut points in equation (4) are known as described in the discussion about the construction of the ordered alcohol use variable in Chapter IV.

Marijuana use is modeled similarly. Let M_{it}^{*} be a latent index that represents woman *i*'s propensity to use marijuana in period *t*, and is assumed to be a linear function of observed characteristics, X_{it} (k-by-1 vector), instruments, W_{it} (m-by-1 vector), and unobserved characteristics, η_{Mit}^{*}, such that

$$M_{it}^{*} = \delta_{M}^{'} Z_{it} + \eta_{Mit}^{*} . \tag{5}$$

We observe

$$M_{it} = \begin{cases} 0 & if \quad 0 \le M_{it}^{*} < 1 \\ 1 & if \quad 1 \le M_{it}^{*} \le 4 \\ 2 & if \quad 4 < M_{it}^{*} \le 30 \end{cases} . \tag{6}$$

Again, the known cut points in equation (6) reflect the construction of the ordered marijuana use variable discussed in Chapter IV.

Independent Models

Before presenting the complete likelihood function for the joint model, I will derive the likelihood function for the independent models. First, I begin with the likelihood function for the eligibility equation. From equation (1), define ε^*_{Eit} as follows:

$$\varepsilon^*_{Eit} = \xi_{Ei} + \varepsilon_{Eit}, \tag{7}$$

where $\xi_{Ei} \sim N\left(0, \sigma^2_{\xi_E}\right)$ and ε_{Eit} is distributed logistically. Let us begin by taking A_{it}, M_{it}, X_{it}, and ξ_{Ei} as given. Let

$$\begin{aligned}\Omega_{Eit} = {} & \alpha_{E1} 1\left(A_{it} = 1\right) + \alpha_{E2} 1\left(A_{it} = 2\right) \\ & + \beta_{E1} 1\left(M_{it} = 1\right) + \beta_{E2} 1\left(M_{it} = 2\right) + \gamma'_E X_{it} + \xi_{Ei}\end{aligned} \tag{8}$$

The likelihood function for woman *i* in period *t* is

$$\ell_{Eit}\left(E_{it} \middle| A_{it}, M_{it}, X_{it}, \xi_{Ei}, \alpha_{E1}, \alpha_{E2}, \beta_{E1}, \beta_{E2}, \gamma'_E\right) = \Lambda\left(\Omega_{Eit}\right)^{E_{it}} \times \left(1 - \Lambda\left(\Omega_{Eit}\right)\right)^{1-E_{it}}, \tag{9}$$

where Λ is the logit cumulative distribution function, $\Lambda(x) = \exp(x) / (1 + \exp(x))$. We can take the product over time to get the likelihood function for woman *i*:

$$\ell_{Ei}\left(E_{it}\middle|A_{it},M_{it},X_{it},\xi_{Ei},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E'\right)$$
$$=\prod_{t=1}^{T_i}\ell_{Eit}\left(E_{it}\middle|A_{it},M_{it},X_{it},\xi_{Ei},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E'\right), \tag{10}$$

where $\ell_{Eit}(\cdot)$ is given in equation (9). Notice that the product over time goes from $t=1$ to T_i. This is because I do not observe all women for the same number of years. Thus, the likelihood contribution for woman *i* may cover a different number of years than woman *j*.

Now, let us only treat A_{it}, M_{it}, and X_{it} as exogenous. I assume the woman knows ξ_{Ei}, but I, the econometrician, do not. I must allow for the fact that I do not know the woman's value of ξ_{Ei}. This leads us to a random effects logit model. Using Cameron and Trivedi (2005) and Wooldridge (2010) as guides, under the assumption that the unobserved effect is normally distributed, the likelihood function for woman *i* is now

$$\ell_{Ei}\left(E_{it}\middle|A_{it},M_{it},X_{it},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E',\sigma_{\xi_E}\right)$$
$$=\int_{-\infty}^{\infty}\ell_{Ei}\left(E_{it}\middle|A_{it},M_{it},X_{it},\xi_{Ei},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E'\right)\left(\frac{1}{\sigma_{\xi_E}}\right)\phi\left(\frac{\xi_{Ei}}{\sigma_{\xi_E}}\right)d\xi_{Ei}, \tag{11}$$

where $\ell_{Ei}\left(E_{it}\middle|A_{it},M_{it},X_{it},\xi_{Ei},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E'\right)$ is given in equation (10) and $\phi(\cdot)$ is the standard normal density function. Thus, I am integrating out the unobserved variable. Finally, take the product over all women. This gives the likelihood function for eligibility:

$$\ell_E\left(E_{it}\middle|A_{it},M_{it},X_{it},\alpha_{E1},\alpha_{E2},\beta_{E1},\beta_{E2},\gamma_E',\sigma_{\xi_E}\right)$$
$$=\prod_{i=1}^{N}\int_{-\infty}^{\infty}\left[\prod_{t=1}^{T_i}\Lambda\left(\Omega_{Eit}\right)^{E_{it}}\times\left(1-\Lambda\left(\Omega_{Eit}\right)\right)^{1-E_{it}}\right]\left(\frac{1}{\sigma_{\xi_E}}\right)\phi\left(\frac{\xi_{Ei}}{\sigma_{\xi_E}}\right)d\xi_{Ei}\ . \tag{12}$$

The same process can be applied to get the likelihood function for participation conditional on eligibility. This would be the likelihood function based on equation (2), where I define

$$\varepsilon_{Pit}^{*}=\xi_{Pi}+\varepsilon_{Pit} \tag{13}$$

where $\xi_{Pi}\sim N\left(0,\sigma_{\xi_P}^2\right)$ and ε_{Pit} is distributed logistically. To derive the likelihood function for participation conditional on eligibility, replace the *E*s in equations (9) through (12) with *P*s. Let

$$\begin{aligned}\Omega_{Pit}&=\alpha_{P1}1\left(A_{it}=1\right)+\alpha_{P2}1\left(A_{it}=2\right)\\&\quad+\beta_{P1}1\left(M_{it}=1\right)+\beta_{P2}1\left(M_{it}=2\right)+\gamma_P'X_{it}+\xi_{Pi}\ .\end{aligned} \tag{14}$$

The resulting likelihood function is

$$\ell_P\left(P_{it}\middle|A_{it},M_{it},X_{it},\alpha_{P1},\alpha_{P2},\beta_{P1},\beta_{P2},\gamma_P',\sigma_{\xi_P},E_{it}=1\right)$$
$$=\prod_{i=1}^{N}\int_{-\infty}^{\infty}\left[\prod_{E_{it}=1}\Lambda\left(\Omega_{Pit}\right)^{P_{it}}\times\left(1-\Lambda\left(\Omega_{Pit}\right)\right)^{1-P_{it}}\right]\left(\frac{1}{\sigma_{\xi_P}}\right)\phi\left(\frac{\xi_{Pi}}{\sigma_{\xi_P}}\right)d\xi_{Pi}\ , \tag{15}$$

where the $E_{it}=1$ under the product operator indicates that the product is to be calculated over all $t\in\left\{1,\ldots,T_i\right\}$ where $E_{it}=1$.

Now consider the alcohol use equation. From equation (3), define η^*_{Ait} as follows:

$$\eta^*_{Ait} = \xi_{Ai} + \eta_{Ait}, \tag{16}$$

where $\xi_{Ai} \sim N\left(0, \sigma^2_{\xi_A}\right)$ and η_{Ait} is distributed logistically. Again, let us begin by taking Z_{it} and ξ_{Ai} as given. The likelihood function for woman *i* is

$$\begin{aligned}\ell_{Ai}\left(A_{it} \middle| Z_{it}, \xi_{Ai}, \delta'_A\right) = \Bigg\{ & \prod_{t=1}^{T_i} \Lambda\left(1 - \delta'_A Z_{it} - \xi_{Ai}\right)^{1(A_{it}=0)} \\ & \times \left[\Lambda\left(3 - \delta'_A Z_{it} - \xi_{Ai}\right) - \Lambda\left(1 - \delta'_A Z_{it} - \xi_{Ai}\right)\right]^{1(A_{it}=1)} \\ & \times \left[1 - \Lambda\left(3 - \delta'_A Z_{it} - \xi_{Ai}\right)\right]^{1(A_{it}=2)} \Bigg\}\end{aligned} \tag{17}$$

Now, let us take only Z_{it} as exogenous. I assume the woman knows ξ_{Ai}, but I do not. I must allow for the fact that I do not know the woman's value of ξ_{Ai}, and as above I do this by integrating out the unobserved variable. This leads us to a random effects ordered logit model. The likelihood function for woman *i* is now

$$\ell_{Ai}\left(A_{it} \middle| Z_{it}, \delta'_A, \sigma_{\xi_A}\right) = \int_{-\infty}^{\infty} \ell_{Ai}\left(A_{it} \middle| Z_{it}, \xi_{Ai}, \delta'_A\right) \left(\frac{1}{\sigma_{\xi_A}}\right) \phi\left(\frac{\xi_{Ai}}{\sigma_{\xi_A}}\right) d\xi_{Ai}, \tag{18}$$

where $\ell_{Ai}\left(A_{it} \middle| Z_{it}, \xi_{Ai}, \delta'_A\right)$ is given in equation (17). Finally, take the product over all women. This gives the likelihood function for alcohol use:

$$\ell_A\left(A_{it}\middle|Z_{it},\delta'_A,\sigma_{\xi_A}\right)=\prod_{i=1}^{N}\int_{-\infty}^{\infty}\left\{\prod_{t=1}^{T_i}\Lambda\left(1-\delta'_A Z_{it}-\xi_{Ai}\right)^{1\left(A_{it}=0\right)}\right.$$
$$\times\left[\Lambda\left(3-\delta'_A Z_{it}-\xi_{Ai}\right)-\Lambda\left(1-\delta'_A Z_{it}-\xi_{Ai}\right)\right]^{1\left(A_{it}=1\right)} \quad . \quad (19)$$
$$\left.\times\left[1-\Lambda\left(3-\delta'_A Z_{it}-\xi_{Ai}\right)\right]^{1\left(A_{it}=2\right)}\right\}\left(\frac{1}{\sigma_{\xi_A}}\right)\phi\left(\frac{\xi_{Ai}}{\sigma_{\xi_A}}\right)d\xi_{Ai}$$

The same process can be applied to get the likelihood function for marijuana use. This would be the likelihood function based on equation (5), where I define

$$\eta^*_{Mit}=\xi_{Mi}+\eta_{Mit} \tag{20}$$

where $\xi_{Mi}\sim N\left(0,\sigma^2_{\xi_M}\right)$ and η_{Mit} is distributed logistically. To derive the likelihood function for marijuana use, replace the *A*s and 3 in equations (17) through (19) with *M*s and 4. The resulting likelihood function is

$$\ell_M\left(M_{it}\middle|Z_{it},\delta'_M,\sigma_{\xi_M}\right)=\prod_{i=1}^{N}\int_{-\infty}^{\infty}\left\{\prod_{t=1}^{T_i}\Lambda\left(1-\delta'_M Z_{it}-\xi_{Mi}\right)^{1\left(M_{it}=0\right)}\right.$$
$$\times\left[\Lambda\left(4-\delta'_M Z_{it}-\xi_{Mi}\right)-\Lambda\left(1-\delta'_M Z_{it}-\xi_{Mi}\right)\right]^{1\left(M_{it}=1\right)} \quad . \quad (21)$$
$$\left.\times\left[1-\Lambda\left(4-\delta'_M Z_{it}-\xi_{Mi}\right)\right]^{1\left(M_{it}=2\right)}\right\}\left(\frac{1}{\sigma_{\xi_M}}\right)\phi\left(\frac{\xi_{Mi}}{\sigma_{\xi_M}}\right)d\xi_{Mi}$$

The four likelihood functions in equations (12), (15), (19), and (21) are the estimable equations for the independent random effects logit and random effects ordered logit models. Parameter estimates for these independent models are presented in the next chapter. I next turn to the joint model.

Error Structure for the Joint Model

As discussed earlier, substance use may be endogenous to TANF eligibility and participation. To address the endogeneity of substance use, I use the following error structure with a person-specific common factor ξ_i:

$$\begin{aligned} \varepsilon^*_{Eit} &= \rho_E \xi_i + \varepsilon_{Eit} \\ \varepsilon^*_{Pit} &= \rho_P \xi_i + \varepsilon_{Pit} \\ \eta^*_{Ait} &= \rho_A \xi_i + \eta_{Ait} \\ \eta^*_{Mit} &= \xi_i + \eta_{Mit} \end{aligned}, \tag{22}$$

where ε_{Eit}, ε_{Pit}, η_{Ait}, and η_{Mit} have logistic distributions that are iid over individuals and time. The common factor, ξ_i, is a random effect that is iid over individuals and is independent of ε_{Eit}, ε_{Pit}, η_{Ait}, and η_{Mit}. This random effect captures person-specific unobserved heterogeneity. The ρ s are scalar loading parameters to be estimated. The model is estimated under the assumption that $\xi_i \sim N\left(0, \sigma^2_\xi\right)$.

Given the complexity of the joint model, I use the statistical program aML to conduct my estimation of both the independent and joint models. The default method for calculating standard errors in aML is known as the BHHH approximation (Berndt et al. 1974). Instead of using this method for calculating standard errors, I have aML calculate standard errors based on the "numerical Hessian" matrix. That is, I calculate standard errors based on numerical first derivatives of analytically computed first derivatives.

Likelihood Function for the Joint Model

In general, allowing a number of outcomes to have correlated errors is challenging. However, the factor structure of the error terms means that, conditional on ξ_i, the outcomes E_{it}, P_{it}, A_{it}, and M_{it} are independent. Given this, I can write the likelihood function for the joint model in terms of several independent probabilities. Let θ be a vector of the parameters to be estimated. For clarity, I need to derive the expressions for the following probabilities:

$$\Pr\left(E_{it}=0, A_{it}, M_{it} \middle| X_{it}, Z_{it}, \xi_i, \boldsymbol{\theta}\right) \tag{23}$$

and

$$\Pr\left(E_{it}=1, P_{it}, A_{it}, M_{it} \middle| X_{it}, Z_{it}, \xi_i, \boldsymbol{\theta}\right). \tag{24}$$

Notice that P_{it} does not appear in equation (23). This is because P_{it} is not defined (i.e., missing) when $E_{it}=0$. In both equations (23) and (24), A_{it} and M_{it} can take the values 0, 1, or 2. In equation (24), P_{it} can take the values 0 or 1. Altogether, there are 27 possible combinations of eligibility, participation, alcohol use, and marijuana use. Because of the factor structure, these 27 possible combinations depend on only 10 independent probabilities which are: eligible, not eligible, participating, not participating, no alcohol use, infrequent alcohol use, frequent alcohol use, no marijuana use, infrequent marijuana use, and frequent marijuana use. I will begin by deriving the 10 underlying probabilities. Let

$$\begin{aligned}\Psi_{Eit} &= \alpha_{E1}1\left(A_{it}=1\right)+\alpha_{E2}1\left(A_{it}=2\right)\\ &\quad+\beta_{E1}1\left(M_{it}=1\right)+\beta_{E2}1\left(M_{it}=2\right)+\gamma_E^{'}X_{it}+\rho_E\xi_i\end{aligned}, \tag{25}$$

then

$$\Pr\left(E_{it}=0\middle|X_{it},Z_{it},\xi_i,\theta\right)=1-\Lambda\left(\Psi_{Eit}\right) \tag{26}$$

and

$$\Pr\left(E_{it}=1\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(\Psi_{Eit}\right)\ . \tag{27}$$

Let

$$\begin{aligned}\Psi_{Pit} &= \alpha_{P1}1\left(A_{it}=1\right)+\alpha_{P2}1\left(A_{it}=2\right)\\ &\quad+\beta_{P1}1\left(M_{it}=1\right)+\beta_{P2}1\left(M_{it}=2\right)+\gamma_P^{'}X_{it}+\rho_P\xi_i\end{aligned}, \tag{28}$$

then

$$\Pr\left(P_{it}=0\middle|X_{it},Z_{it},\xi_i,\theta\right)=1-\Lambda\left(\Psi_{Pit}\right) \tag{29}$$

and

$$\Pr\left(P_{it}=1\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(\Psi_{Pit}\right)\ . \tag{30}$$

Turning to the alcohol equation, the three probabilities are

$$\Pr\left(A_{it}=0\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(1-\delta_A^{'}Z_{it}-\rho_A\xi_i\right), \tag{31}$$

$$\Pr\left(A_{it}=1\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(3-\delta_A'Z_{it}-\rho_A\xi_i\right)-\Lambda\left(1-\delta_A'Z_{it}-\rho_A\xi_i\right), \tag{32}$$

and

$$\Pr\left(A_{it}=2\middle|X_{it},Z_{it},\xi_i,\theta\right)=1-\Lambda\left(3-\delta_A'Z_{it}-\rho_A\xi_i\right). \tag{33}$$

Similarly for the marijuana probabilities:

$$\Pr\left(M_{it}=0\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(1-\delta_M'Z_{it}-\rho_M\xi_i\right), \tag{34}$$

$$\Pr\left(M_{it}=1\middle|X_{it},Z_{it},\xi_i,\theta\right)=\Lambda\left(4-\delta_M'Z_{it}-\rho_M\xi_i\right)-\Lambda\left(1-\delta_M'Z_{it}-\rho_M\xi_i\right), \tag{35}$$

and

$$\Pr\left(M_{it}=2\middle|X_{it},Z_{it},\xi_i,\theta\right)=1-\Lambda\left(4-\delta_M'Z_{it}-\rho_M\xi_i\right). \tag{36}$$

Conditional on ξ_i, the joint probabilities in equations (23) and (24) are products of the underlying probabilities in equations (26) through (36). Using the 10 underlying probabilities, the likelihood contribution for person *i* conditional on ξ_i is

$$
\begin{aligned}
&\mathcal{L}_i\left(\theta \middle| E_{it}, P_{it}, A_{it}, M_{it}, X_{it}, Z_{it}, \xi_i\right) = \\
&\prod_i^{T_i}\Big[\Lambda\left(\Psi_{Eit}\right)^{E_{it}}\left(1-\Lambda\left(\Psi_{Eit}\right)\right)^{\left(1-E_{it}\right)}\Lambda\left(\Psi_{Pit}\right)^{P_{it}E_{it}}\left(1-\Lambda\left(\Psi_{Pit}\right)\right)^{\left(1-p_{it}\right)E_{it}} \\
&\quad \Lambda\left(1-\delta_A' Z_{it}-\rho_A\xi_i\right)^{1\left(A_{it}=0\right)}\left(\Lambda\left(3-\delta_A' Z_{it}-\rho_A\xi_i\right)-\Lambda\left(1-\delta_A' Z_{it}-\rho_A\xi_i\right)\right)^{1\left(A_{it}=1\right)} \\
&\quad \left(1-\Lambda\left(3-\delta_A' Z_{it}-\rho_A\xi_i\right)\right)^{1\left(A_{it}=2\right)}\Lambda\left(1-\delta_M' Z_{it}-\rho_M\xi_i\right)^{1\left(M_{it}=0\right)} \\
&\quad \left(\Lambda\left(4-\delta_M' Z_{it}-\rho_M\xi_i\right)-\Lambda\left(1-\delta_M' Z_{it}-\rho_M\xi_i\right)\right)^{1\left(M_{it}=1\right)} \\
&\quad \left(1-\Lambda\left(4-\delta_M' Z_{it}-\rho_M\xi_i\right)\right)^{1\left(M_{it}=2\right)}\Big]
\end{aligned}
\quad . \quad (37)
$$

I can then write the likelihood contribution for woman *i* that accounts for the fact that ξ_i is unobserved as

$$
\mathcal{L}_i\left(\theta \middle| E_{it}, P_{it}, A_{it}, M_{it}, X_{it}, Z_{it}\right) = \int_{-\infty}^{\infty} \mathcal{L}_i\left(\theta \middle| E_{it}, P_{it}, A_{it}, M_{it}, X_{it}, Z_{it}, \xi_i\right)\left(\frac{1}{\sigma_\xi}\right)\phi\left(\frac{\xi_i}{\sigma_\xi}\right)d\xi_i \,. \quad (38)
$$

Finally, the likelihood function for the joint model is the product of $\mathcal{L}_i\left(\theta \middle| E_{it}, P_{it}, A_{it}, M_{it}, X_{it}, Z_{it}\right)$ over the sample observations:

$$
\mathcal{L}\left(\theta \middle| E, P, A, M, X, Z\right) = \prod_{i=1}^{N} \mathcal{L}_i\left(\theta \middle| E_{it}, P_{it}, A_{it}, M_{it}, X_{it}, Z_{it}\right), \quad (39)
$$

where E is the vector of E_{it} stacked for *i* and *t*, and similarly for the other arrays.

In this chapter I derived five likelihood functions. One likelihood function is derived for each of the four outcome variables: eligibility, participation, alcohol use, and marijuana use. These likelihood functions are presented in equations (11), (15), (18), and (21),

respectively. One likelihood function is derived for the joint model—equation (39). The coefficient estimates for each of these likelihood functions are presented in the next chapter.

CHAPTER VI

RESULTS

Before presenting results of the joint model, I begin by presenting prevalence rates for substance use based on eligibility and participation statuses. I next discuss results from the independent models presented in equations (12), (15), (19), and (21) of Chapter V. These results can be compared to a degree to the existing literature. Finally, I discuss estimates of the joint model presented in equation (39) of Chapter V.

Descriptive Analysis

Mirroring most of the discussion in Chapter III, I begin by presenting substance use prevalence rates between eligibility and participation statuses. Table 6 contains sample means for substance use for all person-years in which women are eligible and ineligible. The sum of TANF ineligible years (24,396) and TANF eligible years (5,398) is the full sample (29,794). Tests for differences in means are calculated between eligibility statuses. These differences are intended to depict substance use variation between TANF ineligible and eligible person-years.

Eligible women are less likely to use alcohol than ineligible women. Sixty-three percent of TANF ineligible person-years are from women who drink, compared to the 38 percent of TANF eligible person-years. Ineligible women are more likely than eligible women to be both infrequent and frequent alcohol users. The same patterns are present for marijuana use. Fourteen percent of ineligible person-years are from women who use marijuana, compared to the eight percent of eligible person-years. Ineligible women are more

likely than eligible women to be both infrequent and frequent marijuana users. This suggests a negative relationship between TANF eligibility and substance use. Specifically, since these differences are by eligibility status, this suggests that eligibility might be associated with a decrease in substance use.

Next, I look at the differences in substance use prevalence rates by participation statuses, conditional on eligibility. Table 7 contains sample means for substance use for all person-years in which women are participants or non-participants, conditional on eligibility. The sum of TANF non-participant years (4,563) and TANF participant years (635) is the number of TANF eligible years (5,398). Tests for differences in means are calculated between participation statuses. These differences between participation statuses will depict substance use variation between TANF participant and non-participant person-years. These results may be compared to the prevalence results discussed in Chapter III.

We see an immediate difference between the substance use means in Tables 6 and 7. Participants are more likely to use alcohol or marijuana than non-participants. Looking at the levels of use, participants are more likely to be frequent alcohol users or infrequent marijuana users. While there are differences in the prevalence of use between participants and non-participants, it is important to note that less than half of the person-years are from participating women who use alcohol (42 percent), and only 13 percent of person-years are from participating women who use marijuana. The rate for alcohol use is less than the 61 to 67 proportion in other studies (Jayakody, Danziger, and Pollack 2000; Pollack and Reuter 2006). This difference may be due to the number of women who are 18 to 20 in my sample. The rate of marijuana use in Table 7 is similar to the lower bound of prevalence rates discussed in Chapter III, which ranged from 10 to 30 percent of recipients.

The prevalence rates presented in Tables 6 and 7 do not provide any indication as to how substance use might affect eligibility or participation. To get some idea about the association between substance use, eligibility, and participation, I next examine how eligibility, participation, and other characteristics differ by substance use categories. These associations can be compared to the conceptual relationships discussed in Chapter V, and they will shape our expectations of the independent and joint models results.[18] Table 8 contains sample means for each alcohol use category. The sum of no alcohol users (12,394), infrequent alcohol users (8,676), and frequent alcohol users (8,724) is the full sample (29,794). Two tests for differences in means are calculated. The first test is between "no alcohol use" and "infrequent alcohol use," and the second test is between "no alcohol use" and "infrequent alcohol use."

Alcohol use seems to have a negative association with eligibility and a positive association with participation conditional on eligibility. According to the differences in means in Table 8, alcohol non-users are twice as likely to be eligible than infrequent alcohol users. Alcohol non-users are three times as likely to be eligible than frequent alcohol users. The opposite relationship is present for participation, where frequent alcohol users are more likely to participate than alcohol non-users though there is no statistically significant difference between non-users and infrequent users.

Turning to the policy variables, alcohol users are more likely to live in states where medical marijuana is legal, and infrequent alcohol users are more likely to live in states where marijuana is decriminalized. Alcohol users are more likely to live in states with lower beer

[18] Specifically, the conceptual relationships were discussed in the first section of Chapter V. Based on that discussion we expect substance use to increase the probability of eligibility. While substance use is expected to increase the probability of participation through most mechanisms, there was one described mechanism through which substance use might decrease participation. This makes the direction of the effect unclear.

taxes. Surprisingly, alcohol users are more likely to live in states with higher cigarette taxes and higher spirits taxes. I might expect cigarette taxes and spirits taxes to have smaller means among alcohol users, like we saw with beer taxes, because cigarettes are a complement to alcohol and spirits are another type of alcohol (Decker and Schwartz 2000; Cameron and Williams 2001). However, I am only examining bivariate relationships at this point, and these relationships may change in a multivariate analysis.

Turning now to the demographic and geographic characteristics, alcohol users are more likely to be white, while alcohol non-users are more likely to be black, Hispanic, or other race/ethnicity. Alcohol users are more likely to be older than alcohol non-users. This is not surprising because older women, especially women who are 21 or older, have easier access to alcohol. Alcohol users have more years of education. Alcohol non-users are more likely to have less than a high school diploma, while alcohol users are more likely to have at least a high school diploma or GED. These differences in means for education make sense since education is highly correlated with age in this sample. Alcohol users are more likely to live in states with lower unemployment rates, more likely to live in an urban residence, and less likely to live in the South.

I now turn to marijuana use to look at differences in means across marijuana use levels and to make comparisons to the differences in means shown in Table 8. Again, the associations in the next table will shape our expectations of the independent and joint models results. Table 9 contains sample means for each marijuana use category. The sum of no marijuana users (25,800), infrequent marijuana users (1,985), and frequent marijuana users (2,009) is the full sample. Two tests for differences are calculated. The first test is between

"no marijuana use" and "infrequent marijuana use," and the second test is between "no marijuana use" and "frequent marijuana use."

Similar to alcohol use, marijuana use appears to have a negative association with eligibility and a positive association with participation conditional on eligibility. According to the differences in means in Table 9, marijuana non-users are more likely to be eligible than marijuana users. The opposite relationship is present for participation, where marijuana non-users are less likely to be participants than marijuana users. These relationships are contrary to the expected relationship discussed in Chapter V between substance use and eligibility where we expected marijuana users to be more likely to be eligible, but they are consistent with the expected relationship discussed in Chapter V between substance use and participation.

Considering the differences in means for the policy variables, we see that infrequent marijuana users are more likely to live in states where medical marijuana is legal or in states with lower spirits taxes. Both marijuana use groups are more likely to live in states with lower beer taxes and higher cigarette taxes. These associations with the states taxes suggest that marijuana use might be a complement to alcohol and a substitute to cigarettes.

Moving lastly to the demographic and geographic characteristics, marijuana users are more likely to be white, while marijuana non-users are more likely to be black or Hispanic. Marijuana users are more likely to be younger than non-users. Marijuana users are more likely to have less education. Infrequent marijuana users are less likely to have less than a high school degree, while both marijuana use groups are more likely to have a high school degree or GED. Marijuana users are less likely to have at least a 4-year college degree.

Marijuana users are more likely to live in states with lower unemployment rates, more likely to live in an urban residence, and less likely to live in the South.

One difference between Tables 8 and 9 is the different means between infrequent and frequent use.[19] That is, there is a different pattern of the eligibility and participation means by infrequent and frequent alcohol use (Table 8) compared to the pattern for marijuana use (Table 9). In Table 8, 14 percent of infrequent alcohol use person-years are from eligible women, compared to nine percent of frequent alcohol use person-years. Twelve percent of infrequent alcohol use person-years are from participating women, compared to 15 percent of frequent alcohol use person-years. In Table 9, 12 percent of infrequent and frequent marijuana use person-years are from eligible women. Eighteen percent of infrequent marijuana use person-years are from participating women, compared to 16 percent of frequent marijuana use person-years.

These different means between infrequent and frequent use suggest the following. First, infrequent alcohol use might have a larger effect than frequent alcohol use on eligibility in the independent or joint models. Second, frequent alcohol use might have a larger effect than infrequent alcohol use on participation. Third, infrequent and frequent marijuana use might have about the same effect on eligibility. Fourth, infrequent marijuana use might have a larger effect than frequent marijuana use on participation.

The means presented in Tables 8 and 9 provide insight into how alcohol and marijuana use might be associated with different covariates. The relationship between eligibility, participation, alcohol use, and marijuana use suggests that substance decreases the probability of eligibility and increases the probability of participation. While the relationship

[19] Keep in mind that tests for differences in means are not calculated between infrequent and frequent use.

between eligibility and substance use suggested by Tables 8 and 9 are contrary to the expected relationship from Chapter V, these differences in means are only associations. The relationship between participation and substance use, as suggested by Tables 8 and 9, is consistent with the existing literature, although the existing literature does not account for unobserved characteristics (e.g., Kaestner 1998). When we move to the multivariate results, we may or may not see different relationships.

Similar to the summary statistics discussed in Chapter IV, Tables 8 and 9 present only means over the entire sample of person-years. These four tables do not provide any indication of how eligibility, participation, alcohol use, and marijuana use vary over time. Figures 7 through 10 present the proportions of eligible and participating women by alcohol and marijuana groups. Recall from Chapter IV that the sample size declines quickly after age 24, dropping below 1,000 women after age 27. Also, the sample size of participating women is less than 1,000 at all ages. Thus, I expect volatility in the following figures after age 27 for TANF eligible women, and across all ages for TANF participating women. Similar to Chapter IV, the purpose of these figures is to shape our understanding of how substance use might affect eligibility and participation as women age. This will lead to better informed expectations when we review the results of the independent and joint models.

Figure 7 plots the proportion of TANF eligible women by alcohol use groups. The line with round bullets plots the proportion of TANF eligible women who do not use alcohol. In other words, this line represents the eligibility rate among alcohol non-users. The line with diamond shaped bullets plots the proportion of eligible women who use alcohol infrequently. The line with triangular bullets plots the proportion of eligible women who use alcohol frequently. Ignoring age 29, eligibility is more common among alcohol non-users

than among infrequent or frequent users, and eligibility is more common among infrequent alcohol users than frequent alcohol users. With the exception of ages 20 through 22 and 29, the proportion eligible is about 5 percentage points greater for infrequent alcohol users than frequent alcohol users. Overall, the trends in this figure suggest that alcohol use may decrease the probability of eligibility, which is consistent with the differences in means from Table 8, but inconsistent with the expected relationship from Chapter V.

Figure 8 plots the proportion of TANF eligible women by marijuana use groups. The line with round bullets plots the proportion of TANF eligible women who do not use marijuana. The line with diamond shaped bullets plots the proportion of eligible women who use marijuana infrequently. The line with triangular bullets plots the proportion of eligible women who use marijuana frequently. Ignoring age 29, eligibility is more common among non-marijuana users than infrequent or frequent marijuana users. At age 26, the proportions are almost identical for non-marijuana users and infrequent marijuana users. In general, the proportion eligible stays around 20 percent, with a proportion closer to 15 percent at age 18 and 26. There is considerable variation for the proportion eligible between the infrequent and frequent use groups. The volatility in these graphs is likely due to the small number of women who are in the infrequent and frequent marijuana use groups. The trends in this figure make it difficult to predict what relationship might exist between marijuana use and eligibility. While there is volatility in the infrequent and frequent use plots, the non-use line is above the infrequent and frequent lines at every age. This suggests that marijuana use may decrease the probability of eligibility, which is consistent with the differences in means in Table 9, but inconsistent with the expected relationship from Chapter V.

Figure 9 plots the proportion of TANF participating women by alcohol use groups. The line with round bullets plots the proportion of TANF participating women who do not use alcohol. The line with diamond shaped bullets plots the proportion of participating women who use alcohol infrequently. The line with triangular bullets plots the proportion of participating women who use alcohol frequently. Remember, TANF participation is conditional on eligibility. This means the total sample size is smaller, and thus the sample size for each group is small. Figure 9 is a much different picture than Figure 7. In general, all of the proportions are close among the three groups. At ages 20, 21, 24, and 25, the proportion participating for frequent alcohol users is greater than the proportion for the other two groups. Overall, alcohol non-use is typically less than one or both of the alcohol use proportions. This suggests that alcohol use might increase participation, which is consistent with the differences in means in Table 8.[20]

Figure 10 plots the proportion of TANF participating women by marijuana use groups. The line with round bullets plots the proportion of TANF participating women who do not use marijuana. The line with diamond shaped bullets plots the proportion of participating women who use marijuana infrequently. The line with triangular bullets plots the proportion of participating women who use marijuana frequently. There is considerable variation in the participation rate among infrequent and frequent marijuana users. Again, this is due to the small sample sizes. The proportion participating for non-marijuana users has an upward trend, beginning around eight percent and ending around 15 percent. Since, marijuana non-use is typically less than one or both of the marijuana use proportions, this

[20] Again, there was no clear expected relationship between substance use and participation from Chapter V.

figure suggests that marijuana use might increase participation. The relationship implied by this figure is consistent with the differences in means in Table 9.

The information presented in Figures 7 through 10 helps us understand variation in eligibility and participation by substance use as the women age. All of the results discussed to this point are of bivariate relationships. I next turn to models that allow for multiple characteristics to simultaneously affect eligibility and participation.

Independent Models

As a first step, I estimate independent random effects logit models of TANF eligibility and participation and independent random effects ordered logit models of alcohol and marijuana use based on the likelihood functions in Chapter V from equations (12), (15), (19), and (21), respectively. Table 10 presents the random effects logit estimates for the independent TANF eligibility and participation equations. Likelihood ratio (LR) test statistics for joint significance are found at the bottom of Table 10.

Each substance use measure is statistically significant and negative in the eligibility equation. The negative signs are consistent with the descriptive analysis above (i.e., Tables 8 and 9, and the figures). Frequent use is estimated to have a larger effect than infrequent use for both substances. This is not surprising because I expect a higher frequency of use to have a greater impact on the choices a women might make that would result in eligibility. Frequent alcohol use has the largest effect. Interestingly, the effects for alcohol use are larger than for marijuana use, where (in)frequent alcohol use has a larger estimated effect than (in)frequent marijuana use.

Shifting to the participation equation, all of the coefficient estimates are positive, but only infrequent marijuana use is statistically significant. Not surprisingly, the LR tests suggest

that the alcohol use measures are not jointly significant, but the marijuana use measures and all four substance use measures are jointly significant at the five percent level. This suggests that alcohol use may not have an impact on participation conditional on eligibility, except through its effect on eligibility. This also suggests the probable importance of infrequent marijuana use because this single variable is contributing to the joint significance suggested by the LR test.

The substance use results for participation in Table 10 are similar to those found in the existing literature.[21] Alcohol use has a positive coefficient, but it is not statistically significant. Jayakody and colleagues (2000) reported statistically insignificant and positive coefficient estimates. Other authors have found negative though generally statistically insignificant effects. Kaestner (1998) reported negative coefficients for alcohol use for both black and non-black women, and those estimates generally were not statistically significant.[22] The papers written by Schmidt with various colleagues (Schmidt, Weisner, and Wiley 1998; Schmidt et al. 2002; Schmidt et al. 2007) reported statistically insignificant and negative coefficient estimates for alcohol use.

Turning to marijuana use, Table 10 showed positive coefficients though only infrequent marijuana use is statistically significant. Kaestner (1998) reported similar statistically significant coefficients on marijuana use for non-black women, and the coefficients in the model for black women were positive but generally statistically insignificant. The other studies that investigated the relationship between substance use and participation did not explicitly include marijuana use. Instead, those studies used a single

[21] One difference between my results and the results in the previous literature is that I am using random effects models that allow for unobserved person-specific heterogeneity while previous studies do not.

[22] The statistically significant coefficients for alcohol use are negative. There are two positive coefficients, which are essentially zero: 0.0002 and 0.0003 (both with a standard error of 0.0003)

variable that grouped marijuana use with other substance use.[23] Their estimates were mixed and statistically insignificant (Schmidt, Weisner, and Wiley 1998; Jayakody, Danziger, and Pollack 2000; Schmidt et al. 2002; Schmidt et al. 2007).

The coefficients on the demographic and geographic characteristics generally have the expected signs given the existing literature. Black women are more likely to be eligible and more likely to participate conditional on being eligible than white women. Hispanic women are more likely to be eligible than white women. Older women are more likely to be eligible or to participate. Women with at least a high school degree are less likely to be eligible or to participate than women with less than a high school diploma. The unemployment rate is associated with an increased probability of eligibility and a decreased probability of participation (although the coefficient on participation is not statistically significant). Women living in an urban residence are more likely to participate than women in rural residences, while women living in the South are less likely to participate than women living in other regions.

The two equations in Table 10 are random effects logit models. The estimate of the standard deviation of the random effect is statistically significant in both equations, which suggests that unobserved heterogeneity is an important addition to estimating eligibility and participation equations.

By themselves, these results address one issue in the literature relating substance use to TANF participation in that the participation model is estimated for only eligible women. The models also allow for unobserved heterogeneity. However, the independent models of

[23] These "other substances" included alcohol use in some cases (e.g., Schmidt et al. 2002). In other cases, "other substances" did not include alcohol use, but did include heroin (e.g., Jayakody, Danziger, and Pollack 2000).

eligibility and participation treat substance use as exogenous when, as discussed in Chapters III and V, there is reason to believe substance use and TANF eligibility and participation may all depend on some common unobserved factors. As discussed in Chapter V, I will address the endogeneity by modeling eligibility, participation, alcohol use, and marijuana use jointly. In order to confirm that I can reliably model alcohol and marijuana use and to provide comparison to the joint results discussed later, I turn to the results of independent models of alcohol and marijuana use. The results for these models are presented in Table 11.

Although the joint model is identified solely on the functional forms chosen for the error terms, I incorporate instrumental variables in the analysis. As discussed in Chapter IV, I refer to these as "policy variables". The policy variables are of particular interest in these substance use results since these are excluded from the eligibility and participation equations. Only state beer tax and marijuana decriminalization are negative and statistically significant predictors of alcohol use. State cigarette and spirits taxes are also negative, although insignificant. I expect negative signs for the tax variables because increases in these taxes should reduce the likelihood that the woman uses alcohol. Since cigarettes and alcohol are complements, a higher cigarette tax should decrease cigarette use and alcohol use (Decker and Schwartz 2000; Cameron and Williams 2001). Higher beer and spirits taxes increase the price of alcohol, which decreases alcohol use. The negative sign on marijuana decriminalization suggests that alcohol and marijuana are substitutes.

The state beer taxes and state spirits taxes are statistically significant predictors of marijuana use. Although not statistically significant, the positive coefficient on state beer taxes suggests that marijuana and beer are substitutes, while the negative coefficient on state spirits tax suggests that marijuana and spirits are complements. There are mixed results on

the demand for marijuana with respect to alcohol taxes, where some findings suggested alcohol and marijuana are substitutes and others suggested that the substances are complements (DiNardo and Lemieux 1992; Chaloupka and Laixuthai 1994; Pacula 1998).[24]

Considering joint significance, the LR test for the five policy variables in the alcohol equation suggests that the policy variables are jointly significant at the five percent level. The policy variables are not jointly statistically significant in the marijuana equation. This suggests that while two of the variables are statistically significant on their own, the policy variables might not be strong predictors of marijuana use. These results of the LR tests suggest that we will need to pay attention to the significance of the policy variables in the joint model.

A number of socioeconomic variables are associated with substance use. Each race/ethnicity variable (black, Hispanic, and other race/ethnicity) is negatively associated with substance use. In other words, white women are more likely to use alcohol or marijuana. A high school diploma or GED is positively associated with substance use, while a 4-year college degree is positively associated with alcohol use only. Age is positively associated with alcohol use, but it is negatively associated with marijuana use. The unemployment rate is negatively associated with alcohol use only. Living in an urban residence is positively associated with substance use, while living in the South is negatively associated with substance use. These signs of these covariates are consistent with previous research exploring the determinants of substance use (DeSimone 2002).

The two equations in Table 11 are random effects ordered logit models, and the standard deviation of the random effect is statistically significant in both equations. This means that unobserved heterogeneity is an important addition to estimating alcohol and

[24] Unfortunately, these studies do not distinguish between types of alcohol (e.g., beer or spirits).

marijuana use equations. The estimates in Tables 10 and 11 are from models that allow for unobserved heterogeneity, but these models continue to treat substance use as exogenous.

Joint Model

In order to address the potential endogeneity of alcohol and marijuana use, I now turn to the joint model presented in equation (39) of Chapter V. The results of this model are presented in Tables 12 through 14. I begin by considering the estimated factor loadings and the standard deviation of the unobserved heterogeneity, as these estimates establish the validity of the joint model.

Table 12 presents the coefficient estimates for the factor loadings and the standard deviation of the unobserved heterogeneity. The factor loadings are ρ_E, ρ_P, and ρ_A from equation (22) in Chapter V. While any factor loading could have been normalized to one, I normalize the factor loading on marijuana to one. This allows for the interpretation of the free factor loadings relative to marijuana use. This seems appropriate given the current policy interests in drug testing. All three estimated factor loadings and the estimate of the standard deviation of the unobserved heterogeneity are statistically significant, which highlights the importance of jointly modeling eligibility, participation, alcohol use, and marijuana use.

The estimates of the ρ's suggest that unobserved factors that increase the probability of marijuana use also decrease the probability of eligibility, increase the probability of participation, and increase the probability of alcohol use. The direction of these effects can also be explained in terms of the six correlations between the composite error terms discussed in Chapter V. The factor loading results in Table 12 imply the following:

$$\begin{array}{ll} \mathrm{Corr}\left(\varepsilon^*_{Eit}, \varepsilon^*_{Pit}\right) < 0 & \mathrm{Corr}\left(\varepsilon^*_{Pit}, \eta^*_{Ait}\right) > 0 \\ \mathrm{Corr}\left(\varepsilon^*_{Eit}, \eta^*_{Ait}\right) < 0 & \mathrm{Corr}\left(\varepsilon^*_{Pit}, \eta^*_{Mit}\right) > 0 \\ \mathrm{Corr}\left(\varepsilon^*_{Eit}, \eta^*_{Ait}\right) < 0 & \mathrm{Corr}\left(\eta^*_{Ait}, \eta^*_{Mit}\right) > 0 \end{array},$$

where the correlation at the top left is interpreted as a negative correlation between the composite error term for the eligibility equation and the composite error term for the participation equation and the other correlations can be interpreted similarly.

The unobserved heterogeneity term captures the relationship (relative to marijuana use) between unobserved characteristics and eligibility, participation, and alcohol use. Since these characteristics are not observed, it is difficult to know what these characteristics might be. The unobserved characteristic or characteristics should increase the probability of eligibility, decrease the probability of participation conditional on eligibility, and decrease substance use.[25]

One possible source of unobserved heterogeneity is preference for leisure. From the discussion in Chapter V, women with a greater preference for leisure are more likely to use substances because substance use is a complement to leisure. This story is consistent with the estimated factor loadings for alcohol and marijuana in Table 12. Unfortunately, we expect women with a greater preference for leisure to be more likely to be eligible and to participate conditional on eligibility. Thus, preference for leisure is unlikely to be the sole source of the unobserved heterogeneity.

Although not discussed in Chapter V, mental health may affect eligibility, participation and substance use. Poor mental health is correlated with higher levels of

[25] Another type of variable that would fit would be one that decreased the probability of eligibility, increased the probability of participation conditional on eligibility, and increased substance use.

substance use (e.g., depression and alcohol use). Poor mental health is also correlated with inconsistent employment patterns, which suggests poor mental health would increase the probability of eligibility. Thus, mental health is unlikely to be the sole source of the unobserved heterogeneity. Another possible source that was not covered in Chapter V is religiosity, which can be thought of as measuring how devout a woman is. A more devout woman might be less likely to engage in behaviors such as unprotected sex which would decrease the probability of eligibility. A more devout woman might also be less likely to use substances for the same reason, also decreasing the probability of substance use. This contradicts the negative correlation between the eligibility and substance use composite error terms. Thus, religiosity is unlikely to be the sole source of unobserved heterogeneity.

The negative correlation between the eligibility and participation composite error terms is an interesting result. Unfortunately, it is difficult to think of a single unobserved variable might lead to the negative correlation. It is entirely possible, however, that a combination of these (or other) explanations could lead to the observed result. Regardless of the specific unobserved variables, we can discuss the relative magnitude of the factor loadings, which informs us of the degree to which unobserved determinants affect the TANF outcomes and alcohol use relative to marijuana use. Specifically, while the unobserved characteristics that increase marijuana use also decrease probability eligibility, these characteristics do not decrease eligibility as much as they increase marijuana use. This is because the coefficient estimates for the factor loadings are smaller in magnitude than one, the forced factor loading on marijuana use. The coefficient estimate on the alcohol use factor loading is the largest, implying that the unobserved characteristics have a stronger effect on alcohol use than on the TANF outcomes.

Table 13 presents the random effects logit estimates of the TANF equations in the joint model, with LR test statistics of joint significance found at the bottom of the table. The coefficients on all of the substance use variables are positive in the eligibility equation, but only the marijuana use coefficients are statistically significant. We can convert the coefficient estimates into odds ratios by calculating $\exp(b)$, where b is the coefficient of interest. Although they are technically changes in odds, odds ratios are frequently interpreted as changes in probabilities. Converting to odds ratios, infrequent marijuana users are 1.85 times as likely to be eligible than non-users, and frequent marijuana users are 2.81 times as likely to be eligible than non-users, all else equal.

This is a considerable change compared to the results in the independent eligibility equation where every substance use variable was negative and statistically significant. Recall that unobserved person-specific factors that increase marijuana use also decrease eligibility. These results from the joint model imply that the negative effect of marijuana in the eligibility equation in the independent model is capturing both the effect of marijuana and the effect of the unobserved characteristics that affect both eligibility and marijuana. After accounting for the negative relationship between the unobserved heterogeneity across the two equations, the estimated effect of marijuana on eligibility is positive. While the coefficients on the alcohol use variables are not statistically significant individual or jointly statistically significant, the four substance use variables are jointly statistically significant.

The results in the joint model reflect the expected causal relationship between substance use and eligibility, where I expected substance use to increase the probability of eligibility by: (1) increasing the probability of unprotected sex or out-of-wedlock children, and/or (2) acting as a barrier to employment.

As with the independent participation model, infrequent marijuana use is still the only statistically significant substance use variable in the participation equation. However, compared to the independent participation model, the substance use coefficient estimates change considerably. The coefficient estimate for infrequent alcohol use is cut by more than two-thirds. The coefficient estimate for frequent alcohol use is cut by more than one-half. The coefficient estimate for infrequent marijuana use is cut by almost one-half. The coefficient estimate for frequent marijuana use is now negative. Again, recall that unobserved person-specific factors that increase marijuana use also increase participation. This suggests that independent models of the effect of substance on TANF participation would likely have inflated coefficient estimates.

While infrequent marijuana use is statistically significant, the LR tests suggest that the substance use variables are not jointly significant as pairs or collectively. The joint statistical insignificance of the substance use variables suggests that the effect of substance use on participation is primarily through the effect of substance use on eligibility.

Table 14 presents the random effects ordered logit results for the substance use equations in the joint model, with an LR test for joint significance of the policy variables found at the bottom of the table. While all of the policy variables are negative in the alcohol use equation, only the cigarette tax is statistically significant. Compared to the independent equation, the sign on medical marijuana has changed, the state beer tax and marijuana decriminalization are no long statistically significant, and the state cigarette tax is now statistically significant. The state beer tax and state spirits tax are statistically significant in the marijuana use equation, which was seen in the independent equation. Compared to the independent equation, the sign on the state cigarette tax changes. While most of the policy

variables are not statistically significant on their own, the LR test suggests that the 10 policy variables from both equations are jointly statistically significant. The joint statistical significance supports the inclusion of these policy variables as instruments.

Turning now to the demographic and geographic variables, the results in Table 9 are similar to those in the current literature (DeSimone 2002; Zhao and Harris 2004). White women are more likely to use alcohol or marijuana than black or Hispanic women, and white women are more likely to use alcohol than other race/ethnicity. Women with at least a high school diploma or GED are more likely to drink alcohol and less likely to use marijuana. Older women use alcohol, while younger women use marijuana. Women are less likely to drink alcohol when the unemployment rate is higher. Women who live in urban residence are more likely to use alcohol or marijuana, and women who live in the South are less likely to use alcohol or marijuana.

There are several takeaways from this chapter. First, the patterns suggested by the descriptive analysis and the independent models are inconsistent with the expected relationships discussed in Chapter V. Second, the estimates support the inclusion of unobserved heterogeneity that affects all four outcomes. Third, controlling for unobserved heterogeneity and jointly modeling eligibility, participation, alcohol use, and marijuana use yields the expected the expected relationships between eligibility, participation, and substance use described in Chapter V. Fourth, the results from Table 13 suggest that studies that do not address the endogeneity of substance will likely obtain estimates that overstate the effect of substance use on participation. Lastly, the estimates suggest that marijuana use in particular increases the probability of being eligible.

Table 6. Substance Use Prevalence Rates by TANF Eligibility for all Person-years

Variable	TANF Ineligible	TANF Eligible
Substance Use Measures		
No alcohol use+	0.37	0.62***
Infrequent alcohol use	0.30	0.23***
Frequent alcohol use	0.33	0.15***
No marijuana use+	0.86	0.91***
Infrequent marijuana use	0.07	0.04***
Frequent marijuana use	0.07	0.04***
Sample Size (person-years)	24,396	5,398

Note: Proportions may not sum to one due to rounding.
Significance: '*'=10%; '**'=5%; '***'=1%.
+ Omitted category in analysis

Table 7. Substance Use Prevalence Rates by TANF Participation for all Eligible Person-years

Variable	TANF Non-Participant	TANF Participants
Substance Use Measures		
No alcohol use+	0.63	0.57**
Infrequent alcohol use	0.23	0.24
Frequent alcohol use	0.14	0.18***
No marijuana use+	0.92	0.88***
Infrequent marijuana use	0.04	0.07**
Frequent marijuana use	0.04	0.06
Sample Size (person-years)	4,763	635

Notes: Proportions for may not sum to one due to rounding.
Significance: '*'=10%; '**'=5%; '***'=1%.
+ Omitted category in analysis

Table 8. Sample Means by Alcohol Use Category

Variable	No Alcohol Use	Infrequent Alcohol Use	Frequent Alcohol Use
TANF State			
Eligibility	0.27	0.14***	0.09***
Participation conditional on eligibility^	0.11	0.12	0.15***
Policy Variables			
Medical marijuana legal	0.19	0.21**	0.21***
Marijuana decriminalized	0.35	0.36*	0.35
Beer tax	$0.34	$0.30***	$0.28***
Cigarette tax	$0.89	$0.99***	$1.07***
Spirits tax	$4.45	$4.58**	$4.70***
Demographic Characteristics			
White+	0.35	0.51***	0.63***
Black	0.38	0.25***	0.16***
Hispanic	0.24	0.20***	0.18***
Other race	0.04	0.04	0.03*
Age	21.54	21.99***	22.30***
Years of education	12.47	13.16***	13.63***
Less than high school diploma+	0.23	0.14***	0.09***
High school diploma or GED	0.71	0.74***	0.72***
4 yr. college or more	0.06	0.12***	0.18***
Geographic characteristics			
Unemployment rate	5.69%	5.63%*	5.57%***
Urban residence	0.76	0.77	0.79***
Lives in the South	0.46	0.38***	0.34***
Sample Size (person-years)	12,394	8,676	8,724

Note: Proportions for categorical variables may not sum to one due to rounding error. Two differences are tested. The first is between no alcohol use and infrequent alcohol use. The second test is between no alcohol use and frequent alcohol use.

Significance: '*'=10%; '**'=5%; '***'=1%.

+ Omitted category in analysis

^ Full sample size for TANF participation is 5,398 TANF eligible person-years. There are 3,347 no use observations, 1,257 infrequent use observations, and 794 frequent use observations.

Table 9. Sample Means by Marijuana Use Category

Variable	No Marijuana Use	Infrequent Marijuana Use	Frequent Marijuana Use
TANF State			
Eligibility	0.19	0.12***	0.12***
Participation conditional on eligibility^	0.11	0.18**	0.16*
Policy Variables			
Medical marijuana legal	0.20	0.23***	0.20
Marijuana decriminalized	0.35	0.37	0.37
Beer tax	$0.31	$0.29***	$0.29***
Cigarette tax	$0.97	$1.02***	$1.03***
Spirits tax	$4.58	$4.36**	$4.50
Demographic Characteristics			
White+	0.46	0.60***	0.61***
Black	0.28	0.19***	0.23***
Hispanic	0.22	0.16***	0.13***
Other race	0.03	0.04	0.02***
Age	21.97	21.27***	21.61***
Years of education	13.04	12.96*	12.75***
Less than high school diploma+	0.17	0.14***	0.16
High school diploma or GED	0.72	0.76***	0.77***
4 yr. college or more	0.12	0.10***	0.07***
Geographic Characteristics			
Unemployment rate	5.66%	5.49%***	5.44%***
Urban residence	0.77	0.80***	0.81***
Lives in the South	0.41	0.32***	0.33***
Sample Size (person-years)	25,800	1,985	2,009

Note: Proportions for categorical variables may not sum to one due to rounding error. Two differences are tested. The first is between no alcohol use and infrequent alcohol use. The second test is between no alcohol use and frequent alcohol use.

Significance: '*'=10%; '**'=5%; '***'=1%.

+ Omitted category in analysis

^ Full sample size for TANF participation is 5,398 TANF eligible person-years. There are 4,931 no use observations, 235 infrequent use observations, and 232 frequent use observations.

Table 10. Random Effects Logit Estimates of Independent TANF Equations

Variables	Eligibility	Participation
Substance Use		
Infrequent alcohol use	-0.5738 *** (0.0614)	0.1967 (0.1471)
Frequent alcohol use	-0.9231 *** (0.0778)	0.2067 (0.1778)
Infrequent marijuana use	-0.3575 *** (0.1189)	0.6728 *** (0.2597)
Frequent marijuana use	-0.7967 *** (0.1323)	0.0246 (0.2891)
Demographic Characteristics		
Black	2.4046 *** (0.1476)	1.5251 *** (0.2379)
Hispanic	1.8921 *** (0.1528)	0.2003 (0.2684)
Other race/ethnicity	-0.2317 (0.2293)	0.3756 (0.6505)
High school graduate or GED	-0.6237 *** (0.0804)	-0.6892 *** (0.1649)
Four-year college degree	-1.8794 *** (0.2074)	-2.6518 ** (1.1542)
Age / 10	2.0632 *** (0.3426)	1.8906 *** (0.6228)
Geographic Characteristics		
Unemployment rate / 10	0.5980 *** (0.1891)	-0.2991 (0.3782)
Urban residence	0.0437 (0.0759)	0.5354 ** (0.2082)
South region	-0.0785 (0.0927)	-0.9535 *** (0.1884)
Year Effects		
1999	-0.0926 (0.2308)	0.2381 (0.5243)
2000	-0.0122 (0.2325)	-0.2235 (0.5220)
2001	-0.0003 (0.2313)	0.1550 (0.5067)
2002	0.0453 (0.2460)	0.0348 (0.5254)
2003	0.1819 (0.2615)	-0.3217 (0.5419)

Variables	Eligibility	Participation
2004	0.3503 (0.2839)	-0.3522 (0.5796)
2005	-0.9378 *** (0.3078)	-0.0380 (0.6076)
2006	-1.1254 *** (0.3343)	-0.6921 (0.6517)
2007	-1.3392 *** (0.3631)	-0.8293 (0.6963)
2008	-1.7616 *** (0.4099)	-0.9050 (0.7636)
2009	-1.7300 *** (0.4464)	-1.2472 (0.8396)
Other Variables		
Constant	-7.6671 *** (0.6247)	-7.4336 *** (1.2028)
Sigma	2.9022 *** (0.0751)	1.9545 *** (0.1274)
ln-L	-9048.34	-1600.81
Sample Size (person-years)	29,794	5,398
Likelihood Ratio Test Statistics (omitted variables)		
Alcohol use (2 df)	172.84 [0.0000]	2.32 [0.3141]
Marijuana use (2 df)	40.36 [0.0000]	6.64 [0.0361]
Alcohol and Marijuana use (4 df)	253.40 [0.0000]	10.66 [0.0308]

Note: Asymptotic standard errors in parentheses. p-values for likelihood ratio tests in brackets.
Significance: '*'=10%; '**'=5%; '***'=1%.

Table 11. Random Effects Ordered Logit Estimates of Independent Substance Use Equations

Variables	Alcohol	Marijuana
Policy Variables		
State cigarette tax ($/pack)	-0.0388 (0.0361)	0.0080 (0.0673)
State beer tax ($/gallon)	-0.2339 ** (0.1125)	0.5233 ** (0.2484)
State spirits tax ($/gallon)	-0.0057 (0.0041)	-0.0155 * (0.0079)
Medical marijuana legal	0.0498 (0.0705)	-0.1093 (0.1264)
Marijuana decriminalized	-0.1081 * (0.0626)	0.1282 (0.1040)
Demographic Characteristics		
Black	-1.6787 *** (0.0794)	-1.2913 *** (0.1667)
Hispanic	-0.9882 *** (0.0909)	-1.4674 *** (0.1597)
Other race/ethnicity	-0.9543 *** (0.1732)	-2.2181 *** (0.2928)
High school graduate or GED	0.6981 *** (0.0577)	0.2806 *** (0.0942)
Four-year college degree	1.0803 *** (0.0814)	-0.0790 (0.1426)
Age / 10	0.7786 *** (0.1926)	-1.7978 *** (0.3700)
Geographic Characteristics		
Unemployment rate / 10	-0.3402 *** (0.1023)	-0.0325 (0.1745)
Urban residence	0.1866 *** (0.0434)	0.3371 *** (0.0781)
South region	-0.2657 *** (0.0732)	-0.7609 *** (0.1278)
Year Effects		
1999	-0.2809 ** (0.1426)	0.3367 (0.2704)
2000	-0.0994 (0.1428)	1.0593 *** (0.2710)
2001	0.0048 (0.1418)	1.0649 *** (0.2698)

Variables	Alcohol	Marijuana
2002	0.1270 (0.1482)	1.1545 *** (0.2824)
2003	0.2189 (0.1560)	0.9099 *** (0.2982)
2004	0.0938 (0.1692)	1.0557 *** (0.3245)
2005	0.2954 (0.1798)	0.9909 *** (0.3462)
2006	0.2257 (0.1943)	1.0263 *** (0.3708)
2007	0.1654 (0.2097)	1.0656 *** (0.4022)
2008	0.2486 (0.2301)	1.5148 *** (0.4318)
2009	0.1777 (0.2503)	1.5623 *** (0.4729)
Other Variables		
Constant	0.0952 (0.3485)	0.5927 (0.6459)
Sigma	1.7146 *** (0.0267)	3.1430 *** (0.0551)
ln-L	-26707.33	-11748.49
Sample Size (person-years)	29,794	29,794
Likelihood Ratio Test Statistics (omitted variables)		
Policy Variables (5 df)	11.50 [0.0423]	8.82 [0.1165]

Note: Asymptotic standard errors in parentheses. p-values for likelihood ratio tests in brackets.
Significance: '*'=10%; '**'=5%; '***'=1%.

Table 12. Random Effects Logit Estimates of the Joint Model, Error Structure

Variable	Estimate
Factor Loadings (ρ)	
Eligibility	-0.2788 *** (0.0164)
Participation	0.0624 *** (0.0224)
Alcohol Use	0.4406 *** (0.0090)
Marijuana Use	1.0000
σ_{ξ}	3.0137 *** (0.0493)
ln-L	-53007.58

Note: Asymptotic standard errors in parentheses.
Significance: '*'=10%; '**'=5%; '***'=1%.

Table 13. Random Effects Logit Estimates of the Joint Model, TANF Equations

Variables	Eligibility	Participation
Substance Use		
Infrequent alcohol use	0.0442 (0.0482)	0.0624 (0.1195)
Frequent alcohol use	0.0137 (0.0640)	0.1117 (0.1409)
Infrequent marijuana use	0.6153 *** (0.0878)	0.3373 * (0.2011)
Frequent marijuana use	1.0322 *** (0.1034)	-0.0651 (0.2293)
Demographic Characteristics		
Black	1.2428 *** (0.0561)	1.1124 *** (0.1234)
Hispanic	0.6288 *** (0.0585)	0.1966 (0.1460)
Other race/ethnicity	0.1031 (0.1229)	0.4832 (0.3009)
High school graduate or GED	-1.4142 *** (0.0448)	-0.5425 *** (0.0910)
Four-year college degree	-3.6883 *** (0.1442)	-2.5771 ** (1.0178)
Age / 10	1.9079 *** (0.1476)	1.1995 *** (0.3260)
Geographic Characteristics		
Unemployment rate / 10	0.3879 *** (0.0965)	-0.2763 (0.2454)
Urban residence	0.0070 (0.0459)	0.6503 *** (0.1459)
South region	-0.0212 (0.0434)	-0.7543 *** (0.0992)
Year Effects		
1999	0.1386 (0.1710)	-0.2089 (0.4164)
2000	0.2456 (0.1694)	-0.3818 (0.4128)
2001	0.2777 * (0.1616)	-0.3100 (0.3876)
2002	0.3056 * (0.1623)	-0.3404 (0.3899)
2003	0.4251 *** (0.1634)	-0.4948 (0.3885)

Variables	Eligibility	Participation
2004	0.5724 *** (0.1699)	-0.6568 (0.4032)
2005	-0.2580 (0.1763)	-0.2190 (0.4088)
2006	-0.3741 ** (0.1836)	-0.5875 (0.4243)
2007	-0.5375 *** (0.1921)	-0.6769 (0.4428)
2008	-0.8943 *** (0.2062)	-0.7604 (0.4752)
2009	-0.7744 *** (0.2253)	-0.9701 * (0.5264)
Constant	-5.5471 *** (0.3087)	-4.4951 *** (0.7088)
Sample Size (person-years)	29,794	5,398
Likelihood Ratio Test Statistics (omitted variables)		
Alcohol use (2 df)	0.954 [0.6206]	0.666 [0.7168]
Marijuana use (2 df)	105.06 [0.0000]	3.18 [0.2038]
Alcohol and Marijuana use (4 df)	116.98 [0.0000]	4.00 [0.4063]

Note: Asymptotic standard errors in parentheses. p-values for likelihood ratio tests in brackets.
Significance: '*'=10%; '**'=5%; '***'=1%.

Table 14. Random Effects Logit Estimates of the Joint Model, Substance Use Equations

Variables	Alcohol	Marijuana
Policy Variables		
State cigarette tax ($/pack)	-0.0524 * (0.0278)	-0.0638 (0.0559)
State beer tax ($/gallon)	-0.0869 (0.0839)	0.3729 ** (0.1858)
State spirits tax ($/gallon)	-0.0049 (0.0037)	-0.0127 * (0.0074)
Medical marijuana legal	-0.0545 (0.0486)	-0.1056 (0.0968)
Marijuana decriminalized	-0.0481 (0.0410)	0.1365 (0.0861)
Demographic Characteristics		
Black	-1.4632 *** (0.0560)	-1.0899 *** (0.1313)
Hispanic	-0.9281 *** (0.0590)	-1.7167 *** (0.1331)
Other race/ethnicity	-0.6085 *** (0.1049)	-0.1837 (0.1943)
High school graduate or GED	0.6197 *** (0.0460)	-0.1409 (0.0911)
Four-year college degree	1.1604 *** (0.0661)	-1.0307 *** (0.1421)
Age / 10	0.7622 *** (0.1388)	-1.1269 *** (0.2986)
Geographic Characteristics		
Unemployment rate / 10	-0.4362 *** (0.0814)	0.0935 (0.1590)
Urban residence	0.1745 *** (0.0362)	0.2079 *** (0.0720)
South region	-0.3264 *** (0.0526)	-0.6272 *** (0.1144)
Year Effects		
1999	-0.1835 (0.1330)	0.2130 (0.2456)
2000	-0.0167 (0.1323)	0.8561 *** (0.2440)
2001	0.0622 (0.1284)	0.9229 *** (0.2400)

Variables	Alcohol	Marijuana
2002	0.1999 (0.1308)	0.9445 *** (0.2472)
2003	0.2792 ** (0.1341)	0.7319 *** (0.2584)
2004	0.1426 (0.1419)	0.8734 *** (0.2756)
2005	0.3266 ** (0.1473)	0.7658 *** (0.2903)
2006	0.2437 (0.1560)	0.8245 *** (0.3110)
2007	0.1491 (0.1651)	0.8645 *** (0.3323)
2008	0.2775 (0.1782)	1.1997 *** (0.3635)
2009	0.2411 (0.1946)	1.2561 *** (0.3958)
Constant	0.1609 (0.2665)	-0.1189 (0.5449)
Sample Size (person-years)	29,794	
Likelihood Ratio Test Statistic (omitted variables)		
Policy Variables (10 df)	29.60 [0.0010]	

Note: Asymptotic standard errors in parentheses. p-value for likelihood ratio test in brackets.
Significance: '*'=10%; '**'=5%; '***'=1%.

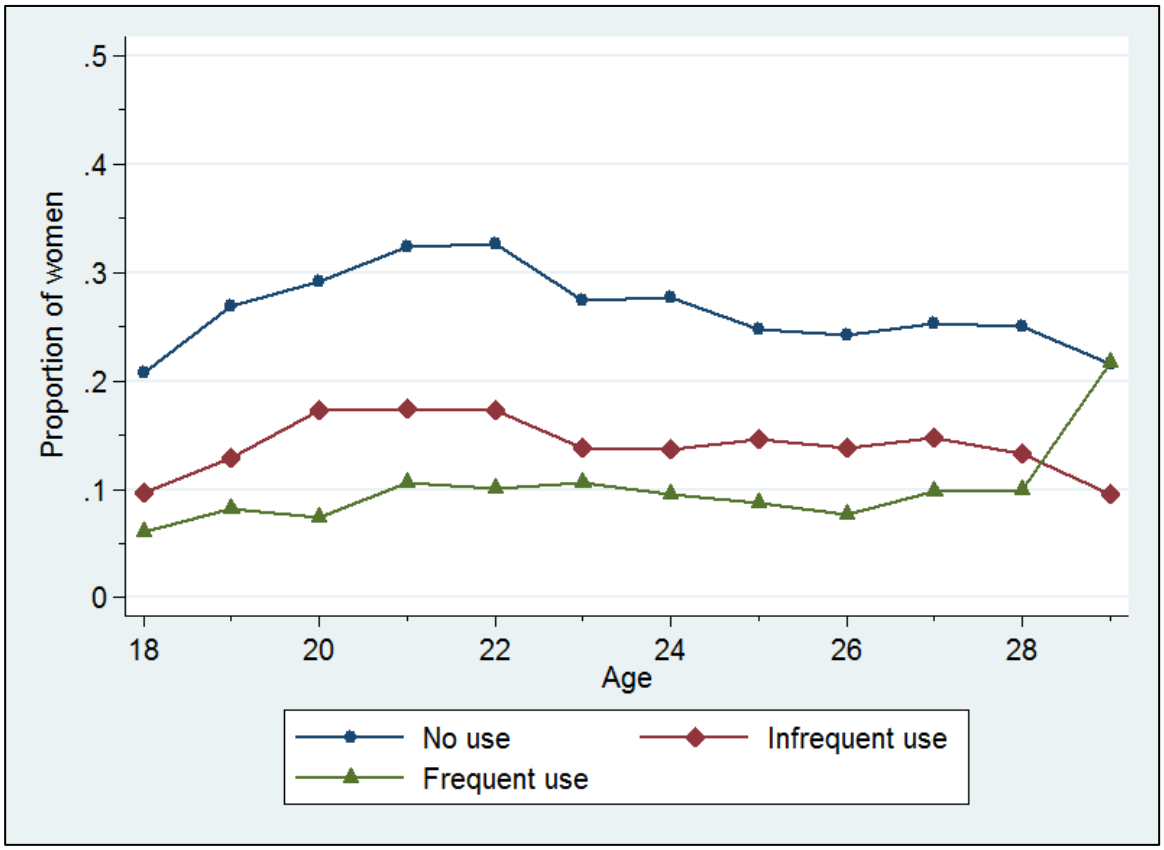

Figure 7. Proportion of TANF Eligible Women by Alcohol Use Categories

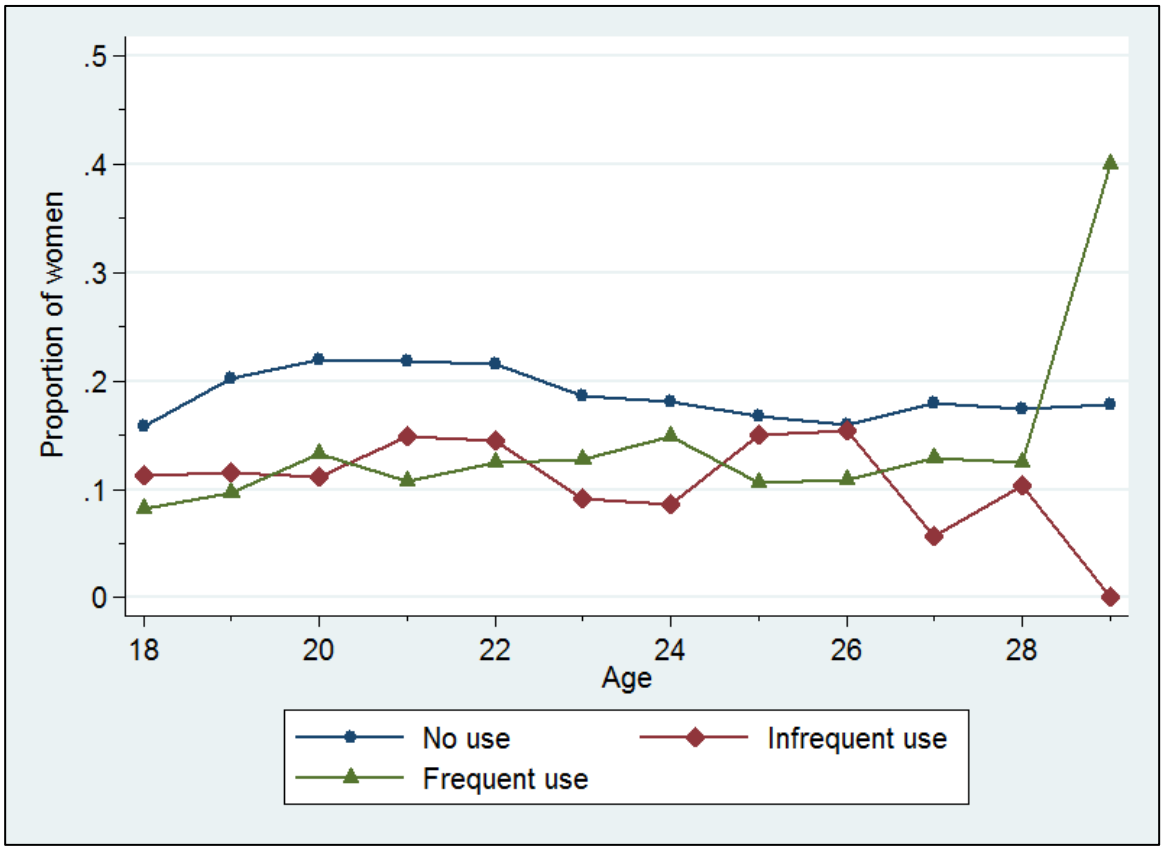

Figure 8. Proportion of TANF Eligible Women by Marijuana Use Categories

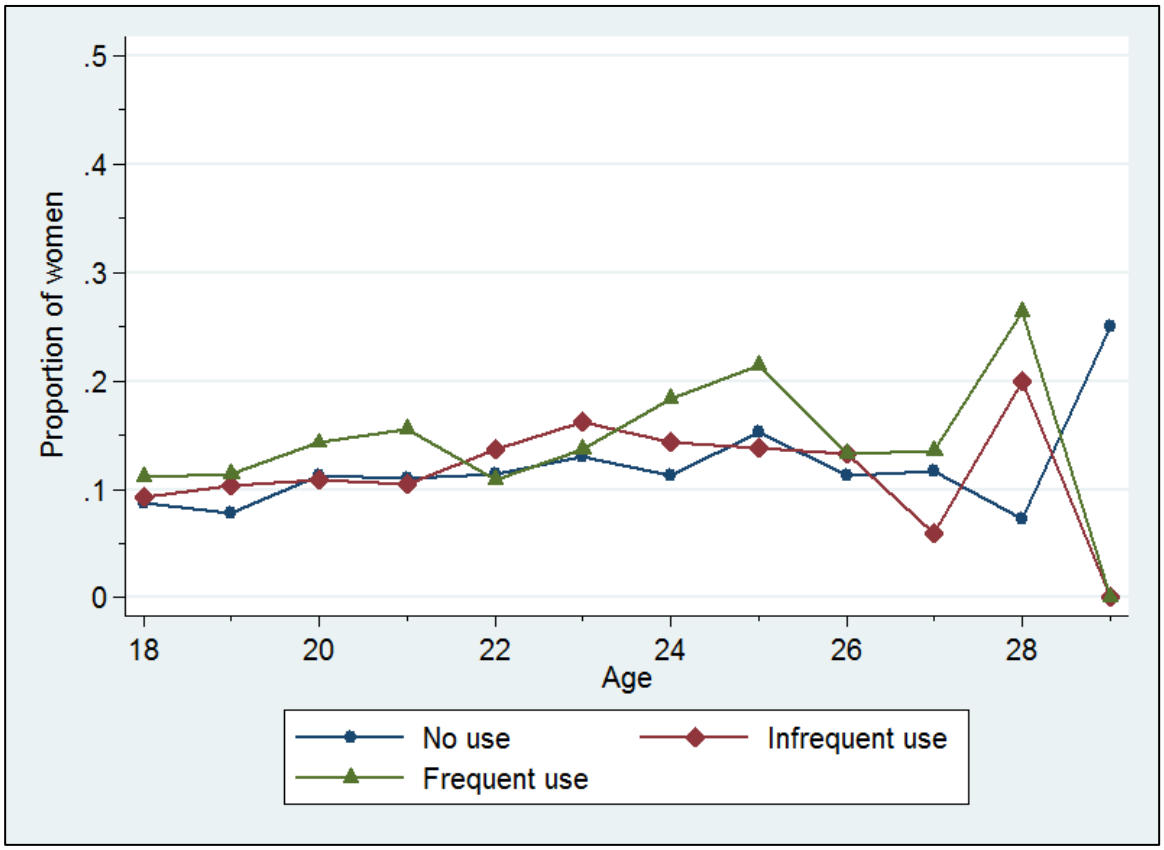

Figure 9. Proportion of TANF Participants by Alcohol Use Categories

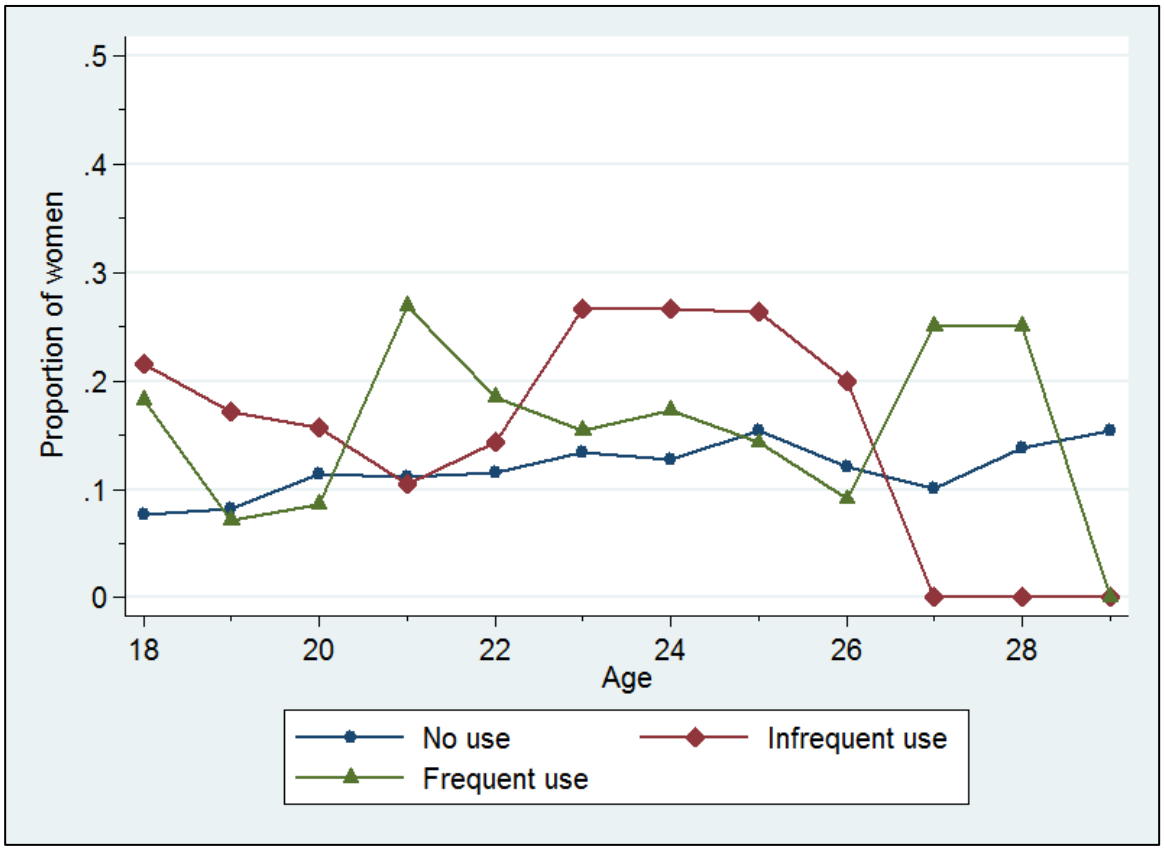

Figure 10. Proportion of TANF Participants by Marijuana Use Categories

CHAPTER VII

CONCLUSION

TANF is a public assistance program that has received considerable attention since its creation in 1996. With origins in the Great Depression as a way to help women raise their children, program rules have become progressively stricter. As it stands today, women in at least 12 states now are subject to drug testing, provided there is reasonable suspicion of drug use. With this current policy trend as a backdrop and research suggesting inefficiencies in identifying substance users through drug screening and testing (e.g., Crew and Davis 2003), it is more important than ever to understand how substance use causally affects TANF eligibility and participation.

There are two key takeaways from this dissertation. First, the previous literature has not addressed the potential endogeneity of substance use. My results suggest that eligibility, participation, and substance use depend on unobserved characteristics that are correlated across equations. While random effects logit models control for unobserved heterogeneity, these models assume the random effect (i.e., unobserved heterogeneity) is uncorrelated with the independent variables (e.g., substance use). Thus, to control for unobserved heterogeneity and allow for correlation between unobserved heterogeneity and substance use, I jointly estimate eligibility, participation, alcohol use, and marijuana use equations. The results show that addressing endogeneity through the joint model defined in Chapter V and controlling for unobserved heterogeneity are important components of estimating the effect of substance use on TANF eligibility and participation.

Comparing the joint model results to the bivariate descriptive statistics and independent models, it appears that failing to control for the endogeneity of substance use biases the coefficient estimates on alcohol and marijuana use. Compared to the independent model, the substance use coefficient estimates in the joint model increase in magnitude and switch signs in the eligibility equation. The substance use coefficient estimates in the participation equation become smaller when addressing the endogeneity of substance use. In particular, the estimated effect of infrequent marijuana use is cut in half. Ultimately, it appears that substance use increases eligibility, but substance use has no effect on participation conditional on eligibility. Specifically, after addressing endogeneity, infrequent and frequent marijuana use increases eligibility, and infrequent marijuana use increases participation.

Second, the previous literature has not addressed the relationship between substance use and TANF eligibility. This is important as my results suggest that marijuana use increases the probability of eligibility. Moreover, it is not sufficient to simply estimate the effect of substance use on eligibility, but it is necessary to allow for substance use to be endogenous in the eligibility equation as well as the participation equation. Again, the independent model of eligibility suggests that substance use decreases the probability of eligibility. After addressing the potential endogeneity of substance use I find that substance use actually increases the probability of TANF eligibility.

As with all empirical work, there are limitations to this study. One limitation of this dissertation is with how eligibility is inferred. Recall from the discussion in Chapter IV that eligibility was created using gross income and the number of children. The approach taken is similar to that taken by others (e.g., Moffitt 1983 or Swann 2005). TANF eligibility, however,

depends on more criteria than income and children. Each state is allowed to define its eligibility criteria, which includes an asset test and has various income-disregard rules. States often have rules with respect to how much income is counted from other household members. Given the complexity of eligibility criteria, it is clear that the imputed eligibility used in this dissertation is imperfect. Future studies should consider using more information to impute eligibility, which will provide for a more accurate variable. Specifically, the closer the eligibility variable definition resembles each state's eligibility criteria, the less likely individuals are misclassified.[26]

A second caveat is that the model presented in Chapter V assumes that neither eligibility nor participation affect substance use. This assumption rules out the possibility that being unemployed, and thus eligible, affects substance use.[27] The assumption also rules out the possibility that participation affects substance use through increased income—a result of the benefits received. Such an assumption is common in policy studies. For example, studies of the effect of food stamp participation on food insecurity frequently assume that food insecurity does not affect food stamp participation (e.g., Schaefer and Gutierrez 2013 among others).

Similar to other empirical studies, there are limitations to the data. One data limitation is the policy variables (i.e., instruments). While the policy variables are jointly statistically significant in the preferred model, only one variable is statistically significant in the alcohol equation and two are statistically significant in the marijuana equation. Price data would be another instrument to consider, but reliable marijuana price data are not available

[26] Misclassification is likely the reason for the relatively low take-up rates reported in Chapter IV.

[27] There is evidence that long-term unemployment and inconsistent employment patterns increase substance use (Jin, Shah, and Svoboda 1995; Lahelma, Kangas, and Manderbacka 1995; Claussen 1999).

across all states for this time period. Additionally, more geographic controls could be considered—ideally state effects. However, based on my sample size, specifically with respect to the number of women participating in TANF, it is unlikely that state dummies could be added. Finally, an "other/hard drugs" variable that groups together illicit drugs like cocaine or heroin could be considered. The challenge is that fewer people use these substances than marijuana which would result in a very small sample size of other/hard drug users.[28]

There are additional avenues for future research. The simplest extension of this dissertation is to apply the joint model to other public assistance programs. Extending this model to the Supplemental Nutrition Assistance Program (SNAP) is a likely first choice because the Gramm Amendment prohibits drug felons from receiving SNAP benefits. Applying this model to SNAP would also be interesting because it would be a deviation from the current research trends which are more focused on obesity and food security. Provided sufficient data are available, the joint model in this dissertation could also be used to investigate the relationship between substance use and the Supplemental Security Income (SSI) program.

This is the first study to explicitly model eligibility with respect to assessing the effect of substance use on TANF eligibility and participation. Furthermore, this dissertation addresses the endogeneity of substance use in models of TANF eligibility and participation. Ultimately, I find that it is important to allow substance use to be endogenous when considering eligibility and participation and that substance use, particularly marijuana use, has

[28] While considering the inclusion of this other/hard drugs, a sensitivity analysis could be conducted to see if and how results change by combining marijuana use with other/hard drug use.

a large and positive effect on TANF eligibility, but only infrequent marijuana use has a statistically significant effect on TANF participation.

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